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Faculty of Energy Engineering

Optimization of energy rehabilitation processes of existing buildings

Summary of the PhD thesis

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Bucharest, 2025

TABLE OF CONTENTS

TABLE OF CONTENTS 2
INTRODUCTION 4
Chapter 1. CONTEXT AND MOTIVATION 6
Chapter 2. APLICATIONS OF OPTIMIZATION ALGORITHMS IN THE BUILDING SECTOR 8
2.1. GENETIC ALGORITHMS 8
2.1.1. Simple Genetic Algorithm (GA) 8
2.1.2. Non-dominated Sorting Genetic Algorithm II (NSGA II) 8
2.1.3. Quantum Genetic Algorithm (QGA) 9
2.2. PARTICLE SWARM OPTIMIZATION (PSO) 10
2.3. OTHER OPTIMIZATION ALGORITHMS 11
2.3.1. Crow Search Algorithm (CSA) 11
2.3.2. Ant Colony Optimization (ACO) 12
2.3.3. Manta Ray Foraging Optimization algorithm (MRFO) 13
2.4. COMPARISON OF OPTIMIZATION ALGORITHMS 13
2.4.1. Strengths of Optimization Algorithms 13
2.4.2. Disadvantages of Optimization Algorithms 14
Chapter 3. DESCRIPTION OF THE FUNCTIONAL MECHANISMS OF GA AND NSGA-II ALGORITHMS 16
3.1. DESCRIPTION OF THE FUNCTIONAL MECHANISMS OF GA 16
3.2. DESCRIPTION OF THE FUNCTIONAL MECHANISMS OF NSGA-II 19
Chapter 4. CASE STUDY - OPTIMIZATION OF THE ENERGY REQUIREMENT FOR HEATING AND COOLING 22
4.1. CASE STUDY 1 – Optimization of Unit Thermal Flow Using a Genetic Algorithm 22
4.2. CASE STUDY 2 – Optimization of the specific energy need for space heating using NSGA -II 27
4.3. CASE STUDY 3 – Simultaneous optimization of the specific energy need for space heating and for space cooling, using NSGA-II 35
Chapter 5. Description of the Hybrid System Used to Meet the Thermal Energy Demand 38
COCLUZII 48

BIBLIOGRAFY 53

INTRODUCTION

The building sector plays a key role in the European Union's (EU) energy strategy, as it is one of the largest energy consumers. In the EU, three sectors dominate final energy consumption: transport, residential buildings, and industry. Approximately 75% of EU buildings are residential, and the majority (around 80%) were built before 1991, a period during which energy efficiency requirements were minimal. This explains their low energy performance and insufficient thermal insulation, highlighting the urgent need to reduce energy consumption in the building sector.

In this context, the present PhD thesis, organized into five chapters, focuses on strategies to optimize energy consumption in residential buildings.

Chapter 1 presents a comprehensive assessment of the energy impact of buildings on overall energy consumption at both the European Union and national levels. It also discusses methods and strategies aimed at enhancing energy efficiency in the building sector.

Chapter 2 provides an extensive review of the practical applications of optimization algorithms in the building sector. It surveys the literature on energy consumption optimization using the following algorithms: the Simple Genetic Algorithm, the Non-dominated Sorting Genetic Algorithm II (NSGA-II), the Quantum Genetic Algorithm, Particle Swarm Optimization, the Crow Search Algorithm, Ant Colony Optimization, and the Manta Ray Foraging Optimization Algorithm. The chapter further offers a detailed comparison, highlighting the main strengths, weaknesses, and practical applicability of each algorithm.

Chapter 3 examines the functional mechanisms of two of these algorithms, namely the Genetic Algorithm and NSGA-II, with a detailed description of the selection, crossover, and mutation techniques applicable to each.

Chapter 4 presents three case studies, each demonstrating a methodology for optimizing building energy consumption. The first case study focuses on optimizing the unit thermal flow through the insulated wall, floor, or roof-ceiling using the Genetic Algorithm. The second case study introduces a method for identifying the optimal choice of insulation materials in terms of thickness and thermal conductivity. It also determines the optimal values of the overall heat transfer coefficients and total solar energy transmittance for doors and windows. The objective is to minimize the specific energy need for space heating while ensuring that the costs of the selected insulation materials, doors, and windows do not exceed the upper bounds specified in the simulation. This method is based on a Non-dominated Sorting Genetic Algorithm II (NSGA-II)

model implemented using the Pymoo (Multi-Objective Optimization in Python) module. The third case study formulates a multi-objective optimization problem: NSGA-II is applied to the same thermally insulated building to simultaneously minimize the specific energy need for space heating and for space cooling, while satisfying the imposed cost constraints.

Chapter 5 is divided into four subchapters. The first subchapter computes the specific energy need for domestic hot water. The second subchapter presents a mathematical model implemented in Python to select the optimal heat pump, sized to cover most of the building's specific energy needs for space heating and domestic hot water, while accounting for investment costs. The third subchapter evaluates the practical applicability of the mathematical model's results using the GeoT*SOL software. To improve the overall performance of the previously simulated system, the fourth subchapter simulates a hybrid system composed of a heat pump, solar thermal panels, and photovoltaic panels.

CHAPTER 1. CONTEXT AND MOTIVATION

A country's energy consumption depends on its level of economic development, the availability of natural resources, climatic conditions, and applicable legislation. Within this context, buildings are significant and steadily growing energy consumers, playing a crucial role in the European Union's (EU) energy strategy. Following its accession to the European Union, Romania must comply with the objectives set by EU Directive 2024/1275 regarding the energy performance of buildings [1]. The directive requires that all new buildings constructed after 2030 meet the net-zero standard, while existing buildings must achieve the same standard by 2050. Consequently, each EU member state must develop a national plan outlining the stages of progressive renovation and implementing concrete measures to reduce energy consumption and greenhouse gas (GHG) emissions in the building sector.

According to Eurostat [2], in 2023, the three sectors dominating final energy consumption in the European Union were transport (31%), residential buildings (26%), and industry (25%). In the building sector, space heating accounts for the largest share of energy use (62.5%), followed by water heating (15.1%). Natural gas supplied nearly one-third of the energy used in buildings (29.5%), followed by electricity (25.9%) and renewable sources (23.5%). The remainder came from petroleum products (10.3%), derived heat (8.5%), and solid fossil fuels (2.2%). Natural gas is the dominant energy source in countries such as Belgium, Germany, Italy, Luxembourg, Hungary, the Netherlands, Slovakia, and Georgia. Electricity consumption is particularly high in Bulgaria, Spain, Cyprus, Malta, Portugal, Sweden, Norway, and Albania. Renewable energy predominates in the Czech Republic, Estonia, Croatia, Latvia, Austria, Slovenia, Moldova, and Serbia. In Ireland, petroleum products are the main source, covering 41.7% of building energy demand [2].

According to the International Energy Agency [3], the building sector is currently responsible for a significant share of carbon dioxide emissions, accounting for approximately 26% of total energy sector emissions, of which 8% are direct and 18% are indirect, resulting from the production of electricity and heat used in buildings. The European Building Performance Institute [4] reports that greenhouse gas emissions in the building sector have decreased by around 15% compared to 2015, while the target is to achieve a 28% reduction by 2030 relative to 2015. These figures underscore the urgent need for measures to reduce the energy impact of buildings on both

energy consumption and GHG emissions across the EU. Consequently, research continues to focus on developing and applying new methods to improve the energy efficiency of existing buildings.

According to data from the European Building Performance Institute [5], 75% of EU buildings are residential, and approximately 80% of these were constructed before 1991, when clear energy efficiency directives had not yet been established. Many of these buildings have inadequate or no thermal insulation. The same source indicates that a substantial portion of Europe's building stock is over 60 years old, with more than 37% of residential buildings constructed before the 1960s [5]. The countries with the oldest building stock in the EU are Sweden, France, the Czech Republic, Denmark, and Bulgaria.

In Romania, residential buildings represent approximately 95% of the building sector [6]. Apartment blocks in urban areas are the most common type, accounting for 42.5% of all dwellings. Most residential buildings are old and poorly insulated, with 70% built before 1980. In these buildings, the average annual energy consumption for heating ranges from 180 to 240 kWh/m² [6]. This high energy demand underscores the urgent need to implement strategies to improve energy efficiency in both new and existing buildings. Romania's energy strategy for the period 2025–2035 foresees that, by 2030, 16% of old residential buildings will be renovated, rising to 20–22% by 2035 [7].

Measures such as insulating building envelopes with thermal materials, installing energy-efficient doors and windows, adopting more efficient electrical appliances, and promoting environmentally friendly behaviors among residents can significantly reduce energy consumption in buildings.

CHAPTER 2. APPLICATIONS OF OPTIMIZATION ALGORITHMS IN THE BUILDING SECTOR

Metaheuristic optimization algorithms are intelligent search techniques designed to identify optimal solutions to complex problems when traditional methods prove inefficient or inapplicable. As buildings face increasingly strict standards on energy consumption and greenhouse gas emissions, these algorithms play a crucial role in enhancing energy efficiency.

2.1. GENETIC ALGORITHMS

2.1.1. Simple Genetic Algorithm (GA)

The first applications of Genetic Algorithms were introduced by John Holland in his foundational research on the biological phenomenon of adaptation [8]. In this context, organisms evolve through the recombination of genetic material, which enables them to survive and adapt to environmental challenges.

A comprehensive review of the literature indicates that GA can be successfully applied to the analysis of building energy infrastructure. An illustrative example is a 2020 study in Oman, where a GA integrated with EnergyPlus optimized the energy performance of three residential buildings in Salalah, Muscat, and Buraimi [9]. The main objectives of the study were to reduce annual energy consumption, minimize environmental impact, and optimize life-cycle costs.

Lei Xia et al. [10] proposed an optimized design strategy for a hybrid system combining a geothermal heat pump with an integrated photovoltaic–thermal collector, optimized through an Artificial Neural Network and a Genetic Algorithm (GA).

In 2019, a Genetic Algorithm (GA) was implemented using the GenOpt optimization platform and integrated with dynamic simulations in TRNSYS to determine the optimal configuration of building envelope parameters and energy systems for a multifamily building in northern Italy, with the aim of optimizing energy performance and minimizing the building's total life-cycle cost [11]. The systems included heat pumps, photovoltaic panels, and ventilation systems with heat recovery.

2.1.2. Non-dominated Sorting Genetic Algorithm II (NSGA II)

Another evolutionary algorithm derived from GA is the Non-dominated Sorting Genetic Algorithm II (NSGA-II). Like GA, it employs evolutionary operators such as selection, crossover,

and mutation. In addition, NSGA-II applies non-dominated sorting, crowding distance, and elitism to preserve solution diversity. A detailed description of the algorithm is provided in Chapter 3.

F. Ascione et al. [12] implemented NSGA-II in MATLAB and coupled it with EnergyPlus. Their study optimized the total annual energy demand for space heating, domestic hot water, cooling, and electricity. It also evaluated the initial investment cost of renewable energy technologies and minimized their life-cycle cost.

In 2017, an NSGA-II algorithm was implemented in MATLAB in China to optimize the fuel consumption of a trigeneration system powered by a gas microturbine and to increase the exergy efficiency of the system during building operation [13].

Another study proposed a method for assessing the energy, economic, and environmental performance of renovation strategies for residential buildings in the context of global climate change [14]. In this case, NSGA-II was integrated with EnergyPlus and applied to a single-family residential building in southern Italy to identify optimal renovation solutions, simultaneously minimizing primary energy consumption, greenhouse gas emissions, and total life-cycle costs.

A. Ciardiello et. al. presented a comprehensive study combining EnergyPlus simulation results with an NSGA-II algorithm implemented in Python to optimize the annual energy consumption and improve the energy performance of a residential building in Italy. The optimization focused on determining the optimal configurations of the building envelope and geometry [15]. Results showed that selecting the optimal geometric form reduced total energy consumption by up to 60.6% compared to the reference case.

A recent 2024 study proposed a hybrid methodology that combines Bayesian optimization with extreme gradient boosting trees (BO-XGBoosts) and an NSGA-II algorithm to simultaneously optimize energy consumption, daylighting performance, and indoor thermal comfort in residential buildings [16]. The results showed implementing the identified optimal configuration reduced energy consumption by 44.1%, decreased the thermal discomfort index by 10.9%, and improved daylight performance by 1.7% compared to the initial design.

2.1.3. Quantum Genetic Algorithm (QGA)

The Quantum Genetic Algorithm (QGA) is a variant of the classical GA that integrates concepts from quantum mechanics, such as q-bits and the principle of quantum superposition [17]. Unlike GA's variation operators (selection, crossover, mutation), QGA updates q-bit probability

amplitudes using quantum rotation gates guided by the best-so-far solution, which helps balance exploration and exploitation and reduces premature convergence.

Bolun Li, Pingfang Hu, Na Zhu, Fei Lei, and Lu Xing [18] applied both a Quantum Genetic Algorithm (QGA) and a Simple Genetic Algorithm (SGA) to optimize the fuel consumption of a hybrid CCHP–GSHP system designed for heating and cooling a residential building in China. The system consists of a combined cooling, heating, and power (CCHP) plant coupled with a ground source heat pump (GSHP).

In 2021, QGA was applied to improve the energy performance of an office building by identifying the most efficient envelope configuration [19]. The study found that the QGA-derived solution reduced annual energy use by 15–20% and cut total operating costs by up to 35.3% compared to the baseline model.

2.2. PARTICLE SWARM OPTIMIZATION (PSO)

Particle Swarm Optimization (PSO) is a metaheuristic inspired by collective behaviors in nature, such as bird flocking and fish schooling. In PSO, each particle represents a candidate solution and is defined by its position and velocity, which are iteratively updated during the search process. The update of each particle is influenced by two key factors: the best position the particle has visited so far, and the best position found by the entire swarm [20]. Through this collaborative mechanism, particles explore the solution space without relying on mutation or crossover [21].

Navid Delgarm et al. integrated EnergyPlus simulations with a PSO algorithm implemented in MATLAB to optimize annual energy consumption for cooling, heating, and lighting in buildings located across four climatic regions of Iran [22].

J. Kim et al. [23] developed a hybrid model that combines PSO with the Hooke-Jeeves (HJ) algorithm to minimize the total energy consumption of a school in Seoul. The method identified optimal configurations of green systems and renewable energy technologies (photovoltaic and solar thermal panels) that balance thermal comfort with energy efficiency.

Yixiang Gao et al. [24] proposed an energy optimization strategy for buildings focused on reducing energy demand during peak hours. PSO was employed to determine the optimal indoor temperature setpoints and airflow rates for each thermal zone, with the objective of balancing occupant thermal comfort and minimizing HVAC energy consumption. Results showed that applying the optimal configuration could lower energy use by 19.09% and reduce associated costs by 30.72% compared to the unoptimized reference case.

PSO has also been applied to determine the optimal configuration that maximizes the production capacity and energy efficiency of photovoltaic systems installed on commercial buildings, while also accounting for financial considerations [25].

