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"Life cost analysis and optimization for steel and reinforced concrete structures"

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ΤΟΥ

ΤΜΗΜΑΤΟΣ ΜΗΧΑΝΙΚΩΝ ΠΑΡΑΓΩΓΗΣ ΚΑΙ ΔΙΟΙΚΗΣΗΣ

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STATE OF ART

The present study seeks to investigate the factors that play a key role in the whole life cost of a new building construction, aiming to its minimization with the use of the optimization theory.

An analysis on the notion of the whole life cost, as well as on the subsystems that primarily influence the whole life cost of a typical building, leads to the conclusion that the subsystems related to its massing, its structural components and its energy performance, are the ones whose optimization -at an early stage- has significant importance.

After extensive research on the available literature, it was deduced that there was no previous study presenting an optimization method coupling in a common objective function the structural, building envelope, mechanical and energy subsystems of a new building, including a life cycle cost analysis of all the relevant building components.

This conclusion led to the first publication on this subject that was completed in March 2014 and presented in June 2014 in OPTi-2014; an Applied Optimization conference held in Kos, Greece [16]. The publication that was submitted, had the title: "Life cycle analysis and optimization of a steel building".

The publication presented a method that was developed to calculate and optimize the most critical parameters related to the energy and the structural design of a steel office building. The life cycle periods examined in the paper had a duration of 10 and 30 years. The building was located on Chania, Crete and had a rectangular shape (10x15 m). The variables of the optimization problem concerned all the characteristic structural, envelope, mechanical and energy subsystems (building envelope U-values, area of windows in every possible orientation of the building, window glazing solar gain coefficient, power and performance of the heating and the cooling HVAC systems, cross section type of all characteristic beam and column elements of the building). The optimization took place with the use of evolutionary algorithms (simulated annealing, genetic algorithms).

A second main innovation that was a result of the study, was the presentation of an energy performance optimization approach along with a life cycle cost analysis according to KENAK; the recent Greek code for the energy design of buildings.

The good reviews that the first publication received, led to an invited chapter where an improved version of the initial publication, was submitted in the book: “Engineering and Applied Sciences Optimization, Computational Methods in Applied Sciences” [15].

In March 2015, a similar methodology was implemented on a timber building (10x15 m) located on Athens, Greece, for a life cycle of 20 years. The publication that was submitted that period, presented an approach the optimization of the whole-life cost of timber building. Similarly, the objective function of the optimization problem dealt with the sum of all the costs that were related to the aforementioned subsystems. A method to the optimal sizing of a photovoltaic array was also proposed. Noteworthily, the subject of the structural optimization of timber elements (especially according to Eurocode 5) was very rare. Another innovation presented in the publication, was the effect of the fuzziness of the design temperature inside a building on its life cycle cost. The study also proposed a method to predict an optimal scenario for the management of the timber frame components at the end of the building's life cycle. The publication was presented with the title: " Life cycle analysis and optimization of a timber building" in the international conference on the Sustainability in Energy and Buildings, SEB-15, that was held in Lisbon, Portugal in 1-3 July 2015 [17]. The publication was after a second review, transferred to the journal ‘Energy Procedia’.

Another study related to the present thesis was published in the scientific conference ‘SBE16 Malta, International Conference - Europe and the Mediterranean Towards a Sustainable Built Environment’ in 15-19 March 2016, with the title: "Structural optimization including whole life cost of a timber building” [19].

This proposal concerns a two-storey 35x30 m office building in Athens. The structural systems are made of timber. The parameters taken into account in the energy performance subproblem are the same with the ones examined in the timber building optimization problem; however, it is enriched with the addition of the existence of lighting control as a variable. A main innovation introduced in the study that was literally nonexistent in previous ones, concerned a proposed methodology for the optimization of the number, the length of structural frame bays, the sizes of the cross sections that constitute the frames, as well as the spacing among the structural frames with the aid of the finite element method. Another rare method proposed in the study is the use of discrete optimization as a means to describe and optimize the cost of an HVAC system with multiple terminal units (Examined variable: number of units) and multiple options with various energy performance characteristics (Examined attributes: Power in kW, SCOP, SEER). The optimal whole life cost for three time-horizons was examined.

The last study related to the present thesis, was published in the scientific journal 'Infrastructures' in May 2017. The study is titled "Machine learning and optimality of Multi Storey Reinforced Concrete Frames" [18] and presents a family of neural networks, used for the prediction of optimality (bay length optimality and sizing/cost optimality) in multi-storey reinforced concrete frames. Parameters such as: number of storeys, total length of frame, loading, characteristics of elements adjacent to an examined element, are used as predictors after creating a database consisting of a set of optimized examples of multi storey frames with various loadings. The genetic algorithms of the optimization toolbox of MATLAB, were used for the optimization of the frames. It is meaningful to note that MATLAB was the programming language that was used to create all the models of the aforementioned publications.

AIMS AND OBJECTIVES

The present PhD thesis aims to investigate methods of optimizing the whole life cost of buildings with steel, timber and reinforced concrete frames.

The research will focus on:

1. Summary and presentation of the necessary scientific background to examine the subject.

2. Analysis of optimization methodologies that have been used in similar problems.

3. Description of the specific nature of each optimization subproblem and their constraints.

4. Creation of algorithms that after having accurately modeled the aforementioned subproblems and their constraints, will allow the unification of the structural optimization of building frames, with that of the optimization of design options for their energy efficiency, considering also parameters about their life cycle.

5. Presentation of the findings of the study, recommendations for future research on similar topics.

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LITERATURE REVIEW

INTRODUCTION

The current chapter presents a historical overview of notable concepts that were encountered in similar studies. The chapter covers studies related to the energy design and optimization of buildings, to life cycle analysis and life cycle cost analysis techniques and to the structural optimization of steel or reinforced concrete buildings and their components. Further details about the models and the methods presented in this chapter, are given in the next chapters.

OPTIMIZATION OF THE ENERGY DESIGN OF BUILDINGS AND LIFE CYCLE ANALYSIS TECHNIQUES

One of the first relevant studies was conducted by Wright J.A. in 1986 [130], where the direct search method was used for the optimization of HVAC systems. Several other publications focused on computer-generated and iteratively improved sub-optimal solutions. Other approaches made use of sensitivity analysis or the ‘‘design of experiments’’ method, offering improved results that did not include optimization techniques. Approaches that have a similar nature can be considered the brute-force search and the expert-based optimization.

Nevertheless, the dominant approach is based on mathematical modeling (using various acceptable procedures that derive from widely used specifications to simulate different types of buildings such as passivhaus buildings, green buildings, low-energy buildings etc.) and on the use of optimization algorithms or strategies. A well-known optimization example applied on high performance buildings was proposed by Wang et al.

It is also meaningful to mention the most well-known software used in building simulation, which is as follows: EnergyPlus, TRNSYS, DOE-2, ESP-r, EQUEST, ECOTECT, DeST, Energy-10, IDE-ICE, Bsim, IES-VE, PowerDomus, HEED, Ener-Win, SUNREL and Energy Express [93].

Another interesting study was conducted by Shahidian A. and Afshar H. [110], where they used genetic algorithms to minimize the energy consumption of a residential building. The objective function of the problem concerned the total thermal load during the summer and the winter period, which was minimized by means of discrete optimization whose variables where the layers or the building envelope. The optimization results from various studies have revealed the significance of various frequently examined variables. The following parameters: External wall profiles, Roof profile, floor insulation profile, number of occupants, are considered to be critical parameters. On the other hand, wall color, roof color and ventilation strategy were found to be less important parameters.

Other interesting approaches include the use of surrogate models in an attempt to minimize computational time. These approaches are extremely useful in summarizing complex and time-consuming energy design approaches such as the hourly method. It is meaningful to note that generally, the use of surrogate models has a decent degree of accuracy. The steps for constructing a surrogate model include [93]:

- Creation of a database containing random inputs of the examined variables and generated responses.

- Data fitting techniques (e.g. Regressions, Kriging, Artificial Neural Networks) applied on the database to compose an efficient substitute model synopsizing the information derived from the initial inputs.

- Validation of the surrogate model (testing and interpreting inadequacies, cleaning unnecessary or marginal data, making additions and improvements etc.).

As regards, the efficiency of various optimization algorithms used in previous similar studies the following observations can be made:

Direct search (Simplex, HJ) or gradient based (Discrete Armijo gradient based algorithm), generally converge to local minima and have worse performance than genetic algorithms and PSO. Especially the Simplex and the Discrete Armijo algorithm are not recommended. A hybrid PSO-HJ algorithm was found to perform better than GA, attaining slightly more improved cost reduction results. Both, GA and PSO are known to be able to search in very large spaces, avoiding getting stuck to suboptimal localities, however a global minimum cannot be guaranteed [93].

The challenges that have to be faced in a building energy design optimization problem include [93]:

• The degree of accuracy of the simulation. There are simulations based on hourly steps, on monthly steps, on seasonal steps. Evidently, the hourly methods are the most accurate, but consume a considerable amount of time. The seasonal step methods are less accurate (often they are considered a poor approach by several national codes), but are faster to compute.

• The degree of friendliness of the optimization technique for potential uses in the future.

• The high number of existing approaches in building simulation.

• The lack of high speed computers attaining optimized solutions in less time.

Another challenge is the termination criteria used in the optimization procedure, these include:

• Maximum number of generations, iterations, step size reductions.

• Time-related termination criteria.

• Termination criteria related to the objective function: optimized results within acceptable boundaries, optimum does not change for a big number of iterations.

- The rate of change of the examined variables is minor.

A well-known study where a surrogate model based on polynomial regression was implemented for optimization purposes in an attempt to substitute the time-consuming CFD simulation results was conducted by Klemm et al. in 2000 [93].

In 2007, M. Santamouris, K. Pavlou, A. Synnefa, K. Niachou and, D. Kolokotsa [108], presented a review of the potential of passive cooling techniques such as: reflecting roofs, night ventilation, solar chimneys in improving the energy consumption and the indoor environmental quality of low income households.

In 2009, Cheng et al used a neural network [29], fuzzy logic and a genetic algorithm to optimize the architecture of the neural network. Interestingly, their database contained 23 examples of projects based on 10 predictors to aid primary cost estimation and 45 predictors for categorized estimations. They also compared the predictive power of neural networks in comparison with regressions.

At this point it is meaningful to mention that a neural network optimal architecture is something that can be found iteratively and problems related to the optimality of its architecture deal with [46], [111]:

- The size of the training set and the test set; the sets on which the data would be divided (e.g.: 50%-50%, 75%-25% etc.).
- The solution algorithm used.
- The number of hidden nodes (neurons) [46] of which the neural network consists.

Some well-known models for the estimation of the hidden nodes are the following:

1. Li et al. method [75]: $N_h = (\sqrt{1 + 8n} - 1)/2$

Where: N_h is the number of hidden neurons and n is the number of inputs.

2. Zhang et al. method [133]: $N_h = \frac{2^n}{n+1}$

3. Shibata and Ikeda method [112]: $N_h = \sqrt{N_i N_o}$

Where: N_i is the input neuron (number of nodes) and N_o is the output neuron.

4. Hunter et al. method [48]: $N_h = 2^n - 1$
5. Number of hidden nodes: between the size of the input layer and the output layer [111].
6. Number of hidden nodes: equal to 2/3 multiplied by the size of the input layer plus the output layer [111].

In 2009, I. Zygomalas, E. Eftymiou and C.C. Baniotopoulos [135] conducted a review about the scope of life cycle analysis studies referring to relevant ISO standards. The project also presented a case study on a steel shed structure. The authors quantified all the constituting components of the steel structure and used the Eco-Indicator method to measure its environmental impact and the crucial byproducts of environmental interest related to it, throughout its life cycle.

In 2010, Christina Diakaki, Evangelos Grigoroudis, Nikos Kabelis, Dionyssia Kolokotsa, Kostas Kalaitzakis, George Stavrakakis [35], developed a multi-objective decision making tool to compute and propose optimality taking into account the following criteria: primary energy consumption of the building, investment cost and carbon dioxide emissions. The study investigates the impact of different heating and cooling systems, different single layer or multilayered insulation systems, window types, hot water supply and solar collector systems. The heating and cooling needs that result from the energy balance of the building are calculated at monthly steps, ignoring any non-positive values. For the determination of the optimal weightings of each objective, the compromise programming technique was used. Specifically, a λ (Tchebyshev) distance between weightings was minimized according to the following formulae:

$$
\begin{aligned}
&[\min]\ z = \lambda \\
&s.t. \\
&\text{all constraints of multiobjective problem} \\
&\lambda \geq (g_1(\mathbf{x}) - g_{1\min})(p_1/g_{1\min}) \\
&\lambda \geq (g_2(\mathbf{x}) - g_{2\min})(p_2/g_{2\min}) \\
&\lambda \geq (g_3(\mathbf{x}) - g_{3\min})(p_3/g_{3\min}) \\
&\lambda \geq 0
\end{aligned}
$$

Where:

$g_{imin}(x)$ are the derived optimum values for each objective.

$g_i(x)$ is each objective that evidently derives from a series of mathematical relationships.

p_i is the relative (specified by the designer) importance of each objective. The sum of all relative importance coefficients must total to 1.

In 2010, Christina Diakaki, Evangelos Grigoroudis, Nikos Kabelis, Dionyssia Kolokotsa, Kostas Kalaitzakis and George Stavrakakis, after a literature review of the factors that affect the urban microclimate, presented a relevant case study with various scenarios and quantifiable results for an urban area in Crete. The simulations were conducted with the use of the software ENVI-met V4. The examined variables of the study were the following: height to width ratio of an urban canyon, sky view factor, percentage of green areas, pavement attributes. The study concluded that the variables with a greatest degree of contribution to the urban microclimate relate to more fixed characteristics such as: exposure to winds and sunlight, orientation and paved areas. The non-permanent variables are the ones that have a lesser contribution, but offer a potential for a bioclimatic impact on a carefully planned urban design that co-estimates the microclimate.

In 2013, D.N. Kaziolas, I. Zygomalas, G.E. Stavroulakis and C.C. Baniotopoulos [63], quantified through the use of the Eco-Indicator 99 method, the environmental impact of a timber building throughout its life cycle. The case study examined three end-of-life scenarios (recycling, reuse, incineration) quantifying the retrievable materials and the environmental byproducts for each scenario. Outputs such as fossil fuels, use of minerals, carcinogens, radiation, acidification, land use, effect on climate change, ozone layer, respiratory organics and inorganics, ecotoxicity etc. were estimated and presented in the study.

Another study that has influenced the current thesis was conducted in 2013, by Kakkaras, Karellas et al [60]. The study compared the cost per kWh of various heating technologies prevalent in the Greek market (Heat pumps, fireplaces, various types of boilers). The main conclusion was that the cost per kWh of the heat pumps is by far the lowest among the compared technologies.

In 2015, Gerardo Maria Mauro, Mohamed Hamdy, Giuseppe P Vanoli, Nicola Bianco, Jan L Hensen [83], proposed a technique to retrofit from an energy design standpoint and in a cost-optimal way, office buildings located on South Italy. The authors employed a Latin Hypercube sampling on a set of building simulations conducted with MATLAB and the building energy simulation program EnergyPlus (which is specialized in detailed building energy modeling). Their sample contained a number (n) of examined independent variables that influence the retrofitting. The authors sought to determine the size of a 'Representative Building Sample' (RBS), basing any judgement on the fact that similar studies recommended a ratio (r) between the aforementioned variables and the size of the sample with values between 2 and 5. By sensitivity analysis that determined the independent variables that displayed the highest correlation coefficients in conjunction with the energy consumption objective (that was described via 4 dependent variables that concerned critical energy consumption parameters, e.g. heating or cooling load per area unit), they distinguished the most critical independent variables for this objective. After analyzing the mean values and the standard deviations of these four dependent variables for a very large sample of simulations (larger than 5n), they observed that their mean values and variances remained unchanged for a ratio (r) value greater or equal to 2.2n (Where: n is the number of all the critical and non-critical independent examined variables).

By using this insight, the authors constructed a family of artificial neural networks to predict the critical energy consumption parameters mentioned above that attained an R coefficient of regression greater or equal to 0.96. Apart from its predictive power, the neural network was also greatly faster than a typical detailed energy simulation. Making use of the neural network metamodel, they published a study in 2017 [7], which relied on the metamodel along with a genetic algorithm to calculate cost-optimal retrofitting design decisions. Finally, the study proposed cost-optimal combinations of independent variables for building models with various budgets (either limited to specific amounts or not).

In 2016, Serge Chardon, Boris Brangeon, Emmanuel Bozonnet, Christian Inard [27], made use of real product databases (partly assisted by the readiness of BIM technologies to provide such data) and professional established practices to estimate and optimize the construction cost and the envelope cost of a hypothetical new residence. Even though the paper does not clarify which predictive model is used to learn from the data in the databases, they refer to previous influential studies that implemented regression models, neural networks, case base reasoning and fuzzy logic, as predictive models. Ultimately, a genetic algorithm is used for the optimization procedure and it proposes optimal regions for the design decisions.

In 2016, Marina Tsitoura, Marina Michailidou, Theocharis Tsoutsos [125], presented a study that included literature review, simulation and real-life measurements to assess the parameters that play a role in affecting the microclimate of urban areas. The study concludes that the permanent characteristics of an area play the most critical role in influencing its microclimate (e.g. exposure to winds and sunlight, orientation, attributes of the paved areas). Therefore, depending on the orientation of an area, the designer has to determine the degree to which he or she will take the modification of the microclimate into consideration.

In 2016, Murat Kucukvar, Gokhan Egilmez, and Omer Tatari [72] after quantifying through life cycle analysis, the environmental and economic impacts regarding various scenarios for the management of the construction waste of LEED-certified building, used multi-objective multi-criteria optimization to propose an optimal solution. The weightings assigned to each objective were computed with the use of the compromise programming (CP) technique.

In 2017, Maria Michael, Lijun Zhang, Xiaohua Xia [86] proposed a method based on multi-objective mixed integer non-linear programming to attain an optimal retrofitting strategy for an existing building. The multi-objective optimization problem formulation included cost, energy, LEED scoring, and water efficiency considerations as objectives. A weighted sum approach was adopted for the computation of the optimal solutions with various scores for each objective (totaling, however, to a sum equal to 1).

LIFE CYCLE COST ANALYSIS TECHNIQUES

As it will be demonstrated in the next chapter in a more detailed way, life cycle cost analysis refers to a series of mathematical, statistical and machine learning methods to associate a particular design decision with its long-term cost impact.

Kishk and Al-Hajj (1999) [67] suggest the following decision tree to deal with an LCC problem. Key factors to determine the methodology that would be finally used are the data availability, the degree of their tangibility, uncertainty and randomness.

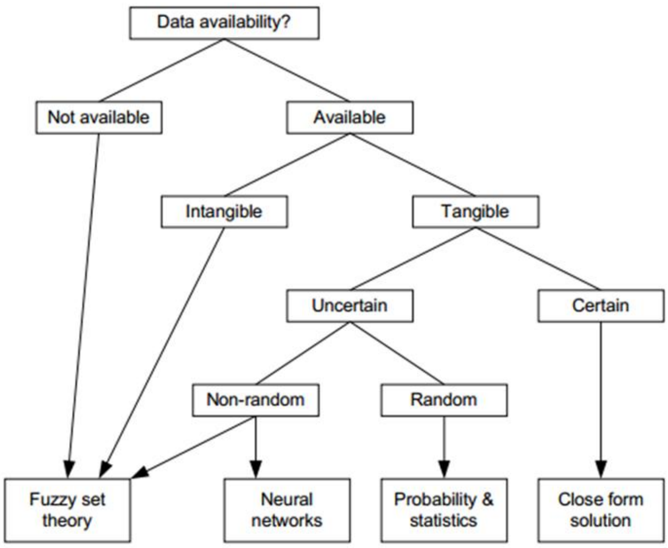


Figure 1: Decision diagram suggested by Kishk and Al-Hajj for the selection of an appropriate method to analyze and interpret data for an LCC problem.

A well-known example of the application of a statistical/machine learning technique (multiple linear regression) in life cycle cost analysis, was developed by Kirkham et al. in 1999 [68], in order to estimate the life cycle energy costs of sport centers in conjunction with their floor area and number of users. Specifically, the regression models developed were as follows:

$$Energy\ cost = 1.203 + 0.97 * \text{area}$$

Or an equivalent model that also took users into consideration:

$$Energy\ cost = 1.217 + 0.642 * \text{area} + 0.206 * \text{number of users}$$

It is meaningful to note that regression methods require a large number of observations in order for reliable models to be developed.

Another example is a process developed by Sterner in 2002 [116], where the total tender price was generated by three inputs: tender sum (p), life cycle energy cost (LCC_E), environmental index (EI_x), as displayed in formula below:

$$TCP = f(p, LCC_E, EI_x)$$

Other examples of mathematical models include the use of Markov chains in life cycle engineering for the prediction of the remaining service life of buildings (Kirkham and Boussabaine, 2005) [69] or the efficiency of building subsystems (Zhang et al., 2005) [134] during their life cycle.

OPTIMIZATION OF THE STRUCTURAL DESIGN OF BUILDINGS

One of the first research attempts in the field of structural /cost optimization of construction elements took place in 1974 by Friel [43] where mathematical expressions were used to calculate the optimal cost and reinforcement areas for simply supported beams. The study concluded that formwork has a less significant effect in the optimization results. A similar study on reinforced concrete beams and one-way slabs was conducted by Naaman in 1976 [92]. A direct search algorithm was used to derive optimized costs and weights. The conclusions of the study place emphasis on the role of cost coefficients; a change in the cost coefficients can have a significant impact on the weight. Therefore, contrary to what was suggested by previous studies; a change in the cost coefficients could mean that the optimal cost could differ significantly from the optimal weight. Cohn and MacRae in 1984 [78] make use of a similar optimization technique for simply supported beams by also including considerations such as cracks, deflection, fatigue and ductility.

Abendroth and Salmon investigated in 1986 [1] the subject of the cost optimization of (partially restrained or fully restrained) reinforced concrete T-beams. Interestingly, the modeling of the stirrup costs took place by multiplying the longitudinal reinforcement costs by 1,5. The study concluded that stirrups have a minor effect in the resultant optimal cost. The typically secondary role of the compressive strength of the concrete in the optimized results was identified in 1991 by Kanagasundaram and Karihaloo [61-2] in a project regarding the optimization of rectangular reinforced concrete columns on which an axial load and a bending moment was applied and the examined variables of the optimization problem included the area of the concrete, the reinforcement ratio and its compressive strength. Even though the addition of the compressive strength as a design variable leads to reduced depths and a requirement for higher compressive strengths, the overall importance of taking compressive strength into account is minor.

Another interesting study took place in 1995 by Samman and Erbatur [107]. By making use of a direct search algorithm to optimize the reinforcement areas of RC beams the following conclusions were generated: The end conditions and the material costs have the most important effect on the optimal reinforcement. The characteristic yield strength of the steel reinforcement and the applied loads were found to have a less important effect on the optimal reinforcement ratio. Especially, the applied loads were found to reduce the requirements for steel reinforcement. Finally, the widths of the RC beams and compressive strength of the concrete had a minor effect on the optimal reinforcement.

Kocer and Arora investigated in 1996 [70] the subject of the optimization of prestressed concrete transmission poles according to the ACI codes. The optimization methods used in the study included Sequential Quadratic Programming and genetic algorithms. The attained savings were found to be close to 25%.

In 1997, M. Papandrakakis, N. Lagaros, Yannis Tsompanakis [97] trained a Neural Network to replace the structural analysis procedure for various structural design examples. As regards the architecture of the neural network, it was a multiple-input multiple-output (MIMO) neural network. For the training set, the authors used a Gaussian normal distribution approach. After the training, they used evolutionary optimization for sizing optimization purposes. In an example of a six storey building presented in the paper, the design variables were corresponding to each separate column and each separate beam and the outputs were the correspondent axial forces and bending moments that were checked and optimized in order to satisfy a combined stress criterion.

Other well-known research efforts were undertaken by Balling and Yao (1997). Balling and Yao [11] developed a non-linear optimization methodology for the design of RC columns, beams and shear walls.

In 2000, S. Pezeshk and C.V. Camp [102] used a genetic algorithm to optimize 2D reinforced concrete frames subjected to non-linear effects. The structural analysis therefore, included P-Δ effect and a discrete optimization modeling philosophy was followed. The authors concluded that the optimized results do not differ significantly when compared to the optimized results derived from analysis that did not take non-linear effects into account.

Lee & Ahn (2003) [74] and Camp (2003) [26] used genetic algorithms to optimize the design of reinforced concrete frames (beam and column elements). Their modeling approach was based on discrete optimization. Another interesting study took place in 2006, where Guerra and Kioussis [45] used sequential quadratic programming to minimize the cost of various reinforced concrete structures. The design code on which the study was based was ACI 318-05.

In 2010, Salim T. Yousif, Ikhlas S. ALsafar and Saddam M. Ahmad used the Lagrangian multiplier technique to derive optimal design for singly and doubly reinforced concrete beams [131]. After creating a very large database, the used artificial neural networks to predict optimum depths and optimum steel areas attaining very high R values (Where: R is the coefficient of regression).

In 2014, T.S. Ketkukah, I. Abubakar and S.P. Ejeh [65], conducted design optimization for a 2-bay reinforced concrete frame in MATLAB. They took into account: geometric constraints, stress block related constraints, shear strength related constraints and reinforcement constraints. The optimization involved different loading cases and the optimization results were plotted in graphs. After curve fitting and linear fitting, the relevant governing mathematical formulae for parameters such as optimal tension or compression reinforcement and reinforcement ratios were produced and visualized.

In 2015, Abobakr A. A. Aga and Fathelrahman M. Adam [2] created a sample of 50 different reinforced concrete frames designed with the use of the ACI code. After the calculation of the cost of each frame, they created a neural network using the dimensions and the tension and compression reinforcement of each beam and column as predictors, whereas the total cost of the frame constituted the dependent variable. The neural network demonstrated a remarkable ability to predict the cost for randomly derived frames with altered values for the predictors.

In 2016, Ashwini R. Kulkarni and Vijaykumar Bhusare [73] implemented a design of experiments assuming a cross-sectional value for each beam and column based on two parameters: a width W and a depth D. The columns are assumed to have W with and a depth equal to 1.25D, and the values of D and W were constant for each storey. The design of experiments contained three scenarios of reinforced concrete grades and each scenario consisted of four cases of feasible width and depth cases with a homogeneous incremental increase of either the width or the depth. The building on which the study was conducted was multi-storey reinforced concrete building with a complex non-rectangular plan view. After a structural analysis of the building, the total cost resulting from the steel and the concrete amount of each scenario, was computed. A metamodel via the software MINITAB was generated for every reinforced concrete grade scenario that associated the cost with the parameters W and D. After setting upper and lower values for W and D, an evolutionary algorithm computed their optimal values for every reinforced concrete grade scenario.

At this point, it is meaningful to point out a very frequently used governing equation for the calculation of the cost of reinforced concrete elements [3]:

$$C = C_{concrete} + C_{steel\,reinforcement} + C_{formwork} + C_{ties}$$

$$\Rightarrow C = w_c * H * (A_c - A_s) * c_c + w_s * H * A_s * c_s + p_f * H * c_f + V_t * c_t$$

Where: w_c is the specific weight of the concrete, L is the length of the column or the beam, Ac is the cross-sectional area of the concrete, As is the area of the steel reinforcement, c_c is the cost of the concrete per kg, w_s is the unit weight of the steel reinforcement, c_s is the cost of the steel per kg, pf is the formwork perimeter, Vt is the volume of the lateral ties and c_t is the cost of the lateral ties per m^3.

It must be clarified that the formwork perimeter for RC columns is given by the following formula [3]:

$$p = 2 * (b + h)$$

Moreover, as regards the formwork perimeter for RC beams, the following expression is used:

$$p = 2h + b$$

In order to dimension a structure a structural analysis precedes, in order to calculate the axial loads, shear forces and bending moments. These parameters influence the cross-sectional areas that will be used for each element of the structure.

Steel structures are generally easier to optimize in comparison with RC structures and this is because steel is a non-composite, homogeneous material with standardized cross-sections. After a relatively small number of iterations, it is generally easy to optimize a steel element especially by means of discrete optimization. Well-known examples of studies conducted about the cost optimization of steel structures include the studies of the following authors:

- Annamalai et al. presented in 1972 [6] a discrete optimization technique to minimize the cost of simply supported plate girders.
- Cheng and Juang presented in 1989 [28] a study about the cost optimization of a rigid frame with 2 bays and 15 storeys. The displacements of the frame as a result of the applied static, wind and seismic loads are taken into account and apart from the necessary presence of the steel members, in the objective function there is also provision about the effect of painting and connections according to empirically derived relationships.
- In 1992, F. Erbatur and M. M. Al-Hussainy [37] created a solution algorithm for the cost optimization of steel frames. The structural checks were done according to the AISC design code, and the total stresses deriving from a combination of all the possible failure modes, was not allowed to exceed the capacity of a cross section.
- Bhatti in 1996 [21] developed a method based on Lagrange multipliers and the AISC specifications for the optimization of composite I-beams carrying RC slabs. The constraints include considerations about strength, deflection and vibration.

An interesting methodology to optimize steel beam and columns -taking advantage of their stress constraints- presented by Cheng and Truman in 2010 [29], will be demonstrated in the following chapter. Optimization methods based on construction codes, however, are far more likely to deliver more accurate and constructible results.

Evidently, the total cost of a (steel or RC) structure is the sum of the costs of each individual component of the structure. Other interesting observations, made in the published work of the same authors are the effectiveness of the expotential regression in associating the cost of the painting or the metal connections of a steel cross section with its cross-sectional area. Another interesting observation that is made for RC elements is the fact that the structural designs that fall into region below the point (M_{bal}, N_{bal}) in an interaction diagram should be avoided due to its unpredictability.

It is meaningful to note that the formula used for the evaluation of the cost of a steel element is the following:

$$C = \rho V c_s = \rho A L c_s$$

Where:

ρ is the specific weight of the steel.

A is the cross sectional area of an examined element.

L is the length of a steel element.

V is the volume of a steel element.

c_s is the cost of the steel per kg.

In 2012, Mehmet Polat Saka and Zong Woo Geem presented a review [106] of commonly encountered practice in steel design optimization. Some interesting concepts and conclusions presented in the paper are the following:

1. The use of least square approximation techniques as a shortcut for evaluating via constant relationships, the characteristics (e.g. moments of

inertia, section moduli) of the large number of the possible steel cross section design choices. In these cases, exponential regression is used to associate the aforementioned characteristics with the cross-sectional area of a steel element.

2. The efficiency of Sequential Quadratic Programming over other Mathematical Programming techniques for steel design optimization purposes. It has to be mentioned that SQP has the constraint that it can be applied for optimization problems by assuming that the optimization variables are continuous.

