MODELING ENERGY CONSUMPTION OF A TYPICAL RESIDENTIAL BUILDING USING EXPERIMENTAL DESIGN

Master's Thesis

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Una Smailbegovic

Examiner(s): D.Sc. (Eng.) Antti Häkkinen, Prof. Dr. Edin Kadric, Prof. Dr.-Ing. Tobias M. Fieback

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Supervisor / scientific member (HU):	Prof. Dr. Edin Kadrić
Supervisor / scientific member (LUT):	D.Sc. (Eng.) Antti Häkkinen
Supervisor / scientific member (TU BAF):	Prof. Dr.-Ing. Tobias M. Fieback

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Prof. Dr. Edin Kadrić	D.Sc. (Eng.) Antti Häkkinen	Prof. Dr.-Ing. Tobias M. Fieback
Supervisor / member HU	Supervisor / member LUT	Supervisor / member TUBAF

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ABSTRACT

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LUT School of Engineering Science

International Master's Program of Science in Engineering, Entrepreneurship and Resources

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Modelling energy consumption of a typical residential building using experimental design

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Examiner(s): Prof. Antti Häkkinen, Prof. Dr. Edin Kadric, Prof. Dr.-Ing. Tobias M. Fieback

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Globally, energy consumption of building sector is enormously high. In Bosnia and Herzegovina, residential sector consumes 59% of the total energy consumption, mainly for heating. B&H is a middle-income country with high heating demands caused by climate conditions and poor energy related properties of the residential building sector.

Therefore, the purpose of this master's thesis is analysis energy consumption of the one selected typical residential building from B&H residential stock and developing mathematical model prediction heating demand. Observed residential building is located in Sarajevo, capital city of B&H and is classified as apartment block built-in period of 1960-1970.

Energy properties selected as relevant for this analysis are external wall heat transfer coefficient, roof heat transfer coefficient, glazing type and efficiency of heating system.

Design Builder is used for modeling selected building, considering architectural, constructional, HVAC system, climate condition, occupant and electrical equipment schedules. EnergyPlus, simulation engine, integrated in Design Builder, is applied for performing dynamic simulations using hourly weather data.

Fluctuations in energy consumption due to influencing factor variations were analyzed using the Design of Experiment method. Mathematical model for predicting energy demand is developed with Minitab, with focus on savings in heating demand and heating carbon footprint. Additionally, annual heating carbon emissions are calculated.

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Symbols and abbreviations

Roman characters

p	pressure	[bar, Pa]
T	temperature	[ºC, K]
U	transmission coefficient	[W/m^2 K]
R	thermal resistance	[m^{2}K/W]
A	area	[m^2]
$Q_{H,nd}$	specific annual required energy for heating	[kWh/m^2]
$Q_{H,del}$	specific annual delivered energy for heating	[kWh/m^2]
$E_{H,CO2}$	annual heating carbon emissions	[t]
e_{co2}	carbon emission factor	[kgCO_2/kWh]

Greek characters

α	significance level	[-]
λ	thermal conductivity	[W/mK]
η_{sys}	system efficiency	[-]
δ	material thickness	[m]

Abbreviations

B&H	Bosnia and Herzegovina
EU	European Union
HVAC	Heating, ventilation and air conditioning
DOE	Design of Experiment
ANOVA	Analysis of Variance
EE	Energy Eficiency
RSM	Response Surface Method
FFD	Full Factorial Design
BBD	Box-Behnken Design
CCD	Central Composite Design

GDP	Gross Domestic Product
ML	Machine Learning
OFAT	One Factor at Time
SS	Sum of Squares
MSS	Mean Sum of Squares
DF	Degrees of Freedom
VIF	Variance Inflation Factor
AB	Apartment Block
SHGC	Solar Heat Gain Coefficient
XPS	Extruded Polystyrene
EPS	Expanded Polystyrene
TABULA	Typology Approach of Building Stock for Energy Efficiency Assessment

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1. Introduction

Rising energy consumption of residential buildings is a symbiosis of different socio-economic, geographical, physical, technical, and human-influenced factors. Due to increased human population and improved quality of life, at the global level, building energy consumption and carbon emission are recently significantly increased (Cao et al., 2016, 2016; Pérez-Lombard et al., 2008). In addition to the increasing scarcity of traditional energy sources, the issue of the global warming has been present for years and its consequences are manifesting exponentially, leaving an indelible mark on the environment.

To overcome this challenging issue, the most feasible solution is to increase the efficiency of energy use and to decrease the energy consumption in buildings by improving the energy characteristics of the constructional sector. Bosnia and Herzegovina, as a medium economic level country with high heating demands caused by climate conditions and poor energy related properties of the residential building sector, should avoid further increases in energy consumption and increase the electrification ratio (Guo et al., 2020). Accordingly, in B&H, insufficient attention has been paid to research into energy efficiency improvement measures and sustainable development. As a consequence of inadequate energy policies, according to WHO, Bosnia and Herzegovina is the third in the world by deaths caused by air pollution (*Air quality and health*, 2018). B&H, as a country in transition, has two main challenges related to further sustainable development: replacing traditional with renewable energy sources and more efficient use of energy.

As it is present on figure 1.1, in B&H is energy consumed by residential sector is 18.44% higher than consumption in EU. Therefore, the huge potential is hidden in improving the performance of buildings. Approximately 72% of the total energy use in residential sector is used for heating (Kadrić et al., 2022).

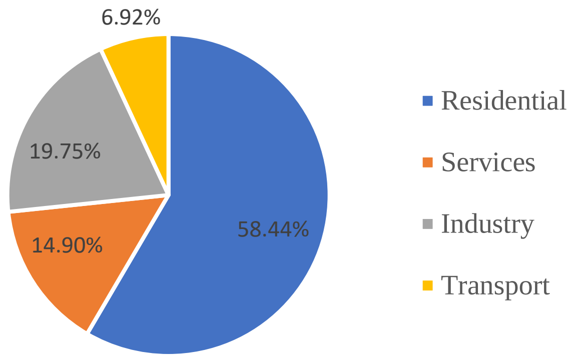


Figure 1.1. Energy consumption per sector in B&H, 2010 (*Energy efficiency action plan of Bosnia and Herzegovina for the period 2016 - 2018*, 2017)

The main purpose of this master's thesis is an analysis of the energy properties of the selected typical residential building from B&H residential stock, for building energy properties ranging from poor to advanced. Energy properties selected as relevant for this analysis are heat transfer coefficient of the building envelope, glazing type and efficiency of the district heating system. Mathematical model for estimation of annual energy demand of selected typical residential building in B&H is developed to analyze how particular energy properties and their correlation influence energy consumption. Observed residential building is located in Sarajevo, capital city of B&H. To analyze influence of different values of building energy properties on energy consumption, building model is created in Design Builder v.6.1.0.006 software [1], graphical user interface. Energy Plus v.8.9[2] is integrated within Design Builder and it is engine applied for performing dynamic simulations. Model is containing relevant information related to climate condition, building construction and architecture, HVAC system, occupant activities and installed equipment.

Statistics is essential and unavoidable tool utilized in analyzing the experimentally obtained data (Antony, 2014). Design of Experiments (DOE) is powerful and often underestimated advanced statistical method and refers to the process of planning experiment and analyzing experiments' results, in order to reach conclusions effectively and efficiently (Jiju, 2014). Given the unbreakable bond between statistics and engineering, changes in energy consumption due

[1] Available at https://designbuilder.co.uk/
[2] Available at https://energyplus.net/

to influencing factor variations were analyzed using the DOE method, used to generate mathematical model in Minitab® v.19.2020.1[3]. Hence, heating carbon footprint is calculated.

In the literature review, insight in related research articles is provided and compared with methodology used in this master's thesis. Since there is noticeable gap in literature related to energy performance of buildings in B&H, this master's thesis emphasizes the undetected research potential of this topic. Chapter 3 is theoretical introduction to DOE, applied statistic method for developing mathematical model. Focus of the chapter 4 is on understanding the thermodynamic laws and quantities that are required to calculate the energy demand in buildings. Architectural, constructional and energy characteristics of the selected building are described in chapter 5, as well as motivation for selecting analyzed residential building. Finally in chapter 6 simulation results are presented, mathematical model for predicting heating energy consumption is developed, and model validation is performed.

[3] Available at https://www.minitab.com/en-us/

2. Literature review

The first conceptualization of DOE was introduced in 1920s by statistician Sir Ronald Fischer (Fisher, 1971; Jiju, 2014; Shina, 2022). Sir Ronald Fischer utilized these statistical methods for investigating influence of the rain on crop growth. In 1925, his conclusions have been summed up in the work 'Statistical Methods for Research Workers', which was subsequently published in nine editions (Fisher, 1971). Another example of interesting application of DOE is found in the World War II, when the United States Naval Experimentation Laboratory investigated the cause of poor-quality welds on shipyards (Astakhov, 2012).

Edward Deming, a well-known engineer, statistician and father of quality management, educated the Japanese about statistical methods, including DOE, and helped raising Japanese production to the top. Japanese scientist and engineer Genichi Taguchi developed characteristic DOE method known as Taguchi design and applied it to improve Toyota production system. After establishment of Six Sigma concept, and the globally acceptance of these methodologies, DOE is characterized as advanced statistic method and it is utilized in remarkable companies as Motorola and General Electric (Astakhov, 2012).

Nowadays, DOE has a wide range of applications that have gone beyond scientific research. Practical example of utilizing this powerful statistic tool is finding optimal design of the letter envelope in order to boost the response rate, performed by credit card company in the United States (Astakhov, 2012). Importance of this method is recognized by psychologists, and it is used in marketing to examine customer's behavior and sales prediction (Muir, 2010).

Antony emphasizes incontrovertible advantage of utilizing DOE in research work, as well as industry. The widely accepted One-Factor-at-Time (OFAT) principle is time-consuming, requires a lot of resources to perform and can lead to misleading conclusions, due to the fact it does not analyze the dependence of the investigated factors. Although primary designed for agriculture, it has found application in all departments of scientific research. Zhang et al., (2022) utilized DOE to enhance performance of lithium-ion batteries management system. Furthermore, this statistical method is widely used in pharmaceutical industry (N. Politis et al., 2017) and optimizing chemical processes, aimed to satisfy requirements of circular and green chemistry and utilize resources and energy more efficient (Huhtanen, 2012; Lamberti et al., 2022; Taylor et al., 2020). Another important factor pertaining the reduction of the number of experiments is decreasing the utilization of critical raw materials.

Researchers and the manufacturing industry have recently made significant investments in developing smart home solutions and zero net building design. In literature, the issue of predicting energy consumption in housing units has been tackled generally in two ways: using machine learning (ML) algorithms (Elbeltagi and Wefki, 2021; Kalogirou et al., 2018; Liu et al., 2021; Martellotta et al., 2017; Olu-Ajayi et al., 2022) and the less represented, using advanced statistics methods (García-Cuadrado et al., 2022; Jankovic et al., 2021; Li et al., 2021; Liu et al., 2019; Sadeghifam et al., 2015). Data is collected with simulation software or using existing data sets.

Although ML algorithms are widely applied for analyzing data, forecasting and pattern discovering, large number of information is required for developing reliable model. However, obtaining large datasets can be time-consuming, uneconomic and in some cases, impossible to perform. In contrast to conventical statistical methods, DOE is advanced statistical approach whose application contributes to significant conclusions, observing reduced amount of data. When a specific case of simulations of a building's energy consumption is considered, reducing the number of required experiments significantly simplifies research. However, DOE requires developing comprehensive plan before conducting experiments. Phases of applying DOE method for analyzing energy consumption data obtained with simulation software according to (García-Cuadrado et al., 2022) are presented in figure 2.1.

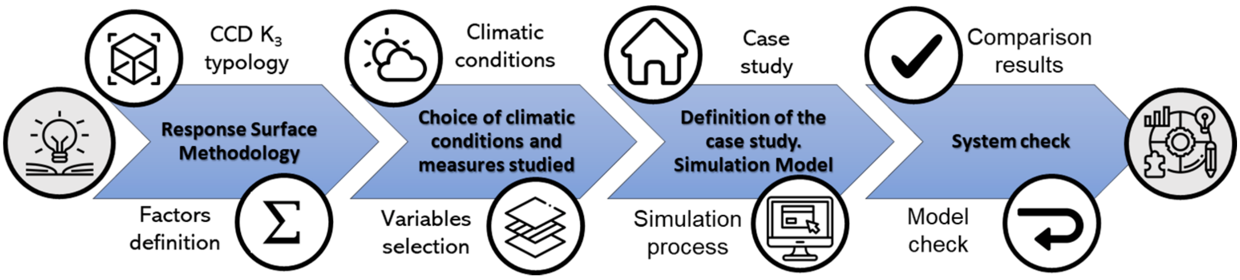


Figure 2.1. Phases of experimental program (García-Cuadrado et al., 2022)

However, there are not many examples in the literature of the cohesive use of DOE with simulation software to predict the energy performance of a building. Given that, collaborative employment of DOE and dynamic energy simulation software is innovative approach and deserves more attention in research related to improving energy efficiency of construction sector.

Jankovic et al., (2021) have analyzed double skin facade (DSF) applying different DOEs in case of four different ventilation modes. On figure 2.2, example of determining experiment numbers for applied DOEs are presented. Significance of this research is the diversity of applied DOE models and therefore, it provides inside into DOE methods and their performance, as well as recommendation for selection of the suitable DOE. On this case study, Full Factorial Design, Screening Design, Taguchi Multilevel Design, Central Composite and Box-Behnken Design have been performed. Examined factors are indoor and outdoor temperature difference, solar radiation, angle of a venetian blinds, infiltration rate, glazing and blinds. In conclusion, Central Composite Design is the most suitable for this study-case.

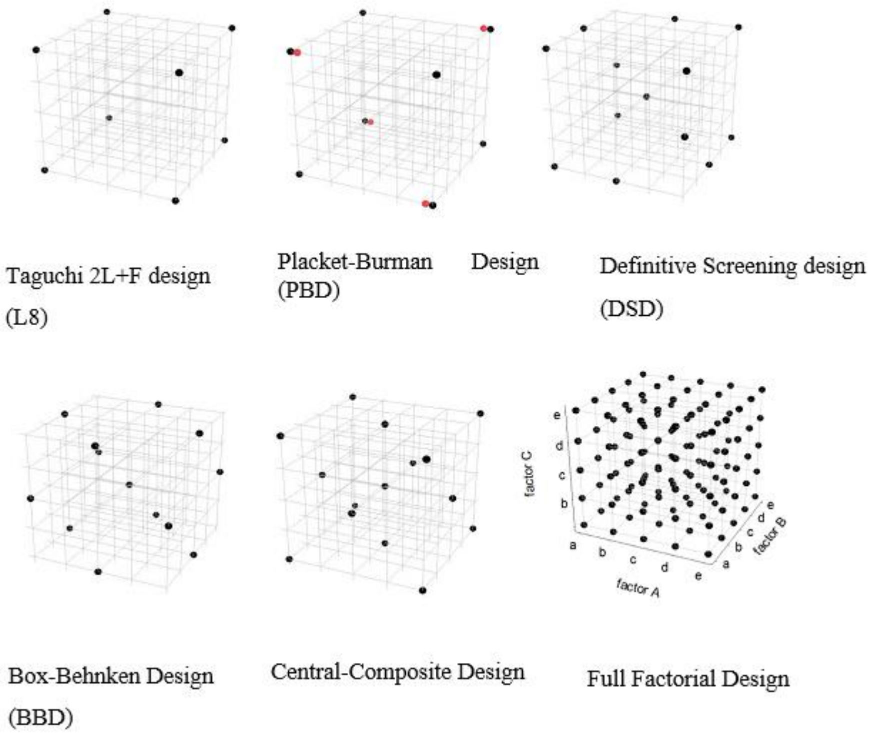


Figure 2.2. Different DOE methods for 3 factors varied on 2 levels (Jankovic et al., 2021). Black dots represent planned experiments with applied DOE method and red dots repeated experiments

In their research, Sadeghifam et al., (2015) used EnergyPlus simulations results to analyze the effect of buildings' characteristics and designed temperature on cooling energy loads in residential buildings located in Kuala Lumpur. Given the characteristics of the climate in which the building is positioned, and HVAC system is installed, the biggest energy consumer is air conditioning systems. In summary, the highest impact on observed model has ceiling construction, followed by the wall construction and designed temperature. Contrary to what was expected, the analysis showed that the windows have no influence on the energy required for cooling.

