# Multi-objective optimization for school buildings retrofit combining artificial neural networks and life cycle cost

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ABSTRACT: The renovation of a school building should be regarded as a process of combining a number of variables and objectives, sometimes conflicting, including energy, indoor environmental quality and costs (initial, operational and maintenance), on a search for an "optimum solution". This multi-objective optimization procedure is particularly important in a time of severe economic crisis, with few available financial resources and, as such, their management and the investment decisions require great prudence from the decision maker. In this research a methodology to optimize the insulation thickness of external walls and roof, in the retrofit of two school buildings, is proposed. The school performance was defined considering two objectives: the annual heating load and the discomfort in the classrooms due to overheating. The calculation of the performance functions implies an annual simulation of the building and Artificial Neural Networks were training to approximate them. The minimization of the Life Cycle Cost of external walls and roof retrofit allowed the economic optimization of the insulation width.

## 1. INTRODUCTION

The energy efficiency of buildings, including public buildings, is a major concern for all European governments. In Portugal, public buildings are responsible for more than 50% of the total energy bill of the state and school buildings play an important role in these costs. The best strategy to reverse this scenario includes efforts on the retrofit of these buildings, improving their energy efficiency, without sacrificing the indoor environmental quality.

The renovation of a school building should be regarded as a process of combining a number of variables and objectives, sometimes conflicting, including energy, indoor environmental quality and costs (initial, operational and maintenance), on a search for an "optimum solution". This multi-objective optimization procedure is particularly important in a time of severe economic crisis, with few available financial resources and, as such, their management and the investment decisions require great prudence from the decision maker.

The compatibility of conflicting objectives in building retrofit optimization procedures is often accomplished by the creation of a large number of construction scenarios, that establishes the decision space, which are simulated and evaluated, resulting in a ranking of the solutions (Santamouris et al. 2007; Diakaki et al. 2008; Calise 2010).

This method is relatively fast and easy to implement, however, the final solution is restricted to the scenarios that were defined. This limitation can be overcome by other approaches based on more complex numerical methods, where the decision space is extended and optimization procedures based on evolutionary algorithms, such as the genetic algorithms, are applied. These methods, when applied to problems with more than one objective, result in a set of optimal solutions, each of which represents a particular level of compromise between the objectives (Pareto front). The optimal solutions of Pareto are situated in a region where it is not possible to improve any of the objectives without degrade at least one of the other objectives (Deb 2001).

However, the evolutionary algorithms require a large number of data, making it almost impractical when applied directly to the thermal and energy computer simulation of complex models over extended periods. This problem can be overwhelmed using Artificial Neural Networks (ANN), trained to approximate the results of the simulation (Kawashima et al. 1995; Tso & Yau 2007).

Other difficulty related to the application of this multi-objective optimization methodology relates to the final choice of a single solution, since all the solutions belonging to the Pareto front are optimal and, therefore, theoretically, none is better than another. One possibility to overcome this is employing a life cycle cost (LCC) analysis in parallel with the multi-objective optimization. The use of LCC analysis is common in buildings retrofit optimization. Gustafsson (2000) applied this method for the optimization of insulation measures in existing buildings. Hasan et al. (2008) have used LCC, combined with simulation, on the optimization of the U-values of typical Finnish constructions.

In this research a methodology to optimize the insulation thickness of the external wall and roof on the retrofit of two typical Portuguese school buildings is proposed. The first part includes the optimization of the building performance considering two objectives: the minimization of the annual heating load and the minimization of the discomfort in the classrooms due to overheating. The second part was the minimization of the LCC of retrofitting external walls and roof, which corresponds to the economic optimization of the insulation thickness.

The school buildings were simulated with the software EnergyPlus and two performance functions were created to quantify the objectives. The calculation of the performance functions implies an annual simulation of the building. Since these simulations are time consuming and an optimization procedure requires a large number of data, it was decided to use ANN to predict the value of the functions. Then, the ANN were optimized using the NSGA-II genetic algorithm. The result was the Pareto front of optimal solutions considering the two objectives.

The computation of the LCC of a specific retrofit solution requires the first performance function, since it estimates the annual heating load of the building. The impact of the solution obtained in the minimization of the LCC in the classroom thermal comfort was then achieved by comparison with the Pareto front.