T. V. Dixit et al. [26] applied PSO to determine the annual optimal tilt angle of solar collectors in various geographic locations across India. The objective was to maximize the incident solar radiation collected by the panel surface by adjusting the tilt angle according to latitude and local climatic conditions.

In 2021, PSO was applied to optimize the mix of renewable technologies (photovoltaic panels, wind turbines, and energy storage batteries) for a building in Algeria. The objective was to supply most of the building's energy demand while maximizing the renewable fraction (RF) and minimizing overall energy costs [27].

2.3. OTHER OPTIMIZATION ALGORITHMS

In addition to the algorithms presented earlier, other widely used optimization algorithms include the Crow Search Algorithm (CSA), Ant Colony Optimization (ACO), and the Manta Ray Foraging Optimization algorithm (MRFO).

2.3.1. Crow Search Algorithm (CSA)

The Crow Search Algorithm (CSA) is a population-based metaheuristic inspired by the intelligent foraging behavior of crows, specifically their strategies of hiding food and using memory to retrieve it. In CSA, each crow retains the best position it has visited (food location) and may follow another crow to exploit its stored information. If the followed crow detects the pursuit, it changes its position to protect its resource. The awareness probability parameter defines the likelihood that a crow recognizes it is being followed, while the flight length parameter specifies the maximum step size a crow can move in a single iteration [28].

Mahdi Gharibi and Alireza Askarzadeh [29] proposed a Multi-Objective Crow Search Algorithm (MOCSA) for the optimized design of a hybrid energy system integrating photovoltaic panels, a diesel generator, fuel cells, an electrolyzer, and a hydrogen storage tank.

Ghaffari et al. [30] proposed an optimization approach to determine the optimal configuration of a hybrid energy system installed in a building in Kerman, Iran. The system included photovoltaic panels, wind turbines, a diesel generator, and an energy storage unit. The objective was to minimize investment, installation, operation, and maintenance costs over the system's

lifetime, while ensuring a predefined level of reliability and maintaining a renewable energy share above a specified minimum threshold.

Yukai Ke et al. [31] applied the Improved Crow Search Algorithm (ICSA) to optimize energy consumption in office buildings in Australia. The algorithm was benchmarked against Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). Results showed that the convergence speed of ICSA toward the optimal solution was two to seven times higher than that of the other two algorithms. In addition, ICSA demonstrated superior performance in terms of solution quality, as applying the optimized configurations reduced energy consumption by 11.8% and 14.05%, respectively.

2.3.2. Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a population-based metaheuristic inspired by the foraging behavior of ants in identifying the shortest paths between their colony and a food source [32]. In nature, ants deposit a chemical substance called pheromone, which guides other ants toward promising paths. Trails with higher pheromone intensity are more attractive and are therefore more likely to be followed. In the algorithm, a population of artificial 'ants' explores the solution space. The probability of selecting a given path depends on both the pheromone level and the quality of the solutions previously found. After each iteration, pheromone is reinforced on high-quality solutions and gradually evaporates on low-quality ones, which prevents premature convergence. As a result, the colony collectively converges toward near-optimal solutions over time.

In 2017, an ACO algorithm was applied to optimize total building energy consumption by identifying optimal combinations of control and design variables [33]. The decision variables included HVAC system parameters, heating and cooling setpoint temperatures, operating schedules, airflow or fluid flow rates, thermal insulation, the type, size, and orientation of windows, artificial lighting schedules, and the control of electrical equipment to minimize peak energy demand. Results showed that, after applying the optimal configuration, annual energy consumption was reduced by approximately 11.4% compared to commercial buildings without energy-saving measures.

One year later, the same researchers enhanced the algorithm by developing a Mixed-Variable Ant Colony Optimization Method (ACOMV-M) to optimize total energy consumption in a commercial building in Australia [34]. In this case, the decision variables were the type and

thickness of thermal insulation, shading, and window type. Results indicated that using the optimal configuration could reduce energy consumption by 8.7% compared to the reference building.

K. Bamdad et.al. [35] also applied an ACO algorithm to optimize the energy consumption of two office buildings located in different Australian cities.

2.3.3. Manta Ray Foraging Optimization algorithm (MRFO)

The Manta Ray Foraging Optimization (MRFO) algorithm is a population-based metaheuristic inspired by three natural foraging behaviors of manta rays: chain foraging (individuals follow a leader toward a food source), spiral foraging (spiral movements around prey), and somersault foraging (rotations around the best food source identified). The algorithm initializes a random population of individuals; at each iteration, their positions are updated via these three operators to balance exploration and exploitation and to preserve population diversity.

MRFO has been applied to optimize the heating, cooling, and lighting energy demand of a residential building in China by adjusting its envelope and geometric form [36]. The results demonstrated that MRFO achieved faster convergence and showed greater effectiveness in escaping local minima compared to PSO and GA. Furthermore, adopting the optimal building form reduced total energy consumption by 8–15% relative to the baseline design

2.4. COMPARISON OF OPTIMIZATION ALGORITHMS

2.4.1. Strengths of Optimization Algorithms

The Genetic Algorithm (GA) is a population-based metaheuristic known for its flexibility, as it can solve both discrete and continuous optimization problems. In contrast, PSO is primarily suited for continuous domains [37]. Compared to ACO, which is specialized in combinatorial optimization, GA offers broader applicability since it can handle complex representations and mixed-variable problems. Relative to CSA and MRFO, GA demonstrates stronger exploration capability. By applying genetic operators such as crossover and mutation, GA explores the search space effectively and reduces the likelihood of premature convergence.

Particle Swarm Optimization (PSO) is a population-based metaheuristic particularly effective for large-scale continuous optimization problems. Its main advantages include algorithmic simplicity, ease of implementation, and comparatively fast convergence with high solution quality relative to GA [38]. In addition, PSO's performance is not highly sensitive to swarm size, provided the number of particles exceeds a minimum threshold [39].

Studies indicate that, for certain problem classes, Ant Colony Optimization (ACO) can converge more rapidly to high-quality solutions than PSO. Another reported advantage is that ACO can run continuously and adapt its solution in real time as input data change [40].

Regarding the Crow Search Algorithm (CSA), previous studies report competitive performance relative to PSO and GA and highlight its algorithmic simplicity and practical applicability. Reference [31] evaluates the Improved Crow Search Algorithm (ICSA) rather than the baseline CSA; in the reported benchmarks, ICSA achieved two to seven times faster convergence than ACO and PSO.

2.4.2. Disadvantages of Optimization Algorithms

GA's principal limitations include relatively slow convergence, sensitivity to parameter tuning (e.g., population size, selection pressure, crossover and mutation rates), susceptibility to loss of diversity and premature convergence toward local optima, scalability challenges on high-dimensional or large-scale problems, and higher implementation overhead than PSO, ACO, and CSA [41] [42] [43].

PSO's principal limitations include poor performance on strictly discrete (combinatorial) search spaces and a high risk of premature convergence [44] [45]. To mitigate these issues, many studies employ hybrid approaches combining PSO with GA or ACO [46]. The algorithm's performance depends strongly on parameter settings: inappropriate inertia weight and cognitive/social acceleration coefficients can lead either to sluggish exploration or to instability in the search process [47] [48]. PSO also performs poorly on very high-dimensional problems [49]. In addition, without appropriate velocity clamping or a constriction factor, particles may exhibit persistent oscillations around candidate solutions rather than converging [50].

ACO's principal limitations include an uncertain time to converge, there is no a priori bound on the number of iterations required to reach high-quality solutions [51]. Another limitation is the risk of premature convergence: insufficient evaporation or excessive pheromone deposition can rapidly concentrate trail intensity on a single path, causing stagnation around a local optimum [32]. As with GA and PSO, ACO is sensitive to parameterization: the pheromone evaporation rate, the pheromone-influence exponent, and the heuristic-influence exponent must be tuned; inappropriate settings degrade the exploration–exploitation balance and lead to insufficient search of the solution space [52]. ACO's effectiveness also depends strongly on the quality of the heuristic information

used to guide ant moves; when this is weak or noisy, the search tends toward quasi-random behavior, convergence slows, and solution quality degrades [32].

As with Particle Swarm Optimization and Ant Colony Optimization, the Crow Search Algorithm has several principal limitations: sensitivity to parameter tuning, susceptibility to premature convergence and degraded performance on high-dimensional or large-scale problems. A drawback specific to the Crow Search Algorithm is that the follow-and-steal mechanism can overexploit a small set of memorized positions: when the awareness probability is low (the followed crow rarely detects the pursuit) or the flight length is too large, many crows converge on the same stored locations; population diversity decreases and global exploration is hindered, particularly on complex, multimodal landscapes [28].

CHAPTER 3. DESCRIPTION OF THE FUNCTIONAL MECHANISMS OF GA AND NSGA-II ALGORITHMS

3.1. DESCRIPTION OF THE FUNCTIONAL MECHANISMS OF GA

For implementing a Genetic Algorithm (GA), the following elements must be defined:

a) the population size and the initialization strategy;
b) the fitness function;
c) the algorithm's stopping criteria;
d) the selection mechanism;
e) the crossover mechanism;
f) the mutation mechanism.

a) The population size and the initialization strategy

In a GA, the population consists of n-dimensional vectors representing candidate solutions. Each vector is a chromosome in which each gene encodes one decision variable of the optimization problem [8].

The initial population is typically generated randomly by sampling gene values uniformly within the search-space bounds [42]. The literature also describes seeded initialization, in which some individuals are constructed from heuristic knowledge or known solutions, while the remainder are generated at random. This hybrid seeding balances exploration of new regions of the solution space and exploitation of regions already identified as promising [53] [54].

Population size denotes the number of individuals in the initial population. It is a critical hyperparameter that governs the search dynamics and the computational cost of a genetic algorithm. If the population is too small, genetic diversity is reduced, and the risk of premature convergence rises. If the population is too large, the number of fitness evaluations per generation grows substantially while improvements in solution quality become marginal. The chosen value should balance genetic diversity and computational efficiency [55]. In the literature, the population size N is typically set between 10 and 160 individuals, with the choice guided by problem complexity and available computational resources [56].

b) The fitness function

The fitness function is the evaluation criterion that measures how well each individual in the population is adapted to the specific problem. Grounded in the principle of natural selection, individuals with higher fitness have a greater probability of survival and reproduction [57] [58]. Also known as the objective function, it assesses the quality of each chromosome relative to the optimization goal and guides the selection step in the GA.

c) The algorithm's stopping criteria

The role of a stopping criterion is to determine when the execution of the Genetic Algorithm should be terminated, so that the current solution is as close as possible to the optimum. The main stopping criteria used in GA include:

- reaching the maximum number of generations;
- reaching maximum run time;

The algorithm runs for a predefined period [59];

- obtaining a value close to an expected value [60];

Individuals compete with each other in order to find the optimal solution, but only those with the best results are selected and pass to the next stage. Fitness function f_i of the selected chromosomes is compared to expected value f_d. The process repeating itself a number of times (number of iterations) until the error falls below an imposed threshold. If $|f_i - f_d| \leq \varepsilon$, then the algorithm will be stopped. The error ε *is a very small number*, *like* $\varepsilon = 10^{-15}$.

- premature convergence: early termination of the algorithm before reaching a global optimum, typically due to rapid convergence to a local optimum.

d) The selection mechanism;

The selection operator does not directly construct new candidate solutions. It uses each individual's fitness to choose which chromosomes enter the mating pool, to set their reproductive share as an expected number of offspring under the chosen selection scheme, and to decide in the survivor selection stage which individuals form the next generation [61]. Common schemes include:

- selection with probability proportional to fitness (roulette wheel selection);
- tournament selection;
- ranking selection;
- truncation selection;
- elitist survivor selection.

e) The crossover mechanism;

Two parent chromosomes are selected at random, and their genetic material is recombined to produce one or two offspring, depending on the implementation. The offspring inherit genetic information from both parents and are included in the new population. Recombination is performed by placing one or more crossover points within the chromosomes and swapping the corresponding segments [62].

Depending on the chosen solution encoding, crossover is implemented using operators tailored to that representation:

1. Binary and integer encodings;

- Single-point, two-point or multi-point crossover;
- Uniform crossover;

2. Real-valued encodings;

- Discrete recombination;
- Arithmetic crossover: single arithmetic crossover, simple arithmetic crossover, whole arithmetic crossover;
- Geometric crossover;
- Blend crossover (BLX-α);
- SBX – Simulated Binary Crossover;

3. Permutation encodings;

- Order Crossover – OX;
- Partially Mapped Crossover – PMX;
- Cycle Crossover – CX;
- Edge Recombination Crossover – ERX [40].

f) The mutation mechanism.

Mutation is applied after crossover and introduces new genetic material into the population to maintain diversity. It randomly modifies one or more genes in a chromosome. The probability that a given gene is altered is the mutation probability.

Depending on the representation, common mutation operators are [40]:

1. Binary representation;

- Bit-flipping mutation;

2. Integer representation;

- Random resetting;
- Creep mutation;

3. Real-valued representation;

- Uniform mutation;
- Nonuniform mutation (Gaussian mutation, Cauchy mutation, Laplace mutation);

4. Permutation representation;

- Insertion mutation;
- Swap mutation;
- Inversion mutation;
- Scramble mutation;
- K-opt mutation.

3.2. DESCRIPTION OF THE FUNCTIONAL MECHANISMS OF NSGA-II

The algorithm is very similar to GA. NSGA-II differs from a simple GA in how parents are selected, because NSGA-II uses non-dominated sorting and crowding distance. NSGA-II model development requires implementing the following procedures:

1. Establishing the input parameters: the population size, the number of generations, crossover probability, mutation probability [63]. A random initial population of size N is generated, respecting the bounds imposed on the decision variables of the optimization problem (the search-space limits), and the fitness functions are evaluated for each chromosome [64]. Selection aims to construct a set of solutions as close as possible to the optimal Pareto front. This front is "*a set of nondominated solutions, being chosen as optimal, if no objective can be improved without sacrificing at least one other objective*" [65].
2. Creating the offsprings from the initial parents by applying binary tournament selection, where individuals are compared using non-dominated rank and crowding distance, followed by the Genetic Algorithm's crossover and mutation operators; a combined population of size $2N$ is thus obtained [66];
3. Sorting to obtain the new population; The combined population is sorted using the non-dominance principle and crowding distance in order to obtain the new population.
   Based on non-dominated sorting, several Pareto fronts are produced as follows:

- each individual is compared with the other individuals in the combined population according to the fitness values, and all non-dominated solutions are identified using the dominance principle, which states: "*A solution x is said to dominate the other solution y if the solution x is no worse than y in all objectives and the solution x is strictly better than y in at least one objective*" [63];
- all such non-dominated solutions are assigned to the first front;
- the remaining individuals not assigned to the first front are then compared in order to assign them to the next Pareto front; this process is repeated until all individuals are assigned to a non-dominated front [67] [68];

Only a subset of the last non-dominated front to be admitted advances to the next generation. The best N solutions are obtained by admitting complete fronts in order of rank and, for the last partially admitted front, selecting solutions with the largest crowding distance (in descending order); the remaining solutions are discarded [69].