Since China is a great contributor to world’s energy demand (Zheng and Wei, 2019), analysis of this problem is widely represented in the literature. (Liu et al., 2019) presented analysis of o energy performance of the public building in China with Orthogonal Experimental Design. For model validation, obtained data are compared with actual building annual energy consumption and error is 4,1%. In conclusion, the highest influence has airtightness of outer window, followed by window- wall ratio, *U* coefficient of window, SHGC of windows, *U* coefficient of wall , and at the end, *U* coefficient of the roof. Authors have proposed optimal values to achieve the lowest energy demand. Due to fluctuating climate conditions in China, importance of including weather data in energy demand calculation is emphasized.

Perceiving problem of ineffective and time consuming energy demand forecasting, in their research García-Cuadrado et al., (2022) and (Li et al., 2021) employed RSM for optimizing energy characteristics combined with EnergyPlus for obtaining data. García-Cuadrado et al., (2022) analyzed typical single-family house located in three different climate types: Mediterranean hot summer climate, Oceanic climate, and Humid continental climate. This research, as well as research conducted by Liu et al., (2019), confirm the influence of climatic conditions on energy demand calculation. Heating set point, cooling set point and *U* coefficient of outer wall have been varied on three levels and fifteen experiments were performed for every climate type.

Analysis demonstrated that in Europe, heating is the most energy-intensive process. Hence, it has been proven that the building envelope contributes to approximately 75% of a building's energy losses.

The focus of study written by (Li et al., 2021) is using RSM for proposing optimal values for analyzed factors, to satisfy thermal comfort in public building in China, with lower energy consumption. After applying Fractional Factorial Design, it is found that insulation thickness, *U* coefficient of the roof and windows-wall ratio are the most significant factor. After optimizing announced factors, 4% energy savings has been accomplished.

Above mentioned examples demonstrated an advantage of collaborative use of DOE and dynamic simulations. Therefore, it is an accurate, time-efficient, reliable way of determining energy demand in building and construction sector. Hence, described examples from literature have shown that there is no unique model that can be applied to all buildings. Influencing factors differ significantly depending on the construction characteristics of the object, its purpose and location. Climate conditions are an important factor affecting energy demand, and the reliability of the model depends on the accuracy of the outdoor temperature data applied for calculation.

Also, selection of the optimal DOE relies on the experiment objective and the amount of available data.

To emphasize the significance and consequences of increasing energy performance of residential buildings in B&H, this master thesis aims to analyze the impact of renovation measures on the heating demand in the apartment building block, that belong to the period of construction from 1960 to 1970, according to Building Typology (Arnautović-Aksić et al., 2016). There is a noticeable gap in the literature related to forecasting building energy consumption in B&H and the focus of this thesis is to build a bridge between world trends and the current situation in the Western Balkans. Considering that B&H is a country that has applied for a membership in the European Union and that energy sustainability and decarbonization are important factors that can accelerate this procedure, building renovation strategies by 2050 have been proposed.

Kadrić et al., (2022) in their study provide analysis of the costs associated with implementing improvement measures in the building sector in B&H. Four levels of restauration measures are proposed, from basic to advanced. The analysis showed that citizens of Bosnia and Herzegovina have four times less financial resources for the implementation of rehabilitation measures compared to EU countries, as it is presented on figure 2.3.

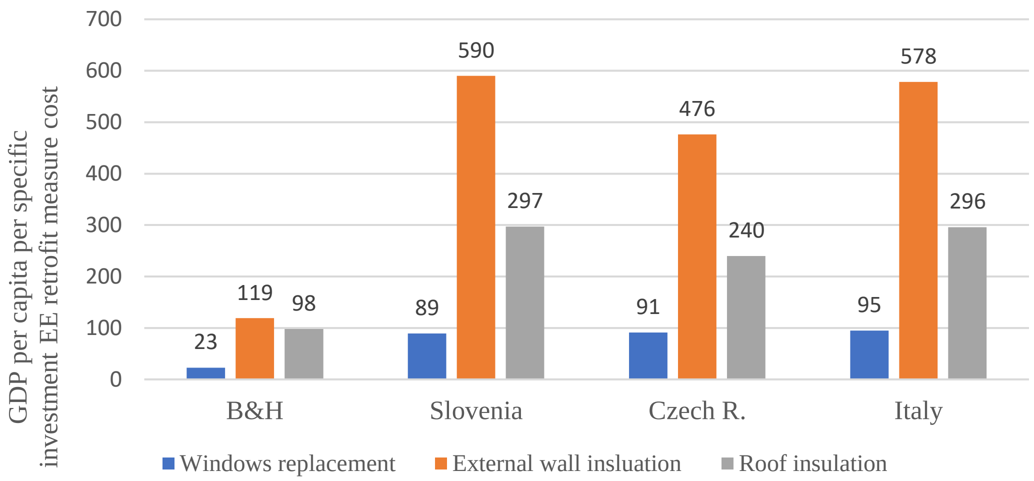


Figure 2.3. Ratio of the GDP/capita to improvement measure cost for B&H, in comparison with Slovenia, Czech Republic, and Italy (Kadrić et al., 2022).

According to Kadrić et al., (2022), apartment blocks in B&H can reduce energy consumption from 40%, when implementing basic restoration measures to 77% for the most advanced improvements.

Arnautović-Aksić et al., (2016) in their comprehensive analysis of residential stock in B&H, for residential building selected in this master's thesis proposed two level of improvements. Improvement measures are adding wall(10cm and 20cm) and roof (20 cm and 30 cm) insulation windows replacement (double and triple glazing), heating system improvements.

Accordingly, energy demand and carbon footprint of analyzed building for above mention cases are shown on figure 2.4. Guidelines for calculation was valid legal regulation in B&H. Quasi-stationary monthly calculation are performed, based on EN ISO 13790. As it can be seen from figure 2.4, 69% energy can be saved with implementing improvement 1 and 81% with improvement 2.

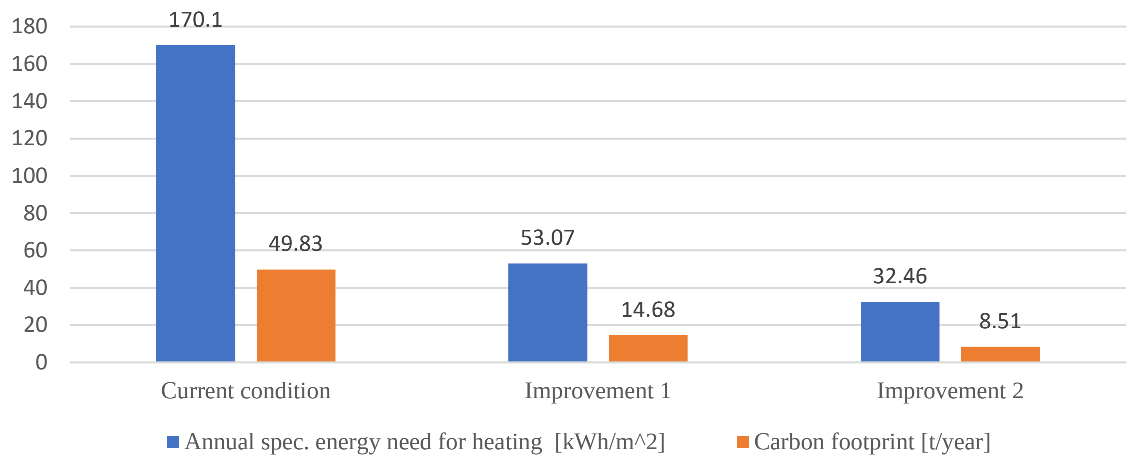


Figure 2.4. Annual specific heating demand and carbon footprint of the selected residential building, for current and improved condition, according to Arnautović-Aksić et al., (2016)

Although research regarding building energy performance in B&H has been performed, the methods used are not precise enough and there are deviations from the actual energy consumption data. Therefore, in this master's thesis, EnergyPlus, as a more precise software for obtaining data, is used for simulations and calculations are performed hourly. As announced examples in literature have confirmed, DOE is reliable method for energy analysis and therefore, in this master's thesis, it is used for developing mathematical model for predicting heating demand, based on hourly weather data, in selected residential building in B&H.

3. Design of Experiments

Experiments are applied to analyze a cause-and-effect relationship and acquire information about process. Developing a set of techniques, procedures and methods to test a hypothesis systematically is referred as experimental design (Antony et al., 2017). Conventionally, dependent variable fluctuations, caused by variation of the independent process variables, are observed. Basically said, process is an established order of the predefined operations, aimed to transform inputs into outputs (Antony, 2014).

Widely represented experimental methodology of varying one factor per experiment is inefficient, uneconomic, and does not include analysis of interactions among variables. DOE is alternative to OFAT approach and refers to the process of planning the experiment, creating experiment schedule and analyzing experimentally obtained data, in order to reach pragmatic conclusions based on reduced amount of data (Antony et al., 2017; Fisher, 1971; Jiju, 2014).

To avoid any misunderstanding, it is necessary to define terminology related to DOE methodology used in this study. In the DOE methodology, response variable is measured output. Controllable input variables are defined as factors and they can be qualitative or quantitative. (Siebertz et al., 2010). For instance, glazing can be single, double, or triple and it is qualitative variable, but *U*-coefficient can take any value in physically reasonable range, and it is quantitative variable. Levels are specific values of factors used in experiments, selected to cover entire range of possible values of factor, and they are presented as coded value. High level is presented as +1, medium as 0, and low level as -1 (Jiju, 2014; Siebertz et al., 2010). Experimental matrix is arrangement of methodically varied levels of examined factors and gives instructions on the order in which individual experiments are performed. Each combination of factors in experimental matrix is called treatment (Montgomery, 2013).

In cases where relationship between response and factors is assumed to be linear, models with factors varied at two levels are sufficient (Huhtanen, 2012). For instance, Full Factorial and Fractional Factorial Design can be used to analyse linear relationship between factors and response (Jankovic et al., 2021). Even though Full Factorial Design analyses process comprehensively, if high number of factors is include in analysis, the number of required experiments increases exponentially, and the Fractional Factorial Design is recommended for simplification (Jiju, 2014). Fractional Factorial Design is modified version of the Full Factorial Design that requires only specified subgroup of original experiments to be performed. In the figure 3.1, difference in the number of experiments for performing above described method is shown (Jankovic et al., 2021).

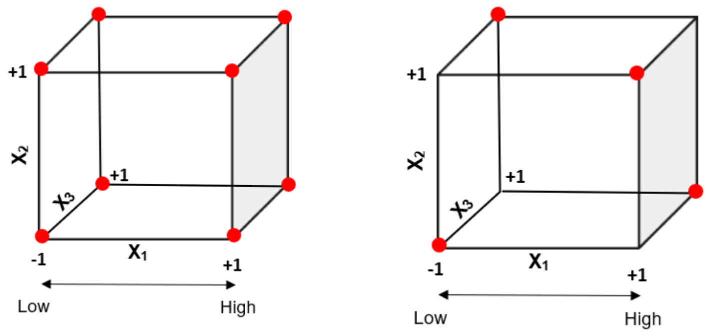


Figure 3.1. Difference between Full (left) 2^3 and Fractional 2^{3-1} Factorial (right) Design (Montgomery, 2013)

Taguchi Design is a standardized approach for determination of the best factor values combination to produce a product or service (Huhtanen, 2012). Taguchi design significantly reduces number of experiments, and it is intended for use in industry to minimize costs (Jankovic et al., 2021). In cases where relationship between response and factors is assumed to be non-linear, models with factors varied at minimum three levels are required. Box-Behnken (BBD) and Central Composite design (CCD), most common RSM, are used to optimize response (Jankovic et al., 2021). Typically, BBD and CCD are employed for reduced number of factors, after screening methods have identified important factors (Huhtanen, 2012).

A well-planned, successfully performed and extensively analyzed experiment contributes to process optimization and detection of the problems in industry and research field. Additionally, it can be utilized to build a mathematical model for prediction of process behavior, reduce costs, optimize process time, and increase capacity. Establishment of a detailed plan is essential for the successful and efficient implementation of the experiment (Jiju, 2014). Process of experiment planning follows typical procedure: problem definition, selection of the response variable, factors, and suitable levels, and according to objective of experiment and given factors, selection of the suitable DOE. Subsequently, the experiments are performed in the order indicated in the experiment matrix, responses are measured and finally, mathematical model is developed (FFD) the optimal values of the variables are determined (RSM). Data analysis is consisted of determining the most influential factors, interactions between factors, development of a mathematical model and verification of model adequacy, applying established statistical tests (Dean et al., 2017; Jiju, 2014; Montgomery, 2013).

A systematically developed plan and the process understanding is essential for the experiment conduction and obtaining relevant information about considered process. Even though many DOE methods have been developed, the optimal method has to be selected.

3.1. Full Factorial Design

Aim of this master's thesis is creating the mathematical model for estimation of annual energy consumption in selected building. Four influencing factors are examined: *U* coefficient of the external walls and roof, glazing and efficiency of the district heating system. Since linear relationship is assumed, two levels of factors are considered, low (-1) and high (+1) level. Considering the relatively small number of factors, FFD is selected.

Calculation of the number of experiments (*n*), when *k* factors are varied on two levels in the FFD is given by:

$$n = 2^k \tag{3.1}$$

According to 3.1, the number of performed experiments in this research is sixteen.

Hence, model that quantitatively describes the process, individual and interaction effect of factors, has to be developed. Main effect of the factor is a difference in the main response value (y) when the factor (x_i) is varied from lowest (-1) to highest $(+1)$ value (Montgomery, 2013). Consequently, the greater the difference between response value when the factor is varied, the greater the influence of the analyzed factor on the measured response. This method is called the contrast method (Siebertz et al., 2010).

Expected regression model for estimation of the response, considering four analysed factors, is given by:

$$\begin{aligned} y \; = \; & \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 + \beta_7 x_1 x_4 \\ & + \beta_8 x_2 x_3 + \beta_9 x_2 x_4 + \beta_{10} x_3 x_4 + \beta_{11} x_2 x_3 x_4 + \beta_{12} x_1 x_2 x_4 \\ & + \beta_{13} x_1 x_3 x_4 + \beta_{14} x_1 x_2 x_3 x_4 \; + \; \epsilon \end{aligned} \tag{3.2}$$

Where:

y – response variable

$\beta_0 -$ intercept

$(\beta_{1,}\beta_{2,}\ldots\beta_{14,}) -$ regression coefficients,

$x_1, x_2, x_3, x_4 -$ analysed factors

$\epsilon -$ normally distributed random error component $\epsilon \in N(0, \sigma)$.

Model defined by (3.2) contains intercept, linear component, two-way, three-way, and four-way interaction components and random, normally distributed error. Depending on the estimated statistical significance of terms in (3.2), statistically insignificant may be excluded from equation. If certain terms are excluded from (3.2), then the new model is called reduced model. Regression coefficients $(\beta_{1,}\beta_{2,}\ldots\beta_{14,})$ are calculated as a half of the corresponding factor's effect and intercept β_0 is grand average of the all observations. Graphic representation of (3.2) is plane called response surface plot (Montgomery, 2013).

Validation is an essential step in DOE and development of reliable and accurate mathematical model. Further explanation of model adequacy testing is given in chapter 3.3.