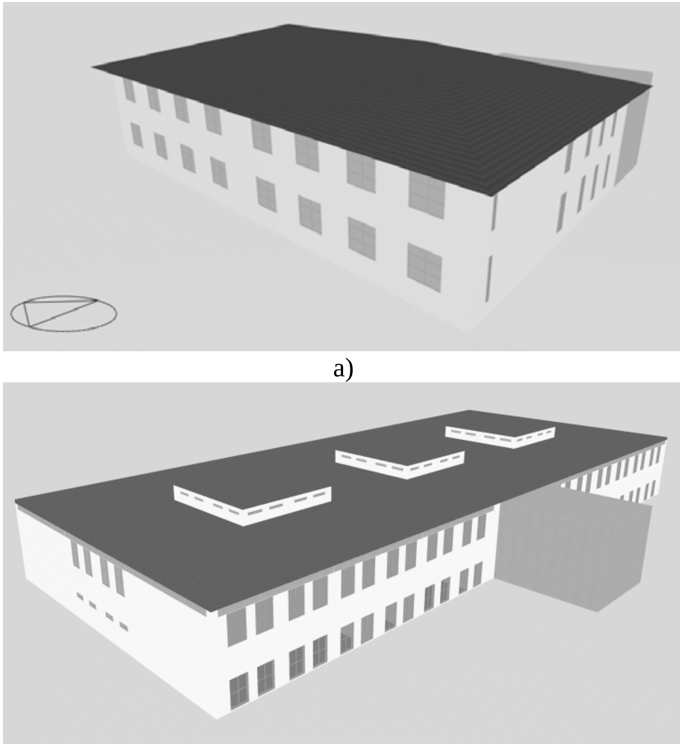
## 2. METHODOLOGY

### *2.1. Simulation models*

In this research two typical Portuguese school buildings have been studied (model A and model B). The building models were created with Design-Builder (Figure 1) and the software chosen for the simulations was EnergyPlus. Four types of zones were considered, each with specific metabolic rates, occupation density and schedules: classroom, circulation, storage and toilet. For the classroom zone was defined a metabolic rate of 94 W/person with an occupation density of 0,40 persons/$m^2$. The simulations were performed on annual bases, with hourly outputs, and 10 time steps per hour. It was considered a summer holiday period of two months, July and August, and a two weeks break in Christmas.

The schools original walls and roof have no insulation, the windows are single glass, there are no heating systems and the ventilation is natural, dependent on the window opening and infiltrations. The values considered in the simulation for the most relevant construction elements properties were defined after a complete survey carried on 20 school buildings. Blinds with medium reflectivity slats were considered as shading devices, with operation by solar radiation control with a set point of 120 W/$m^2$. The air change rate was evaluated experimentally by tracer gas measurements considering different envelope scenarios. The simulation models were validated with *in situ* measurements, as stated in Almeida & Freitas (2010). The retrofitting proposal comprises the introduction of insulation in walls and roof, improvement in the window properties and inclusion of hot water radiators as heating systems.

Since the measurements performed in these buildings revealed that, in winter conditions, temperature is below comfort limits, it is considered in this study that the introduction of heating systems is essential and, as so, when is referred the current performance of the building we are assuming the inclusion of the hot water radiators.



a)

b)

Figure 1. Simulation models: a) model A; b) model B.

The methodology includes simulation in three locations, A, B and C, each with a weather that is considered characteristic of its region and that together represent the different climatic conditions in Portugal. For each, it was also considered four different orientations. Detailed information can be found in Almeida & Freitas (2011).

### *2.2. Decision variables and objective functions*

The main objective of this work is to propose a methodology for the optimization of retrofit solutions for school buildings rehabilitation, based on criteria of energy efficiency, occupant's thermal comfort and LCC. Therefore, the methodology requires the definition of decision variables and objective functions in order to start the multi-objective optimization procedure.

The selected decision variables are properties of the constructive elements of the building envelope whose value is typically improved in a retrofit intervention, namely the heat transfer coefficient of external walls ($U_{wall}$), roof ($U_{roof}$) and windows ($U_{win-}$

dow) and the total solar energy transmittance of windows ($G_{window}$). Since building ventilation represents a major contribution for both energy performance and thermal comfort, the air change rate (ACR) was also considered as decision variable.

Previous studies (Guedes et al. 2009; Almeida & Freitas 2010) have concluded that the Portuguese climate allows the use in schools of simple ventilation systems, with a strong natural component, that combined with a heating system, such as hot water radiators, guarantee adequate temperatures and indoor air quality. However, overheating could be a problem in some classrooms.