3. An overview of the evolutionary optimization algorithms that had been used in steel design optimization problems. Such algorithms and techniques are the following: Genetic Algorithms, Simulated Annealing, Particle Swarm Optimization, Ant Colony Optimization, Harmony Search Method, Big Bang Big Crunch Algorithm, Hybrid Algorithms.

The authors also mention that the use of metaheuristic and evolutionary optimization techniques will certainly dominate the structural optimization landscape in the future, as they are derivative-free and this facilitates the computational processes.

In 2013, Stojan Kravanja, Goran Turkalj and, Simon Šilih, Tomaž Žula [71] proposed a multifaceted method to optimize the total mass of a steel building based on mixed integer non-linear programming. The authors emphasized that the problem has a highly non-linear and non-convex nature and included the following optimization variables for the study:

1. Structural loading

2. Structural geometry (number of frames, rails, purlins and distance between frames, rails, purlins)

3. Beam and column cross sections (all the relevant structural characteristics (e.g. resistance in bending moment or shear, moments of

inertia etc.), were accompanying each beam or column in the formulation of the optimization problem)

4. Structural steel grade

The study was based on first order analysis on non-sway frames in accordance with the structural checks of Eurocode 3; taking into account both the ultimate and the serviceability limit state. The frames' length, the length of the columns, the length of the building and the gradient of the beams are assumed to have unalterable values during the optimization procedure.

As regards the constraints, the following ones were considered:

• Structural checks (e.g. the deflection limits were equal to: span/200, span/250 for the beams and column's height/150 for the columns).

• Constraints related to the building geometry (e.g. a total preset length should not be exceeded).

• Structural analysis constraints (after a simple structural analysis of the frames that therefore didn't include FEA, the structural resistance of each beam and column was modeled as a series of constraints that must not be exceeded).

• Logical constraints: Exclusion of other types of frames or cross sections, once a cross section or frame type is selected, provision for feasible topologies.

The authors proposed that the software GAMS/CONOPT2, and GAMS/CPLEX provide the solution background for the optimization problem.
In 2013, Ioana D. Balea, Radu Hulea, and Georgios E. Stavroulakis [10] presented three examples of 2D and 3D steel structures analyzed by the software Robot Structural Analysis on which sizing optimization via a discrete optimization modeling approach with the genetic algorithm subroutine of the optimization toolbox of MATLAB. The authors also highlighted the difficulty of

classical mathematical programming techniques to outperform genetic and evolutionary algorithms in such optimization problems.

In 2016, Salah R. Al Zaidee and Ali S. Mahdi [4], constructed a metamodel based on non-linear regressions and through the software SPSS. The metamodel represented a series of potential design solutions for cases of multi storey steel frames with a known total length and number of storeys. After the 2D structural analysis and cost calculation of all the frames of which the sample consisted, the resultant data were used to generate the metamodels whose dependent variables were either the cost or the weight of a frame. A uniform beam cross section per storey was assumed, whereas the column cross sections would vary as many as half the times of the total number of storeys.

The metamodel had the following form:

$$\text{Explicit Function, } f = \propto_0 + \propto_1 A_1 + \propto_2 I_2 + \propto_3 Z_3 + \propto_4 S_4 + \cdots \ldots \ldots + \propto_n S_n + \propto_{n+1} A_1^2 + \propto_{n+2} I_1^2 + \propto_{n+3} Z_1^2 + \propto_{n+4} S_1^2 + \cdots .. + \propto_{n+n} S_n$$

Where:

A_i: The cross sectional area of each beam or column.

I_i: The second moment of area of each beam or column.

Z_i: The plastic section modulus of each beam or column.

The authors concluded that similar metamodels can be used to address more complex structural design aspects such as: non-linearities and three-dimensional models.

LIFE CYCLE ENGINEERING, STATISTICAL ANALYSIS AND PATTERN RECOGNITION TECHNIQUES

INTRODUCTION

The current subchapter aims to present critical notions encountered in life cycle engineering. In light of this, important tools used in the life cycle costing of buildings, are described. The description of these tools is a core purpose of the thesis. An overview of the framework used to conduct life cycle analysis (that is a branch of life cycle engineering focusing on the study of the environmental impact of the design decisions of a project with environmental interest during its life cycle), is demonstrated. Research efforts that integrated life cycle costing into life cycle analysis are also presented. There is also discussion, about the estimation of the services lives of the building components that were used in the MATLAB algorithms that were developed, since this would aid the prediction of potential replacements during an examined life cycle period. Furthermore, the chapter provides information about statistical, pattern recognition, stochastic and machine learning techniques. The core philosophy of these techniques is to interpret observed data with minimum error. As life cycle engineering partly deals with collecting, analyzing and interpreting data, the usefulness of such techniques is evident. An illustrative example where a multivariate statistical technique (e.g. multiple linear regression, ridge regression, logistic regression) could be used in life cycle engineering could be as follows: After having collected a large sample of bridges where the observed variables are: time, type of external environment, degree of maintenance, current condition; a consultant wants to develop a model to interpret the data with minimum error.

INITIAL CONSIDERATIONS

A life cycle cost analysis takes place for the purpose of determining the impact of various options on a project's total cost during its life cycle. A notion that is very relevant to a life cycle cost analysis is that of life cycle analysis that is a process that mainly examines the environmental implications of various design decisions of a project during its life cycle.

An overview of the available literature on life cycle cost analysis reveals that there are many different approaches mainly because of the scarcity of available data and of the fact that a life cycle cost analysis is by nature a non-deterministic process [77].

A very common technique used for the financial evaluation of a project is that of the net present value. A net present value is used to project the current value of an asset in the future, assuming a constant annual discount rate that for most advanced economies is considered to be equal to 3%-4% (it is usually defined by a country's national bank). This discount rate reflects the depreciation of a capital's value due to inflation and other financial factors. A net present value is computed through the following relationship [23], [44], [77]:

$$NPV = \frac{FV}{(1 + d\rangle^{n}}$$

Where:

- NPV is the present value of an asset.
- FV is the future value of the asset.
- d is the (%) discount rate.
- n is the number of years (or the number of time segments during an examined period).

The above-mentioned formula can be used (and is generally very frequently used) for a project as whole, by juxtaposing the discounted earnings that an asset generates with the necessary expenses that relate to the asset, during an examined period. Whenever, the total NPV has a positive value (NPV > 0), the asset is profitable, whereas the opposite applies when NPV < 0. In as similar manner, the above-mentioned formula can be used in order to assess the cost of each individual subsystem of which an asset is composed.

A quite generic expression that outlines the parameters that should be taken into account in life cycle cost problems is the following [59], [115]:

1. Initial cost of the system
2. Maintenance costs
3. Operation costs
4. Remaining cost at the end of the system's expected life cycle.

This entails that:

$$LCC = C + PV_{RECURRING} - PV_{RESIDUAL-VALUE}$$

LCC is the total cost of the asset during an examined life cycle.
C is the initial cost of the asset.
$PV_{RECURRING}$ is the present value of all recurring costs (utilities, maintenance costs, replacements, service costs etc.).
$PV_{RESIDUAL-VALUE}$ is the present value of the residual value at the end of the examined life cycle period. In accordance with the aforementioned assumptions the present value of the residual value can be estimated via the following relationship [59], [115]:

$PV_{RESIDUAL-VALUE}$ = Subsystem's initial value (Current year)/(Subsystem's total life cycle (in years))*Factor accounting for the inflation rates*

SERVICE LIFE OF THE SUBSYSTEMS

The service life of a system can be approximated though the data provided by a manufacturer. A well-known formula found in the relevant literature is the following [77]:

$$\mathrm{ESLC} = \mathrm{RSLC} \times \mathrm{A} \times \mathrm{B} \times \mathrm{C} \times \mathrm{D} \times \mathrm{E} \times \mathrm{F} \times \mathrm{G}$$

Where:

ESLC is the subsystem’s assumed service life.
RSLC is the reference service life.
A is the quality of subsystems.
B is the general quality of the design.
C is the work execution level.
D stands for the internal environment.
E stands for the external environment.
F stands for the prevailing conditions.
G is the maintenance level.

The above-mentioned factors’ value can vary and are generally dependent on a designer’s personal priorities and choices. ISO 15686-8 [59] recommends that these values should be taken as equal to: 0.80 and 1.20 (more prudent estimations fall into the range: 0.90-1.10).

Other techniques for the estimation of a system’s service life include [77]:

- Statistical data from experienced parties and professionals (suppliers, specialized consultancies, life cycle analysis software).
- Pattern recognition based-assessments (e.g. multiple linear regression, Markov chains, Monte Carlo methods, Fuzzy set theory).

- Data from research institutions and government bodies (e.g. ICE, RICS, CIBSE, IGreekE etc.).

DETAILED ANALYSIS OF THE COST VARIABLES

In life cycle costing, there are two closely related notions: Life cycle-cost and whole-life cost that encompasses a wider range of parameters (life cycle cost along with externalities, income generated by an asset, non-construction costs).

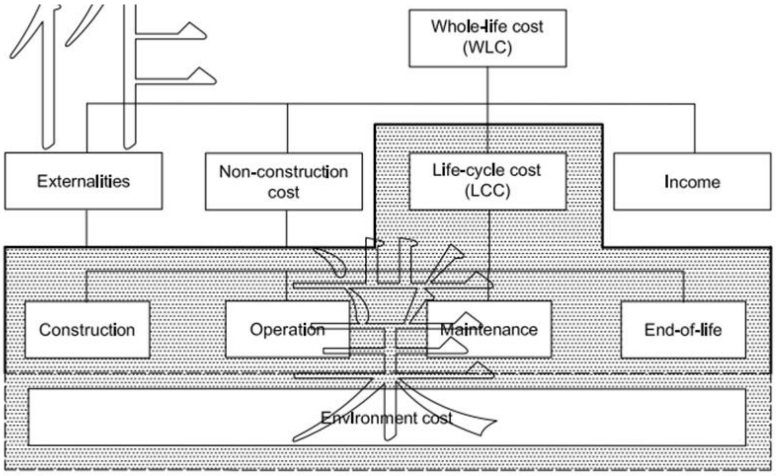


Figure 2: Generalized depiction of the factors affecting whole-life cost and life-cycle cost [59].

An LCC analysis usually necessitates a series of cost inputs for the estimation of costs during different phases of a project. The cost variables are usually classified into groups. In light of this, a list of frequently examined cost variables created by ISO 15686-5 is illustrated below.

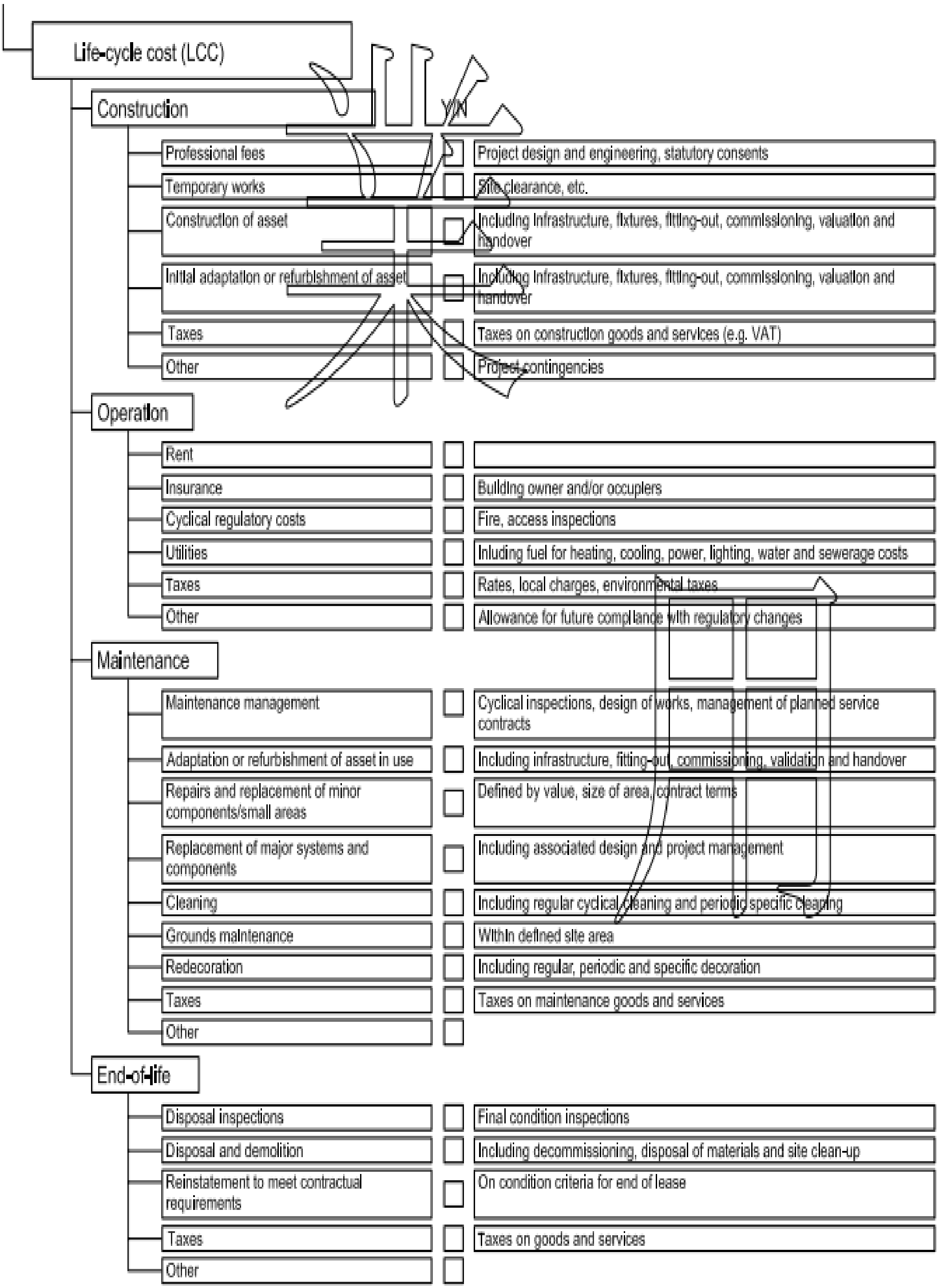


Figure 3: Frequently examined cost variables [59].

A similar albeit more detailed way to classify cost inputs of construction projects during different project phases and levels of decision is shown below:

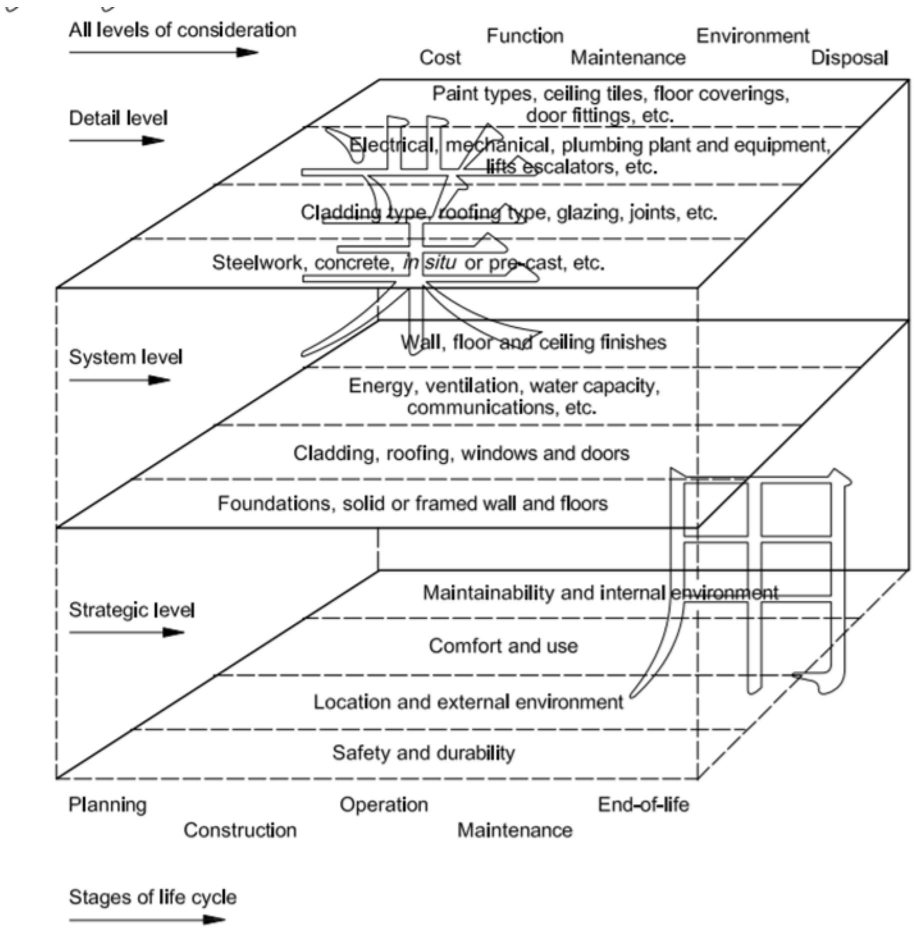


Figure 4: Detailed classification of the cost inputs of construction projects during different project phases and levels of decision [59].

FREQUENTLY ENCOUNTERED MANUFACTURER'S DATA ABOUT VARIOUS BUILDING COMPONENTS

With respect to the life cycle cost related to the energy and structural performance of a typical building, the following subsystems have a considerable impact on it [115]:

- Building Envelope (insulation profiles, shading systems, glazing, roofing, area to volume ratio etc.)
- Mechanical and Energy Systems (use of photovoltaic panels or alternative sources of energy, ventilation systems, water distribution systems, stand-alone alone or central plan-connected systems etc.)

- Structural Systems (form of the frame, sizing of the frame components).
- Electrical Systems (lighting sources and control, distribution)
- Siting (landscaping and irrigation-related design decisions).

The following figure refers to the significance of each subsystem in terms of their contribution to the total life cycle cost of a project:

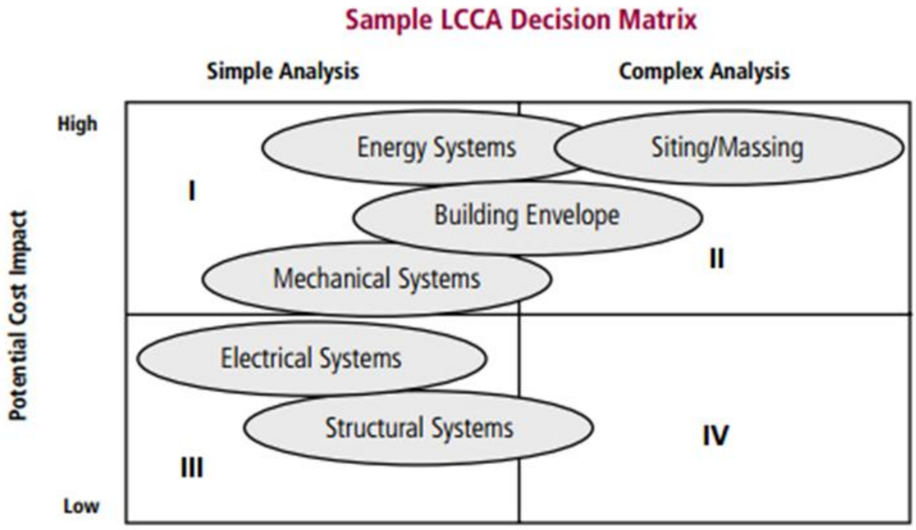


Figure 5: Decision matrix demonstrating the complexity of critical building subsystems and their contribution to the total cost of a building [115].

A literature review has taken place in order to study details about the life cycle of the subsystems that will be examined in the current study. In order to predict potential replacements that may occur during the life cycle period, the service lives of the subsystems that will be used are as follows [56-7], [115]:

- Building Exteriors, Doors, and Windows: 80 years (lifetime)
- Mineral wool insulation profiles: 50 years
- Photovoltaic panels: 25 years
- HVAC systems: 15-20 years
- Structural steel or reinforced concrete: 75-80 years (lifetime)
- Lighting control systems: 15 years

The information about the service lives of the subsystems as well as their maintenance rates can be found in the following software: ATHENA, BEES, Boustead, GaBi [121], SimaPro. There can be various potential combinations of scores for the economic efficiency and environmental friendliness of a particular building; however, the design choices of current study will be based on a score of 50% economic efficiency and 50% environmental friendliness [12].

LIFE CYCLE ASSESSMENT

Life cycle assessment (LCA) is a systematic approach used for the assessment of the environmental impact of a commodity, a production line or a service throughout its life cycle. After conducting an LCA it is possible for various alternatives to be examined with the aim of understanding and improving the implications that a particular practice has on the life cycle of a service or a product. This improvement takes place by: replacing alternatives with less adverse ones, reducing the impact of adverse alternatives, making amends for adverse alternatives with countermeasures.

As far as the field of building construction is concerned, LCA is implemented to compare different design alternatives of a new construction, or for the assessment of the environmental performance of an existing building.

Four ISO standards have been developed specifically for LCA [50-3].

- ISO 14040: Principles and framework.
- ISO 14041: Goal and scope definition and inventory analysis.
- ISO 14042: Life cycle impact assessment.
- ISO 14043: Interpretation.

LIFE CYCLE ASSESSMENT INDICATORS

As it was mentioned above, LCA solely focuses on the assessment of the environmental implications of a particular design decision. A life cycle analysis is largely affected by the notion of sustainability. Sustainability is based on 3 pillars: social, economic and environmental sustainability. As sustainability encompasses a wide range of classified impact parameters, a frame of reference is necessary for any detailed approach considering as many relevant indicators as possible.

The indicators of the UK's frame of reference in sustainability-related issues are demonstrated below [77]:

- Greenhouse gas emissions.
- Resource use.
- Waste.
- Bird populations (farmland birds, woodland birds, birds of coasts and estuaries)
- Fish stocks.
- Ecological impacts of air pollution (habitats sensitive to acidification and eutrophication risks).
- River quality.
- Economic output: Gross Domestic Product.
- Community awareness and participation.
- Crime.
- Employment.
- Poverty.
- Education.
- Health inequality: (infant mortality (by socio-economic group) and life expectancy (by age) for men and women).
- Transport: (number of trips per person by mode and distance travelled per person per year by broad trip purpose).
- Social justice.

- Environmental equality.
- Well-being.

INTEGRATING LIFE CYCLE COSTING INTO LCA

There are several well-known examples of techniques where life cycle costing is conducted simultaneously with LCA. These include:

- Multi-criteria decision-making software (e.g. Logical Decisions [119]) using weights (dependent on expert judgment) to associate LCC with LCA in a quantitative way (e.g. regressions, analytical hierarchical process, linear (and non-linear) programming).
  The analytical hierarchy process can concisely be described as follows: Initially a nxn criteria matrix is built. The scores of importance of between each pair of criteria are introduced. If e(ij) = a, then e(ji) = 1/a (Where: e is a matrix element). The elements of the main diagonal are equal to one (denoting the relationship of importance between the same criterion). The sum of the elements of each column is computed and each element is divided by the sum of each column. After that the average (λ) of each row is computed. This average serves as the importance of each criterion. It is also necessary to check the score assumptions made for consistency. This is done by computing the consistency index: CI = (λ-n)/(n-1) and dividing it by a random index R. The consistency ratio CR = CI/R must be below 0.10 in order for the assumption to be accepted [126].
- Databases such as Eco-costs / Value Ratio [120]. In such databases, the components (e.g. glass, latex, laminates) of a product are converted into monetary cost according to their environmental impact. Some examined parameters to estimate the environmental impact of a component are: eco-costs of human health, eco-costs of ecosystems, eco-costs of resource depletion, eco-costs of global warming.

MULTIPLE LINEAR REGRESSION

Multiple linear regression is a statistical method used to create a multivariate linear function to fit (and also interpret) observed data [103].

Supposing that y_1, y_2, y_3, … , y_n were outputs (representing a single variable) that have to be correlated with a series of inputs, as expressed in the following matrix:

$$\begin{Vmatrix} x_{11} & \dots & x_{1k} \\ x_{21} & \dots & x_{2k} \\ x_{n1} & \dots & x_{nk} \end{Vmatrix}$$

The objective of multiple linear regression is to create a linear function that would have the following form:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \epsilon$$

To attain that objective a system of n equations is created under the assumption that β0, β1, β2, … , βk are the constant coefficients for which minimum error is for a fitted regression model is attained. The figure below illustrates the previously mentioned system of n equations.

$$\begin{aligned} y_1 &= \beta_0 + \beta_1 x_{11} + \beta_2 x_{12} + \dots + \beta_k x_{1k} + \epsilon_1 \\ y_2 &= \beta_0 + \beta_1 x_{21} + \beta_2 x_{22} + \dots + \beta_k x_{2k} + \epsilon_2 \\ &.. \\ y_i &= \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik} + \epsilon_i \\ &.. \\ y_n &= \beta_0 + \beta_1 x_{n1} + \beta_2 x_{n2} + \dots + \beta_k x_{nk} + \epsilon_n \end{aligned}$$

An equivalent matrix expression of that system is shown below:

$$y = X\beta + \epsilon$$

Where:

$$y = \begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ . \\ y_n \end{bmatrix} \quad X = \begin{bmatrix} 1 & x_{11} & x_{12} & . & . & . & x_{1n} \\ 1 & x_{21} & x_{22} & . & . & . & x_{2n} \\ . & . & . & & & & . \\ . & . & . & & & & . \\ . & . & . & & & & . \\ 1 & x_{n1} & x_{n2} & . & . & . & x_{nn} \end{bmatrix}$$

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ . \\ . \\ . \\ \beta_n \end{bmatrix} \text{ and } \epsilon = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ . \\ . \\ . \\ \epsilon_n \end{bmatrix}$$

Evidently, the fitted model would display some degree of deviation from the actual observations (error). The matrix of errors can be expressed via the following formula:

$$e = y - \hat{y}$$

Where:

y is the matrix of actual observations and $\hat{y}$ is the matrix of outputs derived from the fitted model.

The fitted model can be evaluated through the following relationship [103]:

$$\hat{y} = X\hat{\beta}$$

This is done by minimizing the sum of squares that result from the sum of the squared differences between the actual observations and the fitted model (therefore: $(y_{actual} - y_{fitted})^2$). Therefore, the objective is to find the optimal $\hat{\beta}$ coefficients for which the sum of squares reaches a minimum. For this purpose, the derivatives with respect to each coefficient described in the matrix $\hat{\beta}$ are calculated for n times (since there is a system of n equations) and then are summed and finally this results in the following expression that corresponds to the optimal coefficients of $\hat{\beta}$:

$$\hat{\beta} = (X'X)^{-1}X'y \text{ :}$$

Where:

$'$ is the transpose of the matrix and $^{-1}$ is the matrix inverse.

RIDGE REGRESSION

A similar technique that usually reduces the mean error between actual values and the ones estimated by a statistical model is the ridge regression technique [82]. In patterns that are approximate via ridge regression, a λ parameter is added to the regression coefficients as displayed below:

$$\widehat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{X} + \lambda\mathbf{I})^{-1}\mathbf{X}^T\mathbf{y}$$

Where: λ is the ridge parameter and I is the identity matrix.

POLYNOMIAL REGRESSION

Similarly, in polynomial regression the objective is to find out a suitable polynomial, which demonstrates the lowest sum of squared errors, for a given set of observations [x_i, y_i].

A polynomial has the following form [5]:

$$p_m(x) = a_0 + a_1 x + \cdots + a_{m-1} x_{m-1} + a_m x_m$$

Therefore, the objective is to minimize the following expression:

$$F = \Sigma(y_i - (\alpha_0 + \alpha_1 x + \ldots + \alpha_{m-1} x_{m-1} + \alpha_m x_m))^2$$

After differentiating for a_i, the lowest sum of differences between the polynomial model and the actual observations happens if [5]:

$$na_0 + \sum_{i=1}^{n} x_i \, \alpha_1 + (\sum_{i=1}^{n} {x_i}^2) a_2 + \ldots + (\sum_{i=1}^{n} {x_i}^m) a_m = \sum_{i=1}^{n} y_i$$

$$na_0 \sum_{i=1}^{n} {x_i}^1 + \sum_{i=1}^{n} {x_i}^2 \, \alpha_1 + (\sum_{i=1}^{n} {x_i}^3) \alpha_2 + \ldots + (\sum_{i=1}^{n} {x_i}^{m+1}) a_m = \sum_{i=1}^{n} y_i \, x_i$$

...

$$na_0 \sum_{i=1}^{n} {x_i}^m + \sum_{i=1}^{n} {x_i}^{m+1} \, \alpha_1 + (\sum_{i=1}^{n} {x_i}^{m+2}) \alpha_2 + \ldots + (\sum_{i=1}^{n} {x_i}^{2m}) a_m = \sum_{i=1}^{n} y_i \, {x_i}^m$$

The resultant system of equations is solved in order for the required coefficients α_0, α_1, ..., α_m to be evaluated.

OTHER WELL-KNOWN PATTERN RECOGNITION TECHNIQUES

A Monte Carlo simulation [91] is a stochastic technique can be used for the purpose of assessing the impact of variables with known distributions (or at least approximated by making efficient assumptions) and extremes on an examined function. Through a Monte Carlo simulation, a large number of scenarios are collected regarding the response of a function to sets of randomly generated variables (according to their distribution). This leads to valuable information about the function's total range and the distribution of its responses [91].

Similar stochastic models depend on the fuzzy set theory [3]. A fuzzy set Y is a set that has the following form:

$$Y = \{xi, \mu(xi)\}, x \varepsilon Z.$$

Where:

xi are finite states (inputs) and μ(xi), are the responses of a membership function μ(xi), that takes values between 0 and 1. The lower and upper bounds of x_i, are considered to generate a membership function result equal to zero and a value of the membership function equal to 1 is often considered to be the midpoint between the lower and upper bounds of x_i.

Well-known fuzzy optimization techniques include the α-cut level method. An α-cut stands for a value of x, that derives geometrically as a random intermediate value given the fact that the zeros of the membership function are the lowest possible and highest possible values of xi and 1 is the midpoint between those two bounds. The advantage of the method is that it restricts the fuzziness of a variable or a set of variables, to a small number of predefined sets of inputs xi, related to the membership function.