3.2. Analysis of Variance

In mathematical model development, the main objective is to identify factors with greatest influence on the process response. Beside effect calculation, it is important to estimate statistical significance of factors, using Analysis of Variance (ANOVA). One-way ANOVA is a statistical methodology that evaluates two mutually exclusive hypothesis about two or more population means. Without ANOVA, the model cannot be accepted.

Statistical hypothesis is statement about population that can be accepted or rejected, after applying statistical tests (Montgomery, 2013). At the beginning of the testing procedure, two types of hypotheses are developed; null hypothesis (H_0), which assumes the correctness of the formulated statement, and alternative (H_1), which assumes deviations from the basic statement (Kolesaric and Tomasevic-Humer, 2016). Probability of rejecting null hypothesis when it is true is significance level (α) of the test.

When FFD effect model, defined by (3.2), is considered, null hypothesis assumes invariance of the process response with varying factor levels. Hence, analyzed factor is not statistically significant. Alternative hypothesis assumes there is at least one exception from previous statement. Accordingly, similar hypothesis is constructed for factor's interactions.

The lowest level of significance (α) that results in the rejection of the null hypothesis is defined as p value (Dean et al., 2017; Kolesaric and Tomasevic-Humer, 2016; Montgomery, 2013). The most convenient statistical procedure for testing statistical significance of factor is ANOVA. To analyze variability of the process with two factors, sum of squares (SS) and mean squares (MS) are defined. Additionally, Fischer's test, statistical test that compares MS of examined factors and model error, is performed for testing factor significance. Let it be assumed that there are two factors *A* and *B* whose influence on the process is analyzed. Examined factors are varied on total of a, b levels, respectively and n experiments are performed with m replicates. Replicates are repeated treatments performed to reduce the influence of non-controlling variables. Since in this master's thesis simulation software is used for obtaining data, replications are not performed.

SS is square of the differences between each experiment treatment response and overall mean response (Montgomery, 2013).

$$SS_{total} = \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{n}\left(y_{ijk} - \bar{y}\right)^2 =$$
$$= bm\sum_{i=1}^{a}(\bar{y}_i - \bar{y})^2 + am\sum_{i=1}^{b}\left(\bar{y}_j - \bar{y}\right)^2 + m\sum_{i=1}^{a}\sum_{j=1}^{b}\left(\bar{y}_{ij} - \bar{y}_i - \bar{y}_j + \bar{y}\right)^2 + \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{m}\left(y_{ijk} - \bar{y}_{ij}\right)^2, \tag{3.3}$$

Where:
$a, b -$ level of factors A and B, correspondingly, ($i = 1..a, j = 1..b$)
$m -$ number of replicates, ($k = 1..m$)
$\bar{y} -$ overall mean value

As it can be seen from (3.3), total SS is consisted of four parts. Therefore, (3.3) can be written in abbreviated form given by:

$$SS_{\ total} = SS_A + SS_B + SS_{AB} + SS_E \tag{3.4}$$

The first and second terms in (3.3) and (3.4) are a sum of the squares of the differences between the individual experiment averages and the overall mean, for *A* and *B* factors, separately. Third term of the (3.4) is sum of squares of differences between interaction effect of factors in individual experiment averages and the overall mean and the last part is sum of squares of the differences of observations within treatments and the treatment average (Montgomery, 2013). The first, second and third terms are variations due to factor influence on the process response, and the last term represents variation that occurs due to random error in the experiment (Montgomery, 2013).

Mean square (MS) of the source of variation is defined as ratio of the sum of square and corresponding degrees of freedom (Montgomery, 2013) For MS calculation, degrees of freedom (DF), as number of independent variables, are listed in table 3.1.

Table 3.1. Degrees of freedom

Source of variation	Part of equation	Degrees of freedom
A	SS_A	$a-1$
B	SS_B	$b-1$
AB	SS_{AB}	$(a-1)(b-1)$
Error ϵ	SS_E	$ab\,(n-1)$
Total	$SS_{\,total}$	$abn-1$

Equation used for estimation of the MS of individual factor effect, interaction factor effect and model error, respectively, is given by:

$$MS_A = \frac{SS_A}{a-1};\ MS_B = \frac{SS_B}{b-1}\ ;\ MS_{AB} = \frac{SS_A}{(a-1)(b-1)};MS_E = \frac{SS_E}{ab(n-1)} \tag{3.5}$$

Since the focus is to determine whether the variability is caused by the effect of factors on the process or a random error, MS of factors is compared to MS of the error, and the ratio of these two values is defined as F-value. F-test is used for testing factor significance. Therefore, high F-value indicates rejection of the null hypothesis and F-factor around 1 leads to hypothesis acceptance (Dean et al., 2017).

$$F_{oA} = \frac{MS_A}{MS_E}\ ;\ F_{oB} = \frac{MS_B}{MS_E}\ ;\ F_{oAB} = \frac{MS_{AB}}{MS_E} \tag{3.6}$$

If normal distribution with constant variance of model error is assumed, each ratio listed in (3.6) is following the F distribution, where numerator has $(a-1), (b-1), (a-1)(b-1)$ degrees of freedom, respectively, and denominator $ab(n-1)$. The critical value above which the null hypothesis is not accepted, is obtained from statistical tables for *F* distribution, considering DF of nominator and denominator (Montgomery, 2013).

P-value, given in the ANOVA table, is the easiest and most frequently used metric for the determination of the acceptability of the null hypothesis. If calculated p value is smaller than pre-defined significance level α, the influence of the analyzed factor cannot be neglected, and the null hypothesis is rejected (Kolesaric and Tomasevic-Humer, 2016). Otherwise, null hypothesis is accepted.

T-test is the most common statistical test used for determination whether factor is significant for analyzed model. If obtained t-value is exceeding critical value from the t-distribution for the corresponding degrees of freedom, number of observations in sample and significance level, null hypothesis is rejected.

The Variance Inflation Factor (VIF) is statistical measure that is used to measure the multicollinearity in regression analysis and the most desirable value is around 1. If multicollinearity is high, the model cannot be accepted.

3.3. Verification of model adequacy

After experiments are conducted and mathematical model is developed, model validity check must be performed to determine whether developed mathematical model can be accepted.

Since factors are varied on two levels, linear model is developed and therefore the adequacy of the selected model must be checked. When analyzing process, it is assumed that model random errors are following normal distribution ,$\epsilon_{ijk} \in N(0, \sigma)$. In addition, it is assumed that residuals are independent and have constant variance at every level of factor. Therefore, homoscedasticity, normality, linearity, and independence of residuals must be confirmed. If one of the listed assumptions is incorrect, the model cannot be accepted.

For the model with 2 analyzed factors *A* and *B*, with total of *a* and *b* levels, correspondingly, and *m* replicas, residuals can be estimated using following equation.

$$e_{ijk} = y_{ijk} - \hat{y}_{ijk} \tag{3.7}$$

Where:

$\hat{y}_{ijk}$ – overall mean

$e -$ model residual (error)

$i -$ level of factor A, $i\epsilon(1..a)$

$j -$ level of factor B, $j\epsilon(1..b)$

$k -$ replicant order $k\epsilon(1..m)$

The standardized residual equals the value of a residual divided by the square root of MS of the error (Shina, 2022).

Normality is usually examined with Anderson-Darling (AD) test. Null hypothesis assumes that all residuals follow normal distribution. Accordingly alternative hypothesis claims that data are not normally distributed. If the obtained p value is higher than the defined α, the null hypothesis is confirmed, and it is concluded that the model residuals follow a normal distribution. If a residual value deviates significantly from the others, that value is considered an outlier (Montgomery, 2013).

The problem of heteroscedasticity may appear on the residuals and fitted values plot. The residuals should be approximately equally distributed around the zero line and the distance from that line should not follow any trend. The most frequently applied solution is data transformation for the purpose of variance stabilization (Montgomery, 2013). However, many mathematical tests are developed for examination the homogeneity of variance. For instance, Bartlett's test is widely used for testing homoscedasticity (Montgomery, 2013) and model is confirmed if $p < 0.05$. Additionally, for testing homoscedasticity, Levene's test and Multiple comparison test for equal variances can be used, following the same logic as Bartlett's test. Bartlett's test cannot be used on residuals that are not normally distributed (Montgomery, 2013). Levene's test and Multiple Comparison test are less sensitive to deviation from normality.

Since obtained model is linear, the coefficient of determination can be used to determine the regression significance (Shina, 2022). Coefficient of determination is defined as percentage of the dependent variable variation that can be explained with model (Allen, 2010) and can have a value between 0 and 1. Therefore, it is a metric that indicates how well the model fits the data. It is desirable that the coefficient of determination be above 0.9 and then the model can be considered significant (Shina, 2022). On the other side, adjusted coefficient of determination ($R^2(adj)$) considers degrees of freedom in calculation and estimates how particular factor improve the fit of the regression model. If the model is valid, R^2 and $R^2(adj)$ should not differ significantly.

4. Buildings as complex thermodynamic system

This chapter theoretically describes the behavior of the building as a complex thermodynamic system. Although in this research dynamic simulation software EnergyPlus v.8.9. is used for the heating demand calculation in selected residential building, a theoretical background is required for the process understanding and performing analysis with DOE.

4.1. Heat loss in building sector

Heat losses in buildings can be divided into transmission and ventilation losses (Mastelic, 2018). Although there are ventilation losses in the building envelope due to the porosity of the materials, heat transmission is the dominant heat loss in the facade. Ventilation losses are the most often caused by insufficiently insulated windows and connection between windows and frames (Gullbrekken et al., 2020; Odeh et al., 2018). On the other side, ventilation is necessary to ensure living comfort and sufficient air circulation reduces the exposure of people to harmful substances (Medved, 2022). On figure 4.1, typical average heat losses for a single-family house are shown. It should be emphasized that there are significant deviations from these values between buildings of different characteristics.

Figure 4.1. Heat loss in single-family house (Dmytro et al., 2017): Walls (35%), Roof (25%), Floor (15%), Infiltration through windows and doors (25%)

When calculating heat losses in the residential building, the following assumptions are made:

- stationary conditions of heat transfer,
- one-dimensional heat transfer,

- all physical quantities are constant, and the material is homogeneous.

4.1.1. Transmission losses in residential buildings

There are three different methods of the heat transfer: thermal conduction, convention, and thermal radiation (Bocken and Ritala, 2020; Moss, 2007). Thermal conduction is a transport of thermal energy from the surface with the higher temperature to the surface with the lower temperature that are in physical contact (R. Hall, 2010), until the temperatures become equal. Conduction is significant cause of heat loss in the residential buildings (Moss, 2007). Due to the temperature difference, conduction occurs through the material layers of the poorly insulated building envelope (Moss, 2007). To prevent transmission losses, insulation should be installed on the outer walls of the building. Convection is heat transfer through the movement of the fluid molecules that occurs due to the heterogeneity of the fluid temperature (von Böckh and Wetzel, 2012). For instance, convection occurs when heating the air in a room with a heating element. The third method of a heat transfer is radiation (von Böckh and Wetzel, 2012), and it is a heat transfer performed without medium and it occurs for instance in systems that emit electromagnetic radiation. Radiation that occurs in building sector is solar heat absorption. Figure 4.2. shows principle of announced heat transfer mechanism.

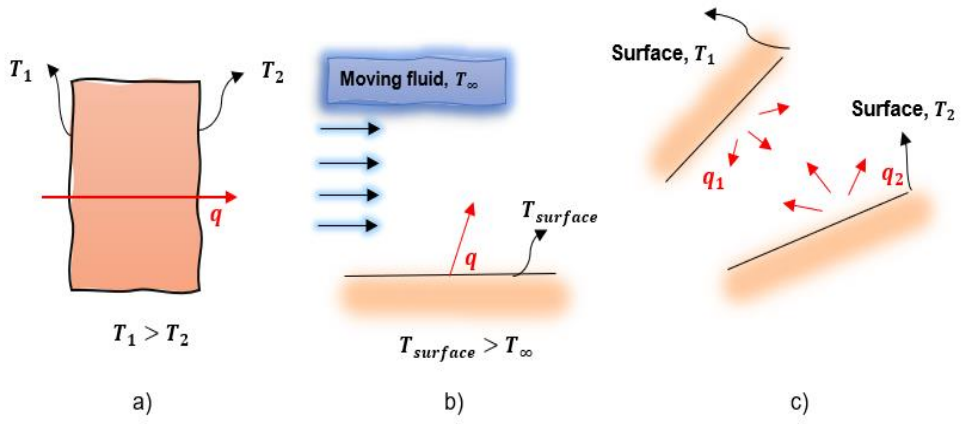


Figure 4.2. Heat transfer mechanisms: a) conduction, b) convection, c) radiation (Bergman and Incropera, 2011)

The properties of the material of the outer walls have the greatest influence on the transmission heat loss. To simplify the process, the explanation of heat transfer by radiation is omitted in this master's thesis and it is assumed that heat transfer through solid building element is performed by convection and conduction.

Thermal conductivity (λ) is a material characteristic that describes the magnitude of the heat amount that can be transferred per unit length and per unit temperature difference in the direction of the heat flux. The thermal conductivity is characteristic of specific material and depends on temperature and pressure difference between two environments.

Generally, in construction sector, to qualify an observed object's ability to transmit the heat, the overall heat transfer coefficient U $[W/m^2K]$ is used (Moss, 2007). Heat transfer coefficient is inverse value of the material's thermal resistance R $[m^2K/W]$. The thermal resistance of specific layer of material is defined as ratio of material layer's thickness (d) and thermal conductivity (λ) (R. Hall, 2010).

In multilayer materials, the thermal resistances are connected in series and the total resistance can be calculated as the sum of the individual ones (Bergman and Incropera, 2011). Higher U-value of the observed building's element results with the increased heat loss and it is often used as indicators of the building energy efficiency (Medved, 2022). To reduce heat losses and at the same time increase energy efficiency the specific transmission heat loss of the building should be as low as possible and are the largest permissible values of this parameter are regulated by law.

In praxis, heat transfer in building elements is caused by combinate action of the all three heat-transfer mechanism described above (Medved, 2022). Heat flux in the building's outer wall is transferred by the mechanism of convention on both sides of the wall and conduction through the layers of the wall material, as it is presented on figure 4.3. Heat is transferred from the side with hot fluid with convective heat-transfer coefficient h_1, through wall layers with thermal conductivity $\lambda_A, \lambda_{B,}\lambda_C$, and thickness $L_{A\,,}L_{B,}L_{c,}$ respectively, and at the and it is transferred to cold fluid with convective heat-transfer coefficient h_2.