Crowding distance is a selection criterion applied to individuals within the same non-dominated front, based on their distance to neighboring individuals in the objective space [70]. It is used to preserve diversity within a front; consequently, individuals that are more isolated in the objective space are preferred over those that are very close to others.

Individuals are selected for the new population as follows: if the size of the first front is smaller than N, all individuals in this front are admitted to the new generation; the remaining individuals (equal to N minus the number of individuals in the first non-dominated front) are filled from the subsequent non-dominated fronts in rank order, selecting solutions with the largest crowding distance in the last partially admitted front [71].

The algorithm then continues from step 2 until the predefined stopping criterion is satisfied. This process is summarized in Figure 3.1.

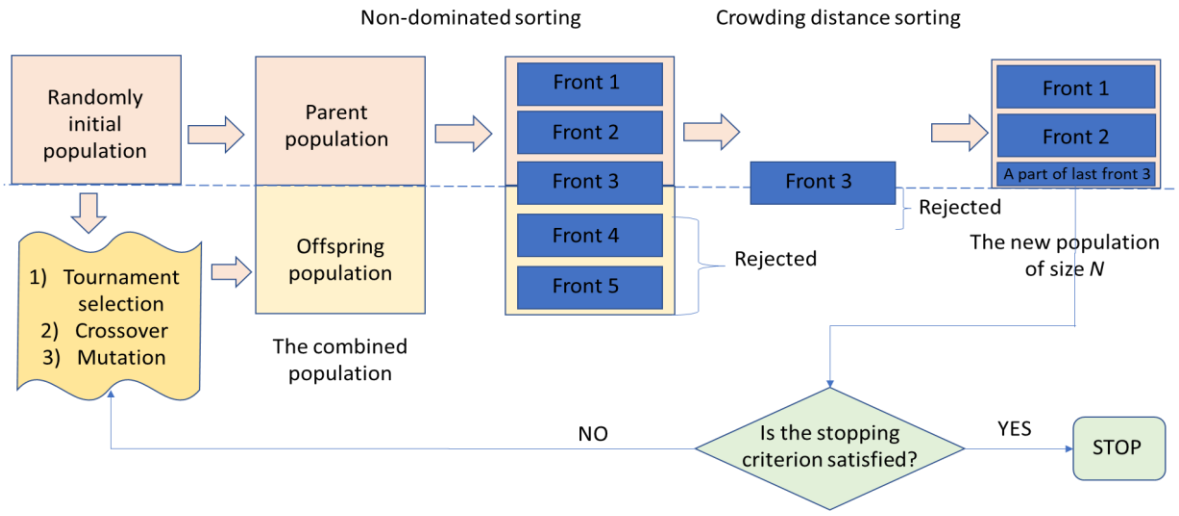


Fig.3.1. Non-dominated Sorting Genetic Algorithm II

CHAPTER 4. CASE STUDY - OPTIMIZATION OF THE ENERGY REQUIREMENT FOR HEATING AND COOLING

4.1. CASE STUDY 1 – Optimization of Unit Thermal Flow Using a Genetic Algorithm

Given its strong performance, the Genetic Algorithm (GA) is employed in this case study to determine the optimal layer thicknesses and thermal conductivities that minimize the unit thermal flow through a south-facing exterior wall insulated with expanded polystyrene, through the floor insulated with extruded polystyrene, and through the roof-ceiling insulated with mineral wool. Accordingly, three similar GAs are implemented, one for each construction assembly.

4.1.1. Optimization Problem Definition and Algorithm Description

The Genetic Algorithm determines the optimal insulation layer thicknesses and thermal conductivities for expanded polystyrene, extruded polystyrene, or mineral wool in order to minimize the unit thermal flow. For computational simplicity, the wall is assumed to have no doors or windows and to be composed of the construction materials shown in Figure 4.1. The total thermal resistance of the uninsulated wall is 1.383 m²·K/W.

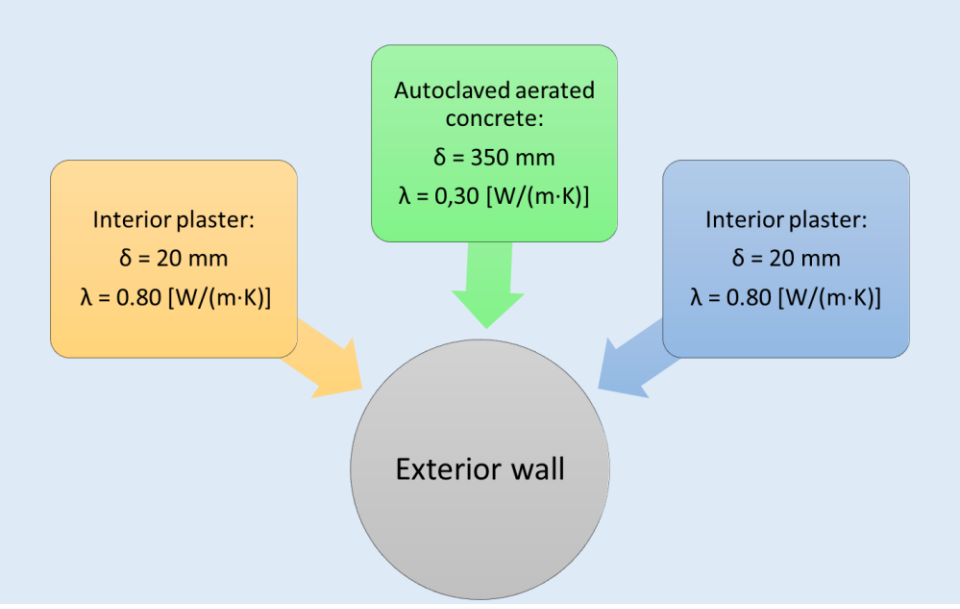


Fig. 4. 1. Exterior Wall Assembly

The floor assembly is shown in Figure 4.2. The total thermal resistance of the uninsulated floor is 2.062 (m²·K)/W.

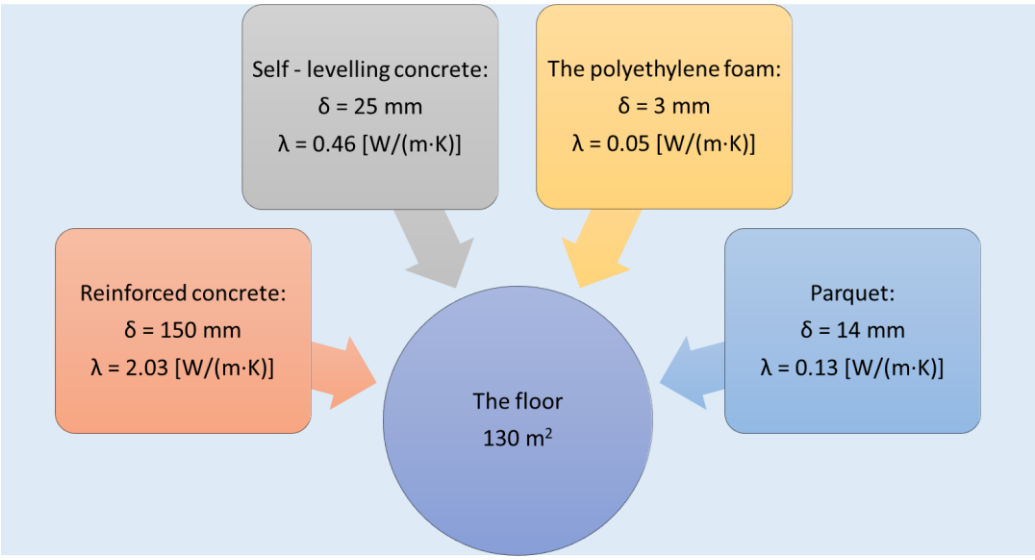


Fig. 4.2. Floor assembly

The materials comprising the ceiling assembly are also shown in Figure 4.3. The total thermal resistance of the uninsulated ceiling is 0.367 (m²·K)/W.

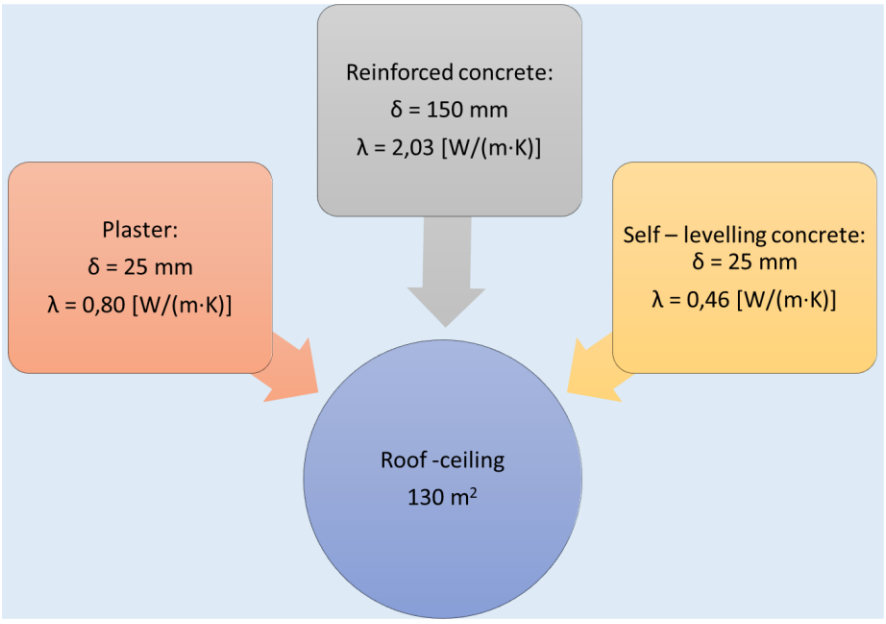


Fig. 4. 3. Roof - ceiling assembly

To compute the three optimal unit thermal flows values, the convection heat transfer coefficients listed in Table 4.1 are adopted. These coefficients are taken from *Methodology MC 001* [72] and from the standard governing the thermal calculation of building elements in contact with the ground [73]. The same table also reports the ground thermal conductivity as a function of

depth, in accordance with that standard. Consistent with the literature, the indoor air temperature is set to $\theta_{in} = 20^{\circ}C$, the outdoor air temperature to $\theta_{ext} = -15^{\circ}C$, and the ground-surface temperature to $\theta_{sol} = 10^{\circ}C$ [73] [74] [75].

Table 4.1. Parameters adopted for the calculation of unit thermal flows

Parameter	Value	Unit
α_{1in}	8	$W/(m^2 \cdot K)$
α_{1ext}	24	$W/(m^2 \cdot K)$
α_2	6	$W/(m^2 \cdot K)$
α_{3in}	8	$W/(m^2 \cdot K)$
α_{3ext}	12	$W/(m^2 \cdot K)$
λ_{1p}	2	$W/(m \cdot K)$
δ_{1p}	1,2	m
λ_{2p}	4	$W/(m \cdot K)$
δ_{2p}	4	m

As a first step in the algorithm, the decision variables are defined and the bounds of the search space are established. These are shown in Figure 4.4.

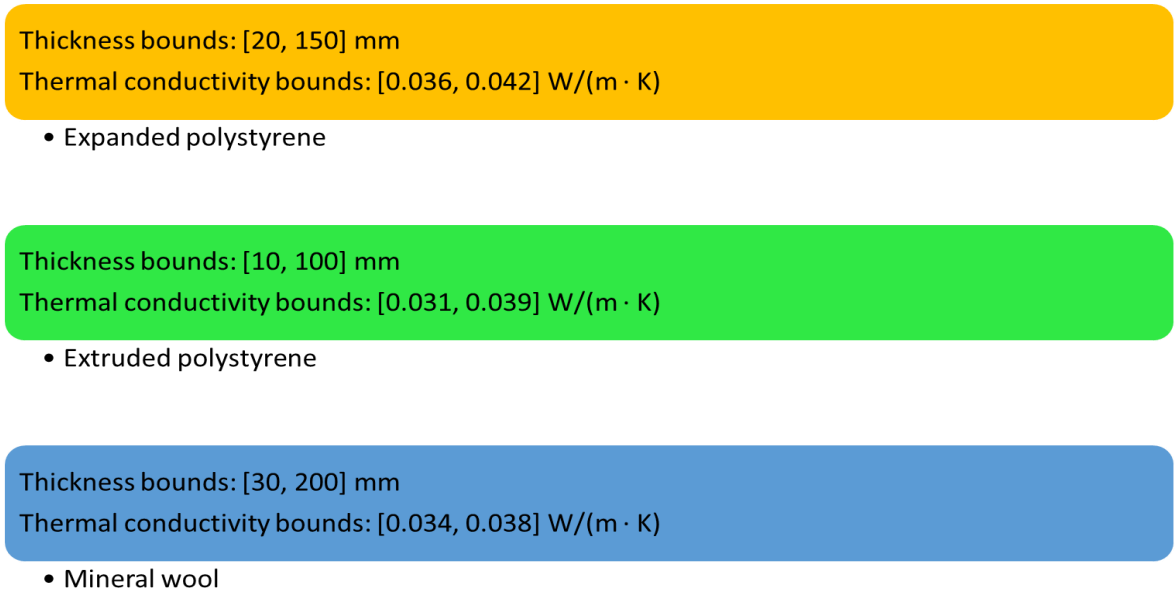


Fig. 4.3. Thickness and thermal - conductivity bounds for insulation materials

Individuals are represented with real-valued chromosomes. The population size is fixed at 30. The initial population is generated by independently sampling each decision variable from a uniform distribution over its bounds. The run terminates after 80 generations, which defines the stopping criterion. Parent selection uses truncation selection. Crossover uses an arithmetic (blend) operator that generates offspring as linear combinations of the parents. The crossover rate is 100%, so all selected parents undergo crossover. The implementation applies a non-uniform mutation operator with a mutation probability of 1%.

This case study demonstrates that a Genetic Algorithm can be successfully employed to identify suitable thermal insulation materials so as to minimize the unit thermal flow through a wall. Figure 4.5 presents the optimization results for the insulated wall, obtained by running the algorithm for a maximum of 80 generations; this serves as the stopping criterion.