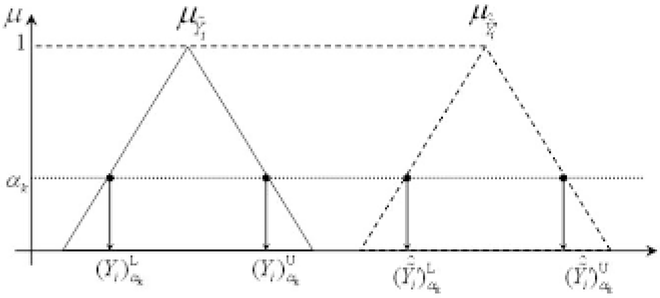


Figure 6: Diagram with fuzzy variables and α-cuts [3]

After using preselected fuzzy sets (e.g. shapes), the response of the function (e.g. weight) whose inputs are these finite states of fuzzy sets, is plotted in order for meaningful conclusions to be derived (e.g. impact of a variable on the function). In cases where there are multiple objectives (e.g. cost, weight, cross section shapes), a fuzzy optimization methodology is depicted below:

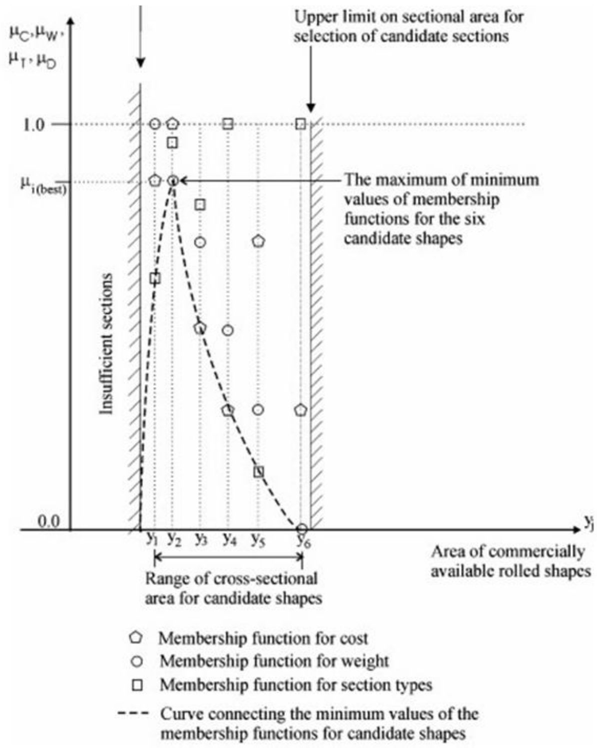


Figure 7: Defuzzyfication and intersection domains [3].

The figure above denotes that the most preferable value for a particular design, is the maximum (hence the most expected) value among the membership function values that generate an intersection domain, if fuzzy set theory would be used in the decision making [3].

A Markov chain is another stochastic technique [98] that can be used in order to associate a future state with a present state (in a memoryless manner), through the use of probabilities. A general formula for a Markov chain could be the following:

$$\Pr(X_{n+1} = x \mid X_n = y) = \Pr(X_n = x \mid X_{n-1} = y)$$

Or, for m states:

$$\begin{aligned} &\Pr(X_n = x_n \mid X_{n-1} = x_{n-1}, X_{n-2} = x_{n-2}, \dots, X_1 = x_1) \\ =&\Pr(X_n = x_n \mid X_{n-1} = x_{n-1}, X_{n-2} = x_{n-2}, \dots, X_{n-m} = x_{n-m}) \text{ for } n > m \end{aligned}$$

For instance, a Markov chain with an initial vector of probabilities equal to:

[0.25 0.50 0.25] and a transition matrix equal to: [0.11 0.58 0.31; 0.20 0.70 0.10; 0.12 0.79 0.09], after n steps will have the form: xn = [0.25 0.50 0.25]*[0.11 0.58 0.31; 0.20 0.70 0.10; 0.12 0.79 0.09]^n, (that expresses the relationship: xn = x0*P^n) . It is meaningful to note that a $x_{i,j}$ element inside a matrix, expresses the transition from an i finite state to a j finite state. Another fundamental property of a Markov chain is that after a certain number of steps the resultant matrix has the same form (therefore its content does not change).

MAXIMUM LIKELIHOOD

The most appropriate theory, on which estimations about the probability of a particular occurrence or occurrences are based, is the maximum likelihood estimation (MLE).

This subchapter outlines how MLE is applied either on two or on k possible outcomes.

At first, an example is given about implementing the method for two possible outcomes. If in 50 cycles, an event occurs for 30 times and does not occur for 20 times, then the function describing the probability of this event to occur is:

$$L(p) = \binom{50}{20} p^{30}(1-p)^{20}$$

The most expected probability is the probability for which the aforementioned function has a maximum:

$$\frac{\partial}{\partial p}\left(\binom{50}{20} p^{30}(1-p)^{20}\right) = 0 \Rightarrow p^{30}(1-p)^{20}[20-30p] = 0$$

The general form for the term $\binom{50}{20}$, along with a way to calculate it is given below [98], [104].

$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$

Where: n is the total number of cycles, k is the number of cycles where a measured occurrence takes place.

The generalization for k outcomes and n cycles is described below.

In k possible outcomes, the probabilities are symbolized as $p_1, p_2, \ldots, p_k$ and the following relationship is true:

$$\sum_{i=1}^{k} p_i = 1$$

If n the number of repeated cycles, where the observed data are collected and X a vector of independent possible outcomes where the random variables X_i symbolize the total occurrences of an outcome i during n cycles, then the final distribution of the aforementioned parameters is as follows [104]:

$$\frac{n!}{x_1!\ldots x_k!} p_1^{x_1} \cdots p_k^{x_k}$$

An illustrative example is as follows:

The measured probability for a bridge to need repair is 45%, the probability, for it to require maintenance is 25% and the probability for it to require nothing is 30%, during one year. After five years the probability of it requiring 3 times maintenance, two times repair and zero times no action at all, is calculated as follows:

$$\Pr(Maintenance = 3, Repair = 2, Nothing = 0) = \frac{5!}{3!2!0!}(0.25^3 x 0.45^2 x 0.30^0) = 0.0316$$

NAIVE BAYES CLASSIFIER

The Bayes theorem is expressed by the following relationship:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Where:

P(A│B) is the probability of A, while the attribute B is unconditionally a given fact.

P(A) expresses in a probability form, the total observations that contain the attribute A.

P(B) expresses in a probability form, the total observations that contain the attribute B.

An equivalent description of the theorem is displayed below:

$$posterior\ prediction(A|B) = \frac{given\ instances(B|A)P(A)}{P(B)}$$

An illustrative example is given as follows: In a given sample the probability of being Friday given the fact there is rain, is equal to the multiplication of the total occurrences of Fridays by the total observations of rain given the fact that there is Friday, over the total observations of rain.

$$P(Friday|rain) = \frac{P(rain|Friday)P(Friday)}{P(rain)}$$

The theorem can also be expressed in a multivariate form, as demonstrated below (multivariate Bayesian theorem) [129]:

$$P(\theta_i|x) = \frac{P(x|\theta_i)P(\theta_i)}{\sum P(x|\theta)P(\theta)}$$

Where: θ is a vector with d dimensions each one corresponding to different observed parameters as displayed below, θ_i is an examined attribute (a distinct dimension of the vector θ).

$$\theta = (\theta_1, \theta_2, ..., \theta_d)$$

Therefore, the occurrence of x, given the occurrence of each separate dimension of θ is examined together with the total number of evidence (denominator term).

An example of a Naive Bayes classifier could be the following:

If the following relationship is true:

$$\prod_i p(w_i|Class\ 1) > \prod_i p(w_i|Class\ 2)$$

Then it is more possible that an examined parameter belongs to class 1 and not class 2.

Where: w_i the examined attributes used to compare if a parameter belongs to a particular class. For the aid of simplification, one of the numerator terms and all the denominator terms of the multivariate Bayesian equation, are ignored as they have minimal impact on the comparison.

NEAREST NEIGHBOOR CLASSIFICATION

If A and B are vectors containing measured parameters (coordinates) with n dimensions, their Euclidean distance (even though there are other approaches to measure distance between multivariate vectors, Euclidean distance is a notion of distance that is commonly used in nearest neighbor classification problems) is calculated as follows [82]:

$$d(A,B)=\sqrt{\sum_{i=1}^{n}(A_i-B_i)^2}$$

Furthermore, if A_i are previous observations that belong to specific classes, any new B_i observation would according to a nearest neighbor classification belong to the class of the A_i observation, that demonstrates the minimum distance from it.

NEURAL NETWORKS

A neural network is another well-known methodology to associate a series of inputs with a series of outputs in a non-linear manner, via arbitrarily selected weights whose total error in generating approximated outputs is gradually minimized. At first an activation function is modeled as the result of the (i is evidently the number of inputs and j the weights that connect to each input to another one) [89], [129].

$$A_j(\overline{x},\overline{w}) = \sum_{i=0}^{n}(x_i w_{ji})$$

The activation function therefore is a sum of weights multiplied by each input [89].

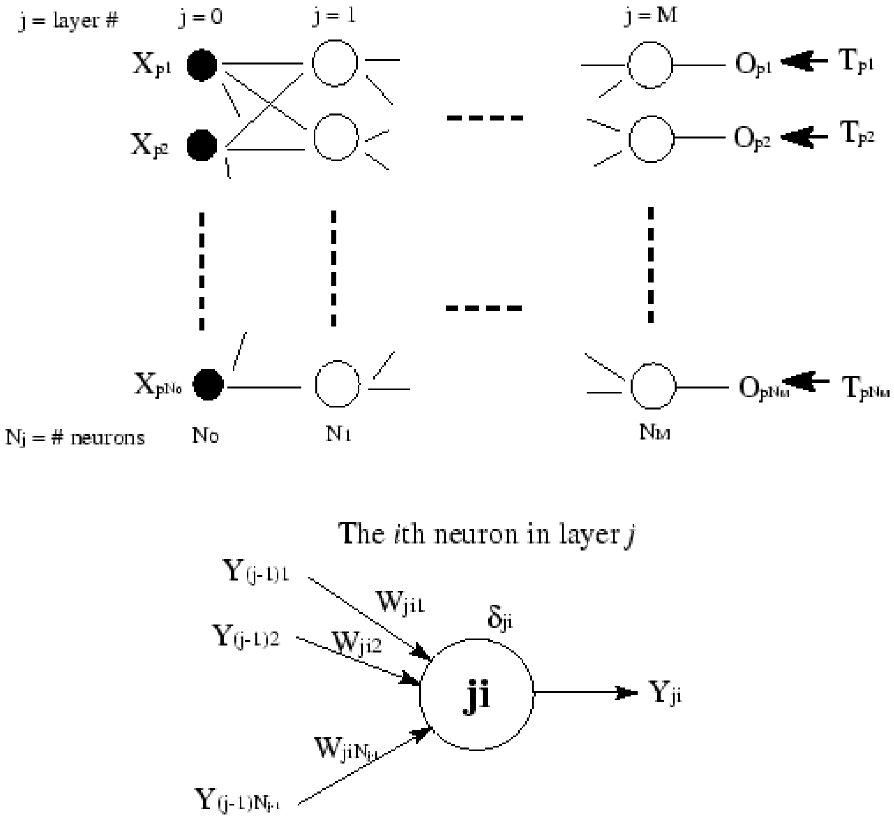


Figure 8: Diagram explaining the concepts of neurons, hidden layers and the interaction among the weights.

A very useful transfer function that generates outputs by given inputs is the sigmoid function.

For the following cases of input values, the sigmoidal functions generate the following outputs:

- 0.5 for input values equal to zero.
- Near 1 for large positive input values.
- Near 0 for large negative input values.

This very small range of possible output values allows the sigmoidal function to easily detect and compute potential associations and relationships between inputs and outputs that are in essence dependent on the inputs, minimizing the potential intermediate transfer noise. Transfer functions with similar properties are the logistic and the tangent function.

The output in a neural network is therefore computed via the following formula:

$$O_j(\bar{x}, \bar{w}) = \frac{1}{1 + e^{A_j(\bar{x}, \bar{w})}}$$

After that the error of as the squared distance between the actual observations and the generated results of the sigmoidal function as response to an initial estimation of weights that is produced randomly at the first iteration.

$$E_j(\bar{x}, \bar{w}, d) = (O_j(\bar{x}, \bar{w}) - d_j)^2$$

The next step deals with the correction of the initially estimated weights, which are updated according to the steepest descent method.

$$\Delta w_{ji} = -\eta \frac{d\mathrm{E}}{dw_{ji}}$$

Where: η is a constant step size.

After algebraic calculations based on the properties of the sigmoidal function, the derivatives of E with respect to each weight, has a known result equal to [89]:

$$\frac{dE}{dw_{ji}} = 2(O_j - d_j)O_j(1 - O_j)x_i$$

Therefore:

$$\Delta w_{ji} = -2\eta(O_j - d_j)O_j(1 - O_j)x_i$$

In cases where there are hidden intermediate layers, the update of weights takes place as follows:

The transition from an input layer i to a hidden layer j, is expressed by the following relationships:

$$\Delta w_{jk} = \eta \delta_j x_i$$
$$\delta_k = o_j (1 - o_j) \sum_k w_{jk} \delta_k$$

The transition from a hidden layer j, to an output layer k, is expressed by the following relationships:

$$\Delta w_{jk} = \eta \delta_k o_j$$
$$\delta_k = (y_{target} - y_k) y_k (1 - y_k)$$

CORRELATION COEFFICIENT

A correlation coefficient between two variables is a measure of the degree of mutual dependence between the variables. The correlation coefficient can take values between -1 (highly negative correlation) and +1 (highly positive correlation). The correlation coefficient is computed through the following formula [103]:

$$\rho_{X,Y} = \mathrm{corr}(X,Y) = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y},$$

Where:

μ_x, μ_y are the average or most expected values of the variables x,y.

X, Y are the observed values of x,y.

σ_x, σ_y are the standard deviations of the variables x,y.

In the case of many observations, a similar formula is used that takes into account the average impact of each observation [103].

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{(n-1)s_x s_y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}},$$

COEFFICIENT OF DETERMINATION

The coefficient of determination (R^2) is a measure of the degree to which a fitted model (that e.g. derives from regression, curve fitting or any other way of data fitting) describes the actual observations. It is meaningful to note that R^2 can take values between 0 and 1 [103].

A very common formula to evaluate R squared is the following:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Where:

SS_{res} is the sum of squares of the residuals, computed through the following equation:

$$SS_{res} = \sum_i (y_i - f_i)^2$$

Where:

f_i are the output values predicted by a fitted model.

y_i are the output values of the actual observations.

SS_{tot} is the total sum of squares, computed through the following equation:

$$SS_{tot} = \sum_i (y_i - \bar{y})^2$$

Where:

y_i are the output values of the actual observations.

$\bar{y}$ is the average of the observed values.

An alternative way to understand the meaning of the formula is to consider that it describes the sum of squares of the distances between the average of the observed values and the output values predicted by a fitted model <u>over</u> the sum of squares of the distances between the average of the observed values and the output values of the actual observations.

SENSITIVITY RATIO

In cases where it is required to analyze the impact of a specific variable on an examined function, a common technique that is used is the sensitivity ratio (SR). SR is calculated through the following relationship:

$$SR\ (\%) = \frac{\left(\frac{Y_2 - Y_1}{Y_1}\right)}{\left(\frac{X_2 - X_1}{X_1}\right)}$$

Where:

X_1 = an initial value for an input variable.
X_2 = a final value for an input variable.

Y_1 = the initial response of a function, when X_1 is input into the function.
Y_2 = the final response of a function, when X_2 is input into the function.

OTHER TECHNIQUES USED IN LCCA

Other techniques used for the estimation of the total life cycle cost of a project include:

- Decision trees. A decision tree is a tree of probabilities that derives from a divide-and-conquer method classifying the possible occurrences related to an examined situation. When a subset of data is pure (not mixed with other attributes) a branch of the decision tree stops. Otherwise, new branches of subsets are generated to further classify the subsets according to their attributes [129].
  ID3 algorithm is commonly used to determine which node will be located on an upper level branch and classifies the degree of information that each attribute contains, when it comes to assigning levels to an examined series of attributes. A frequently formula used by decision trees based on the ID3 algorithm is shown below.
  At first the entropy of a specific attribute is examined:

$$E(S) = -p_{initial+}\, log_2 p_+ \; - \; p_{initial-} log_2\, p_-$$

  Where:

  E is the entropy of a specific attribute.
  p_+ is the fraction of positive examples of the initially examined attribute.

p_- is the fraction of negative examples of the initially examined attribute.

Finally, the node is assigned to the attribute that attains the highest level of information gain, according to the process shown in the following example [129].

In a set of mushrooms beginning with "eatability" as an attribute used to divide the database, the following database needed to be segregated in a decision tree form:

	Color	Size	Points	Eatability
1	red	small	yes	toxic
2	brown	small	no	eatable
3	brown	large	yes	eatable
4	green	small	no	eatable
5	red	large	no	eatable

Figure 9: Example of a database with observations and various traits.

A trial division is attempted for the attribute "color". The a-priori probability for the subfeature "red" of the attribute color is equal to 2/5. Accordingly, the probability for the subfeature "brown" is 2/5 and 1/5 for the subfeature "green".

$$D|_{\text{color}} = \begin{array}{l|cc} & \text{toxic} & \text{eatable} \\ \hline \text{red} & 1 & 1 \\ \text{brown} & 0 & 2 \\ \text{green} & 0 & 1 \end{array} \quad \rightarrow \quad |D_{\text{red}}| = 2, \ |D_{\text{brown}}| = 2, \ |D_{\text{green}}| = 1$$

Figure 10: Calculating the apriori probabilities of each subfeature of a random attribute.

In the following figure, the conditional entropy of the attribute "color" is calculated for all its subfeatures (red, brown, green) the coefficients shown below are the aforementioned a-priori probabilities. The terms inside the secondary parentheses represent the possibility of the two instances of the attribute "eatability" (toxic or eatable), when the subfeatures (red, brown, green) of the attribute "color" are a given.

$$\begin{aligned} H(C \mid \text{color}) &= -(0.4(\tfrac{1}{2}\log_2\tfrac{1}{2} + \tfrac{1}{2}\log_2\tfrac{1}{2}) + \\ &\quad 0.4(\tfrac{0}{2}\log_2\tfrac{0}{2} + \tfrac{2}{2}\log_2\tfrac{2}{2}) + \\ &\quad 0.2(\tfrac{0}{1}\log_2\tfrac{0}{1} + \tfrac{1}{1}\log_2\tfrac{1}{1})) \;=\; 0.4 \end{aligned}$$

Figure 11: Calculating the conditional entropy of an attribute.

The procedure continues until all attributes are examined using the attribute "eatability" as a basis to segregate the database.

The first node is assigned on the attribute attaining the minimum conditional entropy. The process continues till all a node is assigned to all attributes. Therefore, when dividing a decision tree into attributes the ones that contain a higher degree of information (hence lower "entropy") will be sorted hierarchically according to their degree of information and will be placed on upper levels. The main advantage of the method is that it is easily comprehensible.

- Deterministic methods where the life cycle cost of an asset is computed as a percentage of its initial costs. The disadvantage of these methods deals with the fact that they ignore the uncertainty of several variables and this usually is addressed by additional inputs taking uncertainty into account.
- Interviews from industry experts [77].
- Brainstorming [77].

USEFUL STATISTICAL AND MACHINE LEARNING TECHNIQUES THAT WERE NOT ENCOUNTERED IN THE RELEVANT LITERATURE

The LCCA literature review was based on a relatively large number of selected papers which provided a sufficient level of knowledge that made it possible for the current thesis to attain innovation. The statistical and machine learning techniques mentioned below were not encountered in the relevant literature, however, they are considered to be useful for data analysis and interpretation purposes. A more detailed presentation of the techniques is beyond the scope of the project because they are not directly related to the models that were developed in the project and also because it would be quite easy for the reader to implement them on a relevant software by merely understanding the description given in the following paragraphs. Some examples of such software could be: SPSS, PSPP, SAS, Weka, the statistics and machine learning toolbox of MATLAB, the numpy and the scipy toolbox in Python, various functions of the R programming language, various data analysis functions of Microsoft Excel.

1. Logistic regression:

The logistic regression (or logit regression) [103] is preferred over the multiple linear regression in cases where categorical variables are involved as predictors. The purpose of the logistic regression is to create a linear relationship (by identifying coefficients) between the predictors (independent variables) and the dependent variable that is expressed as a binary response with a range of values between zero and one.

2. k-means clustering:

It is a well-known method used to identify relationships of homogeneity between vicinities of a sample [82], [129]. An initial number (k) of clusters and an equal number of initial means (centroids) is assumed and each observation is associated with the nearest cluster by assigning an observation to nearest cluster after the calculation of Euclidean distance between a means and an observation. Furthermore, the following steps take place: Step 1: An observation is classified into the cluster which displays the minimum distance from its means. Step 2: Each iteration recalculates the centroid of a cluster (as the average coordinate). Steps 1 and 2 are repeated till convergence is attained (if a maximum number of iterations is reached or if the (re-)calculated centroids do not change after a certain number of iterations).

3. Local regression:

A local regression can apply to particular range of data (in a particular locality of the total sample) of the total sample for reasons of attaining a higher degree of accuracy.

4. Principal component analysis:

A principal component analysis aims to maximize the effect of the variance of a linear combination of variables. This results, [103] either in dimensionality reduction or in noise reduction. This is done either by: 1. Computing the mean vector of the independent variables, the covariance matrix, its eigenvalues and eigenvectors, by selecting the eigenvectors that are responsible for the greatest impact on the cumulative variance (e.g. 80% of cumulative variance), by multiplying these eigenvectors with the independent variables (predictors). This results in identifying the components that are responsible for the greatest rate of change in a sample. 2. Calculating the eigenvalues of the correlation matrix. By reordering the resultant matrix of the eigenvalues in a descending order the independent variables (predictors) with the greatest cumulative value are the ones that are more important [103]. Furthermore, predictors with eigenvalues with a value less than 1, are generally considered unimportant.

TECHNIQUES USED TO REDUCE THE ERROR OF A SAMPLE AND ASSESS ITS OVERALL QUALITY

Cross-validation

A cross-validation [129] can take place by dividing a sample into a number of portions and by repeating on them the analysis that took place in the original sample. Therefore, if the re-analysis leads to similar predicted results this is an indication of the appropriateness of the sample quality.

Bootstrapping

Boostrapping [82], [129], deals with the random selections of members from a sample used to replace other members for reasons of assessing the overall degree of accuracy of a performed analysis.

INFERENTIAL STATISTICS

The present subchapter discusses briefly some critical notions about inferential statistics. Therefore, the parameters outlined below play a significant role in determining the adequacy of sampled data.

t-tests and z-tests

A t-test and a z-test are two similar notions that relate to the assumption that the distribution of the sampled data is a normal distribution. If the number of observations in a sample is less than 30 [88], then a t-test is used. If the number of observations in a sample is more than 30, a z-test is used. The distance from the distribution mean is expressed through such tests in standard deviation units. Both, t-tests and z-tests are used to evaluate the evidence that a new sample gives to refute a previously known mean. A z value is equal to:

$$z = \frac{\bar{x} - \mu}{\left(\frac{\sigma}{\sqrt{n}}\right)}$$

Where:

$\bar{x}$ is the average of the sampled observations.

μ is the mean of the sampling distribution.

σ is the standard deviation of the sampled observations.

n is the sample size.

Similarly, a t value is equal to:

$$t = \frac{\bar{x} - \mu}{\left(\frac{\sigma}{\sqrt{n}}\right)}$$

p-value

A p-value [124] refers to the probability percentage beyond which a sampling distribution that derived from sampled data is likely to demonstrate values that can be exceeded. When a previous mean is known, upon collection and analysis of the new sampled data, a higher or a lower mean than the previous one and a p-value less than a preset level (usually 0.05 or 0.01) means that there is a 5 percent and a 1 percent probability respectively, for the sampled values to be exceeded and this leads to a rejection of the null hypothesis. The null hypothesis refers to the fact the previous mean does not change.

Confidence intervals

A confidence interval is a term [88] that refers to the percentage of area that falls under the curve that derives from a sample. For the determination of the lower and upper limits of a confidence interval, a critical value z^* is used that relates to preset confidence levels. A confidence interval for a known standard deviation, is as follows:

$$x - z^* * \left(\frac{\sigma}{\sqrt{n}}\right), x + z^* * \left(\frac{\sigma}{\sqrt{n}}\right)$$

If the standard deviation is unknown, then the Student's t distribution is used to define a critical value t^*, as shown in the following relationship:

$$x - t^* * \left(\frac{\sigma}{\sqrt{n}}\right), x + t^* * \left(\frac{\sigma}{\sqrt{n}}\right)$$

SAMPLE SIZE

To collect information from an adequate sample [88], [126] there are many relationships, depending on which statistical measure would be the basis for the determination of the sample size. The subchapter will refer to a few well-known ones.

In order for a sample to be considered sufficient the following criterion is used:

$$n = \frac{N}{1 + N * e^2}$$

Where:

n is the sample size.

N is the total population.

e is the targeted error rate (e.g. 5%).

Another possible formula based on a preset confidence level, a standard deviation that derived from at least 30 observations and margin of error, is the following:

$$n \geq 1.96^2 * \frac{\sigma^2}{E^2}$$

n is the sample size.

σ is the standard deviation.

E is an acceptable, preset margin of error related to the measured variable.

The term 1.96, represents a confidence level equal to 95% and can be replaced with other possible z-values that refer to different confidence levels.

STRUCTURAL DESIGN OF BUILDINGS

INTRODUCTION

The current chapter presents the background theory regarding the structural design of the model buildings. At first critical information is given about the finite element analysis which was employed for the structural analysis of the frame components (beams and columns) of the model buildings of the developed algorithms. After a structural analysis, the designer uses the resultant axial loads, shear forces and bending moments to dimension the beams and columns of building according to a construction code. Since the algorithms of the project were built in accordance with Eurocode 2 (Design of RC structures), Eurocode 3 (Design of steel structures) and Eurocode 5 (Design of timber structures), the relevant theory that has been used for the creation of the algorithms is presented.

FINITE ELEMENT ANALYSIS

The aim of the present subchapter is to present how the finite element method is implemented for a general beam element and a 2D frame.

At first according to the conventions of the Euler–Bernoulli beam theory, the following relationships are true for the start and end moment and shear force, for any beam element [49]:

$$S_{AB} = \frac{12EI}{L^3} v_A + \frac{6EI}{L^2}\theta_A - \frac{12EI}{L^3} v_B + \frac{6EI}{L^2}\theta_B$$

$$M_{AB} = \frac{6EI}{L^2} v_A + \frac{4EI}{L}\theta_A - \frac{6EI}{L^2} v_B + \frac{2EI}{L^2}\theta_B$$

$$S_{BA} = -\frac{12EI}{L^3}v_A - \frac{6EI}{L^2}\theta_A + \frac{12EI}{L^3}v_B - \frac{6EI}{L^2}\theta_B$$

$$M_{BA} = \frac{6EI}{L^2}v_A + \frac{2EI}{L}\theta_A - \frac{6EI}{L^2}v_B + \frac{4EI}{L^2}\theta_B$$

Where:

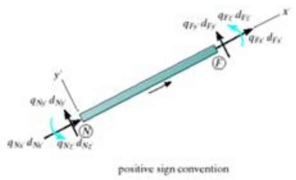
v_A is the end displacement of the A edge of a beam (AB).

v_B is the end displacement of the B edge of a beam (AB).

θ_A is the rotation angle of the A edge of a beam (AB).

θ_B is the rotation angle of the B edge of a beam (AB).

By assembling the previously mentioned relationships in a matrix form according to the equation: q = k'd (Hook's law).



$$\begin{bmatrix} \frac{AE}{L} & 0 & 0 & -\frac{AE}{L} & 0 & 0 \\ 0 & \frac{12EI}{L^3} & \frac{6EI}{L^2} & 0 & -\frac{12EI}{L^3} & \frac{6EI}{L^2} \\ 0 & \frac{6EI}{L^2} & \frac{4EI}{L} & 0 & -\frac{6EI}{L^2} & \frac{2EI}{L} \\ -\frac{AE}{L} & 0 & 0 & \frac{AE}{L} & 0 & 0 \\ 0 & -\frac{12EI}{L^3} & -\frac{6EI}{L^2} & 0 & \frac{12EI}{L^3} & -\frac{6EI}{L^2} \\ 0 & \frac{6EI}{L^2} & \frac{2EI}{L} & 0 & -\frac{6EI}{L^2} & \frac{4EI}{L} \end{bmatrix} \begin{Bmatrix} u_1 \\ w_1 \\ \theta_1 \\ u_2 \\ w_2 \\ \theta_2 \end{Bmatrix} = \begin{Bmatrix} P_1 \\ Q_1 \\ M_1 \\ P_2 \\ Q_2 \\ M_2 \end{Bmatrix}$$

Figure 12: Assembling the effect of all possible forces present at a start or end node of an element in a matrix form.

In cases where there are external loads, the aforementioned equation becomes:

$$q = k'd + q0$$

A global stiffness matrix is created by taking into account the stiffness connectivity of the start and end nodes of each element: $K = \Sigma k_e$. . The global stiffness matrix represents through its cells (ij), all the possible ways that the beam components of a frame can be connected with each other. The displacements are calculated by solving the system of equations that derives from the global stiffness matrix [47].

$$\mathbf{K}'^{e} = \begin{bmatrix} \frac{EA}{L} & 0 & 0 & -\frac{EA}{L} & 0 & 0 \\ & \frac{12EI}{L^3} & \frac{6EI}{L^2} & 0 & \frac{12EI}{L^3} & \frac{6EI}{L^2} \\ & & \frac{4EI}{L} & 0 & -\frac{6EI}{L^2} & \frac{2EI}{L} \\ & & & \frac{EA}{L} & 0 & 0 \\ & & & & \frac{12EI}{L^3} & -\frac{6EI}{L^2} \\ sim. & & & & & \frac{4EI}{L} \end{bmatrix}$$

Figure 13: Stiffness matrix of an element.

A pseudocode that demonstrates the programming logic of the finite element analysis code that was used in the project is as follows [42]:

Specify number of elements

Specify number of nodes

Specify the numbering of nodes by placing the connectivity between elements in a matrix form: elementNodes = [element_a element_b; element_c element_d; ...]

Set GDof (Global degrees of freedom) = 3*number of nodes

Initialize the matrices that contain the elements' cross sectional areas, elements' lengths, elements' moments of inertia

Initialize the displacements matrix as a single-column matrix with GDof elements

Initialize the force matrix as a single-column matrix with GDof elements

Specify the prescribed forces

Specify the prescribed degrees of freedom

Initialize the stiffness matrix as a 2D square matrix whose dimensions are equal to: (GDof,GDof)

for i = 1:number of elements

Construct a matrix of indices that creates 2 nodes for each element in the elementNodes connectivity matrix: elementNodes(i,1) = i

elementNodes(i,2) = i + 1

end

for i = 1:number of elements

Construct a matrix of indices that creates 2 nodes for each element in the elementNodes connectivity matrix: indice=elementNodes(i,:)

Generalize the degrees of freedom of each element by using the following matrix: elementDof=[indice indice+number_of_nodes indice+2*number_of_nodes]

Calculate the k stiffness of each element:

stiffness(elementDof,elementDof)=stiffness(elementDof,elementDof)+k

end

Separate the active degrees of freedom by the prescribed ones

Calculate the displacements of the active degrees of freedom: stiffness(activeDof,activeDof)\force(activeDof)

Calculate forces: Force = Global stiffness*displacements

RECTANGULAR REINFORCED CONCRETE BEAM DESIGN

The design of rectangular reinforced concrete beams takes place through the following procedure:

The parameters K (indicator of the relative compressive stress of a beam in flexure) and K' are computed.

