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MULTI-VARIABLE OPTIMIZATION MODELS FOR BUILDING ENVELOPE DESIGN USING ENERGYPLUS SIMULATION AND METAHEURISTIC ALGORITHMS

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Abstract
The paper presents the method of optimal design of the building envelope. The influence of four types of windows, their size, building orientation, insulation of external walls, ceiling to unheated attic and ground floor on the life cycle costs in a single-family building in Polish climate conditions is analyzed. The optimization procedure is developed by means of the coupling between MATLAB and EnergyPlus. The results using three metaheuristic methods: genetic algorithms, particle swarm optimization, and algorithm based on teaching and learning are compared. The analyses have shown the possibility of reducing the life cycle costs through the optimal selection of the building structure. The high initial investment (above the required standard) pays off in the long run when using a building.

Keywords: **Genetic algorithm; Particle swarm optimizer; Teaching-learning-based optimization; Energy consumption; Building simulation; Building envelope.**

1. INTRODUCTION

In the early stages of design the building designer faces different questions in relation to: building location (which is usually not really a decision of the building designer but of the owner of the building), building orientation, building shape, structural system to be adopted, building envelope and interior finishes. Naturally, this is a challenging procedure as each question has a wide range of different alternatives that globally will lead to an even wider range of different solutions. In addition, from the point of view of the environmental assessment, the problem is more complex as one solution may be beneficial in some environmental categories and simultaneously harmful in others [1].

Several design features can affect the energy efficiency of buildings, including the shape of the building, wall and roof construction, foundation type, insulation levels, window type and area, thermal mass, and shading. For a given floor area, determining the envelope configuration that results in minimum annual energy consumption can be a challenging task, but ultimately not very useful, since economic considerations must play a role in the construction of any real building. Indeed, the problem of building energy efficiency becomes more complex as economic factors are introduced. A building that consumes the absolute minimum amount of energy for its size is most likely not very cost-effective, since additional construction costs would overwhelm any savings from reduced energy use. Therefore, a balance must be found between increases in investment cost and recurring annual savings [2].

Each combination of design variables leads to a certain annual energy demand, under standard building use conditions. It therefore is of interest to characterize the full spectrum of possible combinations of variables, in order to identify those that have expected lower initial costs and those that have lower life-cycle costs, but also how distant from "the best" some other solution (e.g. one preferred due to architectural/non-energy criteria) may be. Therefore, it is important to develop methodologies that allow building designers to identify the combinations of design variables that, while insuring the achievement of the energy and environmental targets established, also have near-optimal lowest life cycle costs, or lowest investment costs, or a good compromise between investment costs and life cycle costs [3].

The designers often adopt building performance simulation (BPS) tools for analyzing the energy behaviours of buildings [4]. In order to improve the energy performance of buildings, one of the first developed approaches has been the "parametric simulation method". This approach makes variable, within a proper range, some design parameters, in order to see their effects on some objective functions, while other variables are constant. Under the point of view of computation, this method is very expensive and not completely reliable because of the non-linear interactions among the design variables. Therefore, starting from the 1990s, numerical optimizations and/or simulation-based optimizations [5] are adopted more and more frequently, also thanks to the very rapid diffusion of the computer science. A numerical optimization methodology can be defined as an iterative procedure that provides progressive improvements of the solution until the achievement of a sub-optimal configuration (the "actual optimal" is normally unknown) [6–8]. In the last years, many studies focused on the combination of BPS tools and optimization programs, in order to improve the optimization algorithms, above all for reducing the required computational time. Presently, several algorithms are available, typically classified as local or global methods, heuristic or metaheuristic methods, derivative-based or derivative-free methods, deterministic or stochastic methods, single-objective or multi-objective algorithms and many more [9].

This paper presents the multi-variable optimization of chosen design parameters in a single-family building. The aim is to determine optimum solutions that will enable maximum energy and economic benefits during the lifetime of the building. The optimization procedure is developed by means of the coupling between MATLAB and EnergyPlus and implementing the optimization tools. Many works in this field used grand simplifications: thermal zones included several rooms or the analyses only one zone, the same casual gains assumed in the whole building, window size defined by the window-to-wall ratio. In this study a detailed analysis of the selected building has been performed. The rooms are modeled as separate zones with scheduled casual gains. The constructed algorithm individually selects optimum values from discreet sets for each design variable as well as automatically selects an external wall for a window in each room. Only such an algorithm enables to determine optimum design solutions for the optimized building. This paper also aims to present the comparison of three metaheuristic methods for the evaluation of the cost-optimality. Optimizations using one selected method (genetic algorithms) have already been carried out in earlier authors' research [26, 27]. The choice of method can affect the final optimal result, therefore this study presents the differences resulting from the application of the optimization method.