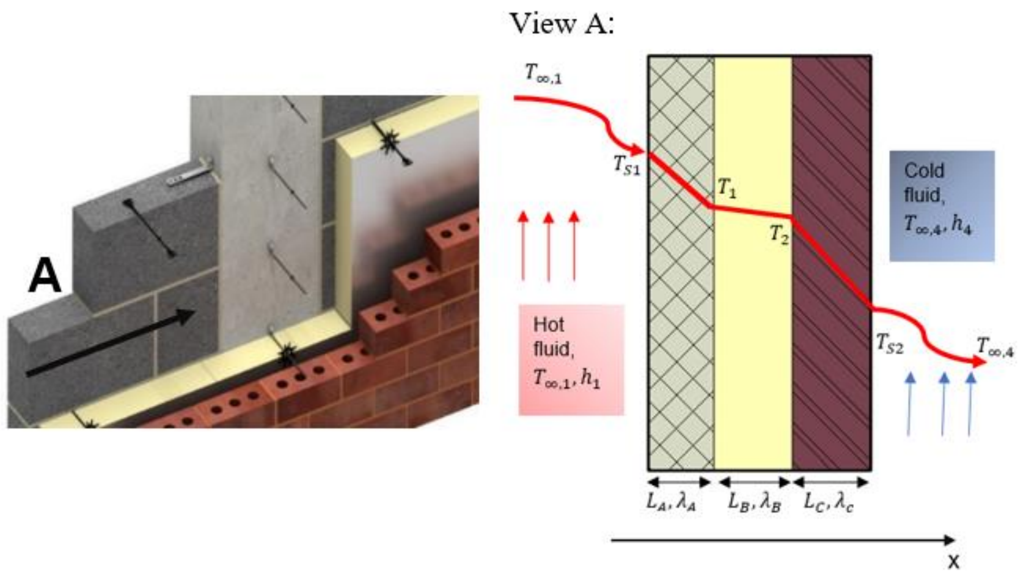


Figure 4.3. Heat transfer through multi-layer wall (Moss, 2007)

Mathematically, heat transfer through multi-layer homogeneous plane wall with n layers, is presented with equation bellow.

$$q = \frac{T_{\infty,1} - T_{\infty,4}}{\frac{1}{h_1} + \sum_{i=1}^{n} \frac{L_i}{\lambda_i} + \frac{1}{h_1}} = \frac{\Delta T}{R_{total}} = U\Delta T \tag{4.1}$$

Transmission losses in residential buildings can be divided into (Mastelic, 2018):

- transmission loss from the heated space to the external environment
- transmission loss from the heated space to the unheated space (for instance, common building corridor)
- transmission loss from the heated space to the ground

4.1.2. Ventilation loss in building sector

Nowadays, the airtightness of buildings has been used for assessment of the energy efficiency (Medved, 2022). Airtightness primarily describes the quality of the constructive solutions for elimination of unwanted air circulation through building elements (Santamouris, 2006). On the other hand, if there is no adequate mechanical ventilation in the building, and the building's structure is designed to minimize ventilation heat losses, there may be an insufficient amount of fresh air in dwelling units. Therefore, aim is to provide the optimal amount of air without unnecessary heat loss.

If sufficient air quality is not maintained, many symptoms of sick building syndrome like can manifested (Suszanowicz, 2018). Therefore, it is legally established how much air circulation is required to provide the occupants with a healthy living environment.. Koiv and Targo (2011) in their research paper investigated thermal comfort in building apartments in Estonia and they emphasized importance of mechanical ventilation installation to prevent appearance of mold on the inner walls of the building. Nevertheless, uncontrollable ventilation of living spaces during the heating season generates high heat loss in the buildings. Air circulation in buildings can be caused by mechanical and natural ventilation. Mechanical ventilation is planned and controlled air circulation, installed for the purpose of ensuring living comfort and meeting health regulations. On the other hand, infiltration is the unintentional leakage of air through cracks between building elements.

In this master's thesis hourly air-change rate is used to quantify the infiltration in the building. It specifies how many times the air in the internal space is replaced by fresh air from outside in one hour. (Medved, 2022) and it is measured experimentally.

Coefficient of ventilation heat loss in the residential building is calculated with equation bellow.

$$H_v = \rho \cdot c_p \cdot V \cdot n \tag{4.2}$$

Where:

- c_p $[\frac{J}{kgK}]$ $-$specific heat of air
- $\rho\left[\frac{kg}{m^3}\right]$ $-$ density of air
- $V[m^3]$ $-$ volume of heated area

Accordingly, heat loss due to outdoor air infiltration can be calculated as follows.

$$Q_V = H_v \cdot \Delta T \tag{4.3}$$

4.2. Annual required heating load

A heating and cooling system major objective is to maintain the living area in a desirable and healthy condition.

The annual required heating load is the calculated amount of heat that the heating system should generate for one year in order to ensure thermal comfort during the heating period, taking into account the outdoor climate conditions. Required heating load is highly dependent on the heat losses in building and it is designed to compensate for these losses. Therefore, there is balance between heat loss and heat gain. Required heating load combines the energy needed to warm up the building's structure and to maintain the indoor space air at a comfortable temperature.

Annual required heating load equation is shown bellow (Kalliomäki, 2010).

$$Q_{H,nd} = Q_T + Q_V - \eta_H (Q_{int} + Q_{sol}) \tag{4.4}$$

Where:

- $Q_{H,nd}$ $[kWh]$ – annual required heating load,
- $Q_T [kWh]$ – transmission heat loss,
- $Q_V [kWh]$ – ventilation heat loss,
- η_H – utilization factor of internal and solar gains,
- $Q_{int} [kWh]$ – internal heat gains of the building (people, devices, lighting),
- $Q_{sol} [kWh]$ – heat gains from solar radiation.

Considering the time step of the calculation, there are three approaches for calculating energy consumption for heating (Mastelic, 2018):

- Quasi-stationary calculation based on seasonal values
- Quasi-stationary calculation based on monthly values
- Dynamic calculation with a time step of one hour or less

For building energy certification quasi-stationary calculation base on monthly values is applied. Annual value of required heat energy for heating is calculated as the sum of positive monthly values. Energy Plus is software for dynamic simulations, and therefore in this master's thesis calculation is based on hourly values.

4.3. District heating system

District heating is an efficient system for heat distribution, from central boiler room where heat is generated, through a system of pipes toward the heating substation of residential and non-residential buildings. It is usually utilized for collective living apartments in urban areas, which includes and selected residential building. Heat is usually generated by fossil fuel combustion or renewable energy sources. In Sarajevo, the mail fuel is natural gas. On figure 4.4, distinct heating schematically presented.

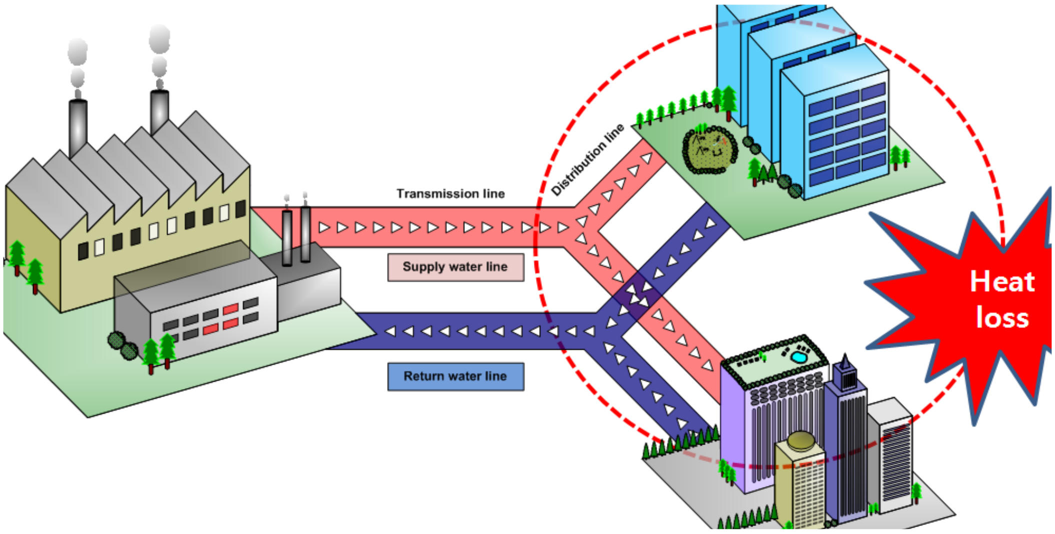


Figure 4.4. District heating system (Byun et al., 2012)

As it is presented on figure 4.4, heat losses occur in distribution system. Therefore, overall system efficiency (η_{sys}) can be defined as ratio of specific annual supplied heat energy and energy delivered from central boiler room. In presented equation, system efficiency considering the delivered energy at the building substation is taken into account:

$$\eta_{sys,overall} = \frac{Q_{H,nd}}{Q_{H,del,centr}} \tag{4.5}$$

4.4. Carbon footprint in the building sector

According to the IEA buildings and construction sector are producing globally 40% of total direct and indirect carbon emissions (“IEA – International Energy Agency,” 2022).

The carbon footprint in residential building can be divided into two types, according to the cause and period of occurrence (Clark, 2019):

• operating carbon footprint, caused by the electricity usage and HVAC system
• embodied carbon footprint, produced by manufacturing, material production and transport, construction, and material disposal

Depending on the different phases of the building's lifespan, the sources of CO_2 emissions are different. In table 4.1, the three main stages and sources of carbon emissions are shown.

Table 4.1. The stages during the life of a typical building (Clark, 2019)

Construction stage	**Usage stage**	**End of life stage**
Raw material supply	Operational energy use	Deconstruction
Manufacturing	Operational water use	Transport
Material installation	Refurbishment	Waste processing and disposal

In this master's thesis focus is on analyzing operating carbon footprint. According to Atmaca (2019), in usage phase 56% CO_2 is produced. Carbon emissions produced by heating is calculated using equation bellow (Morvaj et al., 2008).

$$E_{CO_2} = Q_{H,del} \cdot e_{fuel} \qquad (4.6)$$

Where:

- $E_{CO_2}\left[\frac{kg}{annual}\right]$ – annual heating carbon emission
- $Q_{H,del}[kwh]$ – annual delivered energy for heating
- $e_{fuel}\left[\frac{kgCO_2}{kWh}\right]$ – emission factor

Since in selected residential building district heating system is applied, carbon emissions are generated in station.

5. Selected Residential Building

To obtain data related to energy consumption using simulation software, all relevant building characteristics must be precisely modeled in Design Builder software. In this chapter, architectural constructional and energy properties of the selected building are comprehensively described, as well as motivation for object selection. As it is emphasized in literature review, weather data highly influence required energy for heating. Therefore, data about climate condition in Sarajevo is presented.

5.1. Typology of residential stock in B&H

B&H Building Typology is established on the research project TABULA (IWE, 2013), which originates from the Institute for housing and environment (IWU[4]) from Darmstadt. Due to lack of information regarding building stock in B&H, Arnautović-Aksić et al., (2016) have made comprehensive analysis of existing residential buildings and proposed categorization based on architectural parameters and construction period.

Data from Building Typology provides valuable dataset for developing strategies aimed to increase energy performance of building sector in B&H. Furthermore, it provides base of classified residential objects and offers statistical and energy performance analysis of each category. Clustering is performed according to the year of construction, and architectural and construction characteristics. Representative building of each category is selected, detailed characteristics of that building are presented, and energy consumption of typical buildings is calculated. Additionally, feasible measures for energy savings are proposed.

Statistical representation of total of six categories of residential stock according to urban-architectural parameters in B&H are shown on figure 5.1. (Arnautović-Aksić et al., 2016).

[4] IWU- abbr. from Institut Wohnen und Umwelt GmbH

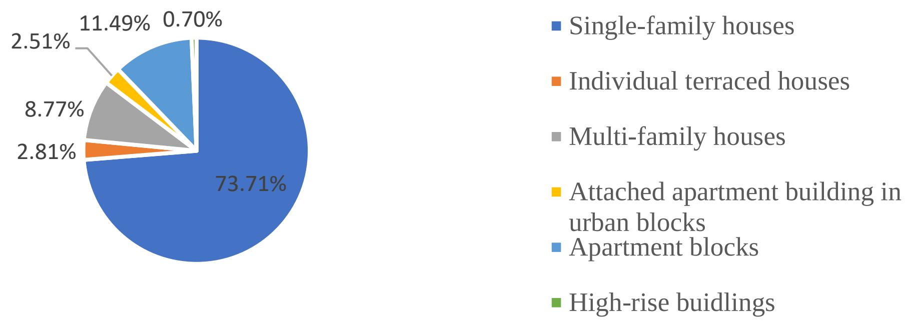


Figure 5.1. Statistical representation of building categories in B&H by gross surface

According to Typology (Arnautović-Aksić et al., 2016), selected building is representative of the category of apartment blocks, built in period 1961 to 1970. The representation of all building categories is shown in the table 5.1.

Table 5.1. Percentage of energy consumption of buildings' categories (Arnautović-Aksić et al., 2016)

Year	**Single-family houses (SFH)**	**Terraced houses (TH)**	**Multi-family houses (MFH)**	**Apartments blocks (AB)**	**High-rise buildings (HBR)**	**Total**
A <1945	1.25	0.04	0.09	0.10	0.00	1.25
B 1946-1960	3.67	0.14	1.00	0.43	0.00	3.67
C 1961-1970	14.05	0.45	1.67	**1.86**	0.30	14.05
D 1971-1980	32.41	0.80	0.97	3.38	0.18	32.41
E 1981-1990	15.83	0.46	0.59	1.03	0.00	15.83
F 1991-2014.	18.01	0.00	0.59	0.72	0.00	18.01
Total	85.22	1.89	4.90	7.51	0.47	85.22

As it can be seen from figure 5.1, statistically, number and gross surface of single-family houses is significantly higher than number of collective residential units. However, in urban areas residential buildings dominate and therefore analysis of energy characteristics of apartment blocks is significant. As it can be seen from table 5.1. selected building category, according to Arnautović-Aksić et al.(2016), 1,86% of the total energy in residential sector is consumed by Apartment Blocks built in period 1961-1970 (AB-C).

Due to the prevalence and the intensive energy consumption, category AB-C is selected for the analysis.

5.2. Basic information about case-study residential object

Selected residential building is located in Sarajevo, capital city of B&H. The apartment block construction is minimalist, as it can be seen on figure 5.2.

Figure 5.2. Selected residential building (from left to right: thermal image, photo, Revit[5] model)

Analyzed apartment block, presented on figure 5.2., is consisted of four separate entrances and each entrance consists of a basement with two apartments and a storage room, a high ground floor and five floors. Each floor has two apartments, and the building does not have an elevator. Floor plan is presented on figure 5.3. The arrangement of the apartments on each floor is the same and the apartment is consisted of separate thermal zones: living room, kitchen with dining room, bedroom, bathroom with toilet, hall and pantry. There are no heating elements in the common corridor in the building and in the common storage rooms. General building data are shown in table 5.2.

Table 5.2. General building data (Arnautović-Aksić et al., 2016)

Gross area of the heated part of the building	$\mathbf{3253.26\ m^2}$
Gross volume of the heated part of the building	8133.15 m^3
Total net area of the heated space	2833.96 m^2
The net volume of the heated part of the building	7084.9 m^3
Form factor	0.48

[5] Autodesk Revit 2021

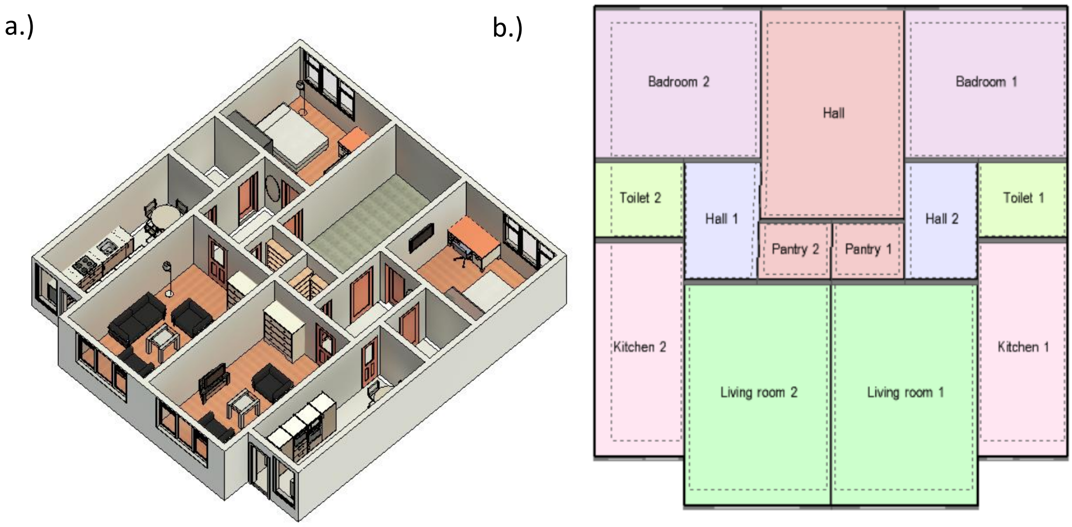


Figure 5.3. Example of the floor plan in selected building, a.) Autodesk Revit 2021 model, b.) Design Builder model

In addition to the architectural characteristics, occupancy of the residential space is an important factor in energy consumption, especially when the consumption of electrical energy is analyzed. With an increase in the number of occupants, the need for air ventilation increases . Human body produces a certain amount of heat, depending on the activity, and this reduces the energy required for heating. Statistically, an average of three people live in one apartment (Arnautović-Aksić et al., 2016). The highest number of occupants in the apartment is at 5 p.m., so it was assumed that these are peak hours of energy demand, as well as morning from 6 a.m. until 9 a.m. The schedule for each zone, considering its purpose, is created. Figure 5.4. shows an instance of a created schedule for the kitchen and light for workdays.