Specifically [20], [22], [38]:

$$K = \frac{M_{sd}}{bd^2 f_{ck}}$$

Where:

b is the width (smaller dimension) of the beam cross-section.

d is the depth (larger dimension) of the beam cross-section minus the cover minus an estimated amount (equal to 15 or 20 mm) that represents a link and the half of a bar diameter.

f_{ck} is the characteristic compressive cylinder strength of concrete at 28 days.

M_{sd} is the design bending moment from the first order analysis.

Moreover, K' is a coefficient used for the evaluation of a limiting value and is calculated through the following formula [22], [38]:

$$K' = 0.598\delta - 0.18\delta^2 - 0.21$$

The values of K' and δ can be taken from the following table:

Percent redistribution	**Redistribution ratio, δ**	**K'**
0.00%	1.00	0.208
5.00%	0.95	0.195
10.00%	0.90	0.182
15.00%	0.85	0.168
20.00%	0.80	0.153
25.00%	0.75	0.137
30.00%	0.70	0.120

Table 1: Values for K' and δ.

There are two cases that can be encountered, namely:

1. $K \le K'$.
2. $K > K'$.

- If $K \le K'$, then the tensile reinforcement A_{s1} is computed as follows:

$$A_{s1} = \frac{M_{sd}}{f_{yd}\, z}$$

Where:

$$z = d[0.5 + 0.5(1 - 3.53K)0.5] \leq 0.95d$$

- If K > K', then there is also requirement for compression reinforcement, that is calculated though the following relationship:

$$A_{s1} = \frac{M - M'}{f_{sc}(d - d_2)}$$

Where:

$$M' = \frac{K'}{bd^2 f_{ck}}$$

$$f_{sc} = \frac{700(x_u - d_2)}{x_u} \leq f_{yd}$$

Where:

d_2 = effective depth to compression steel
x_u = (δ – 0.4)d

Moreover, the tensile reinforcement A_{s1} is computed as follows:

$$A_{s1} = \frac{M'}{f_{yd}\, z} + A_{s2} \frac{f_{sc}}{f_{yd}}$$

MODELING THE INTERACTION DIAGRAMS OF RC ELEMENTS

An interaction diagram corresponds to acceptable combinations of values for the axial and moment resistance of an RC cross section. An interaction diagram therefore encompasses a region of acceptable values of N_{sd} and M_{sd} and any acceptable design for an RC cross section must be encircled by this region.

The simulation approach that has been followed in the project takes advantage of points with constant values, to allow for a quick estimation of the interaction diagram [90]. The coordinates of the points are as follows: (x,y) = point 1: (0, $N_{rd,max}$), point 2: (N_2, M_2), point 3: (M_{bal}, N_{bal}). The points are connected to each other in a consecutive order and this results in the creation of three lines, which are modeled as constraints representing bounds that must not be exceeded by any combination of N_{sd} and M_{sd}.

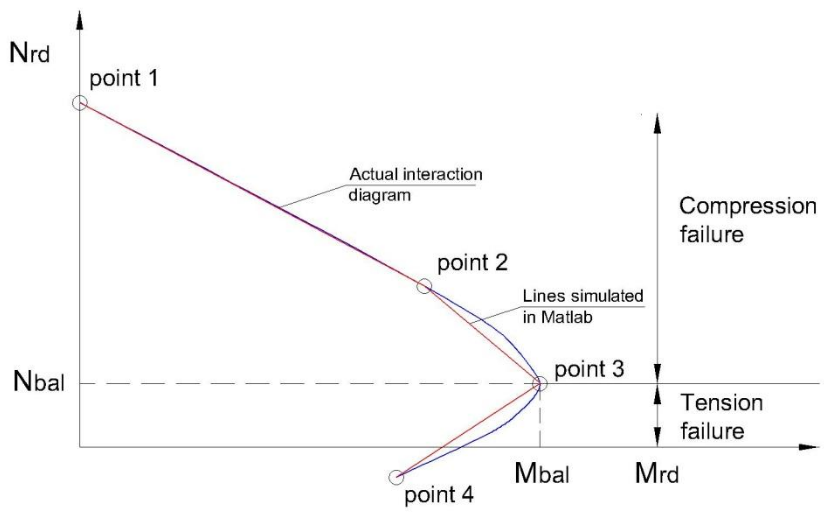


Figure 14: Simulation of the interaction diagram of Nrd and Mrd.

The first line derives from the points 1 & 2, the second by the points 2 & 3 and the third by point 3.

If d is the cover of the cross section, point 2 represents a predictable condition, where the following relationship is true for the neutral axis x [20], [38], [90], [128]:

$$x = h - d$$

$$\varepsilon_s = 0.0035 * \frac{(h - d - h + d)}{h - d} = 0$$

$$\Rightarrow f_s = 0$$

And:

$$f_{sc} = f_{yd} \text{ [90]}$$

Where: $f_{yd} = f_y/1.15$.

Since the values of x, f_s and f_{sc} are known, the axial and moment resistance of the cross section can easily be computed by the following generalized formulae [33], [38], [90], [128]:

$$N_{rd} = k_1 f_{cu} bx + f_{sc} As_{\,1} + f_{st} As_{\,2}$$

$$M_{rd} = F_c(\frac{h}{2} - k_2 x) + F_{sc}(\frac{h}{2} - d) + F_{st}(d - \frac{h}{2})$$

The coefficients k_1 and k_2 are equal to [41]:

$$k_1 = 0.45(1 - \frac{\sqrt{f_{cu}}}{52.5})$$

$$k_2 = \frac{\left(\left[2 - \frac{\sqrt{f_{cu}}}{17.5}\right]^2 + 2\right)}{4\,[3 - \frac{\sqrt{f_{cu}}}{17.5}]}$$

Moreover [38], [90], [128]:

$$N_{rd} = F_c + F_{sc} + F_{st}$$

$$\Rightarrow N_{rd} = k_1 f_{cu} bh + f_{yd} As_{\ 1} - f_{yd} As_{\ 2}$$

As regards the values of N_{bal} and M_{bal}:

$$N_{bal} = k_1 f_{cu} b x_{bal} + f_{sc} As_{\ 1} + f_{st} As_{\ 2}$$

$$\Rightarrow N_{bal} = k_1 f_{cu} b x_{bal} + f_{sc} As_{\ 1} - f_{yd} As_{\ 2}$$

Moreover:

$$M_{bal} = F_c(\frac{h}{2} - k_2 x_{bal}) + F_{sc}(\frac{h}{2} - d) + F_{st}(d - \frac{h}{2})$$

Where: x_{bal} is equal to 0.636d.

If f(x) the function describing the first line, g(x) the function describing the second line and h(x) describing the third line, following constraints must be satisfied in order for an RC cross section to resist a particular combination of N_{sd} and M_{sd}.

$$\Rightarrow N_{sd} - f(M_{sd}) \leq 0$$

$$\Rightarrow N_{sd} - g(M_{sd}) \leq 0$$

$$\Rightarrow N_{sd} - h(M_{sd}) \geq 0$$

OTHER CONSTRAINTS CONSIDERED FOR THE COST/SIZING OPTIMIZATION OF REINFORCED CONCRETE ELEMENTS

Some other constraints that have been taken into account for the structural optimization subproblem of the RC elements are listed below [38]:

- The permissible bounds for the minimum amount of reinforcement according to 9.12 N clause of EC-2, must be met as shown below:

  $$As_{\,min} = \ 0.10\ Nsd/fyd \ \geq \ 0.002Ac$$

  (Where: A_c is the total amount of concrete in a cross section subtracting the contribution of the reinforcement)

  An alternative approach is demonstrated in the following formula:

  $$As_{\,1} + As_{\,2} \geq \ 0.10 N_{sd}/f_{yd}$$

  $$\Rightarrow \ As_{\,1} + As_{\,2} \geq \ \ 0.002 * (b * h - As_{\,1} - As_{\,2})$$

  Apart from that constraint for the maximum amount of reinforcement allowed in the cross section is shown in the following expression:

$$\frac{As_1}{b*h}+\frac{As_2}{b*h} \leq \rho_{\max}\ (\%)$$

Where: ρ_{max} = 8%.

SHEAR CHECK FOR REINFORCED CONCRETE ELEMENTS

In reinforced concrete elements, a significant check is that of its adequacy to resist shear stresses. Shear stresses are generated by any loads or transverse actions to the plane of an element's cross-section. The convention that has been used in the current project for the evaluation of the shear resistance of an RC element was preferred among other available ones, despite the fact that it is considered as over-conservative for cases of RC elements that fall into higher grade categories (f_{ck} > 50) [38].

For the assessment of the shear capacity of an RC element, the following three parameters need to be evaluated: V_{sd}, V_{rd1} and V_{rd2}.

V_{sd} is the maximum shear force acting on the RC element.

V_{rd1} is the shear resistance of the RC element without the consideration of the contribution of the transverse reinforcement.

V_{rd2} is the shear resistance of the RC element, with the co-estimation of the contribution of the transverse reinforcement. The evaluation of V_{rd2} is necessary if: $V_{sd} > V_{rd1}$

In the case where: $V_{sd} \leq V_{rd1}$, the examined cross-section necessitates no additional transverse reinforcement, apart from a nominal amount determined in the relevant national specifications.

V_{rd1} is calculated through the equation:

$$V_{rd1} = [\tau k(1.2 + 0.4\rho) + 0,15\sigma]bh_{eff}$$

Where:

$$\tau = 0,0035(f_{ck})^{2/3}$$

(τ is the basic strength in shear of the concrete grade)

Moreover:

$$k = 1.6 - h_{eff} \leq 1$$

Where:

ρ is the tension reinforcement percentage, calculated by the following relationship:

$$\rho = \frac{100A_{st}}{bh_{eff}} < 2$$

A_{st} is the area of the tension reinforcement.

Furthermore:

$$\sigma = \frac{N_{sd}}{A_c} > 0.4f_{ck}/1.5$$

Vrd_2 (hence; the total shear capacity of the cross-section) is evaluated by the following expression:

$$V_{rd2} = 0.75\nu[\left(\frac{f_{ck}}{1.5}\right) - \sigma_{eff}]bh_{eff}$$

$$\nu = \left[0.7 - \left(\frac{f_{ck}}{200}\right)\right] \leq 0.5$$

$$\sigma_{eff} = (N - \frac{A_{sc}f_{yck}}{1.15})/\,Ac \ \leq\ 0.4fck/1.5$$

Where:

A_{sc} is the area of the compression reinforcement.

If $V_{sd} > V_{rd1}$, the transverse reinforcement area A_{sw} is divided by a designer-defined pitch s (EC-2), that is calculated by the following relationship:

$$\frac{A_{sw}}{s} = (\mathrm{V_{sd}} - \mathrm{V_{rd1}})/(0.9h_{\ eff}\, f_{ywk}/1.15)$$

Where:

f_{ywk} is the grade of the steel transverse reinforcement.

Evidently, in the case where: $V_{sd} > V_{rd2}$ the designer should opt for a cross-section with larger dimensions.

STEEL BEAM DESIGN

The algorithm that has been developed ensures that all the necessary checks needed for typical cases of steel beam design [39], [81] are taken into account. At first, the bending check takes place, as follows:

For class 1 or 2 cross sections (information about the classes of steel cross sections can be found in standardized tables. There are also computation methods for the determination of the class of a steel cross section described in Eurocode 3) [39], [81]:

$$Mcrd = \frac{W_{pl} f_y}{\gamma_{\mu 0}} > M_{sd}$$

(Relationship 1)

Where:

W_{pl} is the plastic section modulus (parallel to the flange) of the cross section of the cross-section.

f_y is the steel strength class in MPa.

For class 3 cross sections:

$$Mcrd = \frac{W_{el,min} f_y}{\gamma_{\mu o}} > M_{sd}$$

Where: $W_{el,min}$ is the elastic section modulus (parallel to the flange) of the cross section of the cross section.

$\gamma_{\mu o}$ is a reduction coefficient equal to: 1.1

The second check for shear takes place as follows:

$$V_{plrd} = \frac{A_V(\frac{f_y}{\sqrt{3}})}{\gamma_{\mu o}} > V_{sd}$$

Where:

$\gamma_{\mu o}$ is a reduction coefficient equal to: 1.1.

Av is the effective area that resists to shear and can be estimated as follows: 1.04*h*t_w.

The third check for combined shear and bending, takes place only if:

$$V_{sd} > 50\% * V_{plrd}$$

The check requires that:

$$M_{Vrd} = [W_{pl} - \frac{\rho {A_V}^2}{4t_w}](\frac{f_y}{\gamma_{\mu o}}) \leq M_{crd}$$

Where:

$\rho = (2V_{sd}/V_{plrd} - 1)^2$.

W_{pl} is the plastic section modulus (parallel to the flange) of the cross section of the cross-section.

The last check required examines if the cross-section is adequate for lateral torsional buckling. Therefore:

$$M_{sd} \leq M_{brd}$$

Furthermore:

$$M_{brd} = \frac{x_{LT} b_w \, W_{ply} f_y}{\gamma_{\mu 1}}$$

Where:

β_A is a coefficient considered equal to 1, for class 1, 2 and 3 cross sections.

x_{LT} is a reduction factor.

$\gamma_{\mu 1}$ is a reduction coefficient equal to: 1.1

W_{ply} is the plastic section modulus (parallel to the flange) of the cross section.

The reduction factor x_{LT} is computed as follows:

$$x_{LT} \ = \frac{1}{(\varphi \ + \ (\varphi^2 \ - \lambda_{LT}^2)^{0.5})} \ \leq \ 1$$

Where:

$$\varphi_{LT} \ = \ 0.5(1 \ + \ \alpha LT(\lambda LT \ - \ 0.2) \ + \ \lambda LT^2)$$

(φ_{LT} is a value used for the determination of the reduction factor x_{LT}).

$$\lambda_{LT} = (Mcrd/Mcr)^{0.5}$$

($\lambda_{\lambda T}$ is a slenderness parameter)

$$M_{cr} = \frac{\pi^2 E I_z}{L^2}[\frac{I_w}{I_z} + \frac{L^2 G I_t}{\pi^2 E I_z}]^{1/2}$$

E is the modulus of elasticity (almost always considered equal to 210 GPa).

G is the shear modulus given by the following formula:

$$G = \frac{E}{2 * (1 + v)}$$

(Where: v is the Poisson's ratio and is considered equal to 0.30),

I_t is the torsional constant (see relevant steel cross section standardized tables).

I_w is the warping constant (see relevant steel cross section standardized tables).

I_z is the second moment of area of the z direction (perpendicular to the flanges).

L is the length of the steel element.

α is an imperfection factor dependent on the lateral torsional buckling curves that describe the beam's structural behavior, as shown in the following table:

Buckling curve	b	c	d
Imperfection factor α	0.34	0.49	0.76

Table 2: Buckling curves and imperfection factors α [39].

For rolled I cross sections if h/b ≤ 2, curve b is considered the most suitable for describing its behavior, while in cases where: h/b > 2 curve c is considered the most suitable for describing its behavior.

STEEL COLUMN DESIGN

The algorithm that has been developed ensures that all the most important checks needed for typical cases of steel column design [39], [81] are taken into account. At first, the compression check takes place, as follows:

$$N_{crd} = \frac{Af_y}{\gamma_{\mu o}} > N_{sd}$$

Where:

A is the area of the cross-section in mm^2.

f_y is the steel strength in MPa.

$\gamma_{\mu o}$ is a reduction coefficient equal to: 1.1

The second most significant check is the bending check that takes place, as follows:

$$M_{crd} = \frac{W_{pl}f_y}{\gamma_{\mu o}} > M_{sd}$$

Where:

W_{pl} is the plastic section modulus (parallel to the flange) of the cross section of the cross-section.

f_y is the steel strength class in MPa.

$\gamma_{\mu o}$ is a reduction coefficient equal to: 1.1

The third check deals with the buckling resistance of the cross-section and takes place as follows:

$$M_{b,Rd} = x\beta_A \frac{Af_y}{\gamma_{\mu 1}}$$

Where:

x is a reduction factor.

β_A is considered equal to 1, for class 1, 2 and 3 cross sections.

A is the area of the cross-section in mm^2.

f_y is the steel stress in MPa.

$\gamma_{\mu 1}$ is a reduction coefficient equal to: 1.1

The reduction factor x is evaluated as follows:

$$x = \frac{1}{(\varphi + (\varphi^2 - \lambda^2)^{0.5})} \leq 1$$

Where:

$$\varphi = 0.5(1 + \alpha(\lambda - 0.2) + \lambda^2)$$

(φ is a value used for the determination of the reduction factor x).

$$\lambda = L_{cr}/i(1/\lambda_1)$$

$\lambda_1 = 93.9\varepsilon$

(λ and λ_1 are slenderness parameters, i is the radius of gyration, L_{cr} is the critical length of the examined element. Both directions are considered and the most conservative value is used)

$\varepsilon = (235/f_y)^{0.5}$

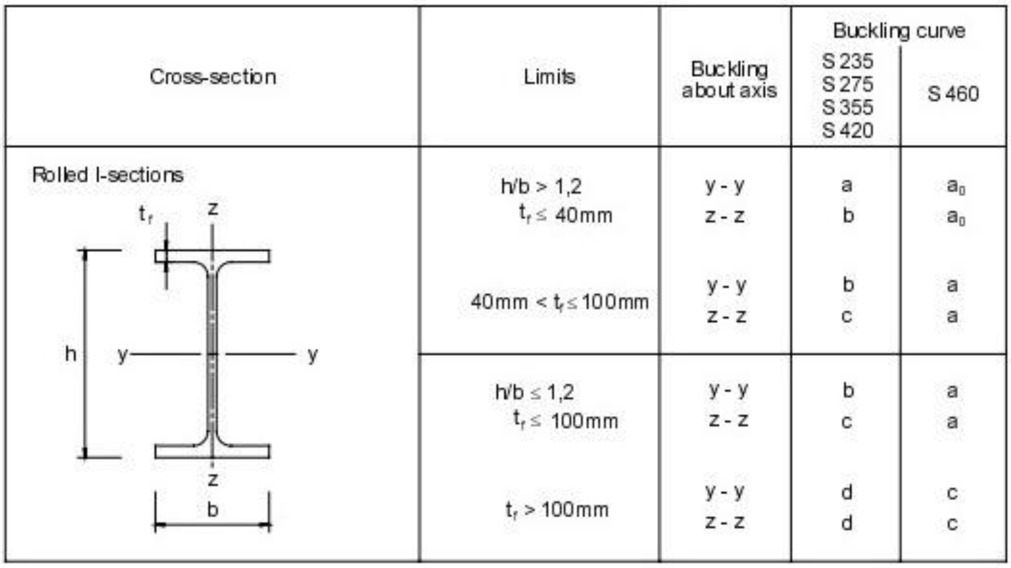
(ε is the strain of the examined cross section).

α is an imperfection factor dependent on the buckling curves that describe the beam's structural behavior, as shown in the following table:

Buckling curve	a_0	a	b	c	d
Imperfection factor α	0.13	0.21	0.34	0.49	0.76

Table 3: Buckling curves and imperfection factors α [39].

For rolled I sections the following image illustrates the considerations made for the selection of appropriate buckling curves.



Cross-section	Limits	Buckling about axis	Buckling curve S 235 S 275 S 355 S 420	Buckling curve S 460
Rolled I-sections	$h/b > 1,2$, $t_f \leq 40mm$	y - y	a	a_0
		z - z	b	a_0
	$40mm < t_f \leq 100mm$	y - y	b	a
		z - z	c	a
	$h/b \leq 1,2$, $t_f \leq 100mm$	y - y	b	a
		z - z	c	a
	$t_f > 100mm$	y - y	d	c
		z - z	d	c

Figure 15: Parameters affecting the selection of a buckling curve [39].

The last check deals with a conservative approximation of the resistance of the cross-section at the combined stress influence of an axial load and moments from two directions (See relationship 1 for the calculation of the moments of resistance of the cross section):

$$Nsd/Nrd + Mysd/Myrd + Mzsd/Mzrd \leq 1$$

TIMBER BEAM DESIGN

The timber beam checks as considered in the project are three [40]:

- Check for bending.
- Check for shear.
- Check for deflection.

The bending check takes place as follows:

It is required that:

$$\frac{\sigma_{myd}}{k_{\ crit} f_{myd}} \leq 1$$

Where:

σ_{myd} is equal to:

$$\sigma_{myd} = \frac{M_{yd}}{W_y}$$

Where: M_{yd} is the design moment of the cross section and W_y is the section modulus of the cross section equal to: $W_y = \frac{bh^2}{6}$.

Moreover:

$$f_{myd} = \frac{k_h k_{sys} k_{mod} f_{myk}}{\gamma\mu}$$

As regards the shear check the following criterion must be satisfied:

$$\tau_d \leq f_{vd}$$

Where:

τ_d is computed as follows:

$$\tau_d = \frac{1.5 F_{vd}}{bh}$$

Where: F_{vd} is the design shear load.

Furthermore:

$$f_{vd} = \frac{k_{sys}k_{mod}f_{vk}}{\gamma_{\mu}}$$

(All the values for the coefficients k are determined by standardized tables)

As regards the check about deflection:

At first the following two amounts are calculated:

$$u_{inst,G} = u_{inst,flex} + u_{inst,shear}$$

$$u_{inst,Q} = u_{inst,flex} + u_{inst,shear}$$

Where:

For the permanent loads, $U_{inst,flex}$ is equal to:

$$uinst, flex = \frac{5G_k L^4}{384E_{0,mean}I_y}$$

For the permanent loads, $U_{inst,shear}$ is equal to:

$$u_{inst,shear} = \frac{\varphi G_k L^2}{8G_{mean}A}$$

The same applies for the moving loads, therefore:

$$u_{inst,flex} = \frac{5Q_k L^4}{384E_{0,mean}I_y}$$

$$u_{inst,shear} = \frac{\varphi Q_k L^2}{8G_{mean}A}$$

Where: φ is a factor related to the form of the cross section and is equal to 1.2 for rectangular sections.

It is required that (beam with multiple bays):

$$u_{inst,Q} < \frac{L}{300}$$

Where: L is the length of the beam bay.

Moreover, after the previously mentioned check the final deflections due to the permanent and moving loads are calculated via the multiplication of the aforementioned parameters with an amplification coefficient:

$$u_{fin,G} = u_{inst,G}(1 + k_{def})$$

And:

$$u_{fin,Q} = u_{inst,Q}(1 + \psi_2(q_1) * k_{def})$$

Where: k_{def} is a factor taking into account the long-term effects of creep.

Finally, the following condition must be satisfied (beam with multiple bays):

$$u_{fin} = u_{fin,G} + u_{fin,Q} \; < \frac{L}{250}$$

TIMBER COLUMN DESIGN

The timber beam checks as considered in the project are three [40]:

- Check for bending.
- Checks for combined compression and bending (two checks).

The following two criteria must be satisfied:

$$(\frac{\sigma_{c,o,d}}{f_{c,o,d}})^2 + (\frac{\sigma_{myd}}{f_{myd}}) \leq 1$$

And:

$$(\frac{\sigma_{c,o,d}}{k_{crit}\, f_{c,o,d}}) + (\frac{\sigma_{myd}}{f_{myd}}) \leq 1$$

Where:

$$\sigma_{c,o,d} = \frac{N_{rd}}{A}$$

Where: A is the cross sectional area.

$$f_{c,o,d} = \frac{k_{sys} k_{mod} f_{cok}}{\gamma_M}$$

Where: γ_M, is a case-dependent reduction factor whose values vary between 1.10 and 1.30.

Moreover:

$$k_c = \min\,(k_{c,y}, k_{c,z})$$

Where:

$$k_{c,y} = \frac{1}{k_y + \sqrt{k_y^2 - \lambda_{rel,y}^2}}$$

And:

$$k_{c,z} = \frac{1}{k_z + \sqrt{k_z^2 - \lambda_{rel,z}^2}}$$

Furthermore:

$$k_z = 0.5(1 + \beta_c(\lambda_{rel,z} + 0.3) + \lambda_{rel,z}^2)$$

$$k_y = 0.5(1 + \beta_c(\lambda_{rel,y} + 0.3) + \lambda_{rel,y}^2)$$

Where: βc a case-dependent coefficient equal to e.g. 0.10 for laminated wood.

Moreover:

$$\lambda_{rel,y} = \frac{\lambda_y}{\pi}\sqrt{\frac{f_{cok}}{E_{0,05}}}$$

$$\lambda_{rel,z} = \frac{\lambda_z}{\pi}\sqrt{\frac{f_{cok}}{E_{0,05}}}$$

And:

$$\lambda_y = \frac{l_{eff,y}}{I_y}$$

$$\lambda_Z = \frac{l_{eff,Z}}{I_Z}$$

Where: l_{eff} is the effective column length and I is the second moment of area of the cross section.

ENERGY DESIGN OF BUILDINGS

INTRODUCTION

The present chapter analyses the background theory on which the algorithms that were developed for the energy design of the model buildings were based. The energy design of a building takes into account the energy losses or thermodynamic effects that take place in the building during an examined period due to the following major modes of heat transfer: convection, conduction and radiation. The algorithms are based on Greek code for the energy design of buildings (KENAK) [117] that is the national interpretation of the European standard EN ISO 13790 [58]. The codes constitute a systematic approach for the quantification of the all the key factors (building envelope, external environment, location, level of occupancy of the building, solar gains, thermal effects due to the air movement, number of building users, characteristic electric appliances expected to be found in a particular type of building, use of alternative sources of energy etc.) that are related to the fundamental modes of heat transfer and have an impact on the energy balance of a building. As it will be demonstrated later on, the energy demand that derives from the energy balance of the building is divided by the coefficients of performance of the heating and the cooling systems and the result constitutes the energy consumption of the building. The chapter also presents the national standards that are used for the sizing of the heating and the cooling system of a building, which were the basis for the MATLAB-based programs that were developed. In short, dimensioning a heating or a cooling system to efficiently cover the energy needs of the building during the most adverse day of the winter or the summer respectively, synopsizes the philosophy of the aforementioned methodologies.

ENERGY BALANCE OF BUILDINGS

The energy design and assessment of a particular building mainly depends on fundamental thermodynamic principles. First and foremost, the formulae used in the energy design of buildings express the most significant ways of heat transfer related to the building envelope; hence the heat transfer takes place through: conduction, convection and radiation. The Greek code for the energy design of buildings (KENAK) is based on the European standard EN ISO 13790.

During the heating period the monthly (or seasonal) energy needs, relate to the energy balance of the building (losses minus gains), therefore [58]:

$$Q_H = Q_{H,ht} - n_H Q_{H,gn}$$

Where:

$Q_{H,ht}$, the total thermal losses in kWh.

$Q_{H'gn}$, the total thermal gains in kWh.

n_h, a utilization factor, whose evaluation will be analyzed later on.

Similarly, during the cooling period the monthly (or seasonal) energy needs, relate to the energy balance of the building (losses minus gains), therefore:

$$Q_H = Q_{H,ht} + n_H Q_{H,gn}$$

GAIN UTILIZATION FACTOR FOR HEATING AND COOLING PERIOD

The gain utilization factor measures the degree to which the heat gains are utilized in a building during the heating and the cooling period.

At first, it is necessary to calculate the heat balance ratio (γ_H) which is a dimensionless indicator of the heat gains over the losses, through the following procedure [58]:

$$\gamma_H = \frac{Q_{H,gn}}{Q_{H,ls}}$$

Where:

$Q_{H,gn}$ the sum of the heat gains.

$Q_{H,ls}$ the sum of the heat losses.

Moreover:

If $\gamma_H \neq 1$ and $\gamma_H > 0$:

$$n_{G,H} = \frac{1 - \gamma_H^{\alpha H}}{1 - \gamma_H^{\alpha H + 1}}$$

(For the heating period)

$$n_{G,H} = \frac{1 - \gamma_H^{-\alpha H}}{1 - \gamma_H^{-(\alpha H + 1)}}$$

(For the cooling period)

If $\gamma_h = 1$:

$$n_{G,H} = \frac{\alpha_H}{\alpha_H + 1}$$

If $\gamma_H \neq 1$ and $\gamma_H > 0$:

$$n_{G,H} = \frac{1}{\gamma_H}$$

(For the heating period)

$$n_{G,H} = 1$$

(For the cooling period)

α_h is a parameter that depends on several time constants and is computed as follows:

$$a_H = a_{H,0} + \frac{\tau_H}{\tau_{H,0}}$$

(For the heating period)

$$a_C = a_{C,0} + \frac{\tau_C}{\tau_{C,0}}$$

(For the cooling period)

$\alpha_{H,0}$ (or $\alpha_{C,0}$) is a base numerical parameter, taken from the table below.

τ_H (or τ_C) is a parameter dependent on the thermal capacity of the building whose evaluation will be displayed below.

$\tau_{H,0}$ (or $\tau_{C,0}$) is a numerical time reference parameter, taken from the table below.

	$\alpha_{H,0}$ (or $\alpha_{C,0}$)	$\tau_{H,0}$ (or $\tau_{C,0}$) (h)
Monthly factors for continuously heated or cooled buildings	1,0	15
Seasonal factors	0,8	30

Table 4: Selecting $\alpha_{H,0}$ or $\alpha_{C,0}$ and $\tau_{H,0}$ or $\tau_{C,0}$ [58].

Furthermore, τh is a parameter measured in hours that is indicative of the thermal inertia of the building in and calculated as follows:

$$\tau = \frac{\frac{C'_m}{3600}}{H_m}$$

Where:

C'_m is the corrected thermal capacity of the building, that is dependent on its mass and can be taken from the following figure.

H_m is coefficient that associates the thermal capacity of the building with the inertia of thermal mass during the heating or the cooling period and can be taken from the following figure.

	Monthly and seasonal method			**Simple hourly method**	
Class	**H_m (W/K)**	**C'_m (J/K)**	**τ (h)**	**A_m (m^2)**	**C_m (J/K)**
Very light	$9.2A_{fl}$	$60000A_{fl}$	1.8	$2.5A_{fl}$	$80000A_{fl}$
Light	$9.2A_{fl}$	$83000A_{fl}$	2.5	$2.5A_{fl}$	$110000A_{fl}$
Medium	$9.2A_{fl}$	$124000A_{fl}$	3.7	$2.5A_{fl}$	$165000A_{fl}$
Heavy	$9.9A_{fl}$	$195000A_{fl}$	5.5	$3.0A_{fl}$	$260000A_{fl}$
Very heavy	$10.4A_{f.}$	$278000A_{fl}$	7.4	$3.5A_{fl}$	$370000A_{fl}$

Figure 16: Selecting C'm and Hm according the floor area and other parameters [58].