Hence, two performance functions were created. The first is the annual heating load, defined as the necessary energy to guarantee a minimum temperature of 20ºC inside the classrooms and the second function intends to assess the discomfort in the classrooms due to overheating by quantifying the time with temperatures above 25ºC, both considering only the theoretical period of occupation (8:30 to 18:00). The functions are obviously dependent on the five decision variables stated before and were computed from the results of the annual simulations of the building performed with EnergyPlus, as defined in Equations 1 and 2:

$$\begin{cases} f_1\left(U_{wall}, U_{roof}, U_{window}, G_{window}, ACR\right) = \dfrac{\sum_{year} H.L.}{A} \\ T_{\text{int}} \geq 20^{o}C \end{cases} \tag{1}$$

$$\begin{cases} f_2\left(U_{wall}, U_{roof}, U_{window}, G_{window}, ACR\right) = \dfrac{\sum_{year} \left(T_{\text{int}} - 25\right)}{A} \\ T_{\text{int}} > 25^{o}C \end{cases} \tag{2}$$

where $H.L.$ = hourly heating load (kWh); $A$ = net floor area of the building ($m^2$); $T_{int}$ = hourly average interior temperature (ºC). $H.L.$ and $T_{int}$ are outputs of the simulation.

## 2.3. *Artificial Neural Networks*

The main concept of ANN is learning. After the definition of the internal architecture, the ANN starts an iterative self-learning procedure of a function by adjusting the internal weights. This training process requires the definition of input data, and respective outputs, in a sufficient number to cover all de variables space in order to achieve reliable approximations. After training, the ANN should be validated with a different set of input/output data.

The architecture of the networks was of the multilayer feedforward type with backpropagation, 20 neurons, 5 inputs and 1 output, as schematically described in Figure 2. The training algorithm was the Levenberg-Marquardt with Bayesian regulation.

The required training sample was defined using the Latin Hypercube Sampling method, which guarantees an effective distribution of the data over the variables space.

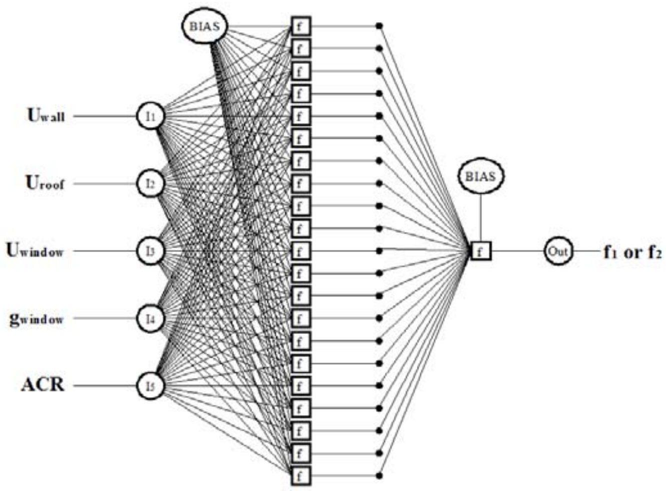


Figure 2. ANN architecture.

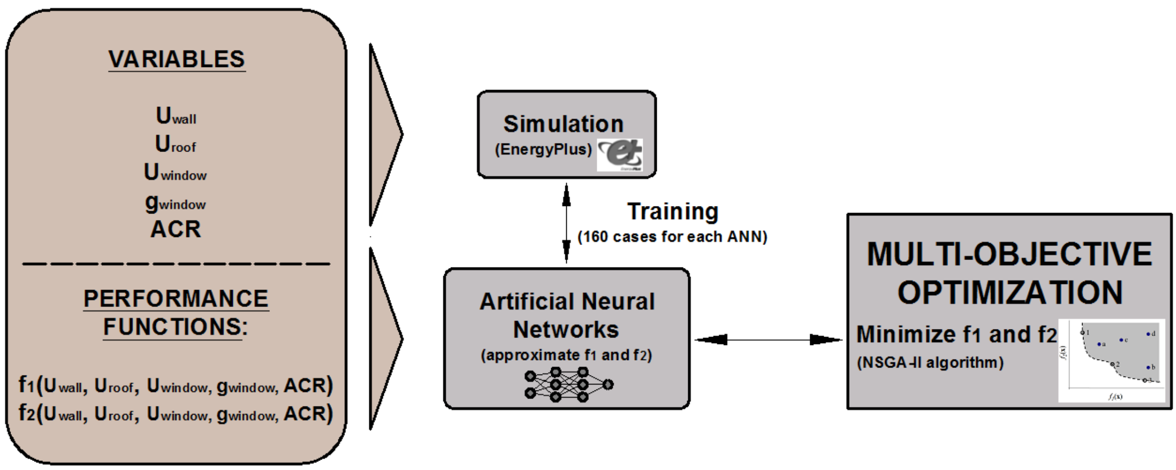


Figure 3. Multi-objective optimization methodology.

### 2.4. Multi-objective optimization

The most common multi-objective optimization procedures are the evolutionary algorithms, inspired from Darwin's theory of natural selection. These algorithms are based on stochastic approaches and their main advantage is that a large number of solutions (population) are used is each iteration, instead of improving one single solution. Additionally, in these algorithms, spreading of the solution front is ensured by internal operators such as the Crowding Distance.