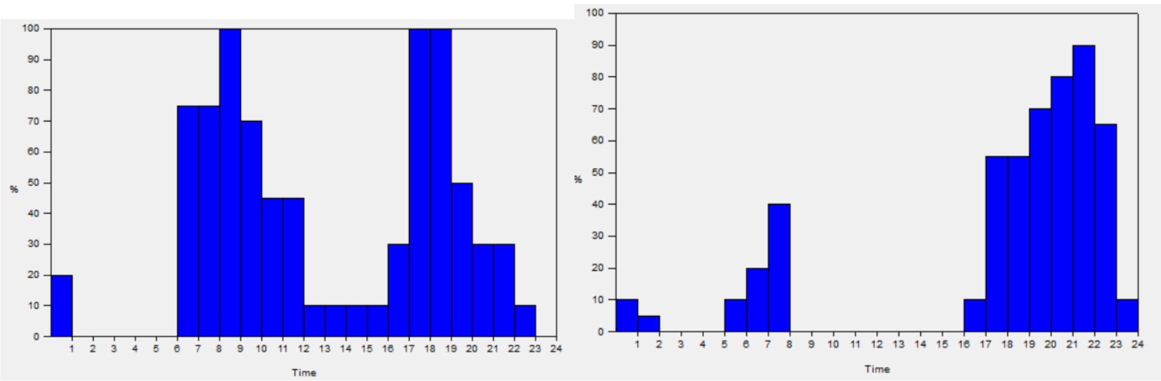


Figure 5.4. Created occupancy schedule in Design Builder for kitchen (left) and light (right)

For calculating energy demand of a residential building, significant influence has climate. Climatic conditions determine whether the required energy for heating or cooling is more dominant. Although a small country in the south-east of Europe, B&H has several climate zones, from a harsh Mountain climate in the north to a mild Mediterranean on the south. The interweaving of these climate influences gives Sarajevo the characteristics of a moderately continental climate.

As a result of the climate change, extreme weather conditions are recently more frequent (Trbic et al., 2021), and therefore there are common occurrences of droughts, heat waves, floods, and extreme snowfalls. According to the data from federal hydrometeorological institute, the average annual temperature for Sarajevo is 12.5 °C, and the average amount of precipitation is about 570 mm ("Federalni hidrometeorološki zavod BiH," 2022). The lowest recorded temperature is -21.8 °C (January 23, 1963), the highest 37.4 °C (July 24, 1987). Figure 5.5. shows average monthly low temperatures and average monthly high temperatures in Sarajevo.

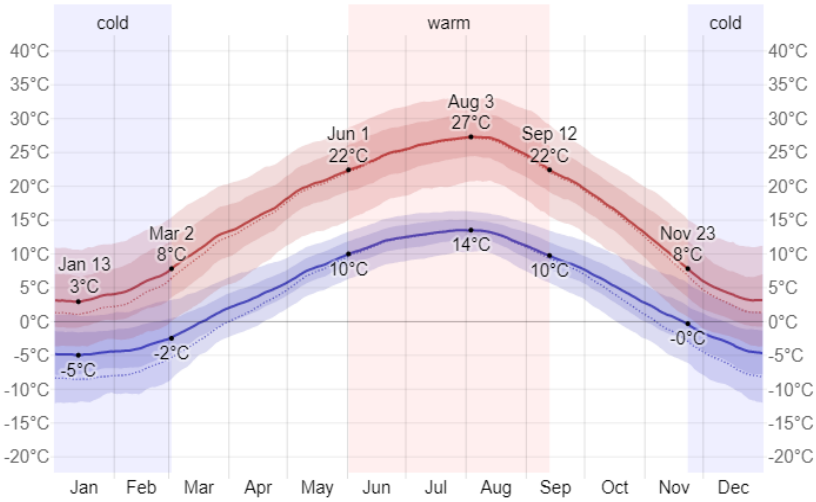


Figure 5.5. Daily average high (red line) and low (blue line) temperature in Sarajevo, Bosnia and Herzegovina for period 1942-2022 (Diebel et al., n.d.)

Figure 5.6. shows average daily solar energy heat gain per square meter. Heating period is longer than the cooling period in Sarajevo and therefore it is economically more profitable to have glazing that retains solar gains.

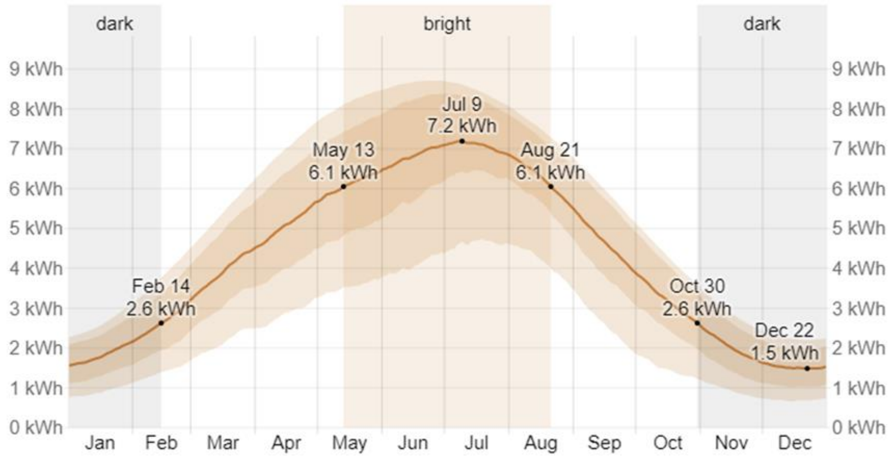


Figure 5.6. Average daily shortwave solar energy reaching the ground per square meter in Sarajevo, Bosnia and Herzegovina for period 1942-2022 (Diebel et al., n.d.)

5.3. Constructional and energy characteristics of the residential building

In this master thesis, the analyzed components of the building are external walls, windows, roof, and efficiency of the heating system. Properties of these elements are introduced in this chapter.

In Sarajevo, buildings built in the 60s were built without thermal insulation. Therefore, walls are mainly made of slag-concrete blocks with plaster finishing. In the analyzed residential building, there are several structurally different external walls, depending on the orientation and wall's position. As it can be seen from table 5.3, the dominant walls above the basement are W1, located on the north and south, and W2, on the east and west sides of the building. On the lowest floor of the building, which is in contact with the ground, there are several walls of different characteristics:

- WB1 - wall below ground level
- WEB1 – outer wall above ground level to upper floor

A flat inaccessible roof has 5 cm of insulation, but due to poor material distribution, losses occur. In table 5.3, the characteristics of the building envelope are shown.

Table 5.3. Properties of building envelope

Element	**Materials**	$U\ [W/m^2K]$	**The total surface of wall that type** $A\ [m^2]$
W1	plaster, low-density concrete	2.31	864.4

W2	plaster, slag-concrete blocks	1.81	512.84
WB1	high-density concrete, bitumen, low-density concrete	2.84	54.83
WEB1	plaster, high density concrete	3.64	139.8
Roof	bitumen, insulation, high-density concrete, concrete with low conductivity, reed slats	2.03	532.7

There are several types of windows that can be found on buildings of this type, listed in table 5.4. It should be emphasized that WIN4 is installed in the unheated part of the building, i.e., in the storerooms and the common corridor.

Table 5.4. Properties of building windows

Element	**Materials**	**U** $[W/m^2K]$	**The total surface of the opening of that type** A $[m^2]$
WIN1	single-glazed, concrete frame, high infiltration	6.2	152.8
WIN2	single glazing with wooden frame, high infiltration	5.2	25.44
WIN3	double glazing with wooden frame, high infiltration	3.6	97.3
WIN4	double glazing with plastic frame, medium infiltration	2	287.5

Heat transfer coefficient of the windows depends on glazing type, insulator between glasses, frame material, thermal bridges. In addition to heat transfer, if the window does not fit to the wall, due to dilapidated frame and thermal bridges, increased air filtration occurs.

On figure 5.7, thermal images of analyzed building components are shown. It can be seen that enormous heat losses occur due to lack of envelope insulation and inadequate window fit. The thermal image shows an uneven distribution of temperature on radiator, which may indicate unbalanced hot water flow system.

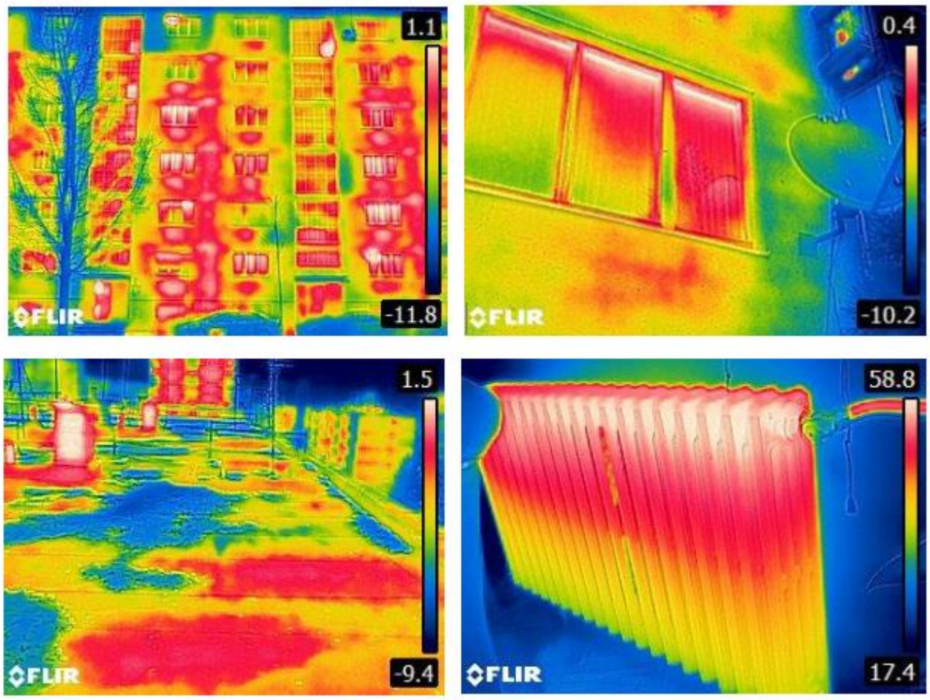


Figure 5.7. Thermal image of the building envelope, windows, roof, heating element

Residential object considered in this paper is connected to the district heating system. Central boiler room is in the vicinity of building, with characteristics shown in table 5.5. Natural gas is used as the main fuel, and fuel oil is the auxiliary fuel. Hot water is distributed towards the heat substation located in the building basement, where it transfers heat to closed circuit of water that circulates between heat exchanger (heat substation) and radiators (heated area in the building). The delivered thermal energy towards the substation is measured via heat meter installed in the substation. Heated water from the heat exchanger circulated through a two-pipe system via centrifugal pump. The hot water distribution system consists of a horizontal pipeline that enters the basement, splits in half in the centre of the structure, and travels to four vertical pipes—two on the right and two on the left—through which hot water is delivered to the heating elements. The heating elements are convector radiators, with a total installed power of 293 kW. This type of system has a very high efficiency, $\eta_{system} = 0.85 - 0.95$ (Kalliomäki, 2010). According to data from heating plant, efficiency of existing system is 0.85 (Kurtalic, 2018). According to data from heating plant and Morvaj et al. (2008), CO_2emission coefficient is $0{,}236\ kg/kWh$.

Table 5.5. Characteristics of the boiler room, plant "Toplane KJKP Sarajevo"

Code	**Boiler room name**	**Installed power [MW]**	**Power in use [MW]**	**Heated living space [m^2]**	**Heated nonresidential space [m^2]**
PS0101000000	Cengic Vila I	12	4,768	65446	3787

6. Application of DOE to experimental data

In this part of the master's thesis, the analysis of the energy demand of the selected residential building is presented. To develop mathematical model for predicting heating energy demand, FFD is used. Four factors are varied on two levels and sixteen simulations were performed. Heating energy demand is, after creating building model in Design Builder v.6.1.0.006, calculated using integrated dynamic simulation software Energy Plus v.8.9. Calculation is based on hourly values, considering detail occupancy and electric equipment schedule, climate condition in Sarajevo. Minitab® v.19.2020.1 is used for applying DOE, performing ANOVA and statistical tests for checking model adequacy. In table 6.1, basic description of utilized software packages is presented.

Table 6.1 Description of utilized software for conducting research

	EnergyPlus v.8.9[6]	**Design Builder v.6.1.0.006**[7]	**Minitab® v.19.2020.1**[8]
Purpose	Building energy simulation tool	GUI for EnergyPlus	Statistical software
Advantage	Dynamic thermal simulation at sub-hourly timesteps, Utilizes the ASHRAE-approved 'Heat Balance' method for calculation	Simple modeling, user friendly	Suitable for conducting industry-leading data analysis, dynamic visualizations and predictions.

6.1. Factor levels selection

In DOE codded value are used and the range of values on which the research was conducted should be defined. The factor’s range was selected to include all possible values that researched factors can physically take, based on statistics provided in Typology (Arnautović-Aksić et al., 2016). In table 6.2, varied factors and their codded values are shown.

Table 6.2. Examined factors and their levels

[6] Available at https://energyplus.net/
[7] Available at https://designbuilder.co.uk/
[8] Available at https://www.minitab.com/en-us/

Factor	Factor label	Level	
		-1	+1
Walls (*U*-coeff) [W/m^{2}K]	A	2.48	0.205
Windows (glazing)	B	single	Triple
Roof (*U*-coeff) [W/m^{2}K]	C	1.33	0.11
η system	D	0.85	0.95

In the current state, the walls have no insulation and transmission coefficient of outer walls without insulation is $2.48\,W/m^2K$. Proposed improvement measure is installing $20\,mm$ expanded polystyrene (EPS), which conduction coefficient (λ) is $0.0440\,W/mK$ (Pruteanu et al., 2013). Maximal transmission coefficient after building renovation is prescribed by law. Therefore, according to Guideline on minimum requirements for energy performance of buildings (. 81/19. Official Gazette of Federation of Bosnia and Herzegovina, 2019), after the building restoration, the maximum transmission coefficient is $0.35\,W/m^2K$. After adding $20mm$ EPS, transmission coefficient of the outer walls is $0.205\,W/m^2K$. Therefore, current condition represents -1 level, and outer walls with 20mm EPS +1 level.

Two distinct effects of building openings were observed in this research. Firstly, windows transmission coefficient varies with the glazing. Furthermore, air infiltration is increased when window frame is unmaintained. The characteristics of the analyzed opening types in the residential part of the building are shown in the table 6.3. The Solar Heat Gain Coefficient (SHGC) is used to quantize ability of windows to transmit or absorb solar radiation.