CORRECTION FACTOR FOR INTERMITTENCY

In the case of intermittent heating or cooling, the energy needs are multiplied by a correction factor that reflects the thermal inertia of the building and is computed through the following procedure [58]:

$$Q_{H,n} = \alpha_{red,H} Q_{H,n,N}$$

(During the heating period)

Or:

$$Q_{C,n} = \alpha_{red,C} Q_{C,n,N}$$

(During the cooling period)

Where:

$Q_{H,n}$ or $Q_{C,n}$ represent the heating or cooling needs of the building that derive from its thermal losses.

$\alpha_{red,H}$ or $\alpha_{red,C}$ is a correction factor that is calculated as shown below.

$Q_{H,n}$ or $Q_{C,n}$ represent the uncorrected heating or cooling needs of the building that derive from its thermal losses under the assumption that the heating or cooling system operates in a continuous mode.

Furthermore:

$$a_{red,H} = 1 - b_{red,H}(\frac{\tau_{H,0}}{\tau})\gamma_H(1 - f_{N,H})$$

(For the heating period)

Or:

$$a_{red,C} = 1 - b_{red,C}(\frac{\tau_{C,0}}{\tau})\gamma_C(1 - f_{N,C})$$

(For the cooling period)

Where:

$b_{red,H}$ or bred,c is an empirical coefficient considered to be equal to 3.

$\tau_{H,0}$ (or $\tau_{c,0}$) is a numerical time reference parameter, that has been described in the previous subchapter.

$\tau_{H,0}$ (or $\tau c_{,0}$) is a numerical time reference parameter, that has been described in the previous subchapter.

τ is a parameter measured in hours that is indicative of the thermal inertia of the building and has also been defined in the previous subchapter.

γ_H or γ_C is a dimensionless indicator of the heat gains over the losses that has been outlined in the previous subchapter.

$f_{N,H}$ or $f_{N,C}$ is a fraction describing the operative hours of the heating or of the cooling system over the total hours of the period under consideration (e.g. 9 hours a day would represent a fraction equal to 9/24 = 0.375).

It is meaningful to note that $\alpha_{red,H}$ or $\alpha_{red,C}$ can take a maximum value equal to 1 and a minimum value equal to $f_{N,H}$ or $f_{N,C}$.

BUILDING ENVELOPE THERMAL LOSSES

The thermal losses of the building envelope take place through conduction and convection (ventilation and infiltration). Therefore, the sum of the thermal losses is expressed as follows [58]:

$$Q_{ht} = Q_{tr} + Q_{ve}$$

Where:

Q_{tr} are the thermal losses due to conductivity

Q_{ve} are the thermal losses due to ventilation and infiltration.

Furthermore, the aforementioned thermal losses are evaluated as follows:

$$Q_{tr} = H_{tr}(\theta_{int,set} - \theta_e)t$$

Where:

H_{tr} is a coefficient expressing the total heat transfer due to thermal conductivity.

$\theta_{int,set}$ is the design temperature of the examined thermal zone.

θ_e is the average monthly temperature of the external environment.

t is the time duration of the examined period in hours.

The H_{tr} parameter concerns the sum of the heat transfer coefficients towards heated and non-heated building areas, towards the ground and towards adjacent buildings. These heat transfer coefficients are based on the sum of three terms namely the heat transfer coefficients related to building envelope, the linear thermal bridges and the point thermal bridges [58]. Due to the fact that the point thermal bridges are generally ignored [117]; the total heat transfer coefficient due to thermal conductivity is ultimately calculated through the following formula:

$$H_x = b_{tr,x}[\sum_i U_i A_i + \sum_k \psi_k l_k]$$

Where:

U_i are the u values of each examined building component W/(mK).

A_i the area of each examined building component in m^2.

ψ_k the linear heat transfer coefficient of the thermal bridge in $W/(m^2K)$.

l_k is the length of the linear thermal bridge in m.

$b_{tr,x}$ is usually equal to 1, but in several other cases it is used as reduction factor to consider the fact that outer layer of the examined building component is not equal to the external temperature (e.g. in the case of a submerged basement wall or a non-heated building zone) [117].

FURTHER DETAILS ON THE EVALUATION OF U-VALUES

A U-value measures the performance of a building element in terms of heat transfer and is calculated though the following relationship [36], [117]:

$$U = \frac{1}{R_i + \sum \frac{d_i}{\lambda_i} + R_e}$$

Where:

R_i is the thermal resistance of the captured air mass at the inner layer of the insulation profile under consideration.

R_e is the thermal resistance of the captured air mass at the outer layer of the insulation profile under consideration.

λ_i is the thermal conductivity of each individual material layer that constitutes an insulation profile and is measured in watts per meter Kelvin (W/(m*K)) and its value is taken from standardized tables.

d_i is the thickness of each individual material layer that constitutes an insulation profile in m.

The parameters Ri and Re depend on the building component under consideration and according to the conventions used in KENAK, their values are displayed below [36]:

THERMAL RESISTANCE OF VARIOUS BUILDING COMPONENTS	R_i	R_e
External walls and windows (adjoining the external air) <u>or</u> any surface (adjoining the external air) with a maximum inclination of ± 30^o from the horizontal level	0.13	0.04
Walls adjoining non-heated areas	0.13	0.13
Floor above a pilotis	0.17	0.04
Floor above an unheated zone	0.17	0.17
Floor in contact with the ground	0.17	0.00
Roof (or any surface -whose inclination- exceeds 30^o from the horizontal level and leads the heat flow direction upwards)	0.10	0.04

Table 5: Estimating the thermal resistance of the captured air mass for various building components.

THERMAL LOSSES DUE TO INFILTRATION AND VENTILATION

The thermal losses due to convection depend on the heat transfer caused by the air movement and are associated with three main factors: infiltration, natural ventilation and mechanical ventilation. According to EN ISO 13790, the aforementioned losses are evaluated as follows [58]:

$$Q_{ve} = H_{ve}\left(\theta_{int,set} - \theta_e\right)t$$

Where:

H_{ve} is the total heat transfer coefficient due to the effects of air movement during the heating and the cooling period.

$\theta_{int,set}$ is the design temperature of the examined thermal zone.

θ_e is the average monthly temperature of the external environment.

t is the time duration of the examined period in h.

Moreover, H_{ve} is calculated thought the following formula:

$$H_{ve} = \rho_\alpha c_\alpha \sum_k b_{ve,k} f_{ve,t,k} \dot{V}$$

Where:

ρ_α*c_α is the thermal capacity of the air in J/(m^3*K). For typical conditions of building thermal zones, the European standard EN ISO 13790 as well as KENAK, considers this amount as equal to [122]: 1200 J/(m^3·K).

$b_{ve,k}$ is a coefficient usually equal to 1, but in the presence of heat recovery systems it acts as a reduction factor and its value depends on the performance and degree of contribution of a heat recovery systems on the air flow.

Besides this, in cases of adjacent buildings that are terraced with the examined building thermal zone it is considered to be equal to zero.

$f_{ve,t,k}$ is a fraction representing the time period during which (total hours per daytime) the air supply takes place or operates.

$\dot{V}$ is the air flow rate in m^3/s. The term m^3 concerns the volume of the examined building thermal zone and the second term (s) is associated with the number of air changes per hour. The air change rates relate to the use of the building are evaluated though national ventilation standards according to the table displayed below. Apart from that, a consummate building energy design requires that the contribution of infiltration is also considered in the total air flow rate and is computed via the methodology described below [117].

Type of prevalent use	**Air changes V_{people} [$m^3 \cdot h^{-1} \cdot people^{-1}$]**
Offices	9
Universities	13.7
Hotels	9
Gyms	36

Table 6: Air changes and various building uses.

As it can be observed the air changes depend on the volume and the type of the building as well as on its occupancy and the predicted number of users of the building (a table where such information can be found according to the Greek national standards is given in the following subchapter). An additional increase by 0.50 $m^3 \cdot h^{-1} \cdot people^{-1}$, is taken into account due to the effects of infiltration [117].

THERMAL GAINS OF THE BUILDING

The thermal gains of a building are calculated as the sum of the solar gains from the transparent and the non-transparent surfaces of the building, the gains from the lighting system and the gains from the users of the building that derive from standardized databases. Therefore, depending on the building type, there are expected values for the occupancy and the theoretical population of the building. The following table shows some of the values proposed by KENAK for various types of buildings [117].

Type of prevalent use	Thermal effect per user (q_{people}) [W*person^{-1}]	Average area occupied per user [m^2*person^{-1}]	Thermal effect per appliance (q_{equip}) [W*m^{-2}]	Average occupancy in hours (t_h)
Offices	80	10	15	6
Universities	70	1.8	5	5
Hotels	70	7.5	4	16
Gyms	100	1.3	4	6

Table 7: Thermal gains and various building uses [117].

THERMAL GAINS FROM THE NON-TRANSPARENT SURFACES OF THE BUILDING

The monthly solar gains from the non-transparent surfaces of the building are calculated through the following relationship [58]:

$$Q_{sun,nt} = \sum_j f_{ab}\, q_{sun,j} U_{c,j} A_{c,j}$$

Where:

f_{ab} is a coefficient equal to 0.045, that expresses the product of an assumed value equal to 0.90 that corresponds to the solar absorption of the surface and the thermal resistance of the outer layer of the surface that is considered equal to 0.05 m^{2}K/W.

$q_{sun,j}$ is the incident solar radiation on the examined surface j, depending on its inclination and orientation in MJ/m^2.

$U_{c,j}$ is the u-value of the examined surface.

$A_{c,j}$ is the area of the examined surface in m^2.

THERMAL GAINS FROM THE TRANSPARENT SURFACES OF THE BUILDING

The monthly solar gains from the transparent surfaces of the building are calculated through the following expression [58]:

$$Q_{sun,t} = \sum_{j} q_{sun,j} f_{sh,j} f_f \, f_{sun,j} g_j A_{r,j}$$

$q_{sun,j}$ is the incident solar radiation on the examined surface j, depending on its inclination and orientation in MJ/m^2.

$f_{sh,j}$ is a coefficient that takes into account the shading of the surface. The previously mentioned coefficient derives from the product of an overhang shading correction factor and a fin shading factor, that depend on the presence overhang and fins in contact with the surface. The parameters that affect the values of the aforementioned factors are the orientation of the examined surface and the conceptual angles that derive from the edge of the overhang or the fins and the centroid of the surface, as displayed in the following figure:

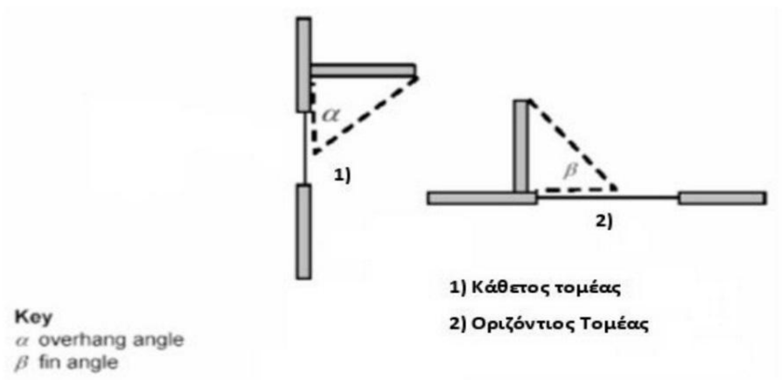


Figure 17: Depiction of the conceptual angles on which the calculations of the shading factors are based.

f_f is a correction factor that takes into consideration the percentage of the surface that is not occupied by a frame, and is usually taken equal to 0.75.

$f_{sun,j}$ a factor that corresponds to the presence of awnings or any moveable external solar protection. Such presence results in a 50% reduction on the incident solar radiation during the summer period.

g is the g value of the surface multiplied by 0.90 that is a correction factor considering the glass type, the climate zone and the latitude of the examined surface. The g value is a coefficient that concerns the solar energy transmittance of glass.

$A_{r,j}$ is the area of the examined surface in m^2.

Some indicative values for the overhang shading correction factor, are shown in the following table:

Overhang Angle	Overhang shading factor		
	S	E/W	N
0	1.00	1.00	1.00
15	0.87	0.87	0.86
30	0.73	0.73	0.71
45	0.58	0.58	0.56
60	0.40	0.41	0.40

Table 8: Shading factors and various overhang angles.

Similarly, as regards the fins shading factor:

Fin Angle	Fins shading factor		
	S	E/W	N
0	1.00	1.00	1.00
15	0.88	0.87	0.87
30	0.74	0.73	0.79
45	0.64	0.62	0.75
60	0.54	0.55	0.74

Table 9: Shading factors and various fin angles.

ENERGY CONSUMPTION DUE TO LIGHTING

The energy consumption due to lighting is evaluated according to the standard CEN EN 15193-1, though the following relationship [58]:

$$W_{light} = \frac{\sum_{j=1}^{12}[N_j x(\sum_{j=1}^{24}[P_j(F_{D_{ji}} xF_{O_{ji}})] + 24x(P_p + P_{dj} xF_{Od}))]}{1000} (\frac{kWh}{m^2}_{year})$$

Where:

N_j is the number of days per examined month.

P_j is the power of the lighting system in W/m^2.

P_p is the parasitic load in W/m^2.

F_D is a correction factor taking into account the influence of the daylight.

F_O is correction factor related to the occupancy of the building.

The parasitic power can be estimated according the following case-sensitive assumptions:

- Manual control of the lighting system: 0 W/m^2.
- Existence of independent light sensors: 0.3 W/m^2.

F_O can be estimated from the following table, only under the assumption that there is at least one sensor per room and at least (as regards greater areas) one sensor per 30 square meters [117]:

Building use	**Type of control**	F_O
Offices, Educational buildings	Manual	1
	Automations over more than 60% of the load	0.9
Athletic centers, Malls	Manual	1
Hotels	Manual	0.7
Hospitals	Manual	0.8

Table 10: Selection of the F_o factor.

It is meaningful to note that F_O is considered equal to 1, in cases of central lighting control systems.

F_D can be taken from the following table. A reduction factor can be implemented <u>only if</u> the dimming mechanisms control over more than 60% of the lighting system of the examined zone [117].

Building use	**Type of lighting control**	F_D
Offices, Athletic centers	Manual	1
	Photo cell dimming and natural light sensors	0.9
Shopping center	Manual	1
Hospitals, Educational buildings	Manual	1
	Photo cell dimming and natural light sensors	0.8

Table 11: Selection of the FD factor.

COOLING SYSTEM SIZING

The most popular method for the dimensioning of the cooling system that has been also used in the project is the CLTD (cooling load temperature difference) method. The method is based on the quantification of the all the factors that have a thermal impact on the building during the most adverse day of the summer (21^{st} of July). Through the use of an hourly step examining the most critical hours during that day, the method aims to the estimation of the most critical cooling load and dimensions an HVAC system so that it can cope with that load.

Specifically, the following parameters are evaluated [36]:

- Parameters that affect the sensible thermal load:
  1. Heat gains due to the thermal conductivity of the building envelope (walls, roof and fenestration).
  2. Heat gains due to ventilation and infiltration.
  3. Heat gains due to the solar irradiation.
  4. Heat gains from people, lights and equipment.
- Parameters that affect the latent thermal load:
  1. Latent heat gains due to ventilation and infiltration.
  2. Latent heat gains from people.

SENSIBLE THERMAL LOAD: BUILDING ENVELOPE GAINS

For the evaluation of the heat gains from the envelope, at first a corrected temperature difference is evaluated. This takes place via the selection of specific values from standardized reference tables that concern the latitude month correction factor (LM) and an equivalent temperature difference (CLTD).

The CLTDs given in the tables that are the result of data collection and analysis from 26 categories of roofs (13 with suspended ceilings and 13 without suspended ceilings) and 96 types of walls that were further categorized into seven different groups. Apart from that, the LM factor is used for adjustment purposes to different climatic conditions.

The corrected temperature differences are -therefore- computed from the following formula [36]:

$$CLTD_{cor} = [k(CLTD + LM) + (25.5 - T_R) + (T_O - 29.4)]f$$

(For roofs)

$$CLTD_{cor} = [k(CLTD + LM) + (25.5 - T_R) + (T_O - 29.4)]$$

(For walls)

Where:

k is a coefficient that describes the color of the roof or the wall. For industrial roofs or for roofs whose color has dark nuance its value is equal to: 1, whereas for light-colored roofs its value is equal to 0.5. Moreover, for dark-colored walls or walls of industrial buildings its value considered to be equal to: 1, for medium-colored walls its value is equal to 0.83 and for light-colored walls its value is equal to 0.65.

LM is an adjustment factor related to the latitude of the building (see standardized tables for further information).

T_O is the average temperature outside the building (for Athens (Greece), a usual value is 35°C).

T_R is the design indoor temperature (a frequently used value is 26°C).

f is a factor that is taken equal to 1 in cases of roofs with air inflow and equal to 0.5 in cases of roofs without air inflow.

Finally, the cooling load from the thermal conductivity of the walls and the roofs is calculated as follows:

$$Q = UA(CLTD)$$

As regards the windows -apart from the thermal gains due to thermal conductivity- the contribution of the solar irradiation is taken into account:

$$Q_{win} = [A(SHGF)_{max}(SC)(CLF) + UA(CLTD)]$$

Where:

$SHGF_{max}$ is the maximum solar heat gain factor; corresponding to the solar irradiation related to the examined latitude and month (see standardized tables for further information).

SC is a shading factor (considered to be equal to 0.64 for internally shaded glazing and equal to 0.15 for externally shaded glazing).

CLF is the cooling load factor (a reduction coefficient applied to the irradiation levels to which a particular surface is exposed and is largely dependent on its orientation) (see standardized tables for further information).

SENSIBLE THERMAL LOAD: SENSIBLE AND LATENT GAINS DUE TO VENTILATION AND INFILTRATION

The heat transfer caused by the air is either voluntary (natural and mechanical ventilation) or involuntary (infiltration through the window chinks). In a similar way to what has been described in the previous subchapters, the thermal capacity of the air is multiplied by an air flow rate that concerns an estimated theoretical population of building users. Since there are different required air changes for smokers in comparison with non-smokers, the designer should estimate that parameter in advance. Therefore, the total air flow rate for which a building is designed should represent a peak value for a combined, simultaneous presence of smokers and non-smokers and each category of users is multiplied by the correspondent air flows rates given by standardized tables. The following formula is among the ones that are frequently encountered in the relevant literature for such estimations and evaluates the thermal load caused by the required air changes [36]:

$$Q_{6,sen} = 1.23 \Delta\dot{V}\ \Delta T$$

Where:

$\Delta\dot{V}$ is the required air flow rate of the examined room in L/s (dependent on the total number of users (see standardized tables for further information)).

ΔT the temperature difference (external temperature minus indoor temperature) for which the cooling system is dimensioned.

SENSIBLE THERMAL LOAD CAUSED BY LIGHTING, PEOPLE AND EQUIPMENT

The logic in calculating the contribution of lighting, people and equipment to the total sensible thermal load lies in with multiplying their thermal effect (in watts) with a CLF factor -that is every time different, dependent on a number of parameters and given by standardized tables.

LIGHTING

The contribution of lighting to the total cooling load is computed as follows [36]:

$$Q_s = (CLF)(HG)$$

Where:

CLF is a cooling load factor.

HG is the power of the lighting system in Watts, multiplied by a fraction that represents the estimated hours within a day during which the system is in operation. A further reduction can apply corresponding to a percentage of lamps that are operating during the examined time period.

PEOPLE

Similarly, the thermal effect of people in the total cooling load is given by the following relationship [36]:

$$Q_s = (CLF)(HG)n$$

Where:

CLF is a cooling load factor (see standardized tables for further information).

HG is the thermal gain per person in Watts (see standardized tables for further information).

n is the highest possible number of people present in the room.

EQUIPMENT

The total power of the appliances that are installed in a building can be calculated by multiplying a CLF factor found in standardized tables by the total installed power related to the operating profile of the building. Their contribution in the total cooling load is calculated as follows [36]:

$$Q_s = (CLF)(HG)n$$

Where:

CLF is a cooling load factor (see standardized tables for further information).

HG is the thermal gain per appliance in Watts (see standardized tables for further information).

n is the number of appliances

LATENT THERMAL LOADS

The CTLD methodology takes into account merely the latent thermal loads that are generated by the building occupants and by the renewed air flow.

As regards the users of the buildings the latent cooling load is calculated as follows [36]:

$$Q_l = n(HG_l)$$

Where:

n is the highest number of people present in the room.

HG_l is the latent cooling load (in Watts) generated by people (that varies depending on their prevalent activity) (see standardized tables for further information).

Furthermore, as the air outdoors is hotter than the air inside the building it retains a greater percentage of humidity; a latent heat is therefore considered to be transferred from outdoors towards the inside of the building generating a considerable cooling load representing that difference in humidity. This load is computed through the following relationship [36]:

$$Q_{6,l} = 3010\Delta\dot{V}\,\Delta w$$

Where:

$\Delta\dot{V}$ is the required air flow rate of the examined room in L/s (dependent on the total number of users (see standardized tables for further information)).

Δw is the humidity difference between the air outdoors and air indoors.

HEATING SYSTEM SIZING

The sizing of a heating system that intends to cover the needs of a building is dependent on its thermal losses due to infiltration and conductivity. Therefore [36]:

$$Q_K = Q_A + Q_a$$

Where:

Q_K: The thermal losses due to thermal conductivity.

Q_a: The thermal losses due to air infiltration.

The thermal losses due to conductivity are evaluated through the following formula:

$$Qo = U \times A \times (ti - ta)$$

Where:

U is the examined surface in W/m^2K

A is the area of the surface in m^2.

t_i is the design inner temperature of the building surface.

t_a is the design temperature of the outer layer of the building surface.

Moreover:

$$Q_A = \sum Qo\,(1 + Z_\Pi + Z_\Delta)$$

Where:

ΣQ_o is the total thermal losses in Watt.

Z_Π is a magnification factor that considers the orientation of a particular building surface. Z_Π can be taken from the following table [36]:

Orientation	**NE**	**N**	**NW**	**W**	**E**	**SE**	**S**	**SW**
$\mathbf{Z_\Pi}$	5%	5%	5%	0%	0%	-5%	-5%	-5%

Table 12: Orientation and Z_Π factor.

Z_Δ is a coefficient that takes into account the duration of the heating in a 24 hr period.

The coefficient Z_Δ is selected through a standardized table, after the calculation of the coefficient D via the following equation:

$$D = \frac{\sum Q_o}{F_{totsl}(ti - ta)}$$

Therefore Z_Δ, can be assessed through the following table:

	D (Average heating coefficient)		<0.34	0.35-0.80	0.81-1.73	≥1.74
Z_Δ	**I**	Continuous Occupancy	7%	7%	7%	7%
	II	12-16 hr Occupancy	20%	15%	15%	15%
	III	8 hr Occupancy	30%	25%	20%	15%

Table 13: Selection of the coefficient Z_Δ.

The thermal losses due to the air infiltration (in Watt) can be evaluated through the relationship displayed below [36], [117]:

$$Q_A = \sum \frac{(\alpha l) RH \rho c (ti - ta)\, Z_\Gamma}{3.6}$$

Where:

α is a coefficient describing the air infiltration of a window type in $m^3/(h*m)$. Specifically, for several well-known window types, typical values for α can be taken from the following table [117]:

	Window frame material	Window type	α ($m^3/(h.m)$)
α	**Timber**	Doubly-glazed casement	2.5
		Triple-glazed casement	1.65
		Doubly-glazed sliding	2
	Metal or Composite	Doubly-glazed casement	1.4
		Triple-glazed casement	0.95
		Doubly-glazed sliding	1.2

Table 14: Estimating α coefficient [117].

l is the length of the window chinks in m.

R is a coefficient describing the air penetration. R is considered to be equal to 0.70 for aluminum/composite or timber framed windows in cases of buildings with a high ratio of external over internal (window and door) openings and 0.90 in cases of buildings with a low ratio of external over internal openings. The bound about the aforementioned ratios between what is considered high and what is considered low, is 3 for timber framed windows and 6 for aluminum/composite framed windows.

H is a coefficient that takes into account the position of the building (surface) with regard to potential adjacent buildings that hinder the movement of the air and the air speed that occurs on the location of the building. H can be estimated by the following window:

	Levels of wind speed	**External surface position**	**Elevations adjoining nearby surfaces**	**Detached elevations**
H	**Normal**	Protected	0.78	1.10
		Detached	1.32	1.87
		Extremely unprotected	1.94	2.71
	High	Protected	1.32	1.87
		Detached	1.94	2.71
		Extremely unprotected	2.65	3.65

Table 15: Estimating H coefficient [36].

$\rho_\alpha * c_\alpha$ is the thermal capacity of the air in J/(m^3*K). For typical conditions of building thermal zones, the European standard EN ISO 13790 as well as KENAK, considers this amount as equal to: 1200 J/(m^3·K) [117], [122].

t_i is the design inner temperature of the building surface.

t_a is the design temperature of the outer layer of the building surface.

Z_Γ is a coefficient that is always considered as equal to 1.20 in cases of corner windows.

PHOTOVOLTAIC ARRAY SIZING

In several cases of buildings, a possible design choice that favors energy autonomy is that part of the electricity needs of the building can be covered with the assistance of a photovoltaic array. Therefore, in cases of buildings, where the fuel of the heating or the cooling system is electricity, the electricity production via a photovoltaic array can reduce their total energy needs. According to KENAK, the total electricity produced by an array over a period is subtracted from the building's energy needs for heating (or cooling) during that period.

A fundamental factor that characterizes an array is its peak power (in kWp) that is calculated through the following relationship [100-1]:

$$P_p = \frac{E_c \, P_{stc} \, m}{E_{sr} \, c_{al}} \left(\frac{N}{N-n}\right)$$

Where:

E_c (kWh/day) is the energy requirements of the building that are intended to be met by a photovoltaic array

P_{stc} is the power of the solar radiation in standard conditions (P_{stc} = 1 kW/m^2)

m is a coefficient equal to 1.2 that concerns potential energy needs that have been underestimated

E_{sr} (kWh/day) is the incident solar radiation on the array, taken from standardized tables. There are various values for the incident solar radiation depending on the orientation and the inclination of the panels

c_{al} is coefficient that corresponds to the losses of the photovoltaic array and will be discussed later on

(N/N – n) is a fraction that considers the autonomy of the photovoltaic system for n days by increasing its peak power. Furthermore, N is the examined time period in days. Therefore, in order for a system to be designed for 6 days of autonomy during the month December the aforementioned fraction would be equal to: 31/(31 - 6) = 1.24.

Furthermore, the coefficient c_{al} is evaluated through the following relationships [100-1]:

$$c = c_a c_d c_t c_d c_{dl} c_c c_h$$

Where:

c_{al} is an averaged coefficient (reflecting a mean system performance reduction and is derived from the yearly coefficients that are used to describe an annual performance reduction) that intends to increase the peak power of the system taking into account its aging during its life cycle and is considered equal to 0.90

c_d is a coefficient that corresponds to the losses of the system due to dirt, dust or snow and is equal to 0.90

c_t is a coefficient that concerns the influence of the outdoor temperature on the absorbed energy of the system. It can be calculated in a more detailed way through the following formula:

$$c_t = 1 - [(t_a + 30) - 25]$$

Where:

t_a is the average air temperature during the examined period of time

Moreover:

c_{dl} is a coefficient accounting for diode losses. For systems with AC-DC inverter it is considered equal to 0.98

c_c is a coefficient taking cable losses into account, equal to 0.98

c_h is a heterogeneity coefficient, equal to 0.98

The total number of panels required for an array is computed after rounding up the result of the following fraction [100-1]:

$$N_{panels} = \frac{P_{p\ array}}{P_{p\ panel}}$$

Where:

$P_{p\ array}$ is the peak power of the photovoltaic array, corresponding to the energy needs for which the array is sized

$P_{p\ panel}$ is the peak power of an individual panel

The final electricity production of a photovoltaic array over a particular period of time derives from the following equation [100-1]:

$$E = \sum_{i} (\mathrm{E}_{\mathrm{sr\ (i)}} A\ N_{panels}\ n_p\ c_m)$$

Where:

$E_{sr(i)}$ is the incident solar radiation, divided in steps reflecting different characteristic periods of time (e.g. at a monthly step)

A is the area occupied by an individual panel

n_p is the nominal yield percentage of an individual panel

c_m is a coefficient taking into account inverter losses or any other losses that occur during the energy transfer. For instance, the use of a single AC-DC inverter would result in the selection of a coefficient equal to 0.85 - 0. 90.

A further reduction on the expected electricity production can apply in cases where the array or a percentage of its panels are shaded. Such decrease is estimated by reduction coefficients taken from standardized tables.

OPTIMIZATION TECHNIQUES USED IN THE PROJECT

INTRODUCTION

The present chapter provides critical information about the techniques that were employed for the optimization of the developed models (simulated annealing, genetic algorithms). It was also considered useful to present in one of the subchapters (the subchapter about stochastic optimization) how optimization would be implemented in cases where some of the variables would display a high degree of uncertainty.

SIMULATED ANNEALING

Simulated annealing (SA) is an evolutionary optimization method that imitates the subsequent cooling a solid after its exposure to high temperatures. Through this procedure, the natural process of solidification and crystal formation is modeled.

A pseudo code that displays the logic of an SA evolutionary algorithm is shown below [80]:

Initialize iteration counter i

Initialize temperature

Initialize initial solutions

Initialize best solutions

Define temperature change function

While a terminating criterion is not satisfied

Generate new set of solutions

Evaluate delta = $f(x_{knew}) - f(x_{k0})$

if delta < 0

Update new solutions

Update counter

Decrease temperature

else

Evaluate x = rand(1)

if x < exp(-delta/T)

Update new solutions

Update counter

Decrease temperature

else

Don't update new solution

Don't update counter

Don't update temperature

end

end

Update best solutions

end

The reader should pay attention to the term x = rand(1), that is compared with

exp(-delta/T). This term is used to introduce some degree of randomness in the decrease of the temperature. Therefore, the temperature decreases only if the condition x < exp(-delta/T) is satisfied. Furthermore, another necessary observation that should be made is the fact that there can be many forms of temperature functions. Some of them are the following [80]:

- Exponential decrease: $T_i = T_0 * e^{i*\alpha}$
- Linear decrease: $T_i = T_0 - i*\alpha$
- Logarithmic decrease: $T_i = T_0/\log(i)$
- Other adaptive or dynamic techniques

GENETIC ALGORITHMS

The term genetic algorithms refer to a set of evolutionary algorithmic techniques that comprise the following characteristics [80]:

1. Selection of an initial population
2. Parent selection
3. Cross-over process
4. Mutation process
5. Selection of the population of the next generation

The first stage deals with selecting an appropriate initial population size depending on the nature of the optimization problem. Evidently, this is a matter of computational time and resources. Another important factor is the definition of a fitness function that would examine the suitability of a specific member in conjunction with the nature of the optimization problem. For instance, in a minimization problem a variable (or a set of variables) attaining lower objective function values is more suitable in comparison with a variable or a set of variables attaining higher objective function values.