The multi-objective algorithm chosen for this research was the NSGA-II, developed by Deb (2001). This algorithm has been successfully employed in several studies regarding building optimization (Magnier & Haghighat 2010; Suga et al. 2010; Chantrelle et al. 2011). Figure 3 schematically describes the optimization methodology.

### 2.5. Life Cycle Cost

LCC is the sum of the present value of investment and operating costs for the building and service systems, including those related to maintenance and replacement, over a specified life span. In the context of this investigation, the absolute value of the LCC of each solution is not required. It can be substituted by the difference $dLCC_i$, between the LCC for any case *i* and that for the reference case. This way, there is no need to include cost data for all components of the building but only the differences produced by the variation on the insulation thickness between the reference case and any other case. This methodology was proposed and applied by Hasan et al. 2008. Thus, the LCC difference, $dLCC_i$, for this situation is:

$$dLCC_i = (dIc)_i + (dOc)_i \tag{3}$$

where $dIc$ = difference in the initial investment cost (€); $dOc$ = is the difference in the operating cost (€).

The difference in the initial investment cost of a retrofit scenario *i* can be computed from:

$$(dIc)_i = \left[ C_{ins} \times \lambda_{ins} \times S \times \left( \frac{1}{U_{re}} - \frac{1}{U_{ini}} \right) \right]_i \tag{4}$$

where $C_{ins}$ = cost of insulation (€/m$^3$); $\lambda_{ins}$ = thermal conductivity of the insulation (W/(m.K)); $S$ = area of the constructive element, wall or roof (m$^2$); $U_{re}$ = heat transfer coefficient of the retrofitted element (W/(m$^2$.K)); $U_{ini}$ = heat transfer coefficient of the element before retrofit (W/(m$^2$.K)).

dOc is due to the difference in the annual heating load. dOc calculated to present value, for scenario *i*, is:

$$(dOc)_i = \left[ df \times c_e \times (HD_{re} - HD_{ini}) \right]_i \tag{5}$$

where $df$ = discount factor which takes into account the effect of inflation and variation of energy price; $c_e$ = energy price (€/kWh); $HD_{re}$ = annual heat demand after retrofit (kWh); $HD_{ini}$ = annual heat demand before retrofit (kWh).

The discount factor $df$ is calculated from:

$$df = \frac{1 - (1+r)^{-n}}{r} \tag{6}$$

where $r$ = real interest rate; $n$ = period of analysis (years).

$HD_{re}$ and $HD_{ini}$ are the output of the first performance function and can be estimated from the respective ANN.

## 3. MULTI-OBJECTIVE OPTIMIZATION

The first multi-objective optimization procedure was the minimization of the two performance functions, $f_1$ (energy) and $f_2$ (overheating), described in Equations 1 and 2. The evolutionary algorithm, specifically the genetic algorithm NSGA-II available in a Matlab Toolbox, was employed.

The optimization was performed for all models, locations and orientations. As an example, Figure 4 shows the Pareto front obtained for the building model A, with east orientation, considering the three locations under study. It is also included the point that represents the current performance of the building, as stated before, assuming that hot water radiators were introduced.

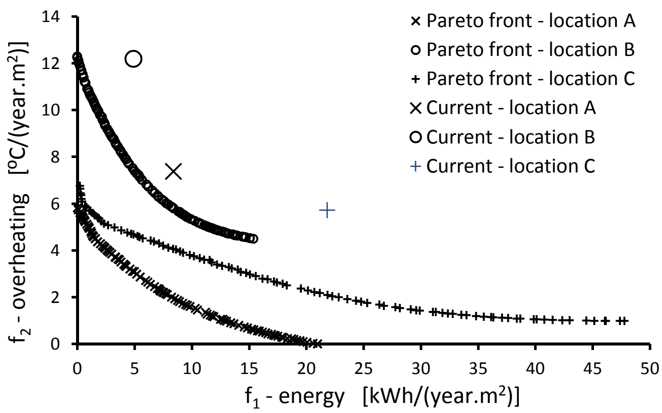



Figure 4. Multi-objective optimization.

Results have revealed that there is a significant improvement potential for all locations and, it was also clear, that it is directly related to the climate: location B is conditioned by function $f_2$, since in this location summer conditions are decisive; location C is strongly conditioned by function $f_1$, since in this location winter conditions are more severe; location A has the mildest climate.

However, it is noted that the results obtained are highly dependent on the minimum and maximum limits imposed on the variables. In fact, most of the optimal solutions correspond to unrealistic constructive scenarios, especially for the ACR, with very low values that cannot be considered valid, since that would lead to inadequate indoor air quality inside classrooms. Therefore, it was decided to proceed to a new multi-objective optimization, establishing a minimum ACR of 1.5 $h^{-1}$, which corresponds to 3.125 l/(s.person). Figure 5 shows the results for this optimization, for the same building model.