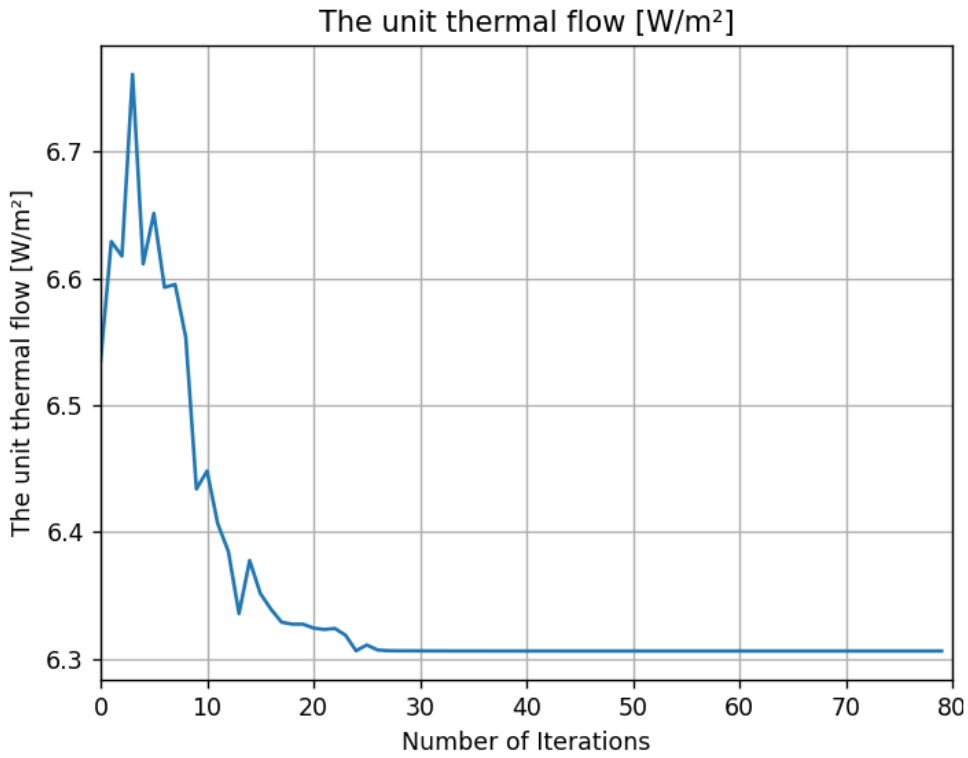


Fig. 4.4. Optimal unit thermal flow through the insulated wall

The expanded polystyrene that achieves the minimum unit thermal flow is characterized by a thermal conductivity of 0.0365 W/(m·K) and a thickness of 149.9 mm. The optimal unit thermal-flow value is 6.378 W/m².

As shown in Figure 4.6, the optimal unit thermal flow through the insulated floor is 1.961 W/m², attained using extruded polystyrene with a thermal conductivity of 0.031 W/(m·K) and a thickness of 94.115 mm.

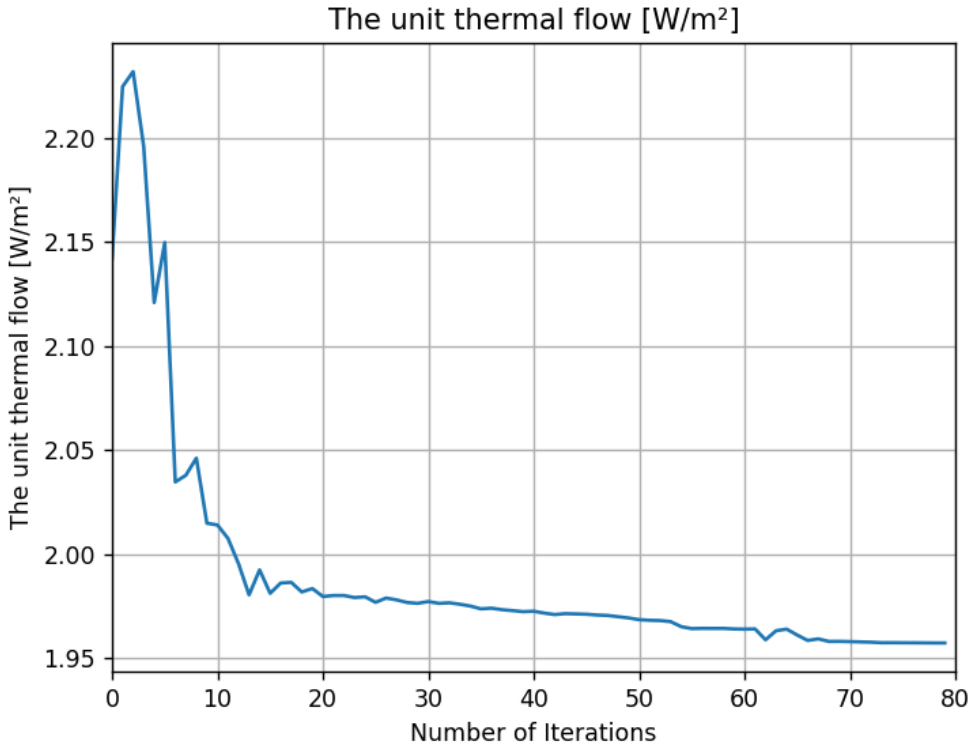


Fig. 4.5. Optimal unit thermal flow through the insulated floor

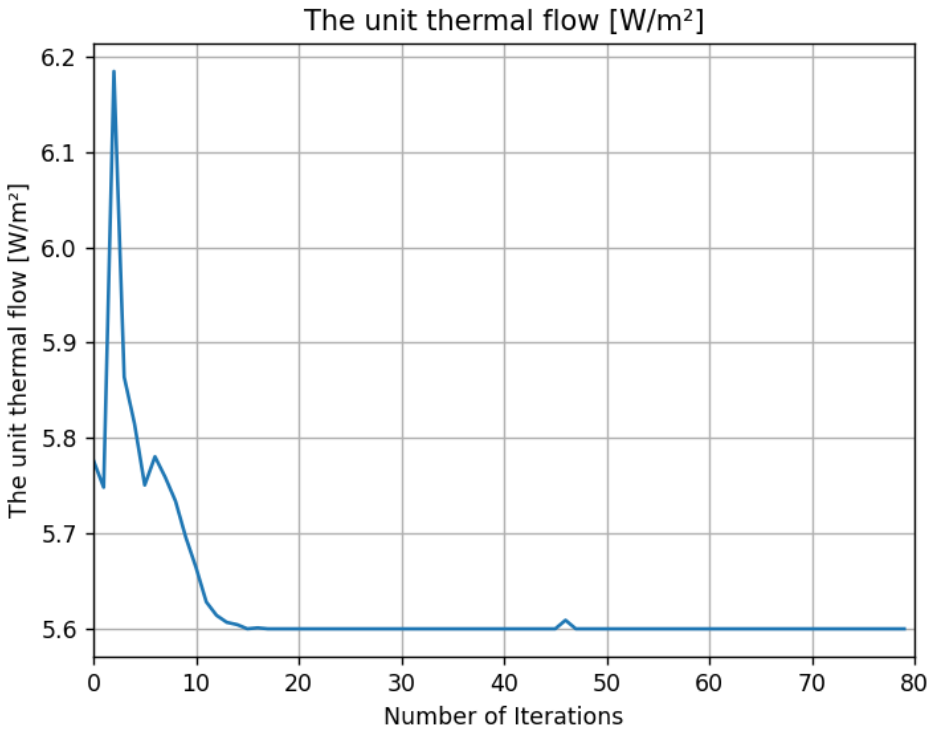


Fig. 4.6. Optimal unit thermal flow through the insulated roof - ceiling

Figure 4.7 presents the optimization results for the insulated roof- ceiling, obtained by running the algorithm with the maximum number of generations set to 80. The mineral wool that yields the lowest unit thermal flow has a thermal conductivity of 0.034 W/(m·K) and a thickness of 199.98 mm. Under these conditions, the optimal unit thermal-flow value is 5.599 W/m².

4.2. CASE STUDY 2 – Optimization of the specific energy need for space heating using NSGA -II

Given its strong performance, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is employed in this case study to identify the optimal thermal envelope configuration that will assure the minimum energy requirement for heating in the case of a residential building, while also considering price restrictions obtained through a specific market survey. The algorithm is implemented in Python using the Pymoo library (multi-objective optimization) and applied to the building under study, whose the exterior walls, floor, and roof-ceiling assembly are insulated with expanded polystyrene, extruded polystyrene, and mineral wool, respectively, while the windows and doors are replaced with higher-performance units whose thermal characteristics are provided in Section 4.2.2. Accordingly, the NSGA-II model explores a search space consisting of insulation-

layer thicknesses and thermal conductivities, together with the thermal properties of windows and doors, to determine the optimal solution.

4.2.1. Description of the Uninsulated Building Envelope

In this study, a hypothetical facility located in Bucharest, Romania emulating a single-family residential building was proposed. The monthly average solar radiation intensity for Bucharest area was considered according to Methodology MC001 – Part I, annex A.9.6, the monthly average of outdoor temperatures according to SR4839 Standard while the ground temperature was obtained from The RETScreen software [75] [78]. These data are summarized in Table 4.2.

Table 4.2. Climate data from Bucharest area

Month	The monthly average solar radiation intensity [W/m2]	The monthly average outdoor temperature [°C]	Ground temperature [°C]
January	59,3	-1,4	-2,2
February	87,3	0,1	0,0
March	91,4	5,1	5,5
April	91,6	11,1	12,0
May	86,0	16,8	18,3
June	92,8	20,7	23,1
July	89,9	22,6	26,0
August	123,8	21,8	25,6
September	119,1	16,5	19,5
October	104,1	10,5	12,2
November	57,4	4,5	5,2
December	53,0	-0,3	-0,7

* Monthly mean solar radiation is computed as the monthly average of the 24-hour daily mean global horizontal irradiance (GHI) incident on a horizontal plane.

According to the national SR1907-2 standard, the computational indoor temperature was considered 20°C for the heating period [76].

Moreover, it was considered that the heating season lasts 4536 hours per year: 744 hours in January, March, October and December, 720 hours in November, 672 hours in February and 168 hours in April. Based on the SR 4839 standard, the heating season in Bucharest area lasts 189 days, assuming an average outdoor temperature of 12°C and a computational indoor temperature of 20°C [75].

The specific energy need for space heating before insulating the exterior walls, floor, and ceiling was 385.128 kWh/(m²·year). To reduce this value, the exterior wall is insulated with expanded polystyrene, the floor with extruded polystyrene, and the roof- ceiling with mineral wool. The windows and doors are also replaced with higher-performance units, whose thermal characteristics are provided in Section 4.2.2. In the uninsulated baseline, the construction materials used for the exterior walls, floor, and ceiling are described in Figures 4.1–4.3.

4.2.2. Optimization problem development

The modeling variables are: the thermal conductivities and thicknesses of the thermal insulation (expanded polystyrene, extruded polystyrene, and mineral wool) used in the exterior walls, floor, and roof- ceiling; for the windows, the overall heat-transfer coefficient (K_{s1}-value) and the total solar energy transmittance (g-value); and for the doors, the overall heat-transfer coefficient (K_{s2}-value). The number of decision variables is *n_var* = 9. The optimization problem has a single objective, namely to minimize the specific energy need for space heating. This problem is implemented as:

$$min\, Q_{heating\,k}\left(\delta_{izol1}, \lambda_{izol1,}\delta_{izol2}, \lambda_{izol2,}\delta_{izol3}, \lambda_{izol3,}K_{s1}, g, K_{s2}\right) = \sum_k h_k \cdot \tag{4.1}$$

$$\left[\Delta T_k \cdot H_V + q_{1k}(\delta_{izol1}, \lambda_{izol1}) \cdot (A_1 + A_2 + A_3 + A_4) + q_{2k}\left(\lambda_{izol2,}\delta_{izol2}\right) \cdot A_5 + q_{3k}\left(\lambda_{izol3,}\delta_{izol3}\right) \cdot A_6 + q_{4k}(g, K_{s1}) \cdot A_7 + q_{5k}(K_{s2}) \cdot A_8\right] \text{ [kWh/year]}$$

where k = January, February, March, April, October, November, December; $Q_{heating}$ = energy requirement for heating [kWh/year]; h_k = the heating period [hours]; H_V = the heat loss coefficient of the building through ventilation [W/K]; ΔT_k = temperature difference [˚C]; $\delta_{ins1,}$ $\delta_{ins2,}$ δ_{ins3} = thickness of the expanded polystyrene, extruded polystyrene and mineral wool [mm]; $\lambda_{ins1,}$ $\lambda_{ins2,}$ λ_{ins3} = thermal conductivities of the expanded polystyrene, extruded polystyrene and mineral wool [W/(m·K)]; $K_{s1,}$ K_{s2} = the overall heat transfer coefficients of windows and doors [W/(m²·K)]; g = total solar energy transmittance [-]; A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8 = the areas of the construction element (western, eastern and northern walls, unglazed surface of the southern wall, floor, roof – ceiling, door and windows [m²]; q_{1k} ($\delta_{ins1,}$ λ_{insl1}), q_{2k} ($\delta_{ins2,}$ λ_{ins2}), q_{3k} ($\delta_{ins3,}$ λ_{ins3}), q_{4k} (g, K_{s1}), q_{5k} (K_{s2}) = the unit thermal flow through the walls, floor, roof – ceiling, windows and door [W/m²].

The aim of the optimization is to find the optimal solutions that minimize the objective function, subject to all problem constraints [76]. In Pymoo, it is necessary to formulate the inequality constraints as less than zero. This will be applied when dealing with price constraints.

Consequently, a survey was conducted and several price combinations for each configuration (consisting of different pairs of thermal properties) were obtained from manufacturers/retailers' websites. Hence, $P_i\ (\delta_{ins\ i},\ \lambda_{ins\ i})$ represents the prices of insulation materials for different combinations of thicknesses ($\delta_{ins\ i}$) and thermal conductivities ($\lambda_{ins\ i}$). Similarly, $P_4(g,\ K_{s1})$ represents the prices of windows, while $P_5(K_{s2})$ contains the prices of different types of doors. These values were further used to compute mean values of the prices for each configuration (consisting of different pairs of thermal properties), resulting the following values: 42.41 RON/m^2 – for expanded polystyrene, 78.91 RON/m^2 – for extruded polystyrene and 91.09 RON/m^2 – for mineral wool. In the case of the windows and doors, these prices were set at 1,500 RON/piece and 6,574.63 RON/piece. The current exchange rate Euro (€) to Romanian leu (RON) is 1€ = 4.97 RON. Consequently, the five price constraints are defined as follows:

$$P_1(\delta_{izol1}, \lambda_{izol1}) - 42{,}41 \ \leq 0\ [\mathrm{RON/m^2}] \tag{4.1}$$

$$P_2(\delta_{izol2}, \lambda_{izol2}) - 78{,}91 \ \leq 0\ [\mathrm{RON/m^2}] \tag{4.2}$$

$$P_3(\delta_{izol3}, \lambda_{izol3}) - 91{,}09 \ \leq 0\ [\mathrm{RON/m^2}] \tag{4.4}$$

$$P_4(g, K_{s1}) - 1500 \ \leq 0\ [\mathrm{RON}] \tag{4.5}$$

$$P_5(K_{s2}) - 6574{,}63 \ \leq 0\ [\mathrm{RON}] \tag{4.3}$$

The lower (x_l) and upper (x_u) variable boundaries are:

$$20 \leq \delta_{izol1} \ \leq 150\ [\mathrm{mm}] \tag{4.4}$$

$$0{,}036 \leq \lambda_{izol1} \ \leq 0{,}042\ [\mathrm{W/(m \cdot K)}] \tag{4.8}$$

$$10 \leq \delta_{izol2} \ \leq 100\ [\mathrm{mm}] \tag{4.5}$$

$$0{,}031 \leq \lambda_{izol2} \ \leq 0{,}039\ [\mathrm{W/(m \cdot K)}] \tag{4.6}$$

$$30 \leq \delta_{izol3} \leq 200 \text{ [mm]} \tag{4.7}$$

$$0{,}034 \leq \lambda_{izol3} \leq 0{,}038 \text{ [W/(m} \cdot \text{K)]} \tag{4.12}$$

$$0{,}4 \leq g \leq 0{,}85 \text{ [}-\text{]} \tag{4.8}$$

$$0{,}6 \leq K_{s1} \leq 5{,}4 \text{ [W/(m}^2 \cdot \text{K)]} \tag{4.9}$$

$$0{,}7 \leq K_{s2} \leq 2{,}47 \text{ [W/(m}^2 \cdot \text{K)]} \tag{4.10}$$

The building under study is single-story and has a net floor area of 130 m². The areas of the building elements are: $A_1 = A_2 = 15{,}6$ [m²]; $A_3 = 48{,}0$ [m²]; $A_4 = 35{,}4$ [m²]; $A_5 = A_6 = 130{,}0$ [m²]; $A_7 = 10{,}8$ [m²], $A_8 = 1{,}8$ [m²]. The linear dimensions of the building are shown in Figure 4.8.