Due to the fact that it is a consideration that is invariably used it is meaningful to note that a very useful formula for the purpose of modeling continuous variables of an optimization problem is following [80]:

If $x \varepsilon [\alpha, \beta]$

$x = \alpha + rand(1)*(\beta - \alpha)$.

After generating an initiation population and determining the objective function values that they attain, a rather easy and simplistic way to assess their suitability would be to rank them in a descending order.

Nevertheless, as this technique frequently leads to premature exclusion of less fit solutions (parents) it should be avoided, since part of their genetic material could be -to some extent- of high quality. This is usually with the assistance of a random “roulette wheel” which associates the probability of a fitter parent to be selected with a (larger) portion on the wheel.

Therefore, the probability of each parent to be selected for the next generation is expressed by the following relationship [80]:

$$p = \text{individual fitness/cumulative fitness}$$

Another suitable relationship for the purpose of evaluating the probability of a particular parent to be selected is the following:

$$p = 2*(n - j)/(n*(n - 1))$$

Where:

n is he population size, j is the ranking of a particular parent (in a descending order).

In the third stage, the genetic material of a fraction of the members of a population (the percentage varies between 50%-90% of the population, but a usual value is 80%), is separated at a particular point. There various ways of separation (hence, one-point cross-over, two-point cross-over, cross-over with the assistance of linear or arithmetic crossover operators) of the parents' genetic material, and after the crossover procedure an exchange of genetic material between couples of parents takes place.

The following expressions demonstrate characteristic examples of that concept [80]:

1. 1-point crossover:

   Parents:

   P1 = 0.15 0.25 0.66 0.77

   P2 = 0.17 0.42 0.88 0.17

   Children:

   C1 = 0.15 0.25 **0.88 0.17**

   C2 = 0.17 0.42 **0.66 0.77**

2. 2-point crossover:

   Parents:

   P1 = 0.15 0.25 0.66 0.77 0.12

   P2 = 0.17 0.42 0.88 0.17 0.24

   Children:

C1 = 0.15 **0.42 0.88** 0.77 **0.24**

C2 = 0.17 **0.25 0.66** 0.17 **0.12**

3. Use of an operator:

   Parents:

   P1 = 0.15 0.25 0.66

   P2 = 0.17 0.42 0.88

   Children:

   O1 = P1 + P2 = 0.32 0.67 1.54

   O2 = g*P1 + (1 - g)*P2 = 0.25*P1 + (1 - 0.25)*P2 = 0.17 0.38 0.83 (after random selection of the operator gε [0, 1])

Some degree of programming adaptation is required in order for feasible solutions to be ensured [80].

The fourth stage involves the mutation of rather small part of the population, not exceeding 20% of its total number of members. The mutation operator that will be selected must ensure feasibility of the generated solutions and small albeit well-adjusted modifications (that therefore generate a wide range of new solutions).

The last stage deals with the selection of the new population. Again, there are various ways to execute this process, including [80]:

- Replacement of all the members of the population (that is a time-consuming strategy).
- Random replacement of the population
- Replacement of the worst percentage of the population
- Other similar techniques (keeping a number of members that constitute an elite, tournament among parents and children etc.)

A pseudo code for the construction of a genetic algorithm is given below [80]:

Define crossover operator

Define mutation operator

Define selection operator

Define population percentage on which crossover will take place

Define population percentage on which mutation will take place

Define fitness function

Initialize initial population sample

Initialize best population member

While a terminating criterion is not satisfied

Select parents

Execute crossover process

Execute mutation process

Assess population fitness

Update new population

Update best population member

end

Recall best population member

STOCHASTIC OPTIMIZATION

Stochastic optimization [109] is a term that refers to a wide range of methodologies used to deal with random variables in an optimization problem. Common approaches to manage the uncertainty of a variable or a set of variables include:

- Minimization of the most expected value of a variable.
- Minimization of the absolute value of the expected deviation from a specified goal.
- Minimization of the maximum costs (minimax approach).

Examples of formulation of stochastic optimization problems are shown in the following relationships.

In cases where there are discrete probabilities (p_i) related to the occurrence of a variable:

Minimize:

$$cx + \Sigma picix$$

Subject to: $A1x \leq b1$

Similarly, a problem where the variables' values have known lower and upper bounds could be modeled as follows [109]:

$$1/2(y_1^+ + y_1^-) + 1/2(y_2^+ + y_2^-)$$

In cases where merely a most expected value E[h(x)] is taken into account:

Minimize:

$$cixi + E[h(x)]$$

Subject to: $A1x \leq b1$

In cases where variance is taken into account along with an expected value [109] E[h(x)]:

Minimize:

$$cixi + E[h(x)] + \theta Var[h(x)]$$

Subject to: $A1x \leq b1$

An equivalent expression is the following [113]:

$$f(x) = k_1 \overline{f} + k_2 \sqrt{Var(f)}$$

Where: $\overline{f}$ is the most expected value of the function and Var(f) is the average variance of the function as a result of the multiplication of the transposed vector X by the variance-covariance matrix and again by the vector X.

$$Var(f) = X^T VX$$

The relationship can be used regardless of the number of variables X contains. Furthermore, the variance-covariance matrix is given by the following relationship [113]:

$$V = \begin{bmatrix} Var(q_{11}) & Cov(q_{11}, q_{12}) & ... & Cov(q_{11}, q_{1,n+1}) \\ Cov(q_{12}, q_{11}) & Var(q_{12}) & ... & Cov(q_{12}, q_{1,n+1}) \\ ... & ... & ... & ... \\ Cov(q_{1,n+1}, q_{11}) & Cov(q_{1,n+1}, q_{12}) & ... & Var(q_{1n+1}) \end{bmatrix}$$

Moreover:

$$Cov(X,Y) = E[(X - E[X])(Y - E[Y])]$$

The coefficients k_1 and k_2 can take values between 0 and 1 depending on the weighting (significance) assigned to minimizing the variance or the average value of the function.

MODELS DEVELOPED IN THE PROJECT

INTRODUCTION

The current subchapter describes the model buildings that were created as a result of the project and published in various journals and conferences. The development of the models and their simulation took place in MATLAB.

MODEL 1: STEEL BUILDING

The fist model building used has a 10x15 m plan and a rectangular shape. The building frame elements (beams and columns) are made of steel whose grade is Fe 345 with a cost 2.75€/kg [95]. The building's height is 3 m and it is assumed that will be used as an office. An intermittent type of heating, a 5day working week and 4hr occupancy is assumed [9], [127]. Considerations such as the expected thermal or cooling loads generated by the theoretical population of building users per sq.m., the minimum required ventilation and the expected thermal impact of the appliances derive from relevant standardized tables described in KENAK. Furthermore, the modeling considered that the building would be heated and cooled by a stand-alone A/C HVAC system that would consist of one unit. The building's walls consist of metallic panels, whose color is a nuance of grey. The temperature inside the building is considered to be 25^{o}C for both the summer (15 May to 15 October) and the winter period (15 October to 15 May) [117]. The building is situated on Chania, Crete and the resultant heating and cooling degree days for this indoor temperature and geographic location are as follows: HDD = 2215, CDD = 218 [117-8]. The electricity cost per kWh is considered to be equal to 0.012269 €. The thermal bridges (symbolized as Ψ, they reflect a linearly distributed loss that occurs in junctions between two building surfaces and is taken into account in the energy balance of the building) are estimated according to the following table that contains values recommended by KENAK [117]:

Connection method	Construction without metallic investment	Construction with metallic investment
	Ψ(W/(m*K))	Ψ(W/(m*K))
Roof to wall	0.12	0.6
Wall to floor (Ground level)	0.28	1.15
Wall to wall	0.09	0.25
Wall to floor (not at the ground level)	0.18	0.07

Table 16: Estimation of the linear thermal bridges for various connection methods.

A cost function was generated via applying multiple linear regression to carefully selected sample of average market values of window types that are made of aluminum and have thermal breaks. The regression serves to shorten the computational time and unify parameters which, on the one hand, interact with each other, and on the other hand, correlate the energy performance parameters with the consequent cost.

It is noteworthy that the cost figures of the subsystems of the algorithm that was developed, are not random. Instead, a market research has been conducted in order to detect average, real-life cost values.
Similarly, the solar gains of the building where the recommended values as described in the relevant standardized tables of KENAK [117] were used. It is meaningful to note that for the winter period the solar gains were not taken into account.

Another assumption that is made is that the thermal impact of the lighting system is equal to: 0.05 kWh/m^2 and its thermal effect is merely taken into account for the summer period.

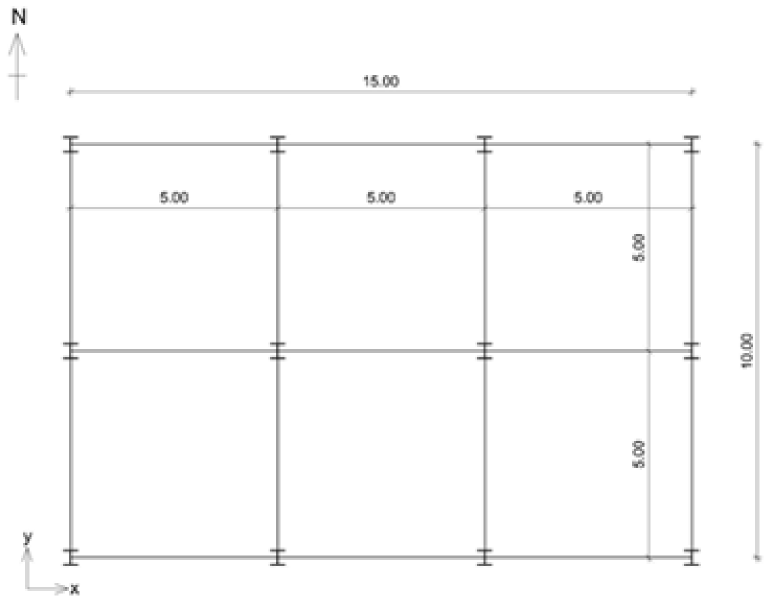


Figure 18: Simplified plan view of the building.

Three scenarios are examined for life cycle periods of 10 and 30 years.

Scenario 1:
-Mineral wool insulation profiles with A energy class A/C as HVAC system.

Scenario 2:
-EPS insulation profiles with A energy class A/C as HVAC system.

Scenario 3:
-EPS insulation profiles with A+++ energy class A/C as HVAC system.

The structural loading of the frames for the mineral wool scenario is as follows:

20.94 kN/m (intermediate span along x-x axis), 10.24 kN/m (side spans along x-x & y-y axis), 20.48 kN/m (intermediate spans along y-y axis).

The structural loading of the frames for the EPS scenario is as follows:

9.38 kN/m (side spans along x-x & y-y axis), 18.76 kN/m (intermediate spans along x-x and y-y axis).

LIFE CYCLE COST CONSIDERATIONS

- A rate equal to 1% per year is used for the estimation of the building maintenance [64], [115]. The rate is applied on all the envelope and structural subsystems after the end of the 5th year of the construction of the building. The rate is not influenced by inflation and is associated with the initial construction cost of the building subsystems.
- A rate equal to 2% per year is used for the estimation of the HVAC maintenance and is applied on the initial cost of the HVAC system [94]. The rate again is not affected by inflation.
- . The HVAC system will be replaced 20 years [115] after the building construction and its value by the end of the 20th years is affected by an inflation rate equal to 3%. Therefore:

$$New\ value = old\ value/(1.03)^{20}$$

OPTIMIZATION PROCESS AND VARIABLES

A structural analysis of the building was conducted on SAP2000 and the results of the analysis were incorporated in the algorithm in order for the sizing optimization of the steel frame elements to take place. The building components that have been modeled as variables of the optimization problem are described below:

•The steel frame cross-sections were modeled as discrete variables reflecting carefully selected predefined choices of cross-sections [85]. To attain optimal cross section from a structural standpoint, stress constraints were imposed [29]. Specifically, the stress constraints for the column members were modeled as follows:

$$f_a + f_b \leq 1$$

Where:

$$f_a = \frac{F_a}{A}$$
$$f_b = \frac{M}{S}$$

F_a is the applied axial load, A is the cross sectional area, M is the applied moment, S is the section modulus of the steel member (the classical beam theory is used in order to compute the section modulus).

The stress constraints for the beam members are as follows [29]:

$$f_a + f_b \leq 1$$

Where:

$$f_a \leq 0.4Fy$$
$$f_b \leq 0.6Fy$$

And:

$$f_a = \frac{V}{A_w}$$
$$f_b = \frac{M}{S}$$

Where:

F_y is the yield stress of the beam element, A_w is the web area, V is the applied shear load, M is the applied moment.

Furthermore, in all characteristic dimensions of the steel elements (t_w, t_f, d, b_f), upper and lower limits were imposed. A multiple-if algorithmic structure aids the optimization of the elements whose cross sections where carefully selected before being introduced to the algorithms.

- **Building envelope u-values.** The simulation aims to the optimization of the insulation thickness that is covered by an inner and an outer layer of metallic panels, whose effect on the U-value of the walls is ignored. The building floor is assumed to consist of the same insulation material, where the varying thickness has an effect on its U-value along with a slab that has a thickness equal to 20 cm. All the components of the building envelope should have acceptable lower and upper limits of u-values. Therefore [117]:

$$0.20 < U_{walls} < 0.60$$

$$0.20 < U_{floor} < 1.20$$

$$0.20 < U_{roof} < 0.50$$

$$2.20 < U_{windows} < 3.20$$

All the building envelope subsystems have their cost functions associated with their u values. The way this is done -for instance- for a wall profile of the EPS scenario is shown below [117]:

Air layer 1	0.130	0.130	0.130	0.130	0.130	0.130	0.130	0.130
Air layer 2	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040
λ (insulation material)	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033
d	0.030	0.040	0.050	0.060	0.080	0.100	0.120	0.140
Cost per squared meter (€)	6.500	8.400	10.300	12.300	16.400	21.300	29.300	35.700
U wall profile value	0.927	0.724	0.593	0.503	0.385	0.312	0.263	0.227

Table 17: Process followed for the calculation of the u-value for a building component.

The table above demonstrated how the calculation of the u value takes place for a wall profile. Finally, the following two columns are used in order for the thickness insulation to be associated with the u-value of a particular wall profile (and ultimately with is cost) [54]:

Cost per squared meter (€)	U (wall profile) value
6.500	0.927
8.400	0.724
10.300	0.593
12.300	0.503
16.400	0.385
21.300	0.312
29.300	0.263
35.700	0.227

Table 18: Cumulative u-values and costs per sq.m. before applying curve-fitting.

A careful curve fitting leads to the generation of the following cost function (its R^2 is 0.9916):

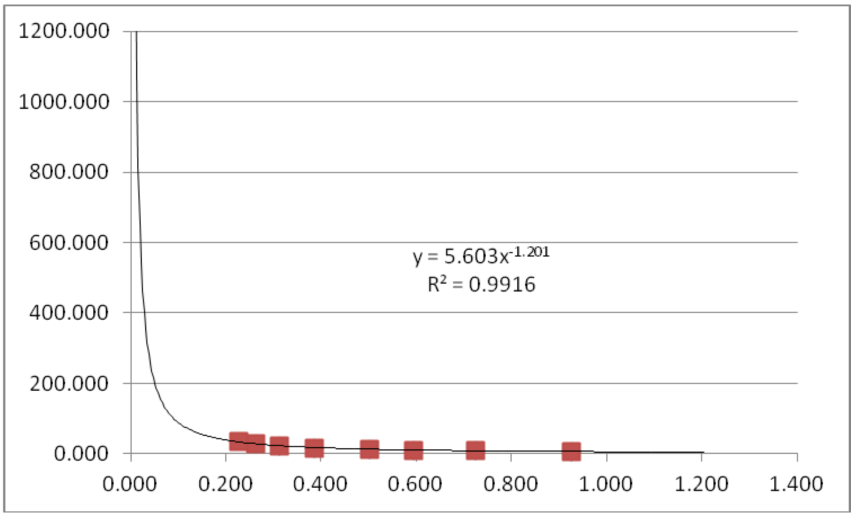


Figure 19: Applying curve-fitting.

Therefore, the aforementioned function associates the cost of a wall profile with its u-value that can have various values as a result of the fact that the insulation thickness is a variable of the optimization problem.

Similarly, for the roof and floor building envelope components (EPS scenario) the following cost functions are generated (Function that correlates the steel wall profile cost with its U-value and depends on the thickness of the insulation) [54]:

$$costinsulationroof = (5.60408 \times U_{roof}{}^{-1.202}) \times A_{roof}$$
$$costinsulationfloor = (2.8479 \times U_{floor}{}^{-1.533}) \times A_{floor}$$

As regards, the mineral wool scenario, the following cost functions were used [54]:

$$\cos tinsulationwall_i = (2.8519 \times U_{wall_i}{}^{-0.911}) \times A_{wall_i}$$
$$costinsulationroof = (2.9798 \times U_{roof}{}^{-0.926}) \times A_{roof}$$
$$costinsulationfloor = (1.7137 \times U_{floor}{}^{-1.418}) \times A_{floor}$$

In all the aforementioned cases of cost functions the value of R^2 is greater than 0.99.

As regards the windows their cost function results from their energy characteristics, by using the following sample [55]:

Type of window	Total Cost per sq. m. (€)	U value	g_{gl}
Doubly glazed	116.73	3.40	0.55
Doubly glazed low-e	127.32	2.42	0.30
Triple glazed	129.44	2.77	0.49
Triple glazed low-e	158.38	2.2	0.29

Table 19: Cumulative table for the windows' cost per sq.m. and the values for the window energy parameters before applying multiple linear regression.

Therefore, the following cost function derives from the sample via the use of multiple linear regression [31]:

$$\text{CostA/C} = 218.38 - 38.93 \times U_{win} + 33.81 \times g_{gl}$$

(Its R^2 is 0.674, its multiple-R (correlation of the fitted model with the actual observations) is 0.821).

- **Area of windows** (all elevations have been considered as independent variables).
- **The ggl value** (the ggl value of the solar gain coefficient of the window glass) should fall into the following limits that are frequently encountered in the Greek market.

  $$0.29 < g_{gl} < 0.55$$

  It was assumed that the glass occupies 75% of the total window area and this results in the multiplication of the initial g values (the g value corresponds to the solar gain coefficient of the window) by 0.75, that is a coefficient representing this estimation.
- **Energy characteristics of the A/C HVAC system (Power in kWh, SCOP (Seasonal coefficient of performance in heating), SEER (Seasonal coefficient of performance in cooling)).** The simulation was based on real market data and the upper and lower bounds for SCOP, SEER and HVAC power, were based on those data. The cost of the A/C systems took place via a cost function in the algorithms. For the A-energy class A/C HVAC systems the following sample was used [31]:

A/C model	Power (in kW)	SEER	SCOP	Cost (€)
1	2.64	3.21	3.66	217.90
2	3.52	3.21	3.66	249.90
3	3.52	5.20	3.80	345.00
4	2.64	5.37	3.40	375.00
5	2.50	5.30	3.40	392.00
6	5.30	3.22	3.62	510.00
7	4.80	5.18	3.40	599.00
8	7.03	3.21	3.61	700.00
9	5.00	5.79	3.51	748.00
10	6.70	5.23	3.83	1293.00
11	7.10	5.88	3.87	1750.00
12	10.55	3.66	3.25	1235.00

Table 20: A-energy class A/C systems and their energy characteristics.

This sample generated the following cost function [31]:

$$\mathrm{CostA/C} = -3461.45 + 172.5595 \times \mathrm{PowerA/C} + 190.222 \times \mathrm{SEER} + 674.565 \times \mathrm{SCOP}$$

Where: Its R^2 is 0.90 and its multiple R is 0.95.

As regards the A+++ energy class systems the following sample [31] was used [31]:

A/C model	Power (in kW)	SEER	SCOP	Cost (€)
1	2.70	5.60	5.10	438.00
2	3.50	6.10	5.10	516.00
3	2.50	8.90	5.30	760.00
4	3.50	8.90	5.10	831.00
5	5.00	6.00	5.30	1515.00
6	5.00	8.60	5.50	2574.00
7	3.50	9.00	5.73	2100.00

Table 21: A+++-energy class A/C systems and their energy characteristics.

This sample generated the following cost function:

$$\text{CostA/C} = -12017.66 + 444.264 \times \text{PowerA/C} + 87.1066 \times \text{SEER} + 2068.775 \times \text{SCOP}$$

Where: Its R^2 is 0.961 and its multiple R is 0.981.

OBJECTIVE FUNCTION

The objective function aims to the minimization of the sum of the costs of the mechanical, energy, structural and building envelope components along with the heating and cooling costs that result from the energy balance of the building multiplied by the exact number of years of an examined life cycle period. Other approaches make use of reduction coefficients that are multiplied by the heating and cooling costs to account for a projection of the devaluation of the electricity costs (UPV values) [44] that occurs during the specified life cycle period, however such data are only available for countries such as the USA [44], [105]. The objective function on which the algorithm was based is shown below [113]:

```
total cost = cost of insulation + Heating cost*Number of years
+ Cooling cost*Number of years + cost of frames + cost of A/C
system + cost of windows + cost of roof + cost of walls + HVAC
maintenance + general building maintenance + cost of the floor
slab +
```
$\sum_{i=0}^{\mu} p_i$

Each of terms p_i represent a particular constraint. The value of each pi is conditional depending on whether the constraint associated with it is satisfied or not. Therefore, if the constraint associated with a particular p_i is satisfied the value of p_i is zero, if not its value becomes extremely high exceeding the highest possible cost of the building. This modeling approach (conditional penalty parameters) leads to the evolutionary exclusion of the undesired solutions.

It is meaningful to note that the total energy demand (in kWh) during winter and summer is divided by the coefficients of performance of the HVAC system (SCOP and SEER respectively). According to KENAK [117] as SEER (seasonal EER) can be approximated by considering the nominal EER value as specified by the manufacturer that represents the functional conditions of the HVAC system in an external temperature equal to 35^{o}C and HVAC inlet temperature equal to 7^{o}C.

Similarly, SCOP (seasonal COP) is approximated by considering the nominal COP value as specified by the manufacturer that represents the functional conditions of the HVAC system in an external temperature equal to 7^{o}C and HVAC temperature equal to 45^{o}C. The reader can refer to the European standard EN 14511:2007 for further information. An additional multiplication of the coefficients SCOP and SEER, by a reduction factor that takes into account the transmission losses can apply. For instance, KENAK [117] uses a coefficient equal to 0.93 to consider the transmission losses of A/C units.

The constraints that were introduced into the objective function are presented below.

CONSTRAINTS

As it was outlined above, the following constraints were incorporated into the objective function:

- The stress imposed on the steel beam and column elements must not exceed the limits that were mentioned above [29].
- According to KENAK the heating system can be quickly dimensioned according to the following formula [117]:

  $$P_{\text{thermal system}} = 2.5 x U_m x A x \Delta T$$

  Evidently the constraint that was incorporated in the algorithm was:

  $$P_{\text{thermal system}} > 2.5 x U_m x A x \Delta T$$

  (Where: U_m is the average u-value of the exposed (to the atmospheric air) building envelope, A is the total envelope area in contact with the atmospheric air, ΔT is a desired temperature difference between the indoor and the outdoor environment and 2.5 is a coefficient that magnifies the product of the aforementioned parameters by taking into account losses etc.) [117]
- The power of the air-conditioning system must not be lower than what is required by the relevant CLTD specification (therefore it should be sufficient for the 21st of July that is the most adverse day of the summer) [25], [36]
- The average U-value of the building must not exceed the limits recommended by KENAK which are demonstrated below [117].

A/V	**Overall average U-value (Um) σε [W/m^2.K]**			
	Zone A	**Zone B**	**Zone Γ**	**Zone Δ**
< 0,2	1,26	1,14	1,05	0,96
0,3	1,20	1,09	1,00	0,92
0,4	1,15	1,03	0,95	0,87
0,5	1,09	0,98	0,90	0,83
0,6	1,03	0,93	0,86	0,78
0,7	0,98	0,88	0,81	0,73
0,8	0,92	0,83	0,76	0,69
0,9	0,86	0,78	0,71	0,64
> 1,0	0,81	0,73	0,66	0,60

Table 22: Maximum permissible limits for the average U-value of the building (4 climatic zones) [117].

Where: A is the area of the building in m^2 and V is the volume of the building in m^3. As regards the climatic zones, Chania belong to climatic zone A and Athens to climatic zone B.

- KENAK [117] requires the presence of at least one passive solar system (e.g. trombe walls, large area of windows in the south elevation) in a new building. Even though this consideration is largely defined by the architectural design, in order for this requirement to be met, it was decided that the window area on the south elevation should represent at least 45% of the total window area of the building.
- Another constraint incorporated in the algorithms derives from empirical rule that the total area of windows should greater than 10% of a building's area as suggested by the Greek building codes.

RESULTS AND DISCUSSION

The optimization problem is possible to be solved with the use of simulated annealing and genetic algorithms and the first method seems to constantly produce better results. It is meaningful to note that the option that was made for the optimization procedure was to mainly use the preset configurations of the optimization toolbox of MATLAB. There are some details, though, of major importance that are discussed below.

When following an optimization approach based on simulated annealing, an exponential update of the temperature function occurs, the number of function evaluations stops at maximum of 150000 iterations and the annealing function used is fast. As regards the options that were made when following an optimization procedure based on genetic algorithms: the initial population varies between 100 and 1000 individuals, a stochastic and uniform selection operator applies, along with a scattered crossover function.

Every optimization scenario needs to run by using the aforementioned configurations at least 10 times to make sure that the optimum found at each trial serves as a good and acceptable global solution. The trial results have been contrasted and compared and the best solution generated by each trial - among the optima- is shown in the following paragraphs. The scenarios reflect a life cycle period of 20 years.

The optimal cross sections for the structural frame members for each of the aforementioned scenarios (Scenarios 1 & 2,3) are shown below [85]:

SCENARIO 1		
Middle span beams	Side span beams	Corner columns
IPE 240	**IPE 200**	**HEB 140**
Middle columns of the west and east elevation	Middle columns of the north and south elevation	Interior columns
IPE 300	**IPE 300**	**IPE 360**

SCENARIOS 2 & 3		
Middle span beams	Side span beams	Corner columns
IPE 240	**IPE 200**	**IPE 100**
Middle columns of the west and east elevation	Middle columns of the north and south elevation	Interior columns
IPE 100	**IPE 100**	**IPE 120**

Figure 20: Optimal cross sections.

The energy performance optimization results that were produced by running several scenarios for a life cycle period of 10 or 30 years are shown in the following paragraphs.

- Window panes with low g values appear to be a favorable option for the optimality of the total life cycle cost. On the other hand, for the current rates the opposite applies for triple glazes low g windows since in no optimization scenario and in no elevation, they participated in the optimal solution.
- The building component requiring thicker insulation is the roof whereas the opposite applies for the floor that seems to be the least important component to insulate. Furthermore, an increase in years as regards the examined life cycle period results in a slight increase in the optimal insulations thickness.

- Subsystems with a high degree of homogeneity (e.g. A+++ or A energy class A/C systems and insulation profiles where the thickness of -merely one- specific material needs to be optimized) can be correlated with energy performance parameters through multiple linear regression and curve fitting, attaining very high R-squared values. This can save considerable computational time.
- Placing larger window areas on the south elevation seems to be a natural choice for the optimization program. The area of openings displays no observable pattern of continuity and the optimality derives from the optimization process.
- In all cases of scenarios, the heating and cooling requirements of the buildings can be met by a typical 4.40-4.70 kW, A/C unit. For the examined rates, an A energy class A/C unit is by 67% a least expensive option in comparison with an A+++ energy class A/C unit.
- The following well-known classification systems according to the building energy consumption levels (measured in kWh/m^2) are presented below. These are:

  -Level 1: Commonly accepted energy consumption upper limit prevalent in Germany [32].

  -Level 2: Minergie; the national practice of Switzerland [87].

  -Levels 3 & 4: Levels that are regarded as low energy consumption levels [123].

  -Level 5: Passivhaus level [99].

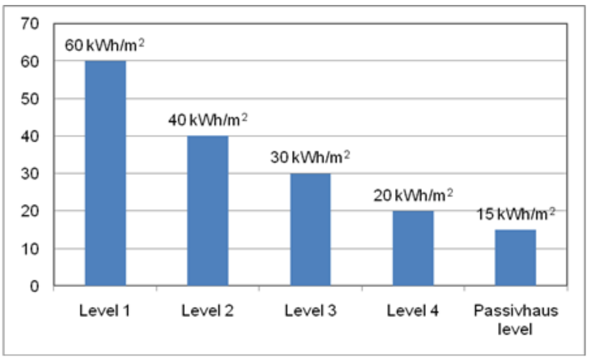


Figure 21: Well-known building energy consumption levels.

The results suggest that in all optimization scenarios the optimal energy consumption level was below level 2. Specifically, the optimal level for the examined life cycle periods equal to 10 years, the optimal energy consumption level was about 32 kWh/m^2. For the examined life cycle periods equal to 30 years the optimal energy consumption levels escalate to slightly above 30 kWh/m^2. The results of the optimization calculations are displayed below.

	Ufloor	SCOP	ggl	Awin south	Awin north	Awin east	Awin west	Uroof	Uwall south	Uwall north	Uwall east	Uwall west	Uwin south	Uwin north	U win east	Uwinwest	Power of HVAC system	SEER	Time Period
1	0.99	3.6	0.29	11.05	4.348	0.500	0.525	0.500	0.591	0.600	0.592	0.600	3.399	2.849	2.45	3.036	4.385	3.202	30 years
2	1.20	3.6	0.29	7.783	4.174	0.500	2.546	0.500	0.600	0.600	0.600	0.600	3.400	2.745	3.05	3.386	4.723	3.200	10 years

Table 23: Scenario 1 results of the optimization calculations (Optimal Energy consumption level: Below level 2).