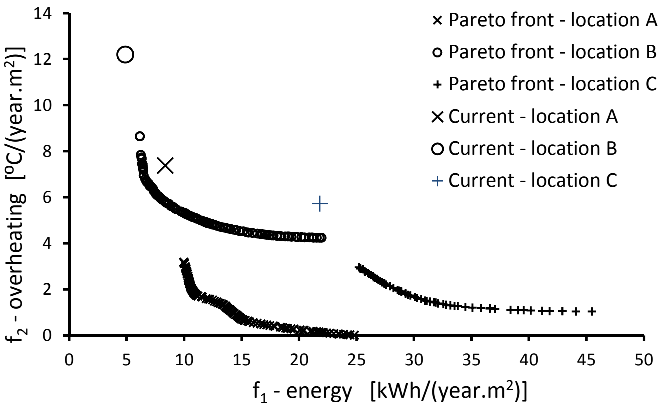



Figure 5. Multi-objective optimization with minimum ventilation.

Results are significantly different from those obtained initially, since Pareto fronts are now less dispersed. In fact, the initial variability of the optimum solutions resulted from the possibility of considering low ACR, allowing for constructive scenarios with unrealistic heating energy demands.

Another important feature, which results from the imposition of a minimum ventilation rate, is that, the solution adopted for the rehabilitation will always lead to an increase in the annual heating load. As described in Almeida & Freitas (2010), current Portuguese school buildings do not provide their users appropriate indoor air quality conditions, allowing, in this way, a minimization of the heating energy demand. In short, the necessary improvement of the indoor air quality will correspond to an increase in the operational cost of the building.

## 4. LIFE CYCLE COST

### *4.1. Introduction*

The methodology described in section 2.5 was implemented for the calculation of the optimum thickness of insulation for walls and roofs in school buildings retrofit. To this end, it was created a software tool, developed in Excel VBA, entitled *Life Cycle Cost (LCC) for School Buildings Retrofit*. This application allows optimizing the life cycle cost of the insulation, after the definition of the economic scenario and the period of analysis (Figure 6).

Since this analysis does not include the discomfort due to overheating on the classrooms, it was necessary to introduce an additional procedure, which allows to indirectly accounting the impact of the optimum solution on the thermal comfort. Thus, it is possible to access the graphical representation of the point corresponding to the optimum solution and compare it with both the current situation of the building and the Pareto front of optimum solutions obtained in the multi-objective optimization of the two performance functions.

To make the application as comprehensive as possible, the user can define all the variables required to the complete characterization of the problem. The input data can be gathered in three groups: initial options, which include model type, location, orientation and air change rate; investment, which include insulation price and its thermal conductivity; and economic analysis, which include period of analysis, energy price, real interest rate, inflation and the expected variation on the energy price.