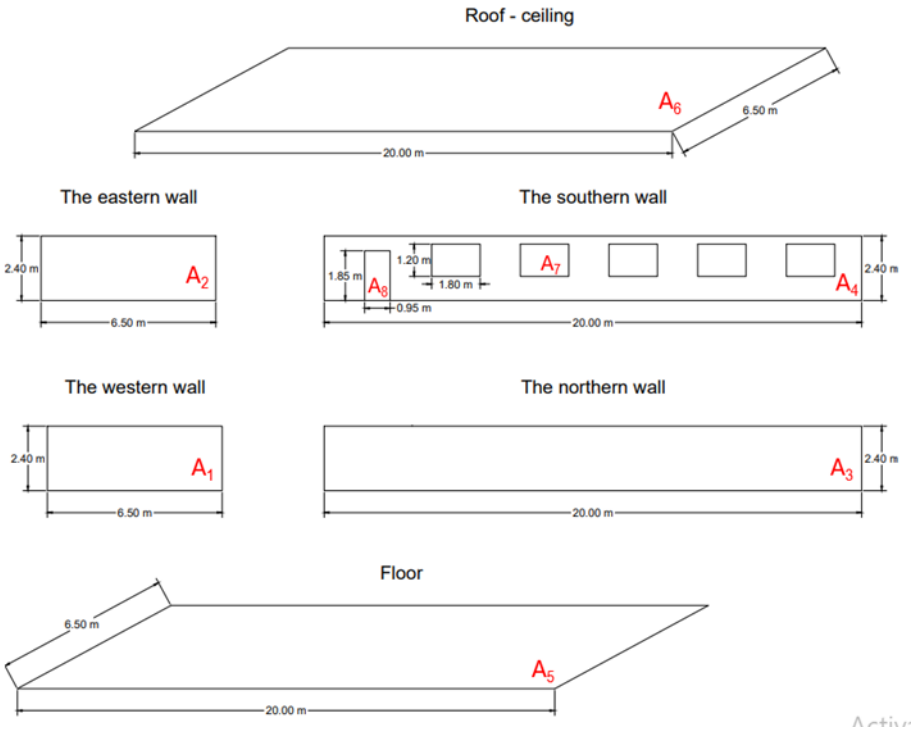


Fig. 4.7. The linear dimensions of the studied single floor building [77]

The heat loss coefficient of the building through ventilation, H_V is determined using the relation 4.16:

$$H_V = \frac{\rho_a c_a n_a V}{3{,}6} \left[\frac{\mathrm{W}}{\mathrm{K}}\right] \tag{4.16}$$

where ρ_a = air density; c_a = specific heat of air; n_a = the average number of air changes; V = heated volume. These parameters are considered: $\rho_a = 1.2 \frac{\mathrm{kg}}{\mathrm{m}^3}; V = 312\ \mathrm{m}^3; c_a = 1.005 \frac{\mathrm{kJ}}{\mathrm{kgK}}; n_a = 0.6\ \mathrm{h}^{-1}$ [78].

To determine the average air-change rate, the building is assumed to be in a moderately sheltered location and to have a medium permeability class.

In the case of the heat fluxes, the Fourier unidirectional conduction equation is written for each of the building's components: walls (relation 4.17), floor (relation 4.18) and roof-ceiling (relation 4.19). The unit thermal flows q_{4k} (g, K_{s1}) and q_{5k} (K_{s2}) for windows and door are computed using relations (4.20) and (4.21).

$$q_{1k}(\delta_{izol1}, \lambda_{izol1}) = \frac{\theta_{in} - \theta_{ext\,k}}{\frac{1}{\alpha_{1in}} + \frac{\delta_1}{\lambda_1} + \frac{\delta_2}{\lambda_2} + \frac{\delta_3}{\lambda_3} + \frac{\delta_{izol1}}{\lambda_{izol1}} + \frac{1}{\alpha_{1ext}}} \left[\frac{\mathrm{W}}{\mathrm{m}^2}\right] \tag{4.11}$$

$$q_{2k}(\delta_{izol2}, \lambda_{izol2}) = \frac{\theta_{in} - \theta_{sol\,k}}{\frac{1}{\alpha_2} + \frac{\delta_1}{\lambda_1} + \frac{\delta_2}{\lambda_2} + \frac{\delta_3}{\lambda_3} + \frac{\delta_4}{\lambda_4} + \frac{\delta_{izol2}}{\lambda_{izol2}} + \frac{\delta_{1p}}{\lambda_{1p}} + \frac{\delta_{2p}}{\lambda_{2p}}} \left[\frac{\mathrm{W}}{\mathrm{m}^2}\right] \tag{4.12}$$

$$q_{3k}(\delta_{izol3}, \lambda_{izol3}) = \frac{\theta_{in} - \theta_{ext\,k}}{\frac{1}{\alpha_{3in}} + \frac{\delta_1}{\lambda_1} + \frac{\delta_2}{\lambda_2} + \frac{\delta_3}{\lambda_3} + \frac{\delta_{izol3}}{\lambda_{izol3}} + \frac{1}{\alpha_{3ext}}} \left[\frac{\mathrm{W}}{\mathrm{m}^2}\right] \tag{4.13}$$

$$q_{4k}(g, K_{s1}) = K_{s1} \cdot (\theta_{in} - \theta_{ext\,k}) + G_k \cdot \mathrm{g} \left[\frac{\mathrm{W}}{\mathrm{m}^2}\right] \tag{4.14}$$

$$q_{5k}(K_{s2}) = K_{s2} \cdot (\theta_{in} - \theta_{ext\,k}) \left[\frac{\mathrm{W}}{\mathrm{m}^2}\right] \tag{4.15}$$

where θ_{in} = computational indoor temperature [˚C]; $\theta_{ext\,k}$ = monthly average outdoor temperature presented in Table 4.2 [˚C]; $\theta_{sol\,k}$ = ground temperature presented in 4.2 [°C]; α_{1in}, α_{1out}, α_2, α_{3in}, α_{3out} = convection heat transfer coefficient [W/(m^2·K)]; δ_1, δ_2, δ_3, δ_4 = thickness of the construction materials in case of exterior walls, floor or roof-ceiling shown in Figures 4.1, 4.2 and 4.3 [mm]; λ_1, λ_2, λ_3, λ_4 = thermal conductivities of the construction materials in case of exterior walls, floor or roof-ceiling shown in Figures 4.1, 4.2 and 4.3 [W/(m·K)]; δ_{ins1}, δ_{ins2}, δ_{ins3} = thickness of the expanded polystyrene, extruded polystyrene and mineral wool [mm]; λ_{ins1}, λ_{ins2}, λ_{ins3} = thermal conductivities of the expanded polystyrene, extruded polystyrene and mineral wool [W/(m·K)]; δ_{1p}, δ_{2p} = depth in the ground [mm]; λ_{1p}, λ_{2p} = ground thermal conductivity [W/(m·K)]; K_{s1}, K_{s2} =

the overall heat transfer coefficients [W/(m^2·K)]; g = total solar energy transmittance [-]; G_k = monthly average solar radiation intensity presented in Table 4.2 [W/m^2].

To compute q_{1k} $(\delta_{izol1}, \lambda_{izol1})$, q_{2k} $(\delta_{izol2}, \lambda_{izol2})$ și q_{3k} $(\delta_{izol3}, \lambda_{izol3})$, the convective heat-transfer coefficients and the ground thermal conductivity are adopted as specified in Table 4.1.

Several types of glazing are considered such as: clear float glass; double glazed IGUs (insulating glass units) consisting of two float glasses separated by a compact layer of air; double glazed IGUs with one float glass and one low emissivity (low – E) glass separated by air or Argon; four seasons (4S) double glazed IGUs consisting of a float glass and a 4S glass separated by Argon; triple glazed IGUs with three float glasses separated by a compact layer of air; triple glazed IGUs with two 4S glasses and one float glass, separated by Argon; triple glazed IGUs with one float glass and two low – E glass, separated by Argon or Krypton; triple glazed IGUs with two float glasses and one low – E glass, separated by Argon; triple glazed IGUs with one 4S glass, one float glass and one low – E glass, separated by Argon; triple glazed IGUs with one 4S glass and two float glasses separated by Argon or air. Moreover, we considered wood, glass, metal, MDF (Medium density fiberboard), PVC (Polyvinyl chloride) and UPVC (plasticized polyvinyl chloride) doors.

4.2.3. Implementation of the Algorithm

Sampling is used to generate the initial population. In statistics, sampling denotes selecting a subset of individuals from a parent population (the sample) to estimate characteristics of the whole population. The initial population size is set to 40 individuals. The NSGA-II algorithm produces 10 offspring per generation, and individuals are ranked into Pareto fronts via non-dominated sorting. The stopping criterion is a maximum of 200 generations. This parameter was chosen by trial and error after testing several settings; the results indicate that 200 generations are adequate to obtain a well-spread approximation of the Pareto front [64].

For crossover, the *Simulated Binary Crossover (SBX)* operator is employed with a crossover probability of 0.9. Offspring are generated according to relation 3.5 in section 3.1.

For mutation, the Polynomial Mutation operator is used with a mutation probability of 0.111 and a distribution index of 20 ($\eta = 20$).

Table 4.3. The values of the overall heat transfer coefficients

Element		Thickness [mm]	Thermal conductivity [W/(m·K)]	R – values, non-insulated building [(m²·K)/W]	*K_s values, non-insulated building [W/(m²·K)/]	R values, insulated buiding [(m²·K)/W]	*K_s values, insulated building [W/(m²·K)]
Exterior wall	Interior plaster	20	0,80	0,025	0,723	0,025	0,249
	Autoclaved Aerated Concrete	350	0,30	1,166		1,166	
	Exterior plaster	20	0,80	0,025		0,025	
	Expanded polystyrene	100	0,038	–		2,632	
Floor	Reinforced concrete	150	2,03	0,074	0,485	0,074	0,189
	Self-levelling concrete	25	0,46	0,054		0,054	
	The polyethylene foam	3	0,05	0,06		0,06	
	Parquet	14	0,13	0,107		0,107	
	Extruded polystyrene	100	0,031	–		3,226	
Roof-ceiling	Plater	25	0,80	0,031	2,718	0,031	0,178
	Reinforced concrete	150	2,03	0,074		0,074	
	Self-levelling concrete	25	0,46	0,054		0,054	
	Mineral wool	200	0,038	–		5,263	

*Ks values of exterior walls, roof – ceiling, and floor were obtained considering the heat transfer by conduction and convection and thermal resistance of the ground

Table 4.3 presents the technical characteristics of the thermal insulation materials identified as optimal. The optimal solution uses a triple-glazed insulating glass unit (IGU) with argon fill, comprising two 4S-coated panes and one float glass pane. These windows have an overall heat-transfer coefficient of 0.6 W/(m²·K) and a total solar energy transmittance (g-value) of 0.40. For the doors, NSGA-II selected stainless-steel-clad laminated oak doors with a K_s-value of 0.7 W/(m²·K). Table 4.3 also compares the overall heat-transfer coefficients for the uninsulated baseline and the insulated case.

Figure 4.9 shows the reduction in space-heating energy demand over the course of the NSGA-II run.

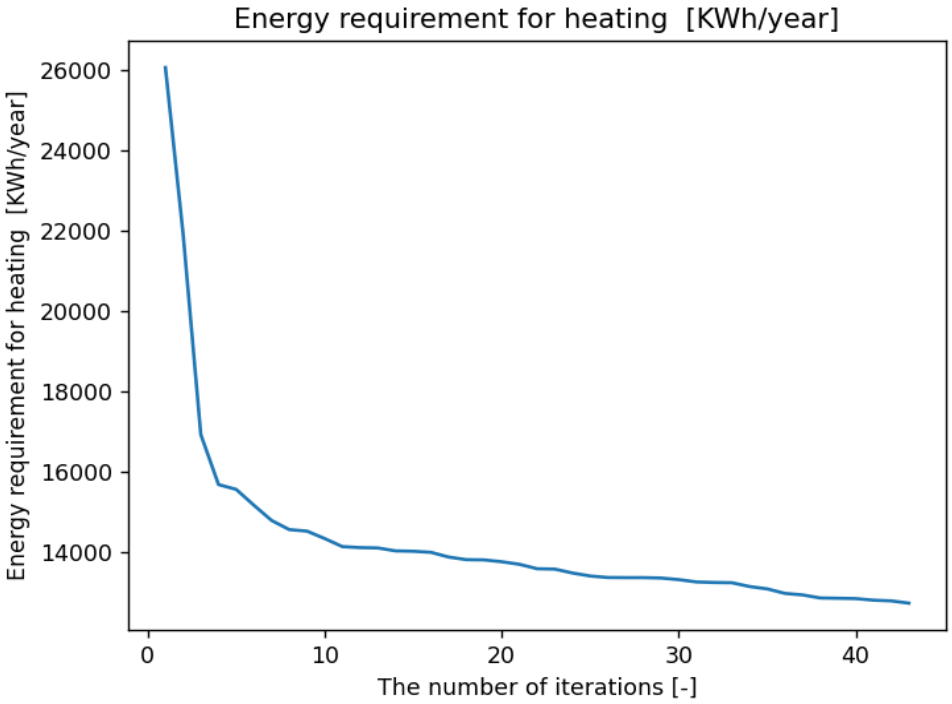


Fig. 4.8. Energy requirement for heating [kWh/year]

It is observed that the optimal space-heating energy demand for the insulated building is 12,486.16 kWh/year. Normalized by the dwelling's net floor area, this corresponds to 96.05 kWh/(m²·year). By using expanded polystyrene (EPS), extruded polystyrene (XPS), and mineral wool with the thermal properties listed in Table 4.3, together with triple-glazed insulating windows with an overall window $K_s = 0.6$ W/(m^2·K) and doors with $K_s = 0.70$ W/(m^2·K), the space-heating energy demand is reduced by approximately 75% compared with the uninsulated baseline.