	Ufloor	SCOP	ggl	Awin south	Awin north	Awin east	Awin west	Uroof	Uwall south	Uwall north	Uwall east	Uwall west	Uwin south	Uwin north	U win east	Uwinwest	Power of HVAC system	SEER	Time Period
1	1.19	3.6	0.290	9.045	4.02	0.531	1.406	0.500	0.566	0.600	0.600	0.600	3.400	3.106	3.03	3.40	4.714	3.20	30 years
2	1.14	3.6	0.291	9.304	4.71	0.500	0.500	0.500	0.599	0.600	0.600	0.600	3.399	2.644	3.05	3.35	4.614	3.20	10 years

Table 24: Scenario 2 results of the optimization calculations (Optimal Energy consumption level: Below level 2).

	Ufloor	SCOP	ggl	Awin south	Awin north	Awin east	Awin west	Uroof	Uwall south	Uwall north	Uwall east	Uwall west	Uwin south	Uwin north	U win east	Uwinwest	Power of HVAC system	SEER	Time Period
1	0.9	5.1	0.29	10.38	3.62	0.500	1.328	0.50	0.58	0.59	0.60	0.57	3.40	2.75	2.55	3.32	2.95	8.33	30 years

2	1.07	5.1	0.34	6.99	4.77	0.500	3.193	0.50	0.60	0.60	0.60	0.60	3.40	2.67	3.00	3.40	3.17	8.15	10 years

Table 25: Scenario 3 results of the optimization calculations (Optimal Energy consumption level: Below level 2).

MODEL 2: TIMBER BUILDING

The second model building used has a 10x15 m plan and a rectangular shape as shown below. The building frame elements (beams and columns) are made of natural pine timber whose strength class is C30 and its specific weight is considered to be equal to 460 kg/m^3. The cost of the structural timber is 350 € per m^3 [95]. The building's height is 3 m and it is assumed that will be used as an office [117].

The model building is demonstrated in the figure below:

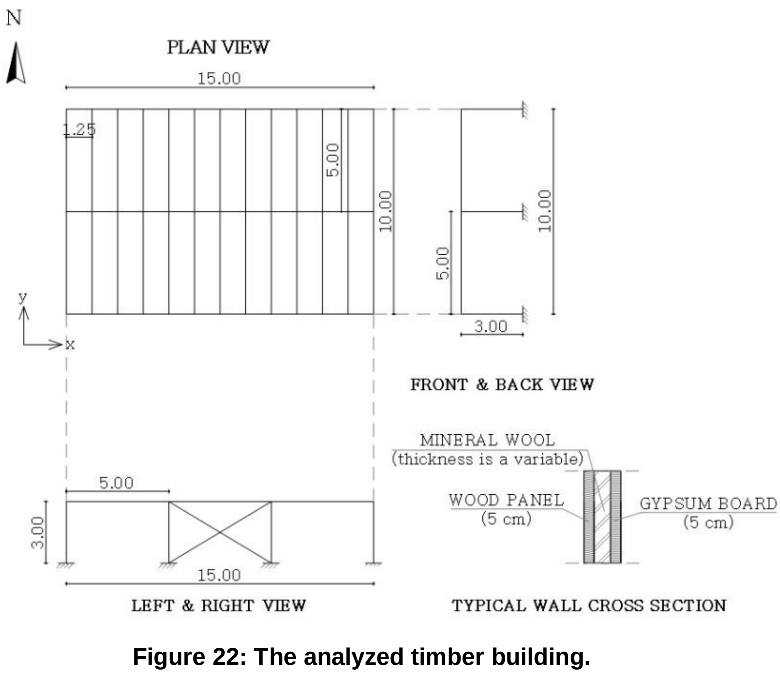


Figure 22: The analyzed timber building.

An intermittent type of heating, a 5-day working week and 4hr occupancy is assumed [9]. The building is situated on Athens, Greece. The indoor temperature during the winter and the summer period is considered to be a fuzzy variable [8] and the following scenarios and resultant heating and cooling degree days for each possible indoor temperature are examined [34]:

- Scenario 1: HDD: 1730 (21 ^{o}C), CDD: 573.5 (25.5 ^{o}C) (Examined period: 20 years).
- Scenario 2: HDD: 1930 (22 ^{o}C), CDD: 679 (24.5 ^{o}C) (Examined period: 20 years).
- Scenario 3: HDD: 2135 (23 ^{o}C), CDD: 794 (23.5 ^{o}C) (Examined period: 20 years).

The electricity cost per kWh is considered to be equal to 0.07 €. Similarly, the expected thermal or cooling loads generated by the theoretical population of building users per square meter, the minimum required ventilation and the expected thermal impact of the appliances derive from relevant standardized tables described in KENAK [117]. Furthermore, it assumed that the building's HVAC system for the heating and the cooling is a stand-alone A/C unit whose requirements in energy would be assisted by a photovoltaic array whose type of panels is known, however, its number of panels is unknown. The cost per kWp is 2933.7 € [31] and the efficiency of each panel (n_{stc}) is 14.9% and their individual power is 245 Wp. The wall and the profile roof envelope profiles consist of gypsum boards (inner layers) and wood (outer layers) and their total cost is equal to 25 € per m^2 (excluding the mineral wool insulation) [95]. The insulation thickness for these building envelope subsystems is a variable. It assumed that the insulation material of the building envelope is mineral wool and its varying thickness is associated with the building envelope u-values via the following formulae [54]:

$$costinsulationwallwest = \left(1.309 \times Uwest^{-0.672}\right) \times Awallwest$$

$$costinsulationwalleast = \left(1.309 \times Ueast^{-0.672}\right) \times Awalleast$$

$$costinsulationwallnorth = \left(1.309 \times Unorth^{-0.672}\right) \times Awallnorth$$

$$costinsulationwallsouth = \left(1.309 \times Usouth^{-0.672}\right) \times Awallsouth$$

$$costinsulationroof = \left(1.3429 \times Uroof^{-0.679}\right) \times Aroof$$

$$costinsulationfloor = \left(1.7137 \times Ufloor^{-1.418}\right) \times Afloor$$

(Functions associating the cost of the varying mineral wool insulation (integration of many different cases of insulation thicknesses) with u-values of various building components)

The floor slab consists of reinforced concrete; its thickness is equal to 20 cm and its cost equal to: 101 € per m^3 and of mineral wool insulation whose thickness is a variable [95].

Alike the previous model, cost functions based on multiple linear regression have been used to associate the cost of a component with critical energy performance parameters. The ones that have been used are as follows [55]:

$$costwindowseast = (218.376 - 38.931 \times Uwindowseast + 47.888 \times ggl) \times Awindowseast$$

(Function that correlates the cost of the window profile with its energy parameters).

$$costAC = -1000.434 + 172.14 \times POWERAC + 179.306 \times SEER - 2.05125 \times SCOP$$

(Air conditioning systems cost function describing A and A+++ energy class A/C systems [31])

A/C model	Power (in kW)	SEER	SCOP	Cost (€)
1	2.64	3.21	3.66	217.90
2	3.52	3.21	3.66	249.90
3	3.52	5.20	3.80	345.00
4	2.64	5.37	3.40	375.00
5	2.50	5.30	3.40	392.00
6	5.30	3.22	3.62	510.00
7	4.80	5.18	3.40	599.00
8	7.03	3.21	3.61	700.00
9	5.00	5.79	3.51	748.00
10	6.70	5.23	3.83	1293.00
11	7.10	5.88	3.87	1750.00
12	10.55	3.66	3.25	1235.00
13	2.70	5.60	5.10	438.00
14	3.50	6.10	5.10	516.00

Table 26: The market data used to generate a cost function via multiple linear regression for high energy class A/C units.

The resultant R^2 is 0.82 and multiple-R is 0.902.

The examined life cycle period of the building is 20 years and the following management scenarios for the timber frame components were considered for the end of the building's life cycle.

The first scenario (Scenario A) assumes that the building will be deconstructed and 80% of the timber frame elements will be retrieved and reused [63]. The second scenario (Scenario B) assumes that the timber frame components will be recovered by a percentage equal to 80% and recycled [63]. The expected profit per kg of recycled timber mass is considered to be equal to 0.90 €.

An inflation rate equal to 3% is taken into account therefore the expected profits from the recycling or the reuse of the timber frame components are devalued in order for this condition to be met. A regular maintenance cost applies to the initial cost of the timber frame components and is considered to be equal to 4% of their initial value per year (unaffected by the inflation rates). Furthermore, a rate equal to 4% applies to the initial value of the timber wall profiles [63] with a start point five years after the construction of the building. It is also possible to expect that a periodic maintenance plan with a known cost could apply, where again the inflation rates would again have to be taken into account.

The structural loading of the frames that results from a loading combination 1.35G + 1.5Q (where G is the permanent load equal to 5.78 kN/m for the (interior beams along x-x axis) or 2.88 kN/m (side beams along x-x axis) and Q is the moving load equal to: 1 kN/m), is presented below:

- Side beams: 5.39 kN/m
- Intermediate beams: 9.28 kN/m

The structural modeling takes place in SAP2000 and (in accordance with the guidelines of Eurocode 5) assumes that the building behaves as a 3D frame and the beam-column connections are fixed. The beams are checked according to Eurocode 5 [40] for bending, shear and deflection. Similarly, each column is checked for compression, buckling and combined compression and bending. As regards the bounds for the optimization of the beam elements, the lower limit for b and h is 100 mm and the upper limit is equal to 800 mm. As regards the bounds for the optimization of the column elements, the upper limit for b and h is equal to 800 mm, whereas the lower limit is for b is 100 mm and 225 mm for h.

For the purpose of sizing the photovoltaic array in an optimal way the variable in the optimization algorithm is the required energy in kWh (intending to cover merely the heating and cooling energy needs), for the most adverse day of the winter in way that a 4-day energy autonomy is ensured even for that day. Losses due to aging [100-1], inverter losses (expressed through a reduction coefficient equal to 0.875) [100-1], monthly temperature losses [100-1], cable losses (expressed through a reduction coefficient equal to 0.98) are taken into account [100-1]. After the determination of the required energy in kWh, for the most adverse of the winter, it is possible for the peak power (kWp) of the photovoltaic system to be evaluated [100-1]. After the evaluation of the peak power of the system it is possible to evaluate the area of the required area of the panels (through a coefficient translating kW into total panel area), the resultant cost of the PV system and the total energy [79] that can be produced during the winter and the summer period. It is meaningful to note that the final panel area is rounded up to the next integer number of panels, in a way that therefore is ensured that the final area of panels is always bigger than the required area that derives from the calculations. This variable that was analyzed above can take a value between 0 and 10 kWh.

total cost = cost of insulation + Heating cost*Number of years + Cooling cost*Number of years + cost of A/C system + cost of windows + cost of roof + cost of walls + HVAC maintenance + general building maintenance + cost of the floor slab + cost of photovoltaic array + PV array maintenance costs + timber frame components costs + $\sum_{i=0}^{\mu} p_i$

LIFE CYCLE ANALYSIS

A life cycle analysis took place by combining information from the following software: ATHENA, BEES, Boustead, GaBi [121], SimaPro [76]. The assumptions were introduced in the algorithms and reflect the most expected decisions that will be taken during the examined life cycle. Whenever this information had scores reflecting different combinations of environmental friendliness and economic efficiency, the hypothesis that was made corresponded to the following combination of scores: 50% environmental friendliness and 50% economic efficiency [12]. Therefore, the following considerations were made:

- It is assumed that the building owner will not be motivated to recycle or retrieve the considerable percentage of the mineral wool insulation material that is recyclable or retrievable at the end of the examined life cycle, so it is expected that the mineral wool insulation material will be disposed in a landfill. Similarly, the gypsum boards are also recyclable to some extent at the end of the examined life cycle period but it is expected that they will be disposed in a landfill [12].
- The relevant bibliography suggests that the PV array commonly requires removal of the dust. This usually takes place twice a year and due to its very low cost it was not incorporated in the algorithm. Another commonly encountered cost during the useful life of the array is the replacement of the inverter. The replacement is expected to occur every 5-10 years and further details are generally provided by the inverter's guarantee. The replacement cost is equal to the initial cost of the inverter multiplied by the effect of the inflation rates during the examined life cycle period [12].
- As it was said before, the timber building envelope walls require some degree of regular maintenance in order for the negative

effects of the humidity, moisture and water penetration to the shell to be minimized [12].

- No other residual values apart from the ones that relate to the frame components will be taken into account.

STRUCTURAL OPTIMIZATION OF THE TIMBER FRAME

The structural optimization of the timber frame components takes place via the addition of the penalty parameters to the objective function that calculates the cost of each structural element. Each check that was mentioned before needs to be satisfied and if not, these parameters take very high values exceeding the highest possible cost of the building. Another constraint that was taken into consideration is that $h > b$.

STRUCTURAL OPTIMIZATION RESULTS

After the structural analysis that maximum values of moments, axial loads and shear forces that were noticed on each characteristic structural element are incorporated in optimization program (MATLAB).

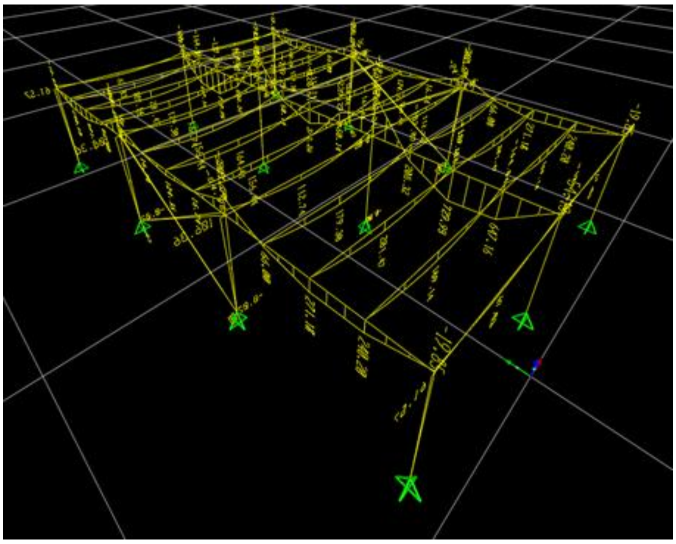


Figure 23: Structural analysis results.

The results of the optimization procedure are rounded up to the closet multiple of 5 mm. The results are as follows:

- Side beams along y-y axis: b = 100 mm, h = 235 mm (Vsd = 15.71 kN, Msd = 14 kNm).
- Interior beams along y-y axis: b = 100 mm, h = 275 mm (Vsd = 29.43 kN, Msd = 22.76 kNm).
- Side beams along x-x axis: b = 100 mm, h = 360 mm (Vsd = 38.95 kN, Msd = 40.98 kNm).
- Interior beam along x-x axis: b = 220 mm, h = 400 mm (Vsd = 104.27 kN, Msd = 106.55 kNm).
- Interior columns: b = 140 mm, h = 225 mm (Nsd = 245.66 kN, Msd = 1.61 kNm).
- Side middle columns along x-x axis: b = 120 mm, h = 235 mm (Nsd = 84.05 kN, Msd = 12.04 kNm).
- Side middle columns along y-y axis: b = 110 mm, h = 230 mm (Nsd = 95.25 kN, Msd = 6.1 kNm).
- Corner columns: b = 100 mm, h = 225 mm (Nsd = 37.58 kN, Msd = 7.31 kNm).

The diagonal beams were sized with the following dimensions: b = 100 mm, h = 100 mm.

The total cost of the timber frame is therefore equal to: 2436.28 € and its total weight is equal to 3201.97 kg.

ENERGY PERFORMANCE OPTIMIZATION RESULTS

The optimization problem is possible to be solved with the use of simulated annealing and genetic algorithms (through the optimization toolbox of MATLAB) and the first method seems to constantly produce better results for the energy design subproblem, whereas genetic algorithms are more effective for the structural design subproblem.

It is meaningful to note that the main option that was made for the optimization procedure was to mainly use the preset configurations of the optimization toolbox of MATLAB. There are some details, though, of major importance: an exponential update of the temperature function occurs, the maximum number of function evaluations stops at a maximum of 150000 iterations and the annealing function used is fast. Every optimization scenarios needs to run by using the aforementioned configurations at least 10 times to make sure that the optimum found at each trial serves as a good and acceptable global solution. The trial results have been contrasted and compared and the best solution generated by each trial -among the optima- is shown in the following paragraphs. The scenarios reflect a life cycle period of 20 years. As regards the options that were made when following an optimization procedure based on genetic algorithms: the initial population varies between 100 and 1000 individuals, a stochastic and uniform selection operator applies, along with a scattered crossover function.

The energy performance optimization results that were produced by running several scenarios are shown in the following paragraphs. An interpretation of the results regarding the three aforementioned scenarios can lead to the following conclusions:

- It seems to be a cost-effective decision to use window panels with very low g values. For all scenarios, the south elevation is the one that necessitates the lower u-values. Moreover, it seems that in no scenario opting for triple glazed windows in any elevation is a cost-effective decision. The area occupied by the windows is every time dependent on the optimization calculations.
- In no optimization scenario, the decision to cover part of the electricity needs for heating and cooling through a PV system of any size was a cost-effective decision.

- The results reflect that the optimal HVAC system for the heating and the cooling requirements of the building is an A+++ energy class with a power close to 2.5 kW.
- A change in the design temperature has a minor impact on the optimal solution. However, in larger scales careful segmentation into thermal zones with higher and lower temperatures could attain significant cost savings.

ECONOMIC IMPLICATIONS OF THE MANAGEMENT OF THE STRUCTURAL ELEMENTS AT THE END OF THE BUILDING'S LIFE CYCLE

The following table displays the results generated by the examined rates for the scenarios A & B [44].

MANAGEMENT SCENARIOS A & B	LCC + TIMBER FRAME MAINTENANCE	LCC COST MINUS REUSE PROFIT	LCC COST MINUS RECYCLING PROFIT
SCENARIO 1	31 697.35 €	30 618.23 €	30 305.37 €
SCENARIO 2	32 688.32 €	31 609.19 €	31 296.34 €
SCENARIO 3	34 369.42 €	33 290.30 €	32 977.44 €

Table 27: Total life cycle cost for scenarios A & B and all the examined heating and cooling degree days.

It can be observed that most profitable decision is to recycle rather than reuse the timber frame components.

FUZZY ANALYSIS OF THE INFLUENCE OF THE HEATING & COOLING DEGREE DAYS ON THE LIFE CYCLE COST FUNCTION

In order for a fuzzy analysis to be performed characteristic α-cuts are incrementally plotted. This results in the depiction of the dispersion of the examined range for the values of HDD and CDD. After that pairs of values of HDD and CDD that had the same α-cut value [8] were incorporated in the LCC function. The results of the optimization scenario 3 were preferred for the determination of the energy design variables and the effect of the selected pairs on the response of the LCC function was plotted in a new diagram. All diagrams that were generated demonstrate a high degree of linearity and this is the main conclusion of the defuzzyfication that was performed. The diagrams generated by the fuzzy analysis are depicted below [8].

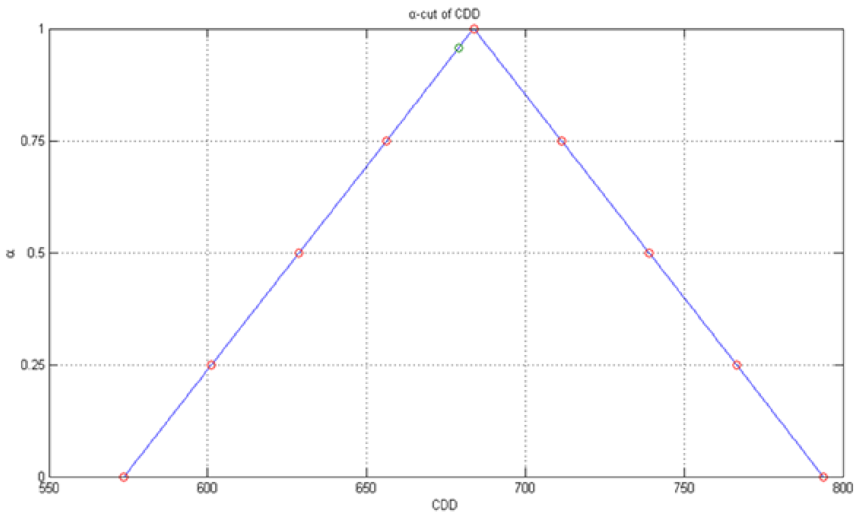


Figure 24: α-cuts of the Cooling degree days.

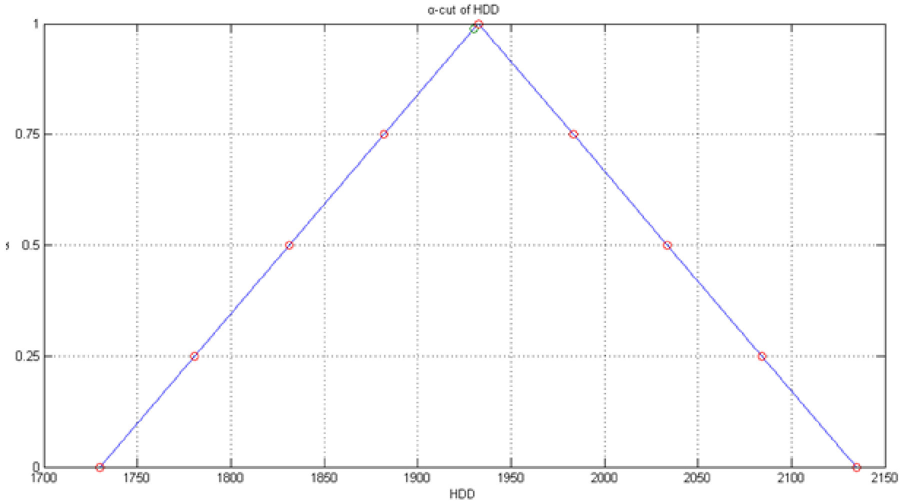


Figure 25: α-cuts of Heating degree days.

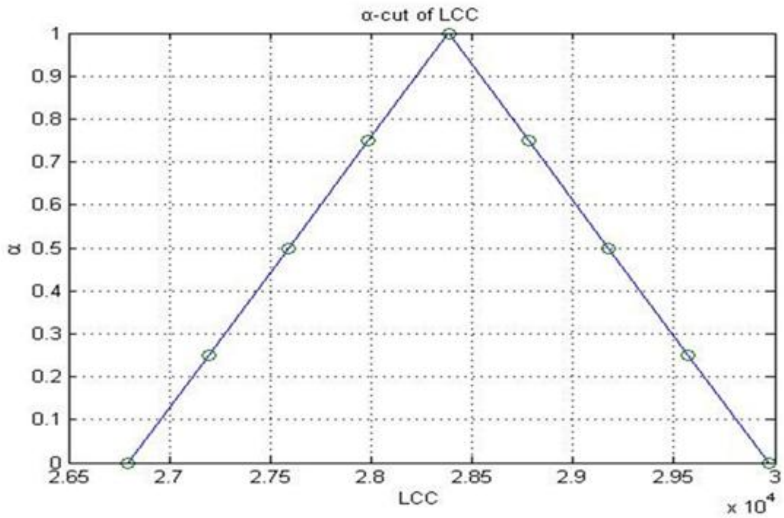


Figure 26: α-cuts of the total life cycle cost.

	SCENARIO 1 HDD: 1730, CDD: 573.5	SCENARIO 2 HDD: 1930, CDD: 679	SCENARIO 3 HDD: 2135, CDD: 794
LCC-M	27312.050	28303.018	29984.120
PV power	0.000	0.000	0.000
SEER	5.600	5.600	5.600
A/C power	2.501	2.500	2.500
$U_{winwest}$	3.398	3.258	3.109
$U_{win\ east}$	3.061	3.396	3.070
$U_{win\ north}$	3.384	3.175	3.201
$U_{win\ south}$	3.206	3.236	2.869
$U_{wall\ west}$	0.490	0.499	0.456
$U_{wall\ east}$	0.477	0.465	0.493
$U_{wall\ north}$	0.459	0.492	0.288
$U_{wall\ south}$	0.393	0.499	0.340
U_{roof}	0.450	0.450	0.450
$A_{winwest}$	5.186	0.501	0.513
$A_{wineast}$	0.506	0.500	0.501
$A_{winnorth}$	8.800	13.571	14.724
$A_{winsouth}$	0.511	0.500	0.500
ggl	0.292	0.291	0.291
SCOP	8.000	8.000	8.000
U_{floor}	0.899	0.900	0.899

Table 28: Results of the optimization calculations for the model building 2. The term LCC-M stands for life cycle cost minus maintenance (without any assumption for the management of the frame components after the end of the examined life cycle period).

MODEL 3: LARGE BUILDING WITH RC OR STEEL FRAMES

The third model building has a rectangular shape of 35x30 m as shown below. The beams and columns of the building (frame elements) are either made of steel or of reinforced concrete (two scenarios) and, as for its use, it is that of an office building. Two simplified, computer generated, plans of the building of both scenarios can be viewed below.

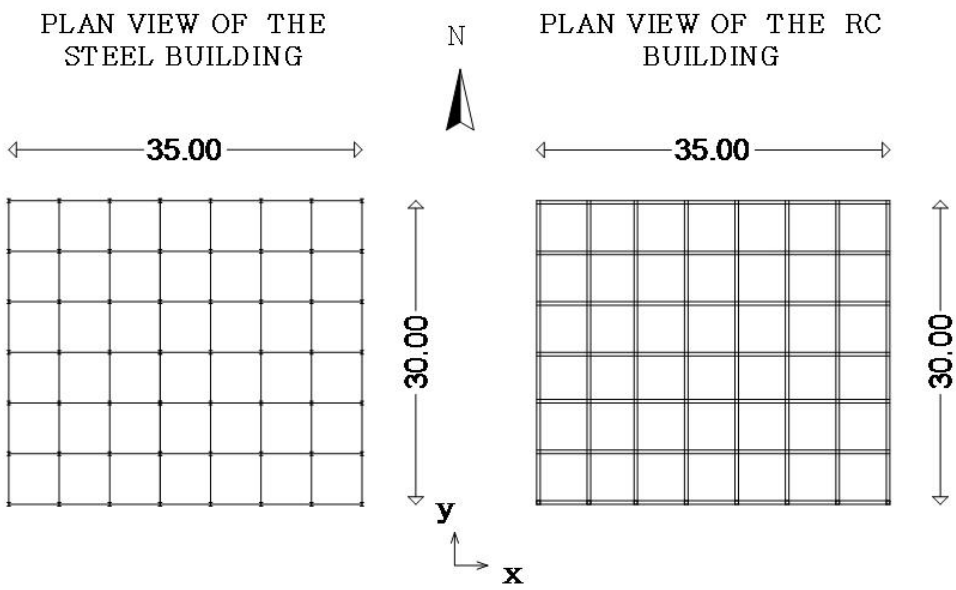


Figure 27: Simplified plan view of the building (RC and steel scenarios).

MATLAB has been used for the development of the relevant algorithm. Alike the previous models, particular attention has been given to mineral wool insulation profiles and to A/C HVAC systems based on the preferences of consumers in the Greek market. The market research has taken into account the cost of the building components [95] mentioned below:

- Wall & roof inner and outer layers (type of wall of the steel building: two layers of metallic panels (see figure below)).
- Wall & roof inner and outer layers (type of wall of the RC building: two layers of bricks (see figure below)).
- Mineral wool insulation whose thickness is a variable of the optimization program.
- Air-conditioning systems with different energy parameters.

- Double & triple-glazed aluminum windows (with regular or low-e values).
- Photovoltaic system cost per kWp.
- Structural steel cost per kg.
- RC forming cost per m^2
- Concrete cost per m^3.
- RC reinforcement cost per kg.
- Cost of the lighting control system.

The cost functions that follow are indicative of the ones used in the algorithms and they are presented so as to help the reader have a better understanding of the concept [55]:

$$costwindowseast = (218.376 - 38.931 \times Uwindowseast + 47.888 \times ggl) \times Awindowseast$$

(Function that correlates the cost of the window profile with its energy parameters).

$$costinsulationwallwest = (2.9264 \times Uwest^{-0.926}) \times Awallwest$$
$$costinsulationwalleast = (2.9264 \times Ueast^{-0.926}) \times Awalleast$$
$$costinsulationwallnorth = (2.9264 \times Unorth^{-0.926}) \times Awallnorth$$
$$costinsulationwallsouth = (2.9264 \times Usouth^{-0.926}) \times Awallsouth$$

$$costinsulationroof = (1.7978 \times Uroof^{-0.66}) \times Aroof$$
$$costinsulationfloor = (1.4397 \times Ufloor^{-0.597}) \times Afloor$$

(Cost functions used in the steel building case study [54])

$$costinsulationwallwest = (2.201 \times Uwest^{-0.828}) \times Awallwest$$
$$costinsulationwalleast = (2.201 \times Ueast^{-0.828}) \times Awalleast$$
$$costinsulationwallsouth = (2.201 \times Usouth^{-0.828}) \times Awallsouth$$
$$costinsulationroof = (1.7978 \times Uroof^{-0.66}) \times Aroof$$
$$costinsulationfloor = (1.4397 \times Ufloor^{-0.597}) \times Afloor$$

(Cost functions used in the RC building case study [54])

Hence, two case studies have been analyzed over a life cycle span of 20 years:

- Case study 1: Steel building with A/C HVAC systems
- Case study 2: RC building with A/C HVAC systems

LIFE CYCLE ANALYSIS AND THE OPTIMIZATION PROBLEM

The span of the life cycle of the examined building subsystems is investigated to predict potential replacements of the subsystems. Therefore, the following data have influenced the algorithms that were developed [56-7], [115]:

- Building exteriors, doors and windows: 80 years (lifetime)
- Mineral wool insulation profiles: 50 years
- Photovoltaic panels: 25 years
- HVAC systems: 15-20 years
- Structural steel or reinforced concrete: 75-80 years (lifetime)
- Lighting control systems: 15 years

The following considerations reflect other relevant assumptions about the life cycle cost of the above-mentioned subsystems that were introduced in the algorithms:

- The building maintenance expenditure amounts to a rate of 1% per year of its initial construction cost. It is, therefore, not influenced by inflation. Moreover, it is not applied prior to the end of the 5th year of the construction of the building [115].
- The HVAC systems maintenance expenditure amounts to a rate of 2% per year of their initial cost. The rate is also unaffected by inflation [94].
- The simulation has not included the remaining NP values of the building components (windows, structural frames, walls, insulation profiles), as there is a predetermined design assumption that they will

not be recycled or re-used by the owner of the building when their life cycle is over.