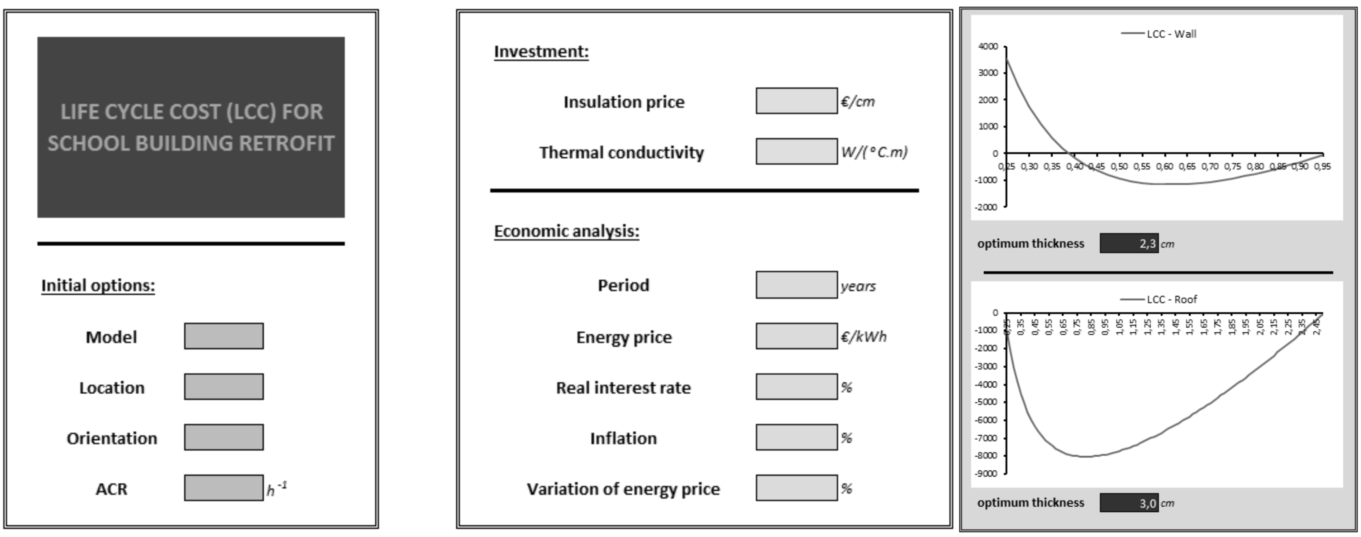



Figure 6. Software layout.

## 4.2. Case study

To illustrate the applicability of the tool it was analysed a school building located in Oporto (location A), with west orientation, whose constructive characteristics corresponds to the simulation model A (Figure 7). It was considered an air change rate of 2.0 $h^{-1}$.

Table 1 includes the values considered for the investment and economic analysis inputs.

Figure 7. Case study.

Table 1. Case study inputs

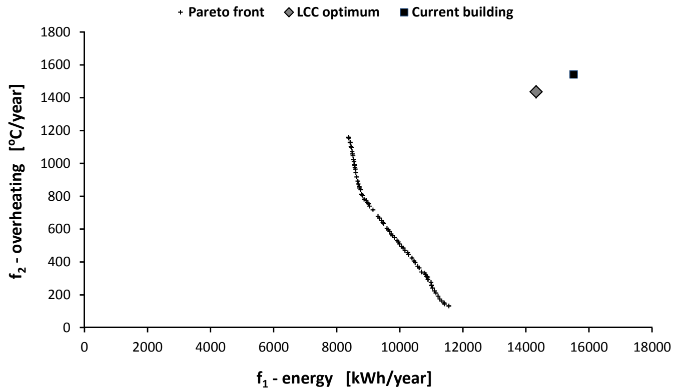
| | |
|---|---|
| Insulation price [€/cm] | 2.0 |
| Thermal conductivity [W/(K.m)] | 0.037 |
| Period [years] | 50 |
| Energy price [€/kWh] | 0.14 |
| Real interest rate [%] | 4.0 |
| Inflation [%] | 2.0 |
| Variation of energy price [%] | 1.0 |

The optimum insulation thickness achieved by the minimization of the LCC was 5.4 cm and 4.2 cm, for walls and roof, respectively.

After the optimization, the effect of the chosen solutions on the thermal discomfort due to overheating can be assessed by visualizing the graphical representation of the respective point against the Pareto front of optimum solutions and the point of the current building. Figure 8 contains this representation for the case study.

It shows that the optimum solutions obtained in the minimization of the LCC also have a positive effect on the thermal comfort of the classrooms. Nevertheless, the positive effect of roof insulation is more relevant than the one obtained with the wall insulation.

The main weakness of the tool is that it doesn't allow realizing the combined effect of the two optimum solutions.

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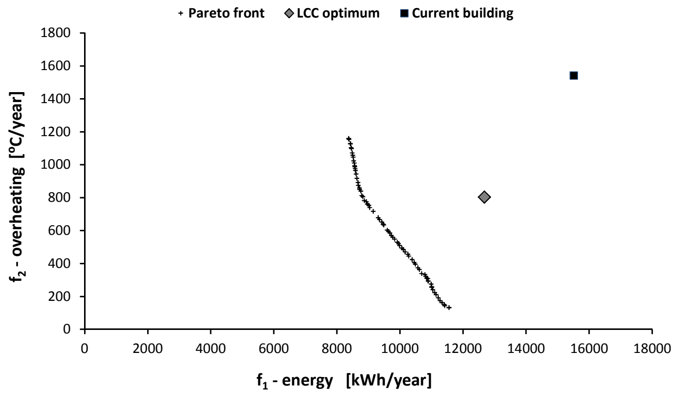


b)

Figure 8. Pareto front: a) wall; b) roof.

## 4.3. Parametric analysis

Testing the application with some examples becomes clear that the economic scenario created is decisive for the final result. By manipulating these variables it can be obtained a large variety of solutions. So, their definition, by the decision maker, should be based on very well established criteria, otherwise the solution will have no technical support.

To highlight this fact, a parametric analysis of the economic variables has been carried, seeking to realize their impact on the final solution. It was considered the school model A, east oriented and assuming an ACR of 2.0 $h^{-1}$. Two periods of analysis were defined: 25 and 50 years.

The first parametric analysis was on the variation of the real interest rate. All the other economic inputs were maintained constant, equal to ones presented in Table 1. Figure 9 shows the results obtained.