2. RELEVANT STUDIES

Normally, in building performance optimization, an analytical formulation of the objective functions is not available [9]. Thus, the most used optimization algorithms in this matter are derivate-free, simulation-based ones, which provide the iterative improvement of the solution until the fulfillment of a stop criterion. Among these methods, the dominant ones are the metaheuristic stochastic population-based algorithms [5], such as particle swarm optimization [10], differential evolution [11, 12] or genetic algorithms [9, 13, 14, 15].

More recently, optimization-based selection approaches have been proposed to select building shapes [16, 17], wall and roof constructions and insulation levels [18], or several other building envelope design features [19, 20]. In addition to selecting the best materials, some studies have focused on identifying the optimum window to wall ratio and windows geometry [21, 22]. Other researches like Tuhus-Dubrow and Krarti [23], Magnier and Haghighat [24] and Znouda et al. [25], Ferdyn-Grygierek and Grygierek [26, 27] developed models with the use of genetic algorithm method to select the best combination of several components of the building envelope (orientation, wall, roof and foundation insulation, window area, glazing type, air leakage level and thermal mass). In turn Bichiou and Krarti [28] compared the performance of three optimization techniques (genetic algorithm, particle swarm optimization, and sequential search methodology) to select HVAC system design features and its operation settings.

To perform the optimization analysis the simulation-optimization environment can consider a various objective functions, most often it is an annual energy demand, annual energy costs or life cycle costs of building. Gasparella et al. [22] studied the impact of different types of glazing systems (two double and two triple glazing), window size and the orientation of the main windowed façade on winter and summer energy demand of a well insulated residential building in four different central and southern European climates. A similar problem, but with energy cost as the objective function, is analyzed in the work by Ferdyn-Grygierek and Grygierek [29] (a detached house in Polish climate conditions). In turn, Bichiou and Krarti [28], Ihm and Krarti [30], Ferdyn-Grygierek and Grygierek [26, 27] and Ferrara et al. [31], in their works applied life cycle costs as the objective function to optimize many design variables in the construction of single-family detached houses.

Some researches apply multi-objective optimization models. In the study conducted by Ascione et al. [32], a procedure combines EnergyPlus simulation and a genetic algorithm which was implemented to determine the best solutions for the HVAC system control in a residential building. The objective of this study was to minimize the primary energy demand and investment cost. Azari et al. [33] utilized a multi-objective optimization algorithm to explore optimum building envelope design with respect to energy use and life cycle contribution to the impacts on the environment in a low-rise office building in Seattle. The simulation tool eQuest was used to assess the operational energy use. A hybrid genetic algorithm and artificial neural net-works was used for the optimization [34].

The optimization of the insulation thickness of a house considering both economic and environmental concerns is presented by Carreras et al. [35]. The authors proposed a systematic framework for the design of buildings that combines a rigorous objective reduction method with a surrogate optimization model. In turn, Ascione et al. [36] proposed a new multi-stage framework for cost-optimal analysis by multi-objective optimization and artificial neural networks, called CASA. A genetic algorithm and EnergyPlus simulation allowed to select recommended retrofit packages by minimizing energy consumption and thermal discomfort. The same energy simulation software and a heuristic algorithm was used by Mostavi et al. [37]. The effect of 65 different building construction materials was analyzed by the authors. The multi-objective design optimization model to minimize life cycle cost and life cycle emission, and maximize occupant satisfaction level in a typical commercial building was developed.

3. METHOD

Multi-variable optimizations by coupling the building performance simulation program with optimization environment using genetic algorithms (GA) or particle swarm optimizer (PSO) or teaching-learning-based optimization (TLBO) were performed to determine the best path to minimize life cycle costs while reducing the energy use of a typical single-family house in Poland.

The energy modeling tool EnergyPlus [38], which allows integrated calculations of the transfer of mass and energy inside the building, taking into account heating and air-conditioning systems and the strategy of control was used for simulation of the heating and cooling demand. In addition, EnergyPlus makes it possible to carry out parallel simulations and consequently to accelerate the optimization process. The multi-zone model, containing all the heated and unheated rooms, was built in a simulation program.