OPTIMIZATION PROCEDURE AND VARIABLES

A finite element analysis is performed on MATLAB and its results are used to size and optimize the structural frame components. Similarly, the other building components have been modeled as variables and are optimized after a simulation of the energy balance of the building. Therefore, the optimization procedure integrates the following variables:

- Building envelope u-values. The simulation optimizes the insulation material thickness. The insulation material is mineral wool and it is placed between the outer layers of the walls of the building. The lower and upper limits of the u-values are [117]:

1. U-values of the walls (separate consideration of each orientation):

$$0.20 < U_{walls} < 0.50$$

2. U-value of the floor (the building floor is assumed to be comprised of a 20-cm thick reinforced concrete slab as well as the same insulation material whose varying thickness has an effect on its u-value and, therefore, has to be optimized):

$$0.20 < U_{floor} < 0.90$$

3. U-value of the roof (the building roof is assumed to be comprised of a 20-cm thick reinforced concrete slab as well as the same insulation material as above whose varying thickness has an effect on its u-value and, therefore, has to be optimized):

$$0.20 < U_{roof} < 0.45$$

4. U-value of the windows (separate consideration of each orientation and the u-value co-calculates the effect of the thermal bridges). Where:

$$2.20 < U_{windows} < 3.40$$

- Window area (south & north elevation). The window area is supposed to be sized between 20 and 60 m^2, on the north and south facade, in the simulation.
- Window area (every other elevation; separate consideration of each orientation). The window area is supposed to be sized between, 10.50 and 60 m^2, in the simulation.
- g_{gl} value. The g_{gl} value -the coefficient used to measure the solar energy transmittance of the window glass- ranges from 0.29 to 0.55. It has been multiplied by 0.75 due to the fact that the glass is considered to approximately occupy 75% of the total window area, whereas the window frame occupies the remaining 25%.
- A/C HVAC system with varying energy parameters. In the simulation, 25 different A/C HVAC types with numerous energy parameters have been accounted. (Parameters: Power in kWh, SCOP (Seasonal Coefficient of Performance), SEER (Seasonal Energy Efficiency Ratio). Specifically, the following units were introduced in the simulation [31]:

1. SEER = 5.1, SCOP = 3.8, Power = 8.3, costheatpump = 1962

2. SEER = 3.25, SCOP = 3.66, Power = 10.55, costheatpump = 1988

3. SEER = 3.3, SCOP = 3.6, Power = 15.53, costheatpump = 2300

4. SEER = 5.1, SCOP = 3.8, Power = 16, costheatpump = 2988

5. SEER = 3.22, SCOP = 3.61, Power = 17.58, costheatpump = 3390

6. SEER = 3.2, SCOP = 3.4, Power = 25, costheatpump = 6675

7. SEER = 3.25, SCOP = 3.6, Power = 20.3, costheatpump = 6000

8. SEER = 5.1, SCOP = 3.8, Power = 16, costheatpump = 2858

9. SEER = 3.7, SCOP = 3.62, Power = 7.1, costheatpump = 1670

10. SEER = 5.1, SCOP = 3.4, Power = 7.1, costheatpump = 1600

11. SEER = 5.2, SCOP = 3.8, Power = 7.1, costheatpump = 1655

12. SEER = 3.21, SCOP = 3.62, Power = 7.03, costheatpump = 1098

13. SEER = 4.65, SCOP = 3.8, Power = 6.8, costheatpump = 2032.5

14. SEER = 5.5, SCOP = 3.86, Power = 6.8, costheatpump = 2566

15. SEER = 5.51, SCOP = 3.8, Power = 6, costheatpump = 2311

16. SEER = 5.11, SCOP = 3.41, Power = 10.5, costheatpump = 2160

17. SEER = 3.21, SCOP = 3.61, Power = 12.5, costheatpump = 3639

18. SEER = 3.21, SCOP = 3.61, Power = 13.4, costheatpump = 4313

19. SEER = 3.33, SCOP = 3.61, Power = 13.4, costheatpump = 4969

20. SEER = 5.3, SCOP = 3.8, Power = 3.52, costheatpump = 850

21. SEER = 3.21, SCOP = 4.1, Power = 3.43, costheatpump = 950

22. SEER = 5.3, SCOP = 3.8, Power = 3.52, costheatpump = 990

23. SEER = 5.11, SCOP = 3.51, Power = 2.5, costheatpump = 990

24. SEER = 5.19, SCOP = 3.8, Power = 2.5, costheatpump = 1321

25. SEER = 3.25, SCOP = 3.6, Power = 20.3, costheatpump = 5999

- Number of AC units. The number of the A/C terminals, in the simulation, varies from 1 to 10.
- Variable used to ascertain if the use of a lighting control system is cost-effective or not.
- Peak power of the photovoltaic array. The variable, in the simulation, represents the heating energy needs, in kWh, in order to size the array in an sufficient way even during the most inclement weather in winter (therefore covering the heating needs on the most adverse day in winter with the minimum expected values of solar radiation [100-1], ensuring also a 4-day energy autonomy). The panels have an optimal inclination which is considered to be 31^o for the city of Athens in Greece while the value of the peak power of the array is assumed to range between 0 and 15 kWp.

- Variable representing the spacing among the structural frames (4 possible planning options reflecting a series of equally spanned frames between 3 (30/3 = 10m) and 6 (30/6 = 5m)).
- Variable representing the shape configuration of the structural frames whose modification may have an effect on the number of bays (4 possible design options reaching a number of beam-column elements between 13 and 19).
- Variable representing the length of each of the front beams. They are placed along the front elevation of the building which is considered to be 35 m long. The length of the beams is considered to range between 3 and 6 meters with a step size value of 0.5 m.
- Variables representing the cross sections of the structural frame elements:

  - Variables representing the cross sections of the columns. The cross sections mentioned below have been considered for the steel building case study: HEM120, HEM140, HEM160, HEM180, HEM200, 'HEM220, HEM240 and HEM260. The following cross sections have been taken into account for the RC building scenario: b = 350 mm h = 350 mm ρ = 1%, b = 350 mm h = 350 mm ρ = 2%, b = 350 mm h = 350 mm ρ = 3%, b = 350 mm h = 400 mm ρ = 1%, b = 350 mm h = 400 mm ρ = 2%, b = 350 mm h = 400 mm ρ = 3%, b = 400 mm h = 400 mm ρ = 1%, b = 400 mm h = 400 mm ρ = 2% (Where: b symbolizes the shortest dimension of the cross section, h symbolizes the longest dimension of the cross section, ρ (%) symbolizes the reinforcement ratio of the cross section).

  - Variables representing the cross sections of the front beams. The cross sections mentioned below have been considered for the steel building case study:

  IPE180, IPE200, IPE220, IPE240, IPE270, IPE300, IPE330. The following cross have been taken into account for the RC building case study: b = 350 mm h = 550 mm ρ = 1%, b = 350 mm h = 550 mm ρ =

2%, b = 350 mm h = 550 mm ρ = 3%, b = 350 mm h = 550 mm ρ = 4%, b = 350 mm h = 550 mm ρ = 5%, b = 350 mm h = 550 mm ρ = 6%.

- Variables representing the cross sections of the back beams. They are placed along the elevation of the building which is considered to be 30 m long. The cross sections mentioned below have been taken into account for the steel building scenario: IPE180, IPE200, IPE220, IPE240, IPE270, and IPE300. The following cross sections have been considered of the RC building scenario: b = 350 mm h = 550 mm ρ = 1%, b = 350 mm h = 550 mm ρ = 2%, b = 350 mm h = 550 mm ρ = 3%, %, b = 350 mm h = 600 mm ρ = 1%, b = 350 mm h = 600 mm ρ = 2%, b = 350 mm h = 600 mm ρ = 3%, b = 350 mm h = 600 mm ρ = 4%.

STRUCTURAL ANALYSIS AND BAY LENGTH OPTIMIZATION

The current model mainly employs discrete optimization techniques for the cost optimization of the building structural elements.

Originally, a preliminary sizing of the building structural elements has been made -based on empirical data- in order to determine the number of beams and columns needed. The estimation has led to a minimum of 13 elements and a maximum of 19, hence, the algorithm contains four distinct possible types of frames. At this point, it is useful to make a few remarks, given that the optimization process is structural analysis is performed through a finite element analysis. The elements are consistently interconnected at the nodes and the following relationships are always true:

$$(number\ of\ nodes\ =\ number\ of\ elements\ +\ 1)$$

And:

$$(number\ of\ degrees\ of\ freedom\ =\ 3xnumber\ of\ nodes).$$

There are a lot of potential programming approaches for modeling the finite element analysis, however, it is necessary to make a few remarks on several modeling techniques used in the algorithms that were created with the view of attaining highly predictable patterns. Initially, the technique that was employed to attain predictability in the sequencing of the degrees of freedom in the finite element analysis is displayed below [24], [42]:

$$\boldsymbol{elementDof} = [\boldsymbol{indice}\ \boldsymbol{indice} + \boldsymbol{numberNodes}\ \boldsymbol{indice} + \mathbf{2} * \boldsymbol{numberNodes}]$$

The first term of the matrix above represents the degrees of freedom of axial displacements, the second term represents the degrees of freedom of shear displacements and the third term represents the degrees of freedom of the assigned to the moments [42], [49].

The global stiffness matrix, which describes the behavior of the entire system, is assembled by taking into account the degrees of freedom, inter alia. The start and end nodes of every beam and column, no matter how big the number of bays is, are numbered in a certain way which is depicted in the figure below. Let us point out, though, that the number of beams is always even, whilst the number of columns is always odd and the relation below holds always true [13-4]:

$$number\ of\ columns = number\ of\ beams + 1$$

The programming logic has been significantly affected by the consideration above. The effect of the relation on the numbering sequence of the nodes is shown below:

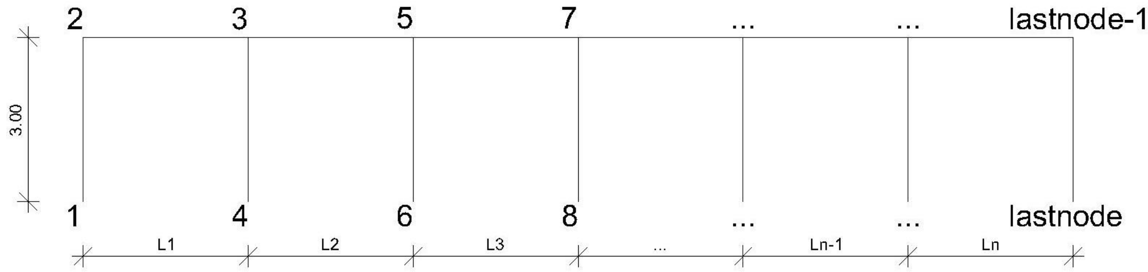


Figure 28: Node indices numbering sequence - frame with multiple bays - generalized depiction.

Similarly, the repeated pattern of the numbering sequence of the nodes aids the predictability of the degrees of freedom- of every element. Hence, the indices of the beams and columns are given by the following relationships:

$$\mathbf{Beam\ nodes}: [\mathbf{2\ 3}: \mathbf{2}: \mathbf{lastnode} - \mathbf{1}], \qquad \mathbf{Column\ nodes}: [\mathbf{1}: \mathbf{1}: \mathbf{lastnode}]$$

As for the columns, their bottom end is assumed to be fixed; thus, the degrees of freedom and their repeatability are demonstrated in the following pseudocode [42]:

$$\mathbf{prescribedDof1} = [\mathbf{1\ 4}: \mathbf{2}: \mathbf{lastnode}]$$

$$\mathbf{prescribedDof2} = [\mathbf{1\ 4}: \mathbf{2}: \mathbf{lastnode}] + \mathbf{numberofelements}$$

$$\mathbf{prescribedDof3} = [\mathbf{1\ 4}: \mathbf{2}: \mathbf{lastnode}] + \mathbf{2} * \mathbf{numberofelements}$$

$$\mathbf{prescribedDof} = [\mathbf{prescribedDof1}, \mathbf{prescribedDof2}, \mathbf{prescribedDof3}]$$

The reinforced concrete slabs of the roof have a certain loading effect on the beams with which they are in contact. The load effect on the beams depends on the dimensions of each slab. That being the case, and by considering all possible length combinations of the front and back beams encompassing a slab, the load effect can be interpreted by applying the theory for one-way or two-way slabs [47]. This classification is used for the design of the load distribution model under which four distinct possible cases are described through a multiple-if structure in the algorithm. The load distribution diagram displayed below concerns all the possible cases of the slab areas that generate a load effect on the front and back beams. It is noteworthy that the load on the intermediate frames is greater compared to the load on the side frames [84].

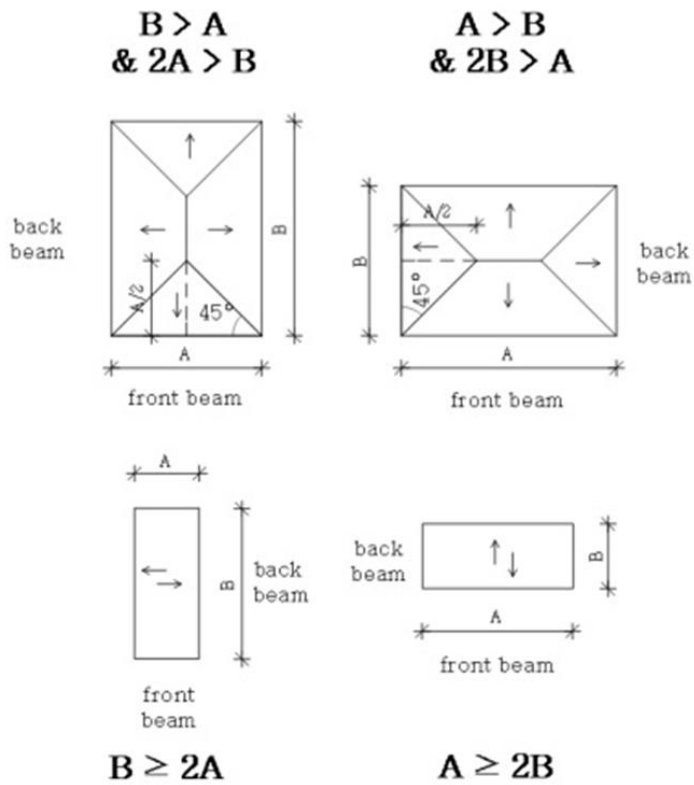


Figure 29: Roof load distribution diagram on the front and on the back beams.

Before proceeding to the solution of the structure, it is essential to define the externally applied forces by assigning them to the relevant degrees of freedom. Let us underline that the top edge of each column is subjected to an axial load. As for the first and last columns, they bear half of the load of the back beam in contact with them, as well as half of the load of the first and the last beam, respectively. The intermediate columns, though, bear half of the load of their adjoining front beams and half of the load of their adjacent back beams.

As far as the externally applied moments are concerned, they should be assigned to each start and end beam element node. In particular, an opposite couple of moments, $-ql^2/12$ and a moment equal to $ql^2/12$ (q = applied load, l = length of the beam element) should be assigned to every start and end beam element node, respectively [47] and as a result of the distributed load generated by the slab in contact with them. Once the structure is solved, the design moments and the axial and shear forces can be computed and used for the sizing of the cross-sections.

FURTHER DETAILS

STRUCTURAL DESIGN

The model building of the simulation is single-storey and it is located on Athens in Greece. Discrete optimization is the key concept on which the modeling is based. The design of the model building has been made using a discrete optimization algorithm with an initial empirical estimation of the number of the beams and columns needed (structural elements), the spacing between frames and the types of cross-sections for the beam and column elements. Accordingly -using discrete optimization- seven cases of possible beam lengths, which are variable-dependent, have been integrated in the algorithm (taking into account all the variations of a beam length, from 3 to 6 m for every 0.5 m). The integration has been performed through the input of a penalty coefficient by which every beam element (of the building dimension equal to 35m) is multiplied. The value of the penalty coefficient is equal to a = 35/(total length), when the total length in a particular iteration is lower than 35 m and a = (total length)/35 when the total length in a particular iteration is greater than 35 m [114]. Apart from the variables concerning the beam length, different cases of variable-dependent beam and column cross-sections have also been integrated in the algorithm.

Additional considerations that have been made for the model building are:

- Building height = 3m.
- Load on the frames: 0.75 kN/m^2.
- Structural steel cost (steel grade Fe 460): 2.75 € per kg [95].
- RC forming cost: 75 € per m^2.
- Concrete cost (concrete grade C 25/30) [95]: 60 € per m^3.
- RC reinforcement cost per kg (rebar steel grade S500) [95]: 4708.2 € per m^2.
- RC cover: 35mm.

Another important detail is that the interaction diagram of the RC elements that has been used in the simulation is as follows [13-4], [66], [128]:

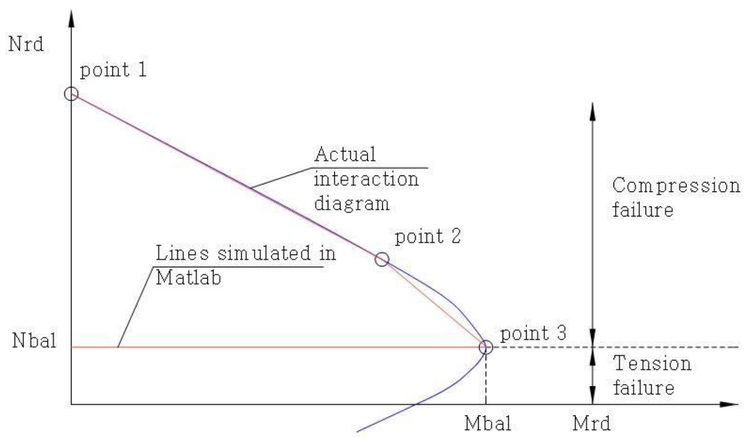


Figure 30: Interaction diagram used in the algorithm.

ENERGY PERFORMANCE

The use of the building was initially considered to be that of an office and a series of inputs were based on that consideration (heating or cooling load applied by the assumed number of people as building users, minimum ventilation requirements, typical appliances intended for use in the building)

[117]. Moreover, a few typical profiles of the building envelope that are also associated with the varying insulation thickness are shown below:

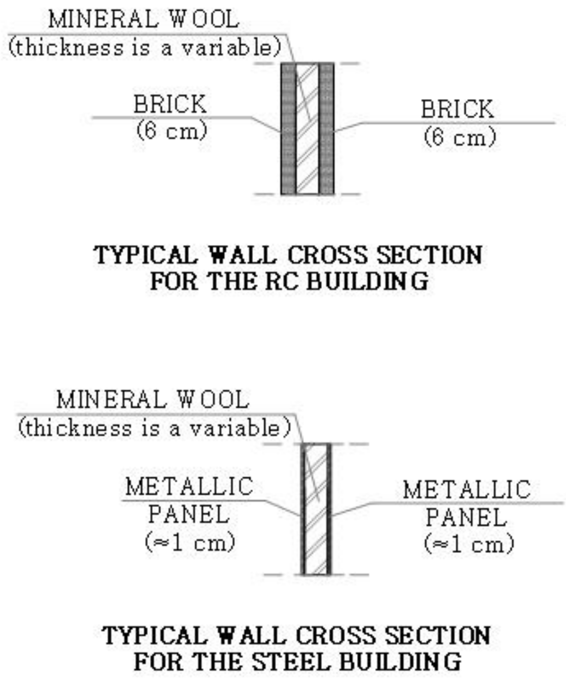


Figure 31: Wall cross sections of the RC and the steel building.

Last but not least, the optimization of the energy design is being performed using the following considerations:

- The calculation of the thermal bridges (which reflect a linearly distributed loss that occurs in junctions between two building surfaces and is estimated in the energy balance of the building) has been carried out using the average measured values of the national standards [117].
- The solar gains during the winter (from October 15th to May 15th) fall out of the total heating load, yet, since they are not exploited to the maximum degree, they are lowered by the introduction of a seasonal utilization factor. During the summer (from May 15th to October 15th),

the solar gains are counted in the total cooling load and area and lowered again by the introduction of a seasonal utilization factor. The solar gains have been specified using the average measured values of the national standards for a certain geographical reference point -the city of Athens in Greece. Both the wall of the building envelope and the windows are considered to be shaded to a known extent, thus a diminishing factor of 50% is set. The wall color is considered to be a nuance of grey [117-8].

- Analyzed life cycle span in years: 20 years.
- Coefficient considering the electricity cost in Euros/kWh = 0.07.
- Cost of the metallic panel profiles (inner and outer layers, subtracting the mineral wool insulation) [95]: 15.7 € per m^2.
- Cost of the brick wall profiles (inner and outer layers, subtracting the mineral wool insulation) [95]: 36.5 € per m^2.
- Cost of the roof profiles (inner and outer layer, subtracting the mineral wool insulation) [95]: 101 € per m^3.
- Cost of the floor slab (inner and outer layer, subtracting the mineral wool insulation) [95]: 101 € per m^3.
- Photovoltaic system cost (€ per kWp): 2933.7 [31].
- When examining the RC building the walls are considered to be a composite material whose outer layer consists of 75% brick and 25% RC. This assessment of ratios is generated in a stochastic way; it is the average (between its lowest and its uppermost expected value) impact of the variation of RC frame on the u-value of a wall profile [117-8].
- Heating Degree days (Geographic reference point: Athens) = *1930 (*Base temperature inside the building: 22 ^oC*)* [9], [117-8].
- Cooling degree days (Geographic reference point: Athens) = *679 (*Base temperature inside the building: 24.5 ^oC*)* [9], [117-8].
- The building is considered to have a lighting system consisted of T5 lamps with its total power to be equal to 1.68 kW.
- Lighting control system cost: 4500 €.

Having made all the relevant settings, it is absolutely meaningful to mention and notice that the office building has an intermittent type of heating and operates for 5 days a week (working week) for 8 hours a day (working hours). That being the case, we culminate in the selection of an appropriate correction factor [9], [117]. Clearly, the correction factors that apply for the RC and the steel building are different, due to the fact that these types of buildings have a different thermal capacity.

OPTIMIZATION PROCESS AND RESULTS

In the current study, the optimization calculations have been performed through the method of simulated annealing. The optimization toolbox of MATLAB has been used to support this approach.

It is meaningful to note that the main option that was made for the optimization procedure was to mainly use the preset configurations of the optimization toolbox of MATLAB. There are some details, though, of major importance: an exponential update of the temperature function occurs, the number of function evaluations stops at a maximum of 150000 iterations and the annealing function used is fast. Every optimization scenario needs to run by using the aforementioned configurations for at least 10 times to make sure that the optimum found at each trial serves as a good and acceptable global solution. The trial results have been contrasted and compared and the best solution generated by each trial -among the optima- is shown in the following paragraphs (Table 1, Table 2, Table 3). The case studies concern a life cycle period of 20 years.

The following conclusions have been reached after assessing the results:

- The total cost of the structural frames for the steel case study amounts to 37633.349 €. With the consideration of the maintenance rates the optimal cost of the structural subproblem rises to 43278.351 €. The optimal structural cost for the RC scenario is equal to 58140.084 € (initial construction cost) or 66861.097 € (construction cost of structural frames and additional maintenance costs). An important remark is that the final reinforcement area of the RC beams does not reflect the initial assumption made by the discrete optimization simulation, due to the fact it is calculated anew under the provisions of Eurocode-2. Nevertheless, it must be emphasized that due to the effect of one of the constraints incorporated into the algorithm it is enforced that the initially assumed reinforcement area by the discrete optimization process would not be surpassed.

- For both scenarios, the optimal total number of elements in the building elevation that is equal to 35 m is 13 and the optimal spacing in the building elevation that is equal to 30m between frames is 7.5 m.
- For both case studies -and given the size of the building- the optimal insulation decision over the examined life cycle span generally is the selection of the lowest possible insulation thickness. The RC building is a comparatively more energy consuming building; therefore, thicker mineral wool insulation is required on several orientations.
- For both scenarios, and as far as the HVAC system is concerned, the most cost-effective solution is that of 6 units with air-conditioning systems of the A-energy class category.
- It seems a natural choice for the program to place the largest total window area on the south elevation (that is, the elevation with the highest amount of solar gains); the placement on the north elevation (that is, the elevation with the lowest amount of solar gains) is a secondary option made by the algorithm. For both case studies, the most cost-effective decision includes double-glazed windows with high g_{gl} values. Such consideration has been formulated by using the nearest neighbor classification to the sample of windows subjected to multiple linear regression.

- For both case studies, the use of a lighting control system does not constitute a cost-effective decision. A photovoltaic array of any peak power does not constitute such a decision either.

Scenarios	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Total life cycle cost (energy design subproblem)
	Ufloor	**Illumination control**	**ggl**	**Awin south**	**Awin north**	**Awin east**	**Awin west**	**Uroof**	**Uwall south**	**Uwall north**	**Uwall east**	**Uwall west**	**Uwin south**	**Uwin north**	**Uwin east**	**Uwin west**	**PV array (kWp)**	**A/C terminals**	**Type of A/C terminal**	
Steel building	0.900	Not needed	0.290	51.926	35.021	10.506	31.723	0.450	0.500	0.500	0.497	0.497	3.400	3.400	3.396	3.400	0.000	6 (six)	SEER :5.30, SCOP : 3.80, P: 3.52 kW	368 046.46 €
RC building	0.900	Not needed	0.290	54.583	46.006	10.801	36.767	0.450	0.500	0.414	0.492	0.367	3.400	3.399	3.399	3.400	0.000	6 (six)	SEER :5.30, SCOP : 3.80, P: 3.52 kW	509 464.95 €

Table 29: Results of the optimization calculations (Energy design subproblem).

Scenarios	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	Number of intermediate frames	**Column 1**	**Beam 1**	**Column 2**	**Beam 2**	**Column 3**	**Beam 3**	**Column 4**	**Beam 4**	**Column 5**	**Beam 5**	**Column 6**	**Beam 6**	**Column 7**
Steel	3	HEM 120	IPE 240	HEM 120	IPE 220	HEM 120	IPE 300	HEM 120	IPE 330	HEM 120	IPE 240	HEM 120	IPE 200	HEM 120
RC	3	350 350 1%	350 550 3%	350 400 2%	350 550 6%	350 400 2%	350 550 4%	350 350 3%	350 550 5%	350 400 2%	350 550 5%	400 400 1%	350 550 5%	350 350 1%

Table 30: Results of the optimization calculations (Structural design subproblem).

Scenarios	15	16	17	18	19	20	21	22	23	24	25	26	27
	Back beam 1	**Back beam 2**	**Back beam 3**	**Back beam 4**	**Back beam 5**	**Back beam 6**	**Back beam 7**	**Front beam length 1**	**Front beam length 2**	**Front beam length 3**	**Front beam length 4**	**Front beam length 5**	**Front beam length 6**
Steel	IPE 180	IPE 180	IPE 180	IPE 200	IPE 200	IPE 200	IPE 180	3.62	6.03	7.24	5.43	5.43	7.24
RC	350 500 1%	350 500 1%	350 500 1%	350 500 1%	350 500 1%	350 500 1%	350 500 1%	6.36	6.36	6.37	7.00	3.82	5.09

Table 31: Results of the optimization calculations (Structural design subproblem).

CONCLUSIONS AND SUGGESTIONS FOR FURTHER INVESTIGATIONS

The thesis has outlined the concepts and the processes that are necessary for the whole life cost analysis and optimization of reinforced concrete, steel and timber buildings, mainly focusing on their structural, their building envelope, mechanical and energy subsystems during their entire life cycle.

The main innovations of thesis are the following:

- Proposing detailed whole life cost optimization models for steel, timber and RC buildings, using a large number of variables. The models were based on the most contemporary design practices used in Greece and can be extended to optimize the design of any new steel, timber or RC building taking into account their components' entire useful life. Therefore, the algorithms that were developed as result of the current project can be a useful tool for practical optimization applications of other Greek or European buildings.

- The thesis has proposed probably the first published optimization attempt coupling the structural design optimization subproblem with the building energy performance subproblem. In general, similar studies have examined a lower number of variables in comparison with the ones examined by the current project. Therefore, the thesis is one of the very few studies (if not the only one) taking into account a rather large number of variables.
- The thesis has proposed a reasonable model for the structural optimization of a rectangular building (therefore a building with a very usual form) considering both its smaller and its larger dimension. Due to its complexity, it is an optimization process that is very rarely encountered in similar studies.
- The thesis was probably the first one to propose a holistic practical application for the optimization of the energy performance of buildings according to KENAK.
- The project has presented reasonable methods to deal with the uncertainty and fuzziness of various variables with which the design of a building is affected.
- Concentration and concise presentation of methods and useful concepts from many different disciplines that directly relate to the design of buildings (energy engineering, structural engineering, life cycle engineering, optimization theory, machine learning, statistics and analytics, fuzzy analysis) or can be used to improve design decisions.
- The cost functions that were proposed by the developed models can also be used for the evaluation of other different design scenarios, including the usage of different materials. Due to the high R^2 and Multiple-R values attained, the cost functions can serve as a way to avoid the computational complexity of a simulation based on discrete optimization.

All in all, in the models developed in the thesis structural and energy optimization including life cycle cost considerations are combined and solved with practical global optimization algorithms (simulated annealing and genetic algorithms). It must be emphasized that the complexity of the models restricts the applicability of classical, local numerical optimization algorithms. Evidently, the use of other sophisticated optimization algorithms (e.g. Differential Evolution, ABC, PSO, Firefly Algorithm, Harmony Search, Shuffled Frog Leaping Algorithm, Hybrid Algorithms) [96] is a rational potential future research effort that would result in comparisons regarding the efficiency of each optimization technique.

Further investigations could take into account additional factors that potentially influence the LCA and the structural optimization results, like the labour and the plant costs, costs related to the painting of the cross sections costs related to landscaping design decisions etc. Moreover, due to the flexibility of the derivative-free, global optimization algorithms used, additional cost parameters, building subsystems, criteria or restrictions can be introduced. Some examples of parameters that could be considered are the following:

- Modeling of subsystems such as: heat recovery systems, BEMS, trombe walls, thermal energy storage techniques, solar greenhouses, geothermal heat pumps, color of walls, cool roofs. The procedures to simulate such subsystems are concisely described in KENAK [117-8].
- Potential constraints related to the effects of moisture and restrict the use of various insulations profiles in various geographic locations. Similarly, there are nationally or internationally acceptable practices that can be used to model this consideration.

Another suggestion for future investigations that could be made is the optimization of buildings with a larger number of storeys. The developed algorithms for both the energy and the structural design subproblem require only small modifications to attain this purpose. The most important additional consideration that has to be made in the modeling is the effect of the larger axial load applied on the columns of the lower floors.

As regards the simulation of the energy balance of a model building, the use of fluid and thermal dynamics is also possible (or equivalent surrogate models based on e.g. regressions, neural networks etc.) and could be considered in future research efforts.

Despite the fact that the structural analysis accuracy level attained in the study is considered to be appropriate, a potential improvement could take place by using general purpose, three-dimensional and nonlinear finite element modeling, although the expected gains will be marginal.

Another proposal for further research could be the use of Artificial Intelligence or machine learning techniques and expert systems, as a means to predict optima in optimization problems of similar nature. Evidently, this would presuppose the construction of a database of many different optimized building case studies and the algorithms developed in the project could be used for this pursuit with merely slight modifications.

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