4.3. CASE STUDY 3 – Simultaneous optimization of the specific energy need for space heating and for space cooling, using NSGA-II

An NSGA-II (Non-dominated Sorting Genetic Algorithm II) developed with the pymoo library searches for solutions that simultaneously minimize the specific energy need for space heating and for space cooling, subject to price constraints. The algorithm is applied to the same insulated building presented earlier, with the aim of automatically identifying the most suitable insulation materials and building components while honoring the specified cost limits. Additional inputs required to define the multi-objective problem, beyond those in Section 4.2, are the conventional indoor design temperature for the cooling season and the duration of the cooling

period. In the modeling, a conventional indoor design temperature of 25 °C is used during the cooling season [79]. A balance-point temperature of 17.1 °C is assumed, and the cooling-season duration is taken as 360 h in May, 720 h in June, 744 h in July, 744 h in August, and 192 h in September.

The building's cooling energy demand prior to applying thermal insulation is 73.855 kWh/(m²·year). The thermal properties of the construction materials are those used in Case Study 2. Unlike the previous optimization problem, the present formulation has two objectives *n_obj* = 2. Two objective functions are defined together with five price-related constraint equations. The first objective—minimization of the space-heating energy demand—is given by relation (4.1). The second objective—minimization of the space-cooling energy demand—is given by relation (4.22). The five price constraints, as well as the lower and upper bounds on the decision variables, are the same as those specified in Case Study 2, relations (4.2)–(4.15).

$$min\, Q_{coolng\,m}\left(\delta_{izol1}, \lambda_{izol1,}\delta_{izol2}, \lambda_{izol2,}\delta_{izol3}, \lambda_{izol3,}K_{s1}, g, K_{s2}\right) = \sum_m h_m \cdot \tag{4.16}$$

$$\left[\Delta T_m \cdot H_V + q_{1m}(\delta_{izol1}, \lambda_{izol1}) \cdot (A_1 + A_2 + A_3 + A_4) + q_{2m}\left(\lambda_{izol2,}\delta_{izol2}\right) \cdot A_5 + q_{3m}\left(\lambda_{izol3,}\delta_{izol3}\right) \cdot A_6 + q_{4m}(g, K_{s1}) \cdot A_7 + q_{5m}(K_{s2}) \cdot A_8\right] \text{ [kWh/an]}$$

where m = May, June, July, August, September; $Q_{răcire}$ = energy requirement for cooling [kWh/year]; h_m = the cooling-season duration [hours]; H_V = the heat loss coefficient of the building through ventilation [W/K]; ΔT_k = temperature difference [˚C]; δ_{ins1}, δ_{ins2}, δ_{ins3} = thickness of the expanded polystyrene, extruded polystyrene and mineral wool [mm]; λ_{ins1}, λ_{ins2}, λ_{ins3} = thermal conductivities of the expanded polystyrene, extruded polystyrene and mineral wool [W/(m·K)]; K_{s1}, K_{s2} = the overall heat transfer coefficients of windows and doors [W/(m²·K)]; g = total solar energy transmittance [-]; A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8 = the areas of the construction element (western, eastern and northern walls, unglazed surface of the southern wall, floor, roof – ceiling, door and windows [m²]; q_{1k} (δ_{ins1}, λ_{insl1}), q_{2k} (δ_{ins2}, λ_{ins2}), q_{3k} (δ_{ins3}, λ_{ins3}), q_{4k} (g, K_{s1}), q_{5k} (K_{s2}) = the heat fluxes through the walls, floor, roof – ceiling, windows and door [W/m²].

The NSGA-II results show that minimum space-heating and space-cooling energy demands can be achieved simultaneously, while satisfying the price constraints, when the following specifications are used:

- expanded polystyrene (EPS) with thermal conductivity 0.038 W/(m·K) and thickness 100 mm;

- extruded polystyrene (XPS) with thermal conductivity 0.031 W/(m·K) and thickness 100 mm;
- mineral wool with thermal conductivity 0.038 W/(m·K) and thickness 200 mm;
- a triple-glazed insulating glass unit (IGU) with two 4S-coated panes and one float pane, argon fill, overall window K_s-value 0.60 W/(m²·K), and total solar energy transmittance (g-value) 0.40;
- stainless-steel-clad laminated oak doors with K_s-value 0.70 W/(m²·K).

Figures 4.10 and 4.11 depict the evolution of the space-heating and space-cooling energy demands over the NSGA-II run, plotting only those iterations that improve upon the incumbent best (i.e., new running minima). The optimal totals are 12,486.16 kWh/year and 2802.28 kWh/year, respectively. The corresponding specific energy demands are 96.05 kWh/(m²·year) for heating and 21.56 kWh/(m²·year) for cooling.

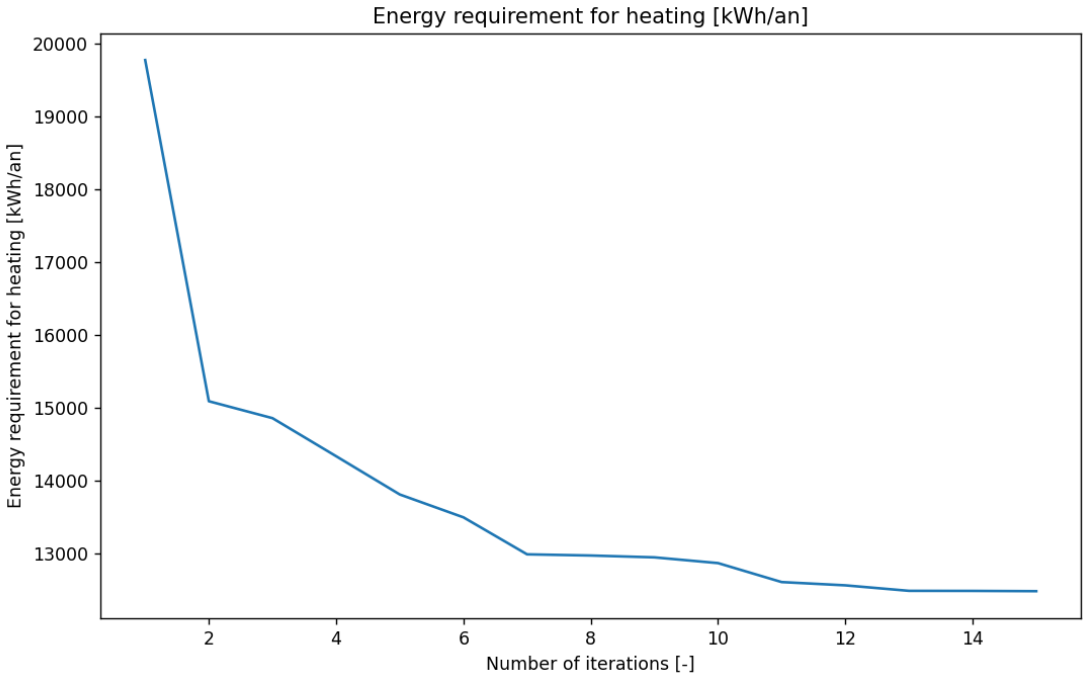


Fig. 4.9. Evolution of the space-heating energy demand during the NSGA-II run [kWh/an]

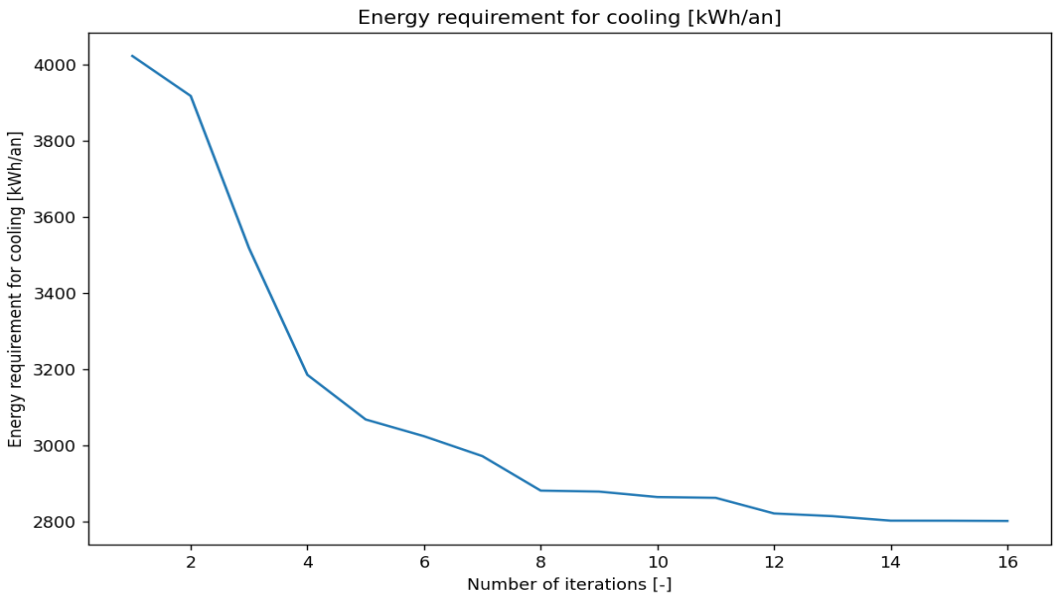


Fig. 4.10. Evolution of the space-cooling energy demand during the NSGA-II run [kWh/an]

The space-heating and space-cooling energy demands thus determined account for the same heat losses and gains as those specified in Case Study 2. By insulating the building and replacing the windows and doors with the higher-performance units described in this chapter, these demands are reduced by approximately 75% and 71%, respectively, relative to the uninsulated baseline.

CHAPTER 5. DESCRIPTION OF THE HYBRID SYSTEM USED TO MEET THE THERMAL ENERGY DEMAND

This section presents a comprehensive study on the integration of heat pumps into the energy retrofit of existing residential buildings. The objective is to select optimal energy-system configurations to meet the energy demand for space heating and domestic hot water (DHW), as follows:

- selection of air-to-water heat pumps that satisfy the technical and economic criteria defined in Section 5.2, with a comparative assessment implemented in Python 3.11;
- verification of the practical applicability of the Python-based model using the GeoT*SOL software;
- selection of a hybrid system comprising a heat pump, solar thermal collectors, and photovoltaic (PV) panels, with emphasis on reducing dependence on fossil fuels in Romania's residential building stock.

5.1. The energy consumption for domestic hot water preparation

The energy consumption for domestic hot water preparation (Q_{am}) was computed using the following equations (5.1) – (5.5) [72].

$$Q_{acm} = Q_{ac} + Q_{ac,c} \text{ [kWh/an]} \tag{5.1}$$

$$Q_{ac} = \sum_{i=1}^{n} \rho \cdot c_{ap\check{a}} \cdot V_{ac} \cdot (\theta_{ac} - \theta_{ar}) \text{ [kWh/an]} \tag{5.2}$$

$$V_{ac} = \frac{a \cdot N_u}{1000} \text{ [m}^3\text{]} \tag{5.3}$$

$$Q_{ac,c} = \sum \rho \cdot c_{ap\check{a}} \cdot V_{ac,c} \cdot \left(\theta_{ac,c} - \theta_{ar}\right) \text{ [kWh/an]} \tag{5.4}$$

$$V_{ac,c} = V_{ac} \cdot f_1 \cdot f_2 - V_{ac} \text{ [m}^3\text{]} \tag{5.5}$$

where Q_{ac} = the energy required for domestic hot water preparation [kWh/year]; $Q_{ac,c}$ = the heat losses related to the waste of domestic hot water [kWh/year]; ρ = 983,2 [kg/m^3] = the density of water [kg/m^3]; c_w = the specific heat capacity of liquid water [kJ/(kg · K)]; V_{ac} = the required volume of domestic hot water for the considered period [m^3]; $V_{ac,c}$ = the volume corresponding to losses and waste of hot water [m^3]; θ_{ac} = 60 ºC = the hot water preparation temperature [˚C]; θ_{ar} = 10 ºC = the temperature of cold water entering the hot water preparation system [˚C]; $\theta_{ac,c}$ = 50 ºC = the temperature of supply/use of hot water at the point of consumption [˚C]; i = 1, n, the calculation index for consumer categories [-]; a = 50 [l/persoană/zi] = the specific demand for domestic hot water at 60˚C [m^3]; N_u = 6 [–] = number of people, f_1 = 1.3 (coefficient that depends on the type of installation to which the consumption point is connected); f_2 = 1.1 (coefficient that depends on the technical condition of the armatures where hot water is consumed)[72].

Thus, the domestic hot water energy demand (Q_{acm}) is: $Q_{acm} = Q_{ac} + Q_{ac,c} = 3238{,}77 + 1114{,}14 = 4352{,}91 \left[\frac{\text{kWh}}{\text{an}}\right]$.

5.2. Optimal Heat Pump Selection Using a Python-Based Mathematical Model

The database used to select air-to-water heat pumps that satisfy the specified technical and economic criteria was created with RETScreen Expert v9.0. A total of 150 heat-pump models from 16 different manufacturers are benchmarked in Python 3.11 against the criteria listed below.

5.2.1. Finance-Prioritized Modeling Scenario

In this modeling scenario, a maximum allowable purchase price is set for the heat pumps, and the units that meet this price cap are compared in terms of: coefficient of performance (COP), condenser heat output (heating capacity), and the number of units required to meet the energy demand for space heating and domestic hot water (DHW):

- Criteria 1: $Preț_{pompe} \leq$ 20200 RON și $N_{pompe} = 1$

where 20200 RON represents the maximum cost that can be allocated to heat pumps. This cost was obtained through a specific market survey.

$$N_{pompe} = \frac{Q_{ctotal}}{Q_{cpompă}} \ [-] \tag{5.6}$$

$$Q_{ctotal} = \frac{Q_{încălzire} + Q_{acm}}{h_{pompă}} \ [\text{kW}] \tag{5.7}$$

where N_{pumps} = the number of pumps selected to cover most of the energy requirements for heating and hot water preparation for the studied building [-]; Q_{cpump} = the thermal load of the capacitor for every studied pump [kW]; Q_{ctotal} = 14.52 kW represents the thermal load for heating and hot water preparation in case of our simulation; $Q_{heating}$ = the energy requirement for heating [kWh/year] (relation 1); Q_{am} = the energy consumption for domestic hot water preparation [kWh/year] (relation 30); h_{pumps} = 2,000 h/year represents the operating hours of the pump.