The optimization algorithm methods and all procedures to exchange data between the simulation and the optimization tools were implemented in MATLAB R2017a language. Figure 1 shows the structure of the simulation and optimization environment.

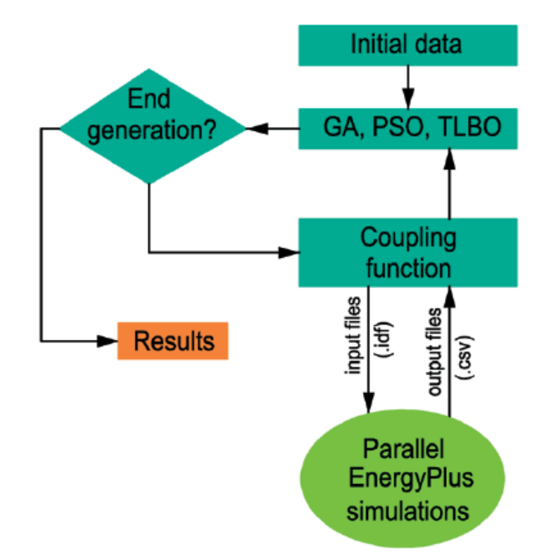

Figure 1.
Flowchart diagram for the developed simulation/optimization

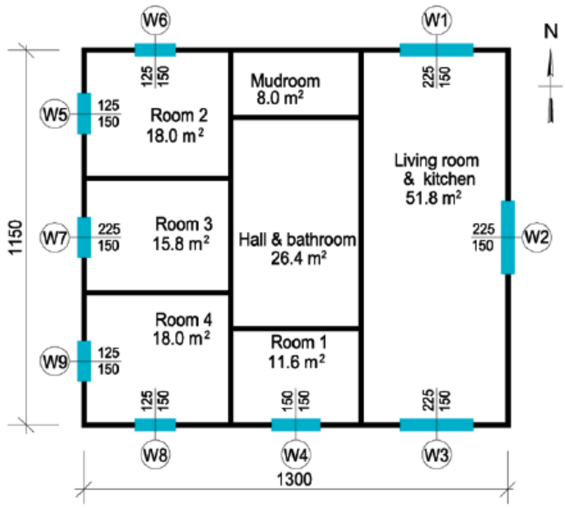

Figure 2.
Ground floor view (dimensions in cm), adopted from Ferdyn-Grygierek and Grygierek [26]

The simulations were performed using reference weather data for Katowice. The simulations were run with a fifteen-minute time step. Internal heat gains were introduced into the model: occupants, equipment and lighting. An hourly schedule for heat gains was adopted in each room [26].

3.1. Reference building

The single-family detached house without a cellar and with unused attic was chosen for the research. The ground floor of the building is shown in Figure 2. Table 1 summarizes the basic characteristics of the reference building.

The house has four bedrooms and an open space kitchen and a living room. The building is air conditioned (split system) and equipped with a hot water central heating system. The cooling set point is kept at 24°C and heating set point at 20°C. The ventilation air flow was adopted in accordance with the Polish standard [39]. For the analyzed house the minimum air flow is 120 m^3/h (it is about 0.3 air change per hour).

3.2. Design variables

In optimization analysis the most common design options available in Poland are chosen as design variables (Table 2):

- Glazing type characterized by two parameters of the glazing, i.e.: heat transfer coefficient (U) and solar heat gain coefficient ($SHGC$). The optimization was performed for four different types of glazing. Glazing systems were prepared with the use of Window 7.4 software [40].
- Windows area (glazing + frame) defined by the sixteen discrete values of windows size. Depending on the size of the window the frame surface is automatically calculated for each window.
- External walls, ground floor and ceiling to the unheated attic defined by the thickness of polystyrene and mineral wool. Six options for all kinds of partition are considered.
- Orientation defined by the azimuth angle between the north and the front of the house. Sixteen options for the orientation are considered.