Table 6.3. Properties of high and low level of building openings

Level	Glazing	Frame	Layers	U $[W/m^2K]$	Infiltration (Mathur and Damle, 2021)	Solar heat gain coefficient
Low	Single	Wooden	Clear glass $3mm$	5.2	1.5	0.871
High	Triple	Plastic	3x Clear glass $3mm$ 2x Air $13mm$	1.75	0.5	0.684

The roof takes 25% of the building envelope. Although even in the worst-case scenario it has a layer of insulation, the material is unevenly distributed and the heat losses in some places are large, as can be seen in the figure 5.7. Extruded polystyrene (XPS) is used for thermal insulation. An inverted flat roof construction (Misar and Novotný, 2017) is applied and therefore thermal insulation is placed above the hydro isolation. According to Rulebook on minimum requirements for energy performance of buildings (81/19. Official Gazette of Federation of Bosnia and Herzegovina, 2019), maximal U-coefficient of the roof after restoration is 0.25. After the installation of 20 cm XPS material on the roof, coefficient of transmission is 0.4 W/m^2K.

6.2. Simulation results

In figure 6.1, building model designed in Design Builder is shown.

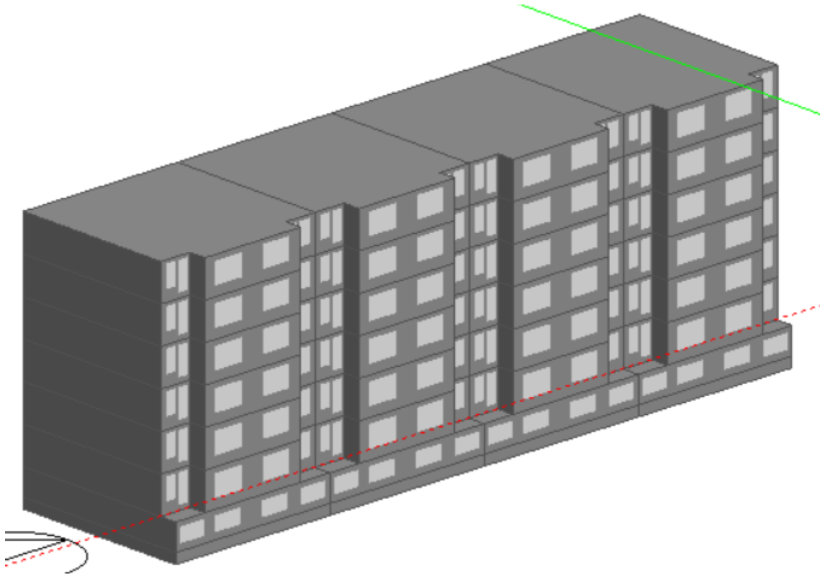


Figure 6.1. Analysed residential building modelled in Design Builder (working model)

As described before, in order to develop mathematical model for predicting energy consumption, full factorial design is applied. Since four factors are varied on two levels, sixteen experiments are conducted. Design Builder and Energy Plus are utilized as dynamic simulation software to obtain experimental results. Accordingly, experimental matrix and simulation results are presented in table 6.4.

Table 6.4. FFD exp.matrix and simulation results: annual specific delivered energy for heating, cooling and electricity

		Factors				Results	
No.	**Walls**	**Window**	**Roof**	η_{sys}	**Del.energy for heating** $[kWh/m^2]$	**Del.energy for cooling** $[kWh/m^2]$	**Electricity** $[kWh/m^2]$
1	-1	-1	-1	-1	119.59	9.47	44.28
2	1	-1	-1	-1	71.95	10.16	44.19
3	-1	1	-1	-1	77.20	11.91	44.28
4	1	1	-1	-1	23.51	8.01	44.20
5	-1	-1	1	-1	104.71	9.27	44.27
6	1	-1	1	-1	61.72	8.86	44.19
7	-1	1	1	-1	67.97	13.47	44.28
8	1	1	1	-1	13.87	9.47	44.18
9	-1	-1	-1	1	107.00	10.16	44.28
10	1	-1	-1	1	64.37	9.47	44.19
11	-1	1	-1	1	69.07	10.16	44.28
12	1	1	-1	1	21.03	11.92	44.20
13	-1	-1	1	1	93.68	8.01	44.27
14	1	-1	1	1	55.23	9.27	44.19
15	-1	1	1	1	60.82	8.86	44.28
16	1	1	1	1	12.41	13.47	44.18

Important conclusion from table 6.4. is that the dominant energy consumption is heating and therefore mathematical model for prediction of heating demand is developed. Additionally, cooling system is not installed in all dwelling units. Heating has the greatest influence on carbon footprint production. Consequently, optimization of the construction characteristics of the building to reduce the heating demand results in decreasing carbon footprint. Electricity has constant value, and it is not influenced by building characteristics.

For a more detailed insight into the heating energy consumption , a graphical presentation of a heat gains and heating demand in a typical winter week is selected. Due to comprehensiveness, not all graphs are shown, considering the most prominent difference, the presentation of the first and the sixteenth experiment was chosen. In figures 6.2. and 6.3., heat gains, indoor temperature, heat balance and air infiltration for the worst-case scenario (the first experiment) and the best-case scenario (the sixteenth experiment) in typical winter week is shown.

Calculations are performed using sub-hourly weather data. As it can be seen from fuel graph, heating period is from 6 a.m. to 10p.m.

It can be seen from heat balance graph, that heat gains (distinct heating, solar gains, lighting, electric equipment, occupancy) compensates for the loss caused by heat transmission and air infiltration. To achieve thermal comfort in the residential space, 22°C is maintained during heating period. In temperature graph, oscillations in indoor air temperature due to intermitted heating are shown. When observing the graphs shown below, after the restoration of the building, other additional gains (electricity, solar gains, occupancy) are dominant and significantly reduce the required heating energy.

Reduced heating demand is a consequence of the improved building energy characteristics and system self-sustainability is a basic concept of zero-net energy buildings.

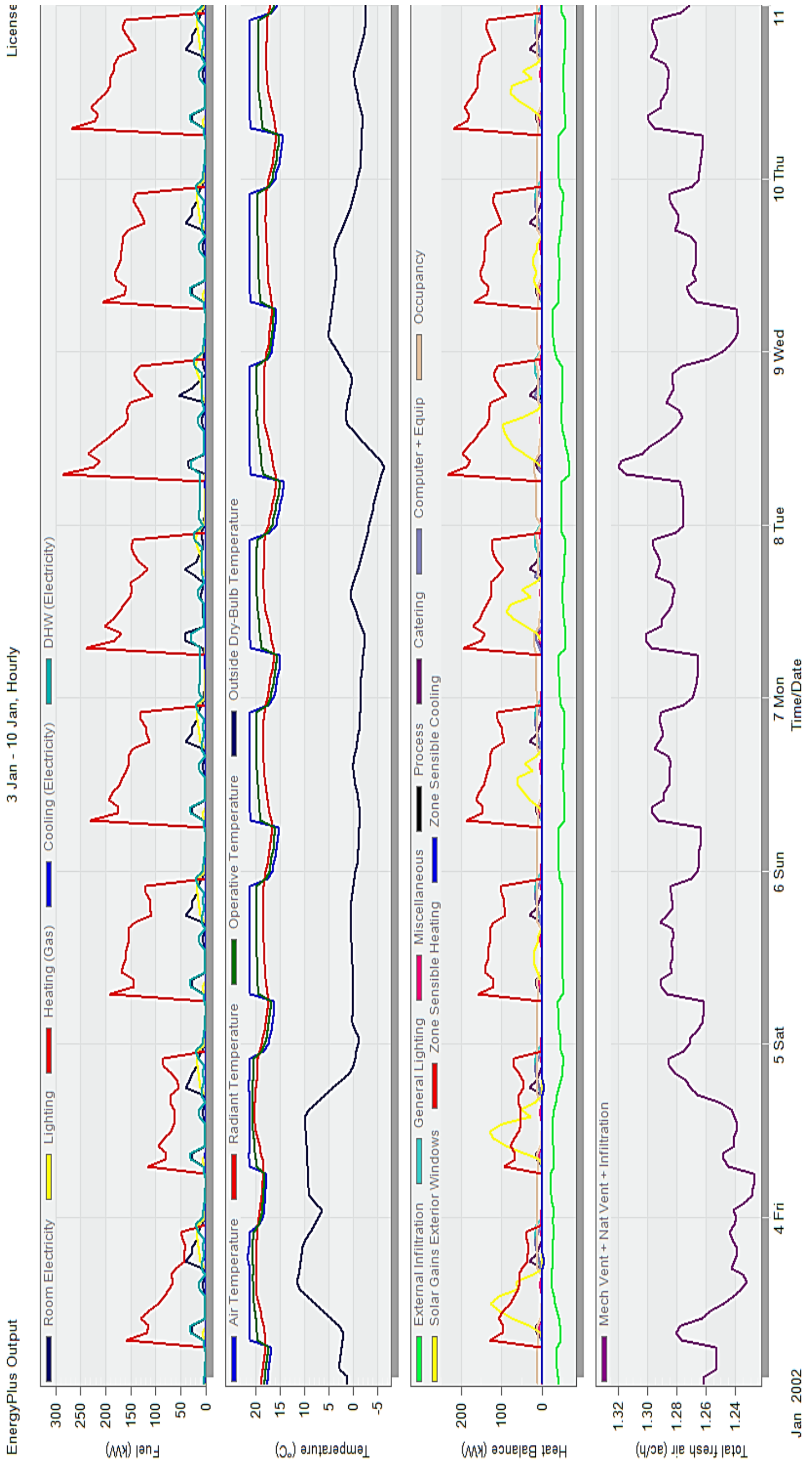


Figure 6.2. EnergyPlus simulation results: temperatures, heat gains, energy consumption and air infiltration for typical winter week for selected building (the first experiment from experimantal matrix)

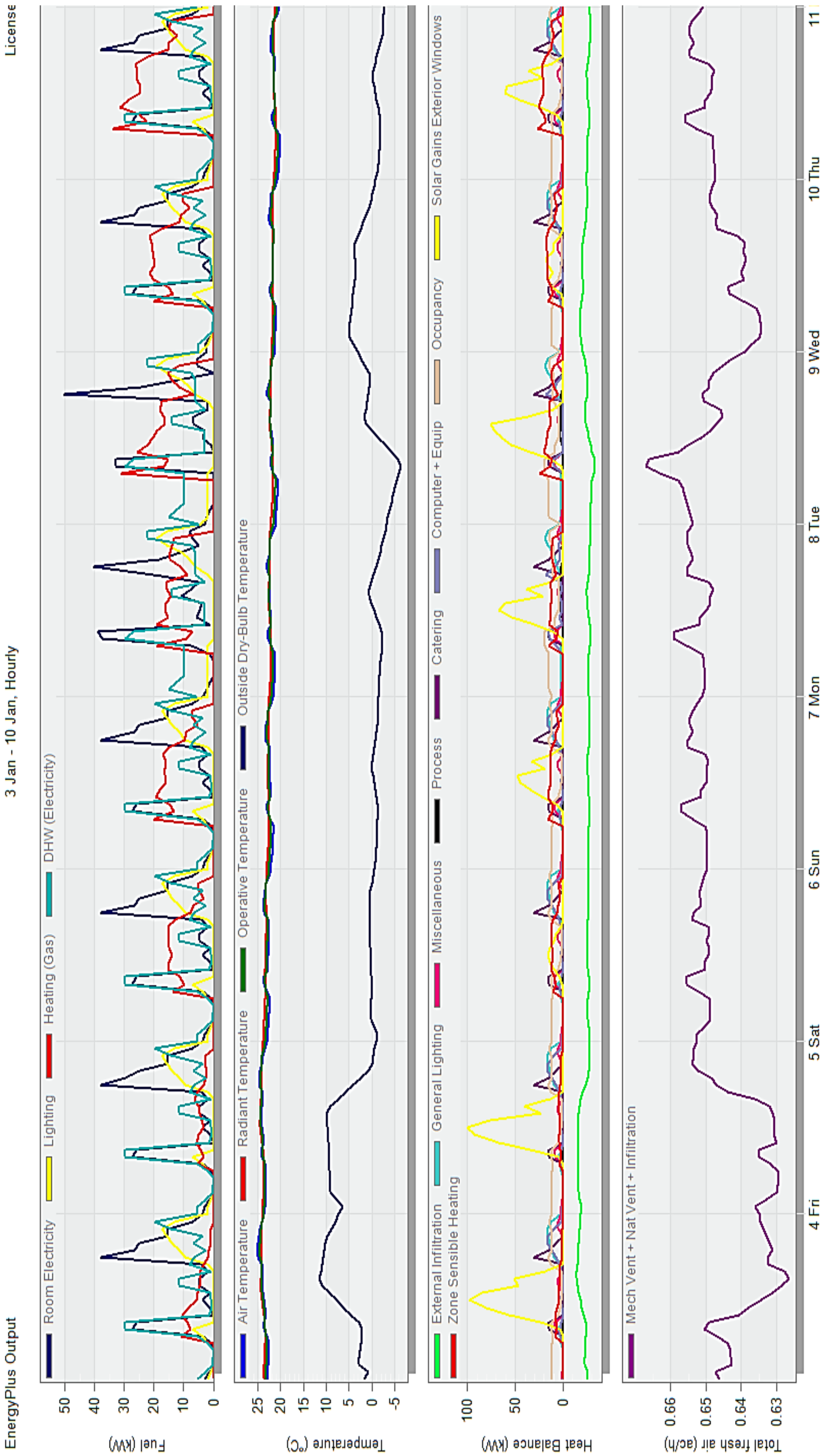
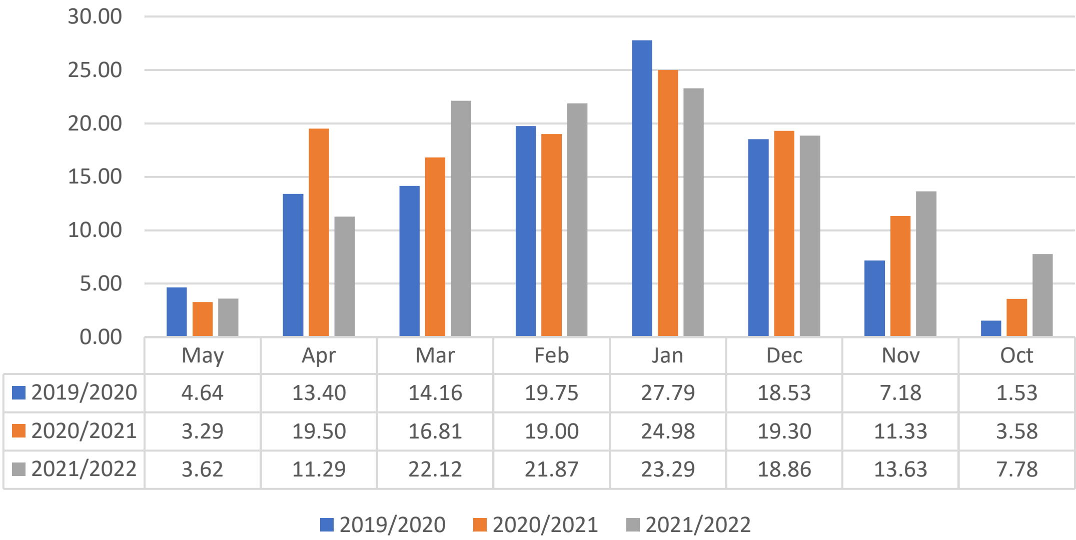


Figure 6.3. EnergyPlus simulation results:temperatures, heat gains, energy consumption and air infiltration for typical winter week for selected building (the sixteenth experiment from experimental matri

6.3. Model calibration

Several analyzes of energy consumption in selected residential building were performed in literature. According to Arnautović-Aksić et al. (2016), calculated specific energy required for intermitted heating is $Q_{H,nd}$ is 170,1 kWh/m^2. The calculation is based on valid legal regulations in B&H, with quasi-stationary monthly calculation based on EN ISO 13790. It can be seen that there is significant deviation from the heating plant data. Therefore, the advantage of using dynamic simulations to obtain data is emphasized.