The heat pumps selected after applying the first criterion are listed in Table 5.1.

Table 5.1. Heat Pumps Selected under Criterion 1

Manufacturer		Fedders	Luxaire	Shandong
Brand		H30BA1	BUA-030	LAWHRPA08
$Q_{cpompă}$	[kW]	8,78	8,47	9,60
$Q_{0pompă}$	[kW]	4,50	5,65	6,40
$P_{pompă}$	[kW]	4,28	2,82	3,20
COP	[–]	2,05	3,00	3,00
$Preț_{pompe}$	[RON]	20158	20040	20000

- Criteriul 2: $COP \geq 3$

$$COP = \frac{|Q_{cpompă}|}{P_{pompă}} = \frac{|Q_{cpompă}|}{|Q_{Cpompă}| - Q_{0pompă}} \ [-] \tag{5.8}$$

where COP = the coefficient of performance [-]; Q_{opump} = the refrigerating power of the evaporator for every studied pump [kW]; Q_{ototal} = total refrigerating power of evaporators [kW]; P_{pump} = the power consumed by the compressor for every studied pump [kW]; P_{total} = total power consumed by compressors [kW].

The coefficient of performance (COP) of a heat pump depends on several factors, the most relevant being the supply temperature of the heat-transfer fluid at the load, proper system sizing, pressure drops in the hydronic circuits, and the efficiency of auxiliary components such as circulation pumps and fans. For air-to-water heat pumps, performance also depends on the outdoor air temperature and humidity, which constitute the heat source [80]. At higher outdoor temperatures, the temperature lift between source air and heating medium decreases, reducing compressor work and increasing the COP. Under low-temperature conditions, the lift increases, which raises energy consumption and lowers the COP [81]. Other aspects influencing the COP include installation quality, pipe insulation, and the thermal characteristics of the building in which the heat pump is integrated [82].

In this modeling scenario, a minimum COP of 3 (COP ≥ 3) is adopted based on manufacturer specifications. This threshold represents an appropriate trade-off between energy efficiency and capital cost. Under typical operating conditions, such equipment maintains high energy performance throughout the heating season and provides stable, reliable operation across the anticipated temperature range.

According to the model, the heat pumps selected under Criterion 1 that also satisfy Criterion 2 are Luxaire model BUA-030 and Shandong model LAWHRPA08. The characteristics of these heat pumps are listed in Table 5.1.

- Criteriul 3: $8{,}42 \leq Q_{cpompă} \leq 9$

The Luxaire heat pump listed in Table 5.1 also satisfies Criterion 3. According to the first modeling scenario, this unit is the optimal choice on both technical and financial grounds.

5.2.2. Second Modeling Scenario Prioritizing Technical Criteria

In this modeling scenario, the heat pumps are compared on the basis of the technical specifications defined in Modeling Scenario 1; the selected units are then checked for compliance with the imposed maximum price cap.

- Criteriul 1: $N_{pompe} = 1$ și $COP \geq 3$

After applying this criterion, the algorithm selects a total of 16 heat-pump models.

- Criteriul 2: $8{,}42 \leq Q_{cpompă} \leq 9$

The modeling results indicate that air-to-water heat pumps with the specifications shown in Figure 5.2 must be installed to meet the 9 kW heating load required for space heating and domestic hot water (DHW) during the heating season in the building under study, in accordance with the technical criteria.

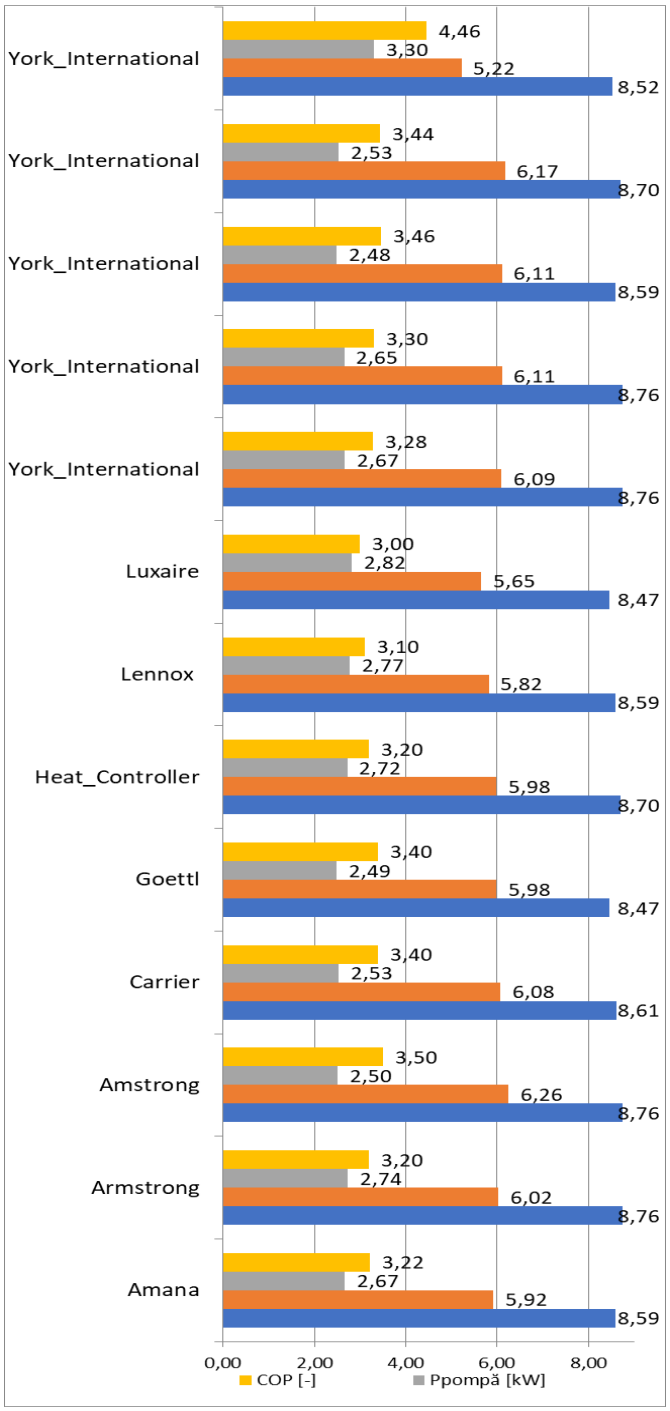


Fig. 5.1. Heat Pumps Selected under Technical Criteria

The third criterion applied is financial. After applying it, the remaining unit is the Luxaire BUA-030 air-to-water heat pump, with a condenser heat output (heating capacity) of 8.42 kW, an evaporator heat input of 5.65 kW, and a COP of 3.0. According to the two mathematical models implemented in Python, this heat pump best satisfies the imposed technical and financial criteria.

5.3 Validation of the Practical Applicability of the Mathematical Model Result

This subsection validates the practical applicability of the Python-based mathematical model using the GeoT*SOL software. GeoT*SOL is licensed commercial software developed by Valentin Software, intended for dynamic modeling of air-, water-, and ground-source heat pumps, including hybrid systems composed of heat pumps together with solar thermal collectors and/or photovoltaic (PV) panels [83]. GeoT*SOL uses its own climate data set, MeteoSyn, derived from the Meteonorm 8.2 database [84].

After selecting the climate zone, the heat-pump type is chosen; an air-source unit is selected from the software database. The next step in the simulation is to input the net floor area of the building under study and its space-heating energy demand, determined in Section 4.2.4 as 12,486.16 kWh/year. Additional inputs include the indoor design temperature and the outdoor design temperature. According to the literature, the indoor temperature is set to 20 °C and the outdoor design temperature to −15 °C [72].

For the simulation of the domestic hot water (DHW) energy demand, a per-capita hot-water consumption of 50 L/day is assumed [72]. It is further assumed that six persons occupy the dwelling.

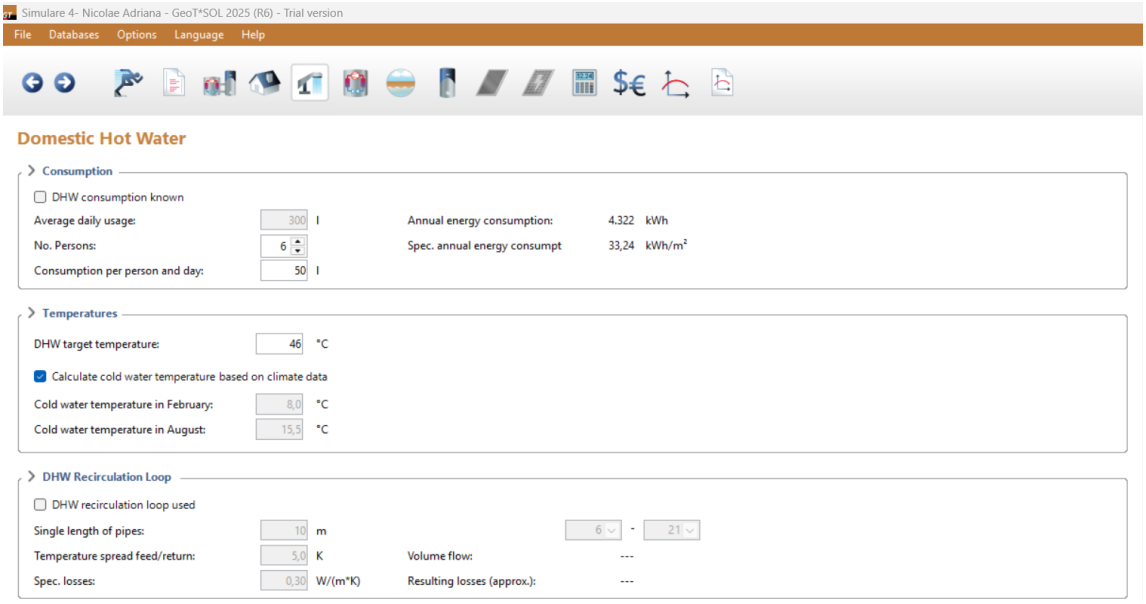


Fig. 5.2. Domestic Hot Water (DHW) Energy Demand in the GeoT*SOL Simulation

Figure 5.2 shows that the energy demand thus determined is close to the value obtained with the mathematical model presented in Methodology MC001 (relation 5.1) [72]. The difference between the two values is 30.91 kWh/year.

The next step in the simulation is to select the heat-pump technical specifications from the GeoT*SOL database. To match the unit chosen by the Python-based model (Section 5.2.3), a Schüco International KG heat pump, model HPSol11, with COP = 3.1 and a rated capacity of 8.8 kW, is selected. According to the simulation results, the seasonal performance factor (SPF) of the simulated air-to-water heat pump is 2.73. This value is relatively low by current standards, where SPF ≥ 3 is considered acceptable and high-performance systems reach SPF ≈ 4. Figure 5.3 presents the dynamic simulation results produced by Geo*TSOL. The selected heat pump delivers 16921 kWh of thermal energy over the heating season, fully covering the thermal load; about 75% of the generated heat is used for space heating. The electrical energy consumed by the heat pump is 6189 kWh per season.

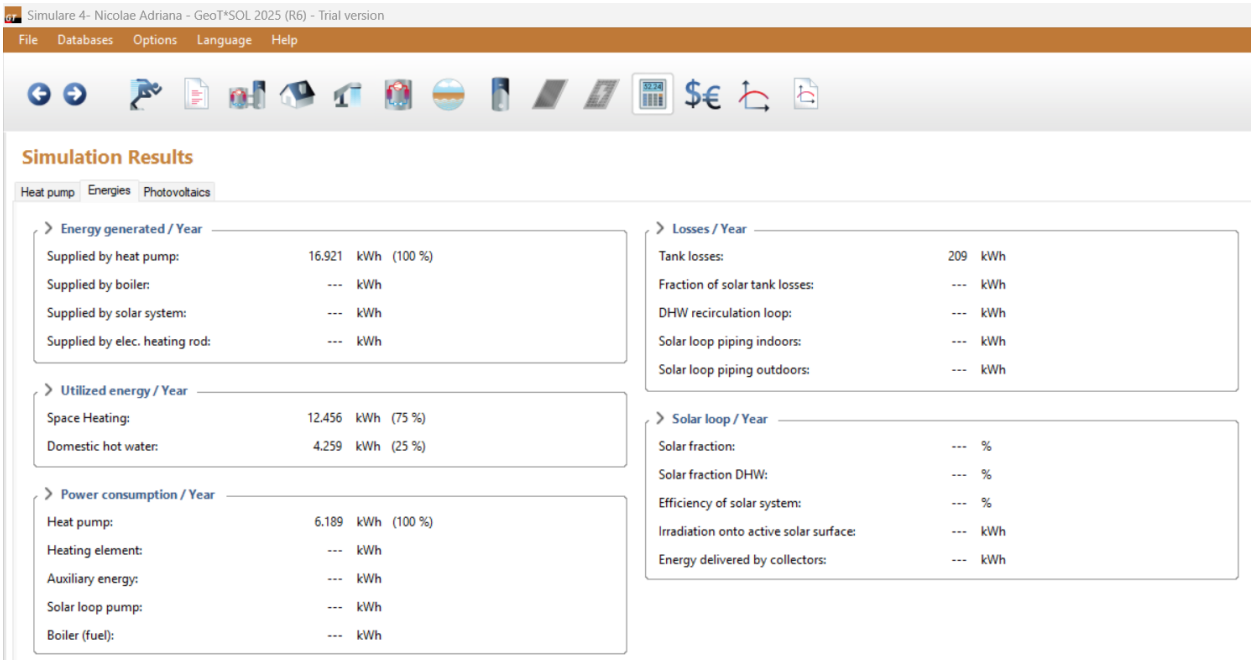


Fig. 5.3. Thermal energy delivered by the heat pump

The dynamic simulation results confirm the practical applicability of the Python-based mathematical model: the heat pump selected by the model can meet the entire thermal energy demand without oversizing. However, the system can be improved, as the Seasonal Performance

Factor (SPF) is relatively low, which implies lower overall system efficiency and higher operating costs.

5.4. Simulation of a Hybrid System Consisting of a Heat Pump, Solar Thermal Panels, and Photovoltaic Panels

To improve the overall efficiency of the previously simulated system, a hybrid configuration is simulated in GeoT*SOL consisting of a heat pump, solar thermal collectors, and photovoltaic (PV) panels. In this analysis, the system comprises five Schulte GmbH SFK 2300 solar thermal collectors with a total area of 10.61 m², and twenty PV panels with a total area of 32.6 m². These components are shown in Figure 5.4.