Table 1.
Characteristics of the reference building

Number of occupants	4
Number of heated floors	1
Area of heated floor	150 m^2
Floor-to-floor height	2.6 m
External wall construction	Brick with polystyrene insulation, U = 0.22 W/m^{2}K
Ceiling construction	Ferroconcrete with mineral wool insulation, U = 0.18 W/m^{2}K
Roof construction	Covered with ceramic tiles and uninsulated
Ground floor construction	Concrete with polystyrene insulation, U = 0.29 W/m^{2}K
Windows construction	Double glazed, PCV frame, U_{glass} =1.00 W/m^{2}K
Opaque external wall	102.15 m^2
Window area	23.25 m^2
Ventilation	Natural
Cooling System	Split system air conditioner (electricity)
Heating System	Central heating with radiators (natural gas boiler)

Table 2.
Cost data for design variables and options used for the optimization analysis

Design variable	Options	Cost*
Glazing type for window	G10 (U_{glass}=1.0 W/m^2 K, $SHGC$=0.49) G07 (U_{glass}=0.7 W/m^2 K, $SHGC$=0.61) G06 (U_{glass}=0.6 W/m^2 K, $SHGC$=0.51) G05 (U_{glass}=0.5 W/m^2 K, $SHGC$=0.43)	148 PLN/m^2 278 PLN/m^2 230 PLN/m^2 249 PLN/m^2
Windows area	Height: 1.5 m Width: 0 and 0.75 m – 4.25 m with step 0.25 m Windows area for RB: 23.25 m^2	0 PLN for all options
Insulation		
Ground floor: polystyrene (λ =0.031 W/mK)	5, 6, 8, 10, 12, 15 cm (thickness)	223 PLN/m^3
External wall: polystyrene (λ =0.031 W/mK)	12, 15, 18, 20, 22, 25 cm (thickness)	198 PLN/m^3
Ceiling to unheated attic: mineral wool (λ =0.038 W/mK)	20, 22, 25, 28, 30, 35 cm (thickness)	1.36 PLN/ m^2 for 1 cm of thickness
Azimuth (orientation of the building relatively to the north)	0–337.5 with step 22.5	0 PLN for all options
Additionally included the costs of window frame and installation and cost of external wall construction		

*1 PLN = ~0.23 EURO

The newly-constructed buildings in Poland must meet Technical Conditions [41]. The partitions' structure (Table 1) in a reference building (RB) (which will be used in the comparison) was determined so that heat transfer coefficients of external partitions would be according to these requirements. Technical Conditions [41] also specify the minimum ratio of glazed area of the windows to the floor area of the rooms they are located in. It should be minimum 1:8. Such a minimum glass area in the analyzed building is 14.4 m^2. In the reference building the glazing area amounts to 15.7 m^2. The overestimated value results from the adopted assumptions: there are all windows in each room (Figure 2), they have the same surface area and are selected from the allowable options (Table 2). Figure 2 shows the windows' dimensions in the reference building (they are the overall dimensions with a frame).

3.3. Objective function

Objective functions are the selected simulation results which vary depending on the parametric input combinations, and are the values to be minimized by the optimization algorithm. In this study, the cost function is selected as the life cycle cost (LCC). The 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 lifespan" [42].

In the study life cycle cost was defined by Eq. (1). The investment costs of the analyzed design variables have been used for calculations. The remaining investment costs are equal in each case and do not affect the optimization result. Only extra investment costs involved in the reference building that result from the changes introduced in each optimization option have been analyzed.

$$LCC = dIC + a(r_e, N)\cdot EC, \tag{1}$$

where:

dIC – the differences between sum of investment cost for implementing all the design and operating features in the reference and optimized case of the building. In this study it is the cost (material and labor) of external walls, ceiling and floor insulation, cost of windows and external walls structural material. Table 2 provides the cost data for various design and operating options,

EC – the annual energy cost (heating and cooling) to maintain indoor temperature within the building for the selected design, from Eq. (2),

a – discount factor which takes into account the effect of inflation and escalation of energy price. More information on how this parameter was calculated can be found in the paper by Ferdyn-Grygierek and Grygierek [26].

$$EC = \frac{Q_H}{\eta_H}\cdot P_{H(gas)} + \frac{Q_C}{\eta_C}\cdot P_{C(el.)}, \tag{2}$$

Where:

Q_H – annual heating demand, kWh,

Q_C – annual cooling demand, kWh,

η_H – annual efficiency of heating system,

η_C – annual efficiency of cooling system,

$P_{H(gas)}$ – price of energy from natural gas, according to the applicable tariffs,

$P_{C(el.)}$ – price of electrical energy, according to the applicable tariffs.