Fluctuations in monthly specific energy consumption, according to data from heating plant, in the period from 2019-2022 are shown in the figure 6.4. It can be concluded that the highest heating demand is in January, which is in line with the average monthly temperatures shown in figure 5.5.



	May	Apr	Mar	Feb	Jan	Dec	Nov	Oct
2019/2020	4.64	13.40	14.16	19.75	27.79	18.53	7.18	1.53
2020/2021	3.29	19.50	16.81	19.00	24.98	19.30	11.33	3.58
2021/2022	3.62	11.29	22.12	21.87	23.29	18.86	13.63	7.78

Figure 6.4. Specific monthly energy consumption for heating per month for three seasons (Data collected from heating plant)

Annual average heating demands for observed dwelling unit, according to data from heating plant are listed in table 6.5. and average value is 115.856 $\frac{kWh}{m^2}$.

Table 6.5. Specific delivered heating energy in selected building according to data from heating plant

Year	$Q_{H,nd}[\frac{kWh}{m^2}]$
2019	106.98
2020	117.789
2021	122.799

Heating energy demand, according to simulation results for the worst-case scenario is 119.59 $\frac{kWh}{m^2}$. Therefore, the difference of data obtained in this study from the heating plant data is approximately 3.22%.

6.4. Mathematical model for prediction of heating demand

After simulation results are obtained, shown in table 6.4, FFD is applied. As mentioned in previous chapters, the objective of this study is to develop mathematical model for prediction of the heating energy consumption in selected residential building. The expected mathematical form of the model, with 4 analyzed factors, is shown in (3.2). Results of ANOVA are presented in table 6.6.

Table 6.6. ANOVA table in Minitab

	DF	SS	MSE	F-Value	P-Value
Model	11	16510.2	1500.93	22957.42	0.003
Linear	4	16375.6	4093.89	62618.02	0.002
A	1	8834.5	8834.47	135127.49	0.001
B	1	6905.0	6904.96	105614.67	0.004
C	1	433.8	433.81	6635.34	0.000
D	1	202.3	202.32	3094.59	0.022
2-Way Interactions	6	128.9	21.48	328.51	0.010
A*B	1	66.1	66.14	1011.67	0.042
A*C	1	4.0	4.04	61.85	0.016
A*D	1	27.3	27.27	417.06	0.029
B*C	1	8.8	8.76	134.01	0.000
B*D	1	21.3	21.31	325.97	0.018
C*D	1	1.3	1.34	20.48	0.073
3-Way Interactions	4	6.0	1.51	84.41	0.081
A*B*C	1	5.8	5.78	324.0	0.035

A*B*D	1	0.2	0.2	11.44	0.183
A*C*D	1	0.0	0.01	0.7	0.557
B*C*D	1	0.0	0.03	1.51	0.434
Error	1	0.3	0.02		
Total	15	16510.5			

As it is presented in table 6.6, F-values are significantly high.). In order to accept alternative hypothesis about factor significance, calculated p-value have to be smaller than 0.05. Since all p-values of calculated F-values are less than 0.05, it can be concluded that variability is not random and null hypotheses are rejected for every factor and its interaction, except interactions *CD, ABD,ACD* and *BCD.*

To understand considered process and analysis resluts in depth, Pareto chart, presented in figure 6.5., is used for graphical presentation of effects. All effects higher than critical *t*-value (12.7) are significant. Since interactions *CD*, *ACD*, *ABD* and *BCD* have $p > 0.05$, they are excluded from analysis.Further analysis is performed on reduced model. From Pareto chart, it can be seen that the most significant factors are *U*-coeff of the walls and glazing type. The lower importance of the *U*-coeff of the roof can be explained by the smaller area of the roof compared to the overall building envelope.

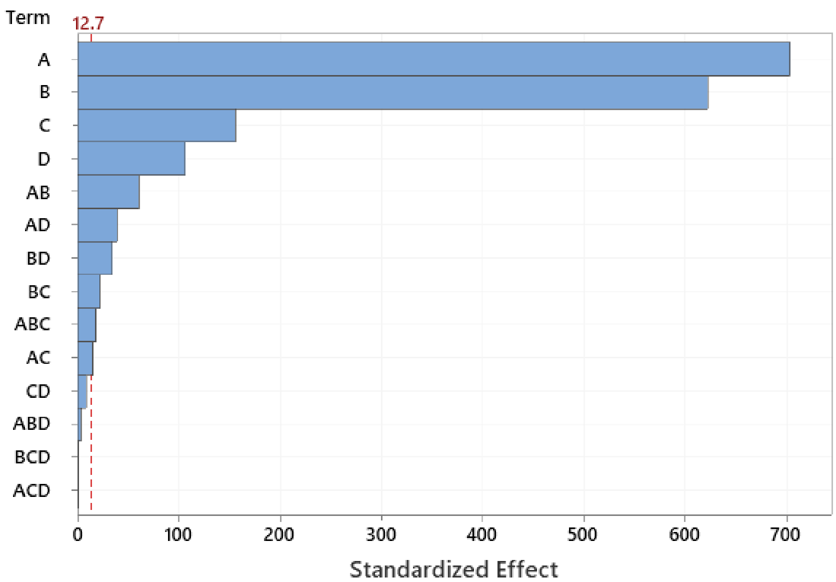


Figure 6.5. Pareto chart of factor's effects

The same conclusion can be drawn from figure 6.6. Transmission coefficient of the wall and glazing have the greatest slopes and therefore, they are the most significant.

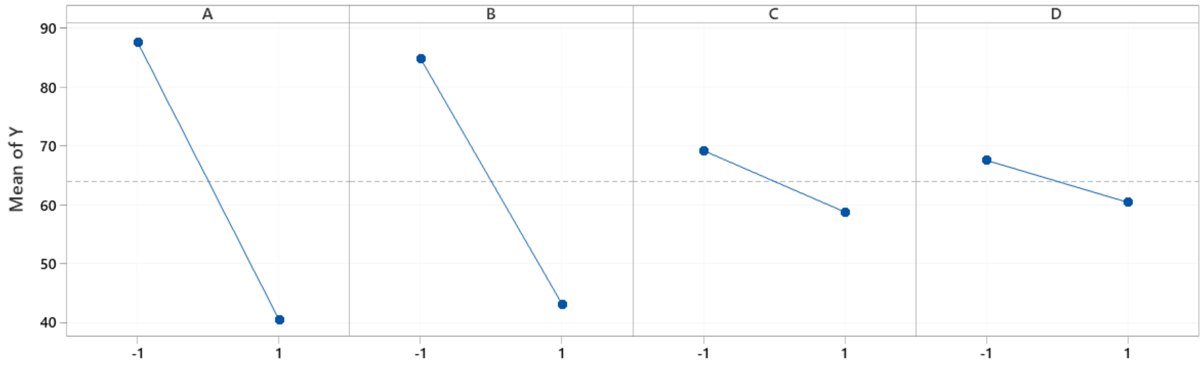


Figure 6.6. Main effect plot for analysed factors

Finally, quantized factor's effects are utilized for development of the mathematical model. Effect table, (Appendix C) obtained in the Minitab, apart from factor effects shows standard error of coefficients, *t*-value, *p*-value, VIF. Standard error of each coefficient is the same because orthogonality of design matrix. *T*-test leads to the same conclusion as *F*-test. For performing t-test, critical *t*-value obtained from statistical table is required. According to *t* statistical table, critical value for 1 degree of freedom and significance level of 0.05 is 6.314. Therefore, according to *t*-test, interactions *ABD*, *ACD* and *BCD*, can be excluded from the model. VIF coefficient is 1, and therefore there is no multicollinearity.

Finally, regression model for prediction of the delivered energy for heating, considering four influencing factors, is developed and presented with following equation.

$$Q_{H,del}\left[\frac{kWh}{m^2}\right] = 64 - 23.5A - 20.77B - 5.2C - 3.55D - 2.03AB + 0.5AC + 1.3AD + 0.7BC + 1.15BD - 0.6ABC \tag{6.1}$$

Coefficient of determination of developed model is 100% and adjusted coefficient of determination is 99.99%. It can be concluded that model is reliable and capable for predicting heating demand.

6.5. Model validity check

As described in chapter 3.3 , model validity check must be performed before accepting the model.

Normality of residuals is tested with Anderson-Darling normality test. Since calculated *p >0.05*, as it is shown in figure 6.7, null hypothesis is confirmed and it is possible to state that residuals are normally distributed, with confidence level 95%. Probability plot of residuals, shown below, confirms the assumption that residuals follow normal distribution, since all residuals are within 95% confidence interval limited by the red curve in the figure 6.7.

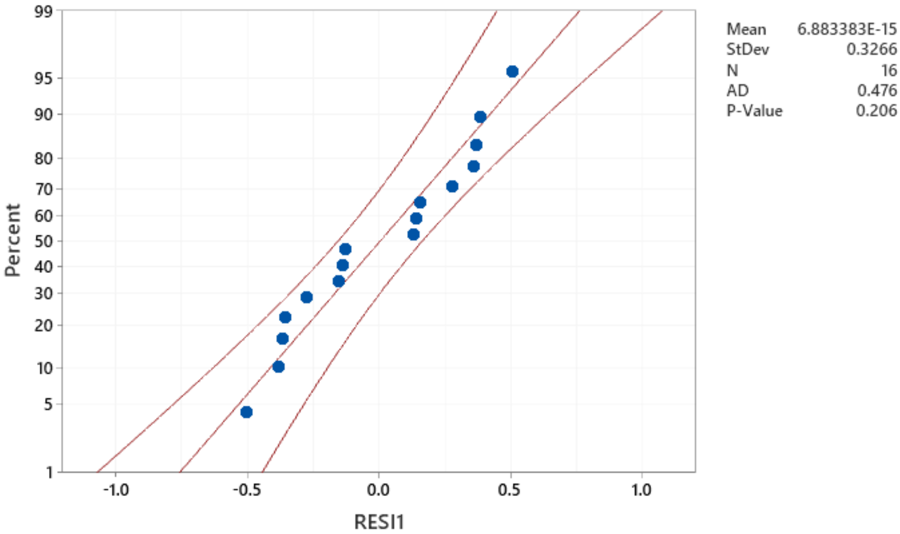


Figure 6.7. Normal probability plot of residuals of model for predicting delivered heating energy, $\alpha = 0.05$

Plot of fitted values versus standardized residuals plot is shown in figure 6.8. From this graphic representation, it can be seen that residuals are distributed around zero line and therefore, it is possible to conclude that linear relationship is adequate for this model. In addition, homoscedasticity can be tested using figure 6.8. The values of the residuals are roughly similarly distributed around the zero line and that confirms the assumption that the variances of the error are equal.

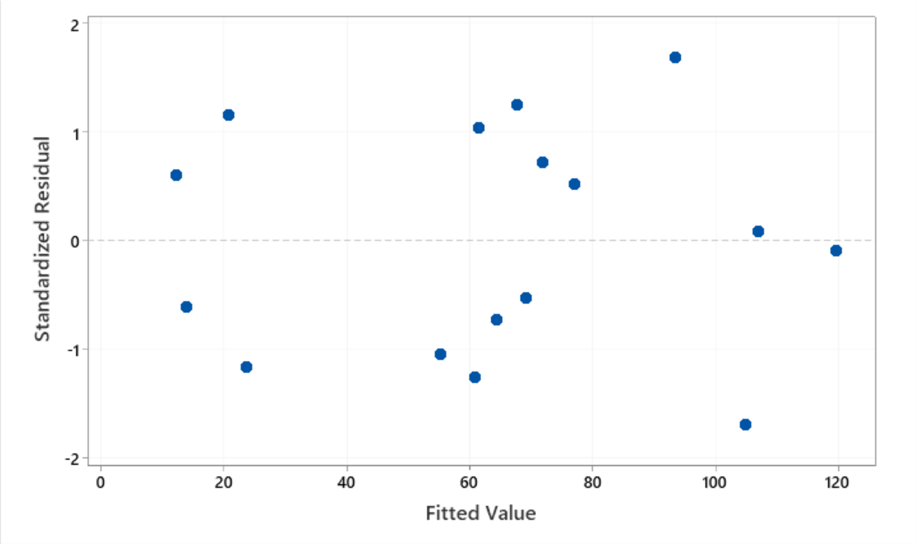


Figure 6.8. Fitted value versus standardized residuals plot of model for prediction of the delivered heating energy

Furthermore, test for equal variances is performed. The null hypothesis claims that the variances are equal, and the alternative hypothesis is that there is at least one different variance. For *p* values greater 0.05, zero hypothesis about equal variances is accepted. Since residuals are following normal distribution, *F*-test can be used in Minitab.

In table 6.6 summary or the performed F-test is presented. It can be seen that $p>0.05$ for all factors levels and therefore null hypothesis is accepted and homoscedasticity is confirmed.

Table 6.7. F-tests for equal variances, 95% confidence level

Coefficient	Level	p-value	Standard deviation	Confidence interval	Individual confidence level
Transmission coefficient of outer walls	-1	0.66	1.15	(0.722816, 2.64637)	97.5%
	+1		0.97	(0.610036, 2.23345)	
Glazing type	-1	0.77	1.138	(0.705948, 2.58461)	97.5%
	+1		1.01	(0.629479, 2.30464)	
Transmission coefficient of the roof	-1	0.21	0.784	(0.490711, 1.79658)	97.5%
	+1		1.292	(0.808585, 2.96038)	
System efficiency	-1	1	0.338	(0.211524, 0.774430)	97.5%
	+1		0.338	(0.211524, 0.774430)	

After performing validity check, developed model satisfy all requirements and can be used for predicting annual heating demand in residential buildings, that have the same or similar characteristics as the analyzed object and belong to the same statistically determined category.

6.6. Carbon emission

Using (4.6) , carbon emission produced by heating in selected residential building is calculated. Carbon emissions in the case of district heating are generated in the main boiler room, where natural gas is used as the main fuel.

The CO_2 emission factors include the direct emissions during combustion and embodied emissions (Clark, 2019). According to data from heating plant and Morvaj et al. (2008), emission coefficient is $0{,}236\ kg/kWh$.

In figure 6.11 specific annual carbon emissions caused by fuel combustion is presented. It can be concluded that implementing renovation measures presented in this master's thesis also reduces building's direct carbon footprint. More advanced improvements can be achieved by switching heating plants to renewable energy sources.

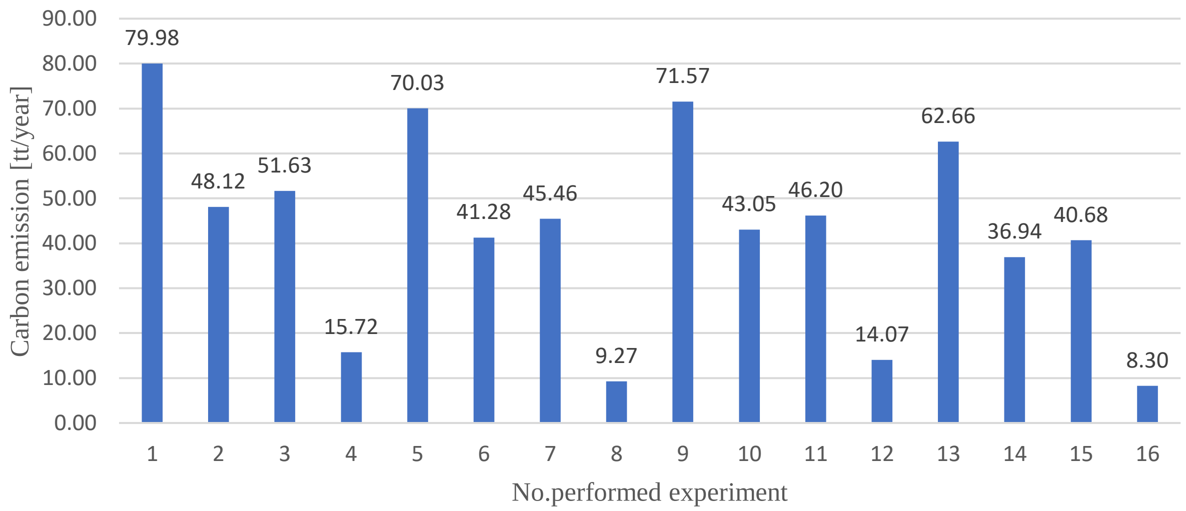


Figure 6.9. Carbon emissions caused by fuel combustion for heating in selected residentil building per performed experiment

Since there is linear relation between carbon emission and delivered energy for heating, reduction of the required fuel for heating results in decreased carbon emissions.