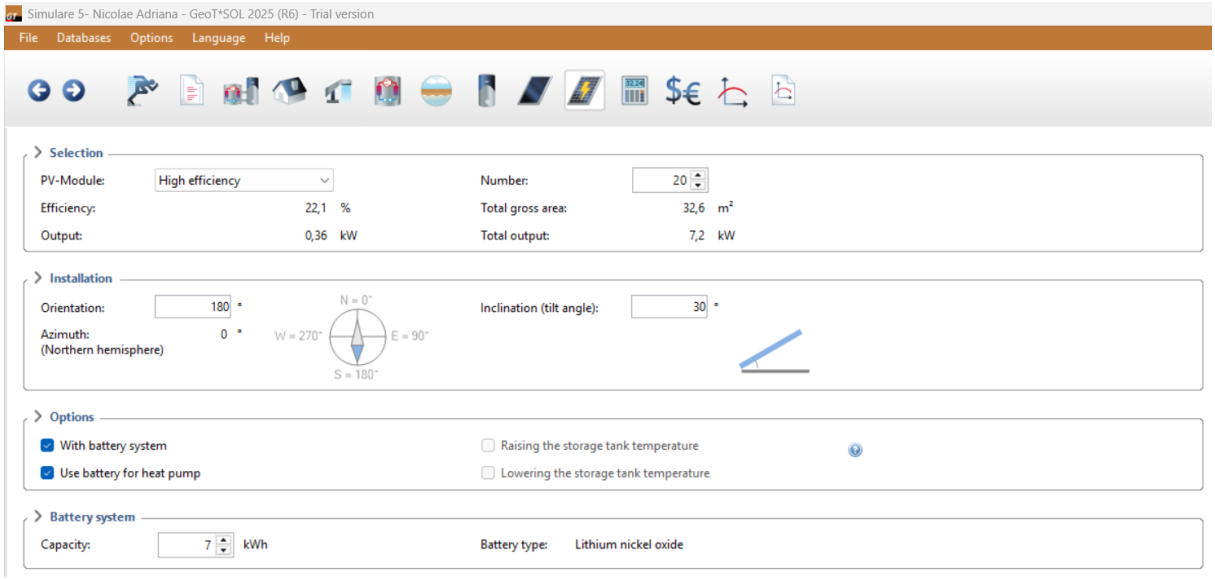


Fig. 5.4. Photovoltaic panels used in the simulation

The simulation results show a significant improvement in the system's Seasonal Performance Factor (SPF), which reaches 3.59. Figure 5.5 also presents the energy-related results of the dynamic simulation. The figure shows the amount of thermal energy produced by each system component. For example, the heat pump now supplies 79% of the thermal energy demand during the heating season (13,420 kWh), while the solar thermal collectors cover the remaining 21% (3,462 kWh). The largest electricity consumption is attributable to the heat pump, totaling 4,594 kWh over the heating season. The solar thermal system's auxiliary electricity use is estimated at 110 kWh in the same season.

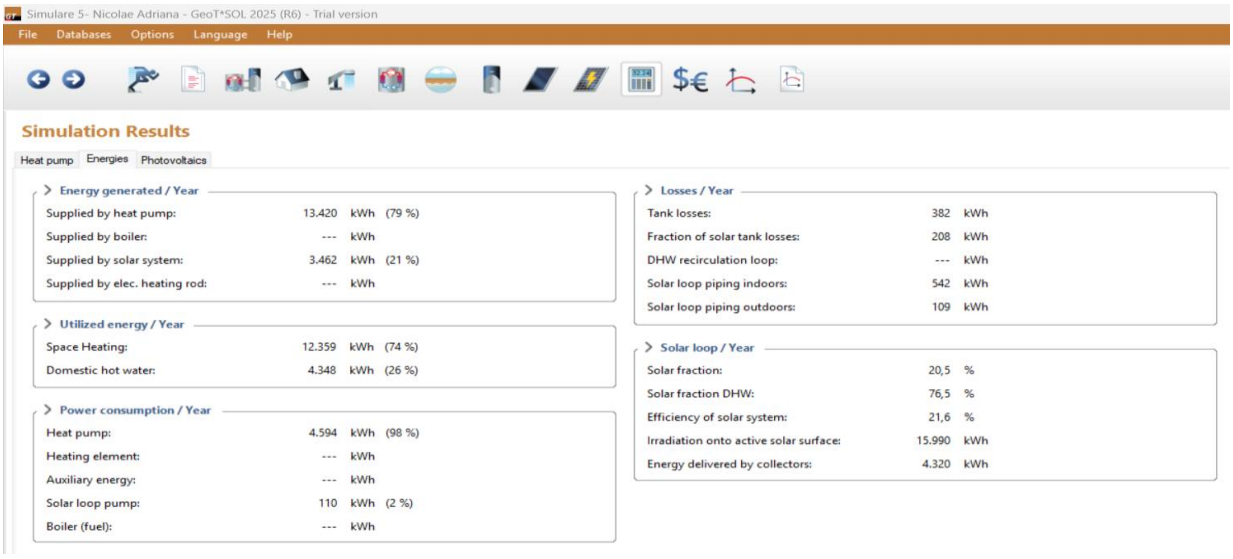


Fig. 5.5. Thermal energy generated by the hybrid system

Additionally, the installed photovoltaic (PV) array produces 10,291 kWh, of which 51.5% is self-consumed by the system and 49.9% is exported to the grid as surplus electricity. This has a positive impact by reducing electricity bills.

In conclusion, beyond the financial benefit (lower electricity bills), the hybrid system underscores the importance of shifting from purely fossil-fuel-based energy systems to environmentally friendly hybrid alternatives, thereby aligning with the national targets, even in the presence of technological constraints (e.g., available installation area) and financial constraints (high upfront costs).

COCLUZII

This chapter synthesizes the main results obtained in the doctoral thesis, highlighting the author's original contributions and outlining research directions that follow from the work conducted to date. The thesis is structured into five chapters, each addressing a topic of interest in the field of building energy efficiency.

GENERAL CONCLUSIONS

CHAPTER 1 examines in detail how buildings influence energy consumption, considering both the European perspective and the national context. It also presents the rationale for the thesis through an in-depth assessment of energy use in the building sector. The key takeaway from the statistics is that the building sector is the second-largest end-use energy consumer in the EU, after transport. Within buildings, the largest share of energy use is for space heating (62.5%), followed by water heating (15.1%). Natural gas supplies nearly one third of building energy (29.5%), followed by electricity (25.9%) and renewables (23.5%). The remainder comes from petroleum products (10.3%), derived heat (8.5%), and solid fossil fuels (2.2%). Moreover, the building sector currently accounts for about 26% of energy-sector CO_2 emissions, of which 8% are direct and 18% are indirect (from the production of electricity and heat used in buildings). These figures underscore the need for prompt action to reduce the energy impact of buildings on both energy use and greenhouse gas (GHG) emissions across the EU. Consequently, research continues to focus on developing and applying new methods to improve the energy efficiency of existing buildings.

CHAPTER 2 presents a broad literature review of applications of seven optimization algorithms in the building sector. Its central element is a comparative assessment of these algorithms, including their main advantages and limitations. Compared to Ant Colony Optimization (ACO), which is specialized for combinatorial problems, the Genetic Algorithm (GA) offers broader applicability and can handle complex representations and mixed variables. Relative to the Crow Search Algorithm (CSA) and Manta Ray Foraging Optimization (MRFO), GA has strong exploration capability. Particle Swarm Optimization (PSO) can address complex optimization tasks efficiently and is well suited to continuous optimization, particularly for large-scale problems. PSO is known for its simplicity and ease of implementation, exhibits high predictive accuracy, and generally converges faster than GA. Its performance is not highly sensitive to swarm size, provided the number of particles is not too small. In addition, the velocity–position update mechanism gives PSO a strong ability to avoid premature trapping in local minima.

Studies report that ACO can converge more rapidly to an optimal solution than PSO. Prior work also reports higher performance for CSA than for PSO and GA, with high efficiency on optimization problems; CSA is easy to implement and often more feasible than GA or PSO. Some results indicate that CSA's convergence speed can be 2 to 7 times higher than that of ACO and PSO.

CHAPTER 3 describes the operating mechanisms of two algorithms— the Simple Genetic Algorithm and the Non-dominated Sorting Genetic Algorithm II (NSGA-II)—including the selection, crossover, and mutation methods applicable to them. NSGA-II follows the GA framework but differs in how parents and survivors are selected, using non-dominated sorting and crowding distance. Crowding distance is a selection criterion applied within the same non-dominated front, based on Euclidean distance to neighboring individuals in the objective space, and is used to preserve diversity within that front.

CHAPTER 4 presents three case studies, each describing an optimization model applicable to energy-efficiency strategies in buildings.

The first case study optimizes the unit thermal heat flow transmitted through an insulated wall, the insulated slab-on-grade, or the insulated roof-ceiling using a Simple Genetic Algorithm. The expanded polystyrene that minimizes unit heat flow has a thermal conductivity of 0.0365 W/(m·K) and a thickness of 149.9 mm. The optimal unit heat flow through the wall is 6.378 W/m². For the insulated slab-on-grade, the optimal unit heat flow is 1.961 W/m², obtained with extruded polystyrene (λ = 0.031 W/(m·K), thickness 94.115 mm). The mineral wool that yields the lowest unit heat flow has λ = 0.034 W/(m·K) and a thickness of 199.98 mm; in this case, the optimal unit heat flow is 5.599 W/m².

The second case study proposes a method to identify the optimal configuration of the thermal envelope of a residential building to achieve the minimum specific energy need for space heating, while also respecting price constraints derived from a targeted market study. Using expanded/extruded polystyrene and mineral wool with superior thermal characteristics (as presented in the chapter), together with triple-glazed insulating windows (overall heat transfer coefficient K_{s1} = 0.6 W/(m²·K) and doors K_{s2}=0.7 W/(m²·K), the energy need for space heating is reduced by approximately 75% compared to the uninsulated building.

The third case study addresses a multi-objective optimization problem: the simultaneous minimization of the energy need for space heating and the energy need for space cooling, subject

to price constraints. The optimal annual energy needs are 12,486.16 kWh/year (heating) and 2,802.28 kWh/year (cooling). The optimal specific energy need for space heating is 96.05 kWh/(m²·year), and for cooling it is 21.56 kWh/(m²·year). Relative to the uninsulated reference building, the heating and cooling energy needs are reduced by about 75% and 71%, respectively, through building insulation and by replacing windows and doors with higher-performance products as presented.

CHAPTER 5 is divided into four subchapters. The first computes the energy need for domestic hot water (DHW).

The second presents a Python-implemented mathematical model for selecting air-to-water heat pumps that meet specified technical and economic criteria. The heat pump selected is a Luxaire BUA-030, with condenser heat load 8.42 kW, evaporator heating capacity 5.65 kW, and COP = 3.

The third assesses the practical applicability of the Python model via dynamic simulation in GeoTSOL. The results confirm that the selected heat pump can meet the entire thermal energy demand without being oversized. However, the system shows optimization potential because the Seasonal Performance Factor (SPF) is relatively low, implying lower overall system efficiency and higher operating costs.

To improve overall efficiency, the fourth subchapter simulates in GeoTSOL a hybrid system consisting of the heat pump, solar thermal collectors, and photovoltaic (PV) panels. In the analyzed configuration, the system includes five solar thermal collectors with a total area of 10.61 m² and twenty PV panels with a total area of 32.6 m². The PV array produces 10,291 kWh, of which 51.5% is self-consumed and 49.9% is exported to the grid, helping reduce electricity bills. In conclusion, beyond the financial benefit, the hybrid solution underscores the importance of transitioning from purely fossil-fuel-based systems to environmentally friendly hybrid alternatives, aligned with national targets, even in the presence of technological constraints (e.g., available installation area) and financial constraints (high upfront costs).

ORIGINAL CONTRIBUTIONS

The thesis begins by building a theoretical foundation to support measures for improving energy efficiency in the building sector. Within this framework, the author conducted a comprehensive analysis of how buildings influence energy consumption at the national and European levels, followed by an extensive study of the practical applications of seven optimization

algorithms in the building sector. Two algorithms—the Simple Genetic Algorithm and NSGA-II—are presented in detail, including their full operating mechanisms. Each chapter provides the conceptual basis needed to understand and justify the methods used in the analyses.

The author designed and developed three Simple Genetic Algorithms to optimize the unit thermal heat flow through the insulated wall, the insulated slab-on-grade, and the insulated roof-ceiling.

In addition, two NSGA-II algorithms were developed: one to optimize the energy need for space heating, and another to simultaneously minimize the energy needs for space heating and space cooling, in both cases considering price constraints derived from a targeted market study. These algorithms search an optimization space defined by insulation thicknesses and thermal conductivities and/or the thermal properties of doors and windows. The results are encouraging in terms of practical applicability, both for energy efficiency and for economic performance.

Another important contribution of the thesis is the development of an integrated framework for evaluating and optimizing heat pumps in the context of energy retrofits of existing residential buildings. The author proposed a Python-based mathematical model capable of selecting equipment that is optimal both technically and economically to meet the energy needs for space heating and DHW during the heating season. The novelty lies in the practical validation of the model's results via dynamic simulation with GeoT*SOL. Furthermore, to improve overall system performance, a dynamic simulation of a hybrid system was performed, consisting of the selected heat pump, five solar thermal collectors, and twenty photovoltaic panels. This approach is an original contribution, providing a useful tool for designing and optimizing energy-efficient systems in residential buildings.

RESEARCH PERSPECTIVES

This thesis integrates the essential aspects of applying evolutionary algorithms to the optimization of energy use and the improvement of energy efficiency in buildings. The author has developed a theoretical and practical framework that can serve as a solid foundation for further developments and analyses.

As a primary research direction, the author proposes validating the Non-dominated Sorting Genetic Algorithm II (NSGA-II) across a wide range of building types, in order to assess its capability to select optimal energy solutions under diverse contexts. In the absence of a complete validation dataset, the algorithm's estimates of the energy need for space heating can be compared

with the values reported in the building's Energy Performance Certificate (EPC), providing a relevant criterion for evaluating the model's correctness and accuracy.

A second direction is to vary the thermal properties of the wall, slab-on-ground, and roof constructions to reflect differences in the thermal capacity of building elements. Thermal capacity governs how a building stores and releases heat and thus affects both indoor thermal comfort and the energy need for space heating. Using materials with distinct thermophysical characteristics enables a more accurate simulation of the building's energy behavior.

Another perspective is to simulate the energy need for heating and/or cooling while accounting not only for heat losses due to infiltration and transmission between the conditioned space and the exterior, but also for thermal inertia, solar gains, and internal heat gains from equipment and occupants.

It is also proposed to develop a comprehensive database of thermal insulation materials. In addition to the traditional insulation options discussed in the thesis, the database should include modern solutions with superior technical performance that can further enhance building energy efficiency.

Finally, the mathematical model for heat-pump selection can be extended so that the selected air-to-water units are capable of covering, in winter, the energy needs for space heating and domestic hot water (DHW), and in summer, the thermal energy needed for space cooling as well as DHW. This enhancement would support year-round operation and broaden the model's practical applicability.

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