The following data are assumed for the LCC calculations:

- efficiency of heating system $\eta_H = 0.78$ [43],
- efficiency of cooling system $\eta_C = 3.79$ [43],
- price of energy from natural gas $P_{H(gas)} = 0.1694$ PLN/kWh at 1st June 2018,
- price of electrical energy $P_{C(el.)} = 0.5565$ PLN/kWh at 1st June 2018,
- investment costs (Table 2),
- nominal interest rate $i = 7\%$, inflation rate $f = 2\%$ and escalation in energy price $e = 2\%$. Accordingly, the real interest rate $r_e = 2.8\%$,
- lifespan $N = 30$ years [44, 45].

3.4. Optimization algorithm

The energy performance of a building depends on a great number of parameters and is further influenced by external conditions and internal gains. In order to improve the energy performance of a building the correct parameters should be determined, which requires the right optimization tool. Bearing in mind a great number of variables which can be combined we might end up facing a vast number of combinations while the building itself will not be so complex. It is of vital importance to choose the right tool to solve such a complex problem [25].

Metaheuristic search techniques are developed to make this search within computationally acceptable time period. They also are classified as population-based or nature-inspired optimization methods The main idea of all metaheuristic optimization methods is to follow some heuristics in order to obtain the best solution for an optimization problem. In this study, three optimum design algorithms are applied for the solution of the discrete programming problem: genetic algorithm (GA), particle swarm optimizer (PSO) and teaching-learning-based optimization (TLBO). The first two are most often used in building envelope optimization. TLBO is a relatively new method and requires a minimum number of parameters (population size and number of iteration steps). In this work, it was assumed that design variables are discrete, therefore the special version of these methods are used.

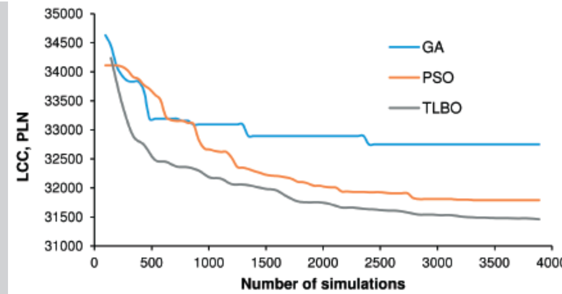

Figure 3.
Life cycle costs convergence history

GAs are the most popular methods, which have found vast amount of applications in a wide spectrum of diverse engineering disciplines [2, 18, 19, 46], including structural and energy optimization. The fundamentals of this algorithm are outlined in the work of Goldberg [47] in 1989. Today, many variations and extensions of the technique have been proposed in the literature for applications to discrete and continuous variable problems. In the present study, method proposed by Deep [48] is applied. In this method special creation, crossover, and mutation functions enforce variables to be integers.

PSO was proposed by Kennedy and Eberhart in 1995 [49]. The method is based on the social behavior of animals such as fish schooling, insect swarming and birds flocking. This behavior is concerned with grouping by social forces that depend on both the memory of each individual as well as the knowledge gained by the swarm. The original method [49] performs very well on small-scale problems as well as on problems with continuous design variables. However, when applied to large-scale discrete optimization problems, the performance of the algorithm has been observed to degenerate significantly. Due this fact in this study modification proposed by Hasançebi et al. [50] is used to solve our problem.

Rao et al. [51] in 2011 introduced a TLBO method which used simple models of teaching and learning within a classroom as the basis for an evolutionary optimization algorithm. A TLBO algorithm has two main parts: a teacher phase, where the average performance or knowledge of the class is moved toward that of a teacher, and a learner phase, where students share information and cooperatively interact with each other. TLBO method is a relatively simple algorithm with no intrinsic parameters controlling its performance. In the present paper the original version of algorithm is applied.