In the parametric analysis on the variation of energy price a real interest rate of 7% was admitted and the other parameters kept constant. The results are shown in Figure 10.

As it was expected, results show that a shorter period of analysis dilutes the impact of the economic parameters. Overall, it is clear that there is enormous variability in the solutions, based on the definition of the economic scenario.

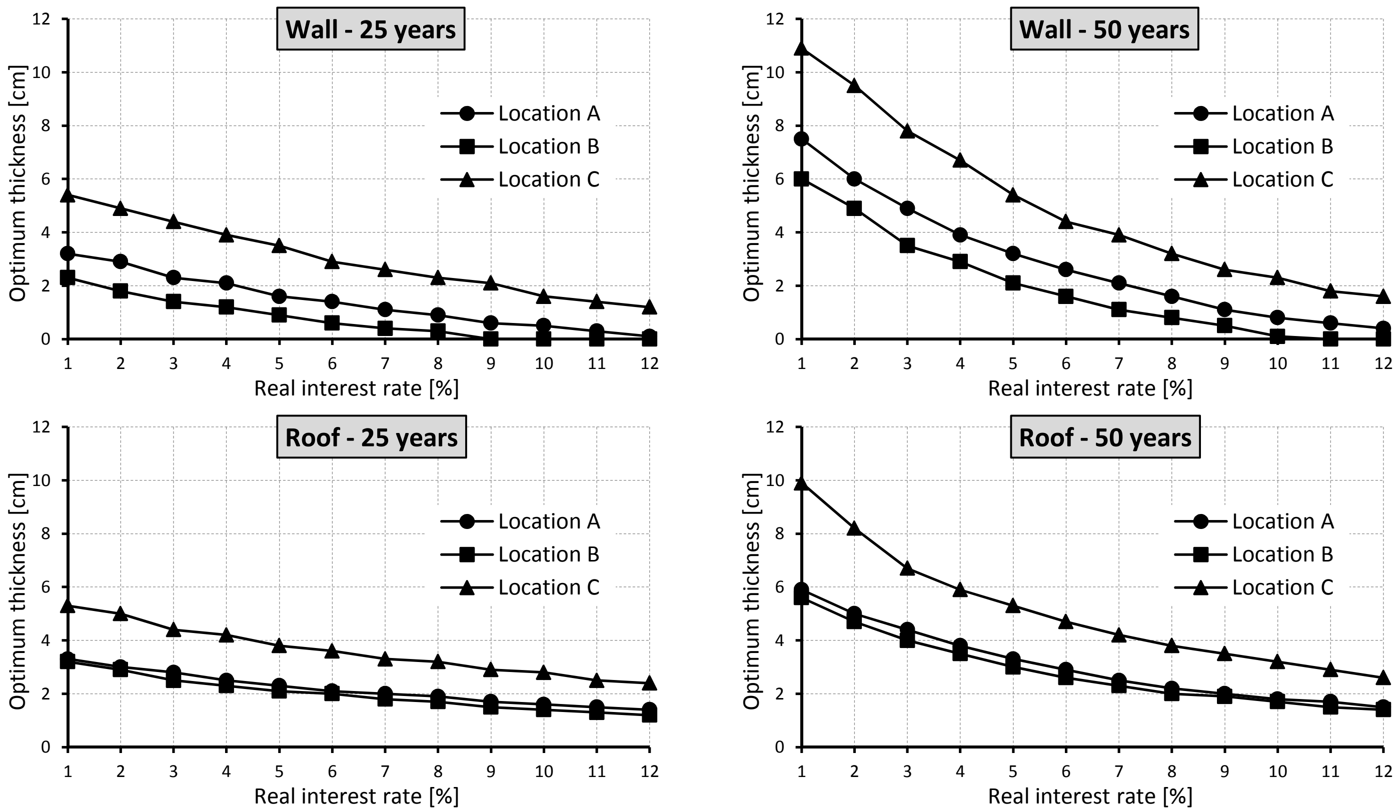

Figure 9. Parametric analysis of the real interest rate.