These methods have already been used in many optimization problems. The optimization algorithm used

Table 3.
Optimal results

Case		Reference building	Building after optimization		
			GA	PSO	TLBO
Type of glazing		G10	G05	G05	G05
Window area, m^2	W1	3.375	5.250	3.000	3.000
	W2	3.375	4.500	0	6.375
	W3	3.375	4.125	6.375	0
	W4	2.250	3.375	2.250	2.250
	W5	1.875	4.125	2.250	3.375
	W6	1.875	0	1.500	0
	W7	3.375	3.375	3.375	3.375
	W8	1.875	3.000	2.250	0
	W9	1.875	1.125	1.500	3.375
Insulation, cm	external walls	12	15	18	18
	ground floor	5	15	10	12
	ceiling	20	22	28	28
Building orientation, deg (clockwise)		0	180	247.5	247.5
Sum of windows area, m^2		23.25	28.875	22.500	21.750
Sum of glazing area, m^2		15.711	19.592	15.396	14.941
LCC, PLN		38 408	32 611	31 760	31 299
LCC savings, %		0	15	17	19
Heating demand, kWh/m^2		52.6	32.1	30.9	29.1
Cooling demand, kWh/m^2		9.7	19.1	13.2	13.4
Total energy savings, %		0	18	29	32

in this study, based on all-year building performance simulations, is time-consuming. Therefore, it is important to choose a method that gives good results in an acceptable time. This study is to demonstrate the method with the best compromise between the simulation duration and the quality of the obtained results. 48 individuals and 80 (40 for TLBO) simulation steps were assumed in the simulations. The duration of the simulation on the AMD Ryzen 5 1600X processor is 1.5 h (12 parallel simulations in EnergyPlus).

4. RESULTS

The results will be compared to the reference building. The aims of the simulations are: to determine whether higher investments costs that improve the thermal performance of a building are cost-effective for an investor and to check which optimization method gives better results.

It was assumed that there must be at least one window in each of the rooms and two windows in the living room. In the simulations it was assumed that the minimum glazing area is at least 1:8 of the floor area in the room (according to Technical Conditions [41]). The glazing area was calculated automatically in optimization program depending on the total area of the window.

Figure 3 shows the LCC convergence that was obtained for the three chosen methods (in the Figure there is the mean value from three simulations for each method). The best results were obtained for the TLBO method and the worst for GA method. The results for PSO method are similar to TLBO method. TLBO and PSO methods have better performance in local searches and therefore their convergence is better than GA method, which has a better global performance. This method (GA) needs more number of simulations to improve results. Therefore, in optimizations limited by a small number of simulations (e.g. due to the duration of calculations) it is better to use TLBO or PSO methods.

Table 3 lists LCC costs, heating and cooling demand and savings for optimal results of design variables for each method and for reference building. In the following, the best result was analyzed, which was obtained in the TLBO method.

After optimization, the thermal parameters of the external partitions have changed in comparison to the reference building. The insulation thicknesses increased by 6 cm (50%) for external walls, by 8 cm (40%) for ceiling to the unheated attic, and by 7 cm (140%) for floor on the ground. A window with the lowest *U*-value and lowest *SHGC*-value has been selected, even despite the fact that it is the most expensive option. It should be noted, that after optimization only the heating demand decreased, while the cooling demand increased. High insulated external partitions limit free cooling of the building in summer, hence the cooling demand is higher. However, the location and climate of Poland determine the need to heat buildings for most of the year, i.e. from September to May. The demand for cooling is a much smaller share of total energy demand. In reference building, the demand for cooling is only about 18% of the heat demand. Therefore the total energy demand (heating+cooling) decreased by as much as 32%.

The total area of the glazing has changed slightly, decreased by 5%. However, the number of windows has decreased to the minimum value (one in rooms and two in the living room). As a result, the area of some windows increased significantly, for example W2 window (almost twice).

The building has been rotated so that the windows of rooms with small internal gains (rooms 2–4) face the south-east side. In turn the largest window of the living room (large internal gains) was directed to the north-west side. What makes it possible to balance the heat in the whole building both in winter and in summer.

Despite the choice of the most expensive window option and additional costs related to thicker isolation of external partitions, optimization has reduced life cycle costs by 19%.

5. SUMMARY

The paper presents the methodology and the tool aimed at supporting the choice of economically effective building solutions. The detailed multi-zone model of a building and the gains that are attributed to the relevant zones contributed to maximize the obtained results (reduced LCC). In many works on this subject, the size of the windows is determined only by the ratio of their area to the façade area [28]. The window optimization tool built in this study analyses each window separately and allows to remove windows that overstate the energy consumption.

The analyses have shown the possibility of reducing the life cycle costs through the optimal selection of the building structure. The high initial investment (above the required standard) pays off in the long run when using a building.

The developed simulation environment can also be used to optimize other building parameters. The simulation environment can easily be extended to other types of buildings.

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