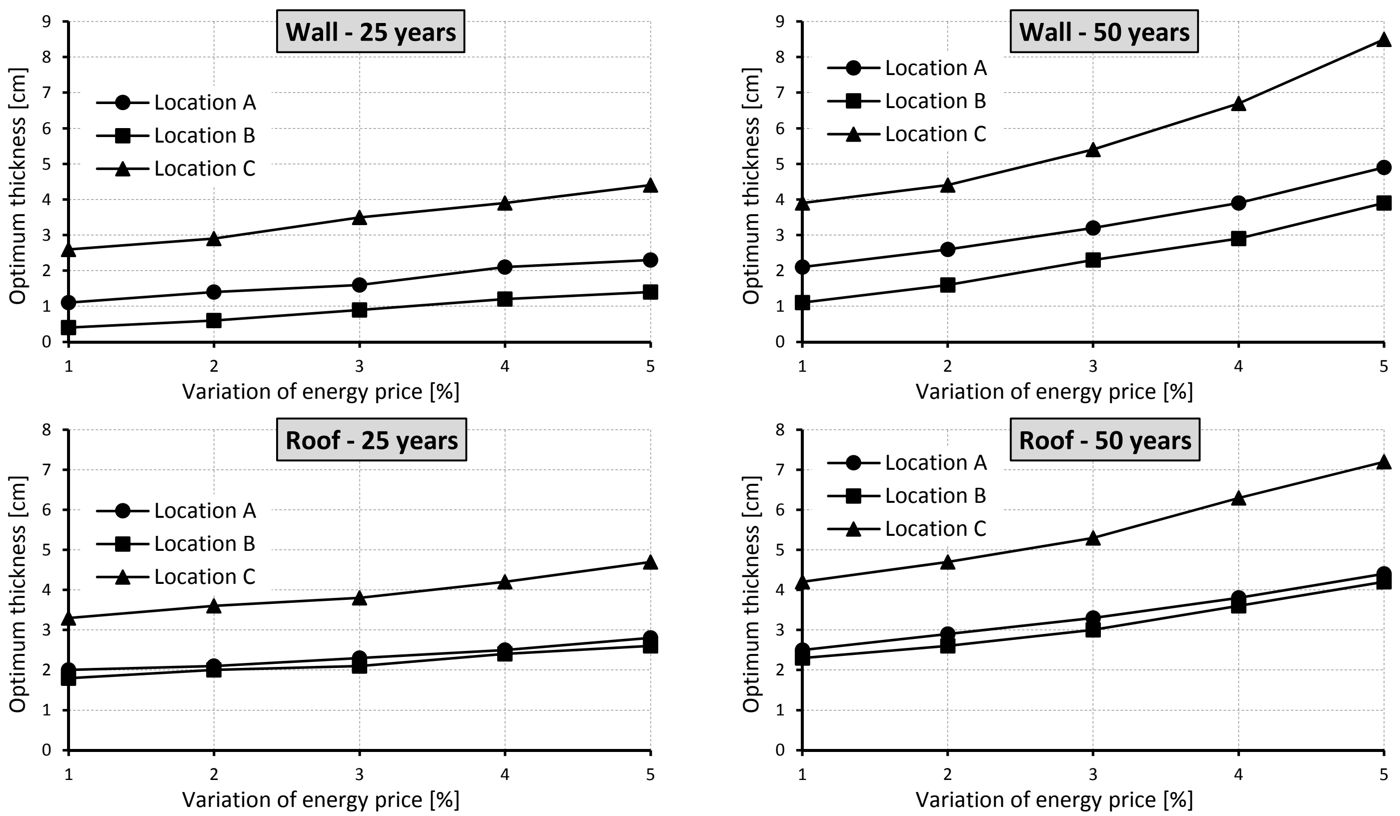

Figure 10. Parametric analysis of the variation of energy price.

## 5. DISCUSSION AND CONCLUSIONS

A multi-objective optimization methodology for school buildings retrofit, combining artificial neural networks and life cycle cost, was proposed. From the optimization procedure the following conclusions can be stated:

- since the multi-objective optimization procedure is based on evolutionary algorithms, which require a large number of computer simulations, it was employed approximation methods. The ANN proved to be effective and useful to approximate complex functions and can be used to replace the annual computer simulations. In this study 96 ANN were created and the respective $R^2$ was computed. The mean value obtained was $R^2 = 0.9818$ and $R^2 = 0.9892$, for model A and B, respectively. Still, ANN require a large number of input data to their training in order to achieve a good approximation. For each, were used 160 cases, 150 for training and 10 for validation;

- Pareto fronts, i.e. the set of optimal solutions, revealed highly dependent on the minimum and maximum limits imposed for the variables space. This is particularly important for the minimum limit of the air change rate;- the interpretation of Pareto fronts and subsequent definition of a criteria for the selection of a single solution is very complicated in problems like the one presented in this paper. Thus, these mathematical models have proved unsuitable for direct use.

To overcome this problem it was decided to engage the multi-objective optimization procedure with the LCC analysis for the calculation of the insulation thickness of walls and roofs in school buildings retrofit. The use of this methodology showed that the LCC is a simple and appropriate instrument for this kind of problems.

Its implementation was accomplished by the development of a software tool, which also allows assessing the impact of the chosen solutions in the thermal comfort of the classrooms.

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