To develop mathematical equation for prediction of the carbon emissions by fuel combustion, DOE is applied. Similar as previous case, factors *A*,*B* and *C* have the highest influence on the response and interaction effect *CD*,*ACD*, *ABD* and *BCD* are not statistically significant ($p > 0.05$). ANOVA results are shown in table below.

Table 6.8. ANOVA results for analysing carbon emissions

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	14	7385.34	527.52	66064.32	0.003
Linear	4	7325.00	1831.25	229335.99	0.002
A	1	3951.77	3951.77	494899.00	0.001
B	1	3088.68	3088.68	386809.50	0.001
C	1	194.05	194.05	24301.67	0.004
D	1	90.50	90.50	11333.81	0.006
2-Way Interactions	6	57.64	9.61	1203.15	0.022
A*B	1	29.59	29.59	3705.22	0.010
A*C	1	1.81	1.81	226.51	0.042
A*D	1	12.20	12.20	1527.47	0.016
B*C	1	3.92	3.92	490.82	0.029
B*D	1	9.53	9.53	1193.86	0.018
C*D	1	0.60	0.60	75.01	0.073
3-Way Interactions	4	2.70	0.67	84.41	0.081
A*B*C	1	2.59	2.59	324.00	0.035
A*B*D	1	0.09	0.09	11.44	0.183
A*C*D	1	0.01	0.01	0.70	0.557
B*C*D	1	0.01	0.01	1.51	0.434
Error	1	0.01	0.01		
Total	15	7385.34			

Developed regression model for estimating carbon emissions in selected building, considering 4 analyzed factors is presented below.

$$E_{CO_2}[t/year] = 42.8 - 15.71A - 13.89B - 3.48C - 2.37D - 1.35AB + 0.34AC + 0.87AD + 0.49BC + 0.77BD - 0.41ABC \quad (6.2)$$

Accordingly, model validity check is conducted.

In figure 6.10, fitted values versus standardized residuals plot is shown. Residuals are distributed approximately equally around the zero line and have no pattern. Therefore, it can be concluded that residuals have constant variance.

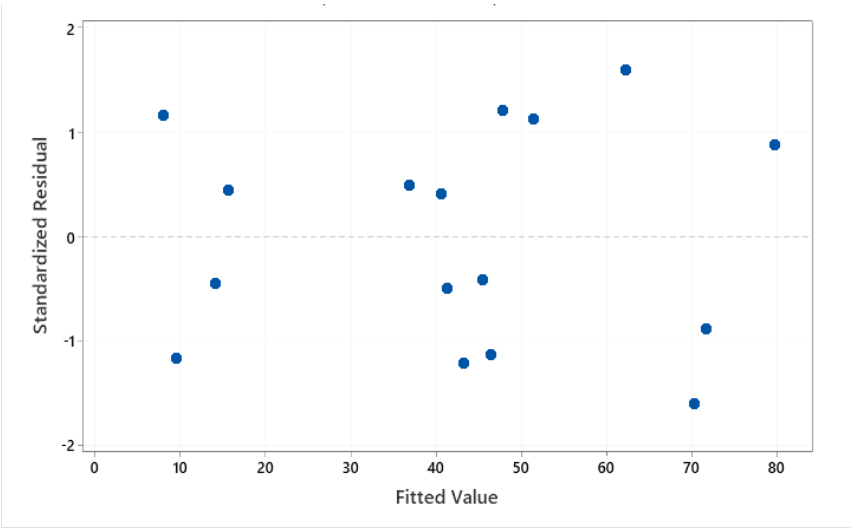


Figure 6.10. Standardized residuals versus fitted value, response is carbon footprint for selected building

Observing figure 6.11, conclusion that residuals are following normal distribution is reached.

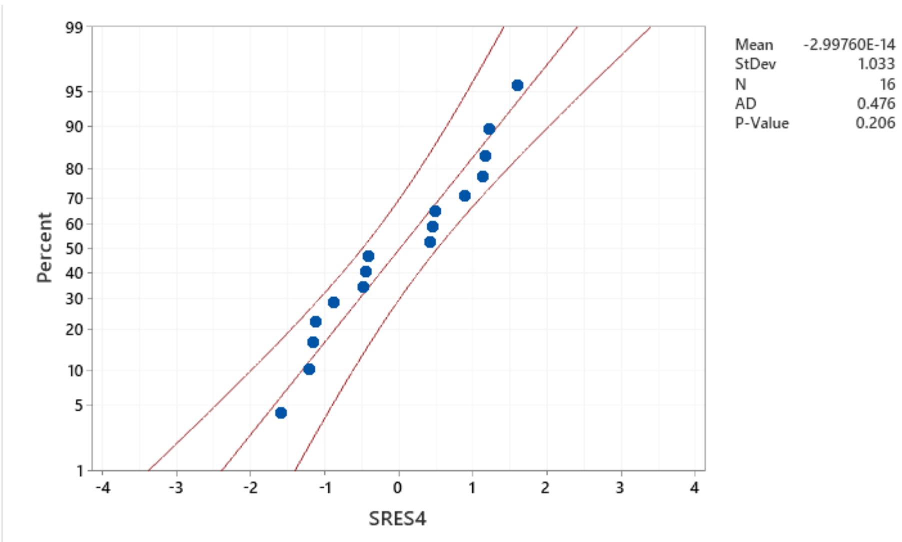


Figure 6.11. Normal probability of residuals of model for prediction carbon emissions

7. Conclusion

The world is currently facing a global energy crisis. Compared to last year, gas prices are 400% higher ("Open Energy Market - Open Energy Market," 2022), causing market volatility and uncertainty. On the other hand, energy demand in residential buildings is increased by 8% as a result of the implemented isolation measures due to the covid pandemic ("Buildings – The Covid-19 Crisis and Clean Energy Progress," 2020). Also, population growth affects energy consumption. In addition to the current crisis, the consequences of global warming are manifesting exponentially. Therefore, the aim is to ensure thermal comfort with lower energy consumption. According to Melville (2022), improvement building energy characteristics is the most effective way to mitigate the consequences of the crisis.

Bosnia and Herzegovina, as middle-income country with high heating demand, needs adequate strategy for realization Sustainable Development Goals ("A Partnership for Sustainable Development," 2021). Having this in mind, this master's thesis aims to analyze energy consumption of a typical residential apartment block built in period 1960-1970 in Sarajevo, capital city of B&H, and propose measures to save energy for heating and lower CO_2 emissions.

Energy consumption data are obtained using simulation software and DOE is utilized for the analysis of the factors' effect on the response. According to the DOE results, the highest influence on the delivered energy for heating has the U coefficient of outer wall and glazing type. Analyzed improvement measures are installation of 20mm EPS on outer walls, 20mm XPS on the roof, replacement of single glazing windows with triple glazing with improved air tightness and improving heat delivery system. Accordingly, applying proposed improvement measures saves 89% of the heating energy and 25.29 t CO_2 emissions annually.

However, several analyses of energy consumption of the selected building are performed, but the results differ significantly from the actual data. Therefore, quasi-stationary calculation based on seasonal or monthly temperature values is not adequate approach for building energy analysis. Additionally, calculation process is time-consuming. From the other side, dynamic simulation software incorporates all relevant data as occupancy, and enables precise modeling of the system. Moreover, hourly weather data is used for comprehensive calculation of heating energy demand.

According to statistical analysis of residential stock in B&H, apartment blocks account for 11.5% gross area of the total residential area (Arnautović-Aksić et al., 2016). The most significant benefit of this research it that this model can be applied for prediction heating demand in all buildings that statistically belong to the same category. Therefore, applying simulation software with DOE for energy analysis in building sector is accurate, reliable, and time-efficient method.

Finally, the developed mathematical model offers time-efficient analysis of the building characteristics improvement measures, in order to reduce energy consumption and carbons emissions while maintaining a comfortable indoor environment.

It outlines best practices for managing energy efficiency during the sustainable development process.

8. References

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Appendix A: Percentage Points of the t Distribution

ν \ α	0.40	0.25	0.10	0.05	0.025	0.01	0.005	0.0025	0.001	0.0005
1	0.325	1.000	3.078	6.314	12.706	31.821	63.657	127.32	318.31	636.62
2	0.289	0.816	1.886	2.920	4.303	6.965	9.925	14.089	23.326	31.598
3	0.277	0.765	1.638	2.353	3.182	4.541	5.841	7.453	10.213	12.924
4	0.271	0.741	1.533	2.132	2.776	3.747	4.604	5.598	7.173	8.610
5	0.267	0.727	1.476	2.015	2.571	3.365	4.032	4.773	5.893	6.869
6	0.265	0.727	1.440	1.943	2.447	3.143	3.707	4.317	5.208	5.959
7	0.263	0.711	1.415	1.895	2.365	2.998	3.499	4.019	4.785	5.408
8	0.262	0.706	1.397	1.860	2.306	2.896	3.355	3.833	4.501	5.041
9	0.261	0.703	1.383	1.833	2.262	2.821	3.250	3.690	4.297	4.781
10	0.260	0.700	1.372	1.812	2.228	2.764	3.169	3.581	4.144	4.587
11	0.260	0.697	1.363	1.796	2.201	2.718	3.106	3.497	4.025	4.437
12	0.259	0.695	1.356	1.782	2.179	2.681	3.055	3.428	3.930	4.318
13	0.259	0.694	1.350	1.771	2.160	2.650	3.012	3.372	3.852	4.221
14	0.258	0.692	1.345	1.761	2.145	2.624	2.977	3.326	3.787	4.140
15	0.258	0.691	1.341	1.753	2.131	2.602	2.947	3.286	3.733	4.073
16	0.258	0.690	1.337	1.746	2.120	2.583	2.921	3.252	3.686	4.015
17	0.257	0.689	1.333	1.740	2.110	2.567	2.898	3.222	3.646	3.965
18	0.257	0.688	1.330	1.734	2.101	2.552	2.878	3.197	3.610	3.922
19	0.257	0.688	1.328	1.729	2.093	2.539	2.861	3.174	3.579	3.883
20	0.257	0.687	1.325	1.725	2.086	2.528	2.845	3.153	3.552	3.850
21	0.257	0.686	1.323	1.721	2.080	2.518	2.831	3.135	3.527	3.819
22	0.256	0.686	1.321	1.717	2.074	2.508	2.819	3.119	3.505	3.792
23	0.256	0.685	1.319	1.714	2.069	2.500	2.807	3.104	3.485	3.767
24	0.256	0.685	1.318	1.711	2.064	2.492	2.797	3.091	3.467	3.745
25	0.256	0.684	1.316	1.708	2.060	2.485	2.787	3.078	3.450	3.725
26	0.256	0.684	1.315	1.706	2.056	2.479	2.779	3.067	3.435	3.707
27	0.256	0.684	1.314	1.703	2.052	2.473	2.771	3.057	3.421	3.690
28	0.256	0.683	1.313	1.701	2.048	2.467	2.763	3.047	3.408	3.674
29	0.256	0.683	1.311	1.699	2.045	2.462	2.756	3.038	3.396	3.659
30	0.256	0.683	1.310	1.697	2.042	2.457	2.750	3.030	3.385	3.646
40	0.255	0.681	1.303	1.684	2.021	2.423	2.704	2.971	3.307	3.551
60	0.254	0.679	1.296	1.671	2.000	2.390	2.660	2.915	3.232	3.460
120	0.254	0.677	1.289	1.658	1.980	2.358	2.617	2.860	3.160	3.373
∞	0.253	0.674	1.282	1.645	1.960	2.326	2.576	2.807	3.090	3.291

ν = Degrees of freedom.

[a]Adapted with permission from *Biometrika Tables for Statisticians*, Vol. 1, 3rd edition, by E. S. Pearson and H. O. Hartley, Cambridge University Press, Cambridge, 1966.

Appendix B: Percentage points of the F distribution ($\boldsymbol{\alpha = 0.05}$)

ν_2 \ ν_1 (Degrees of Freedom for the Denominator (ν_2))	Degrees of Freedom for the Numerator (ν_1)																		
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**12**	**15**	**20**	**24**	**30**	**40**	**60**	**120**	**∞**
	161.4	199.5	215.7	224.6	230.2	234.0	236.8	238.9	240.5	241.9	243.9	245.9	248.0	249.1	250.1	251.1	252.2	253.3	254.3
2	18.51	19.00	19.16	19.25	19.30	19.33	19.35	19.37	19.38	19.40	19.41	19.43	19.45	19.45	19.46	19.47	19.48	19.49	19.50
3	10.13	9.55	9.28	9.12	9.01	8.94	8.89	8.85	8.81	8.79	8.74	8.70	8.66	8.64	8.62	8.59	8.57	8.55	8.53
4	7.71	6.94	6.59	6.39	6.26	6.16	6.09	6.04	6.00	5.96	5.91	5.86	5.80	5.77	5.75	5.72	5.69	5.66	5.63
5	6.61	5.79	5.41	5.19	5.05	4.95	4.88	4.82	4.77	4.74	4.68	4.62	4.56	4.53	4.50	4.46	4.43	4.40	4.36
6	5.99	5.14	4.76	4.53	4.39	4.28	4.21	4.15	4.10	4.06	4.00	3.94	3.87	3.84	3.81	3.77	3.74	3.70	3.67
7	5.59	4.74	4.35	4.12	3.97	3.87	3.79	3.73	3.68	3.64	3.57	3.51	3.44	3.41	3.38	3.34	3.30	3.27	3.23
8	5.32	4.46	4.07	3.84	3.69	3.58	3.50	3.44	3.39	3.35	3.28	3.22	3.15	3.12	3.08	3.04	3.01	2.97	2.93
9	5.12	4.26	3.86	3.63	3.48	3.37	3.29	3.23	3.18	3.14	3.07	3.01	2.94	2.90	2.86	2.83	2.79	2.75	2.71
10	4.96	4.10	3.71	3.48	3.33	3.22	3.14	3.07	3.02	2.98	2.91	2.85	2.77	2.74	2.70	2.66	2.62	2.58	2.54
11	4.84	3.98	3.59	3.36	3.20	3.09	3.01	2.95	2.90	2.85	2.79	2.72	2.65	2.61	2.57	2.53	2.49	2.45	2.40
12	4.75	3.89	3.49	3.26	3.11	3.00	2.91	2.85	2.80	2.75	2.69	2.62	2.54	2.51	2.47	2.43	2.38	2.34	2.30
13	4.67	3.81	3.41	3.18	3.03	2.92	2.83	2.77	2.71	2.67	2.60	2.53	2.46	2.42	2.38	2.34	2.30	2.25	2.21
14	4.60	3.74	3.34	3.11	2.96	2.85	2.76	2.70	2.65	2.60	2.53	2.46	2.39	2.35	2.31	2.27	2.22	2.18	2.13
15	4.54	3.68	3.29	3.06	2.90	2.79	2.71	2.64	2.59	2.54	2.48	2.40	2.33	2.29	2.25	2.20	2.16	2.11	2.07
16	4.49	3.63	3.24	3.01	2.85	2.74	2.66	2.59	2.54	2.49	2.42	2.35	2.28	2.24	2.19	2.15	2.11	2.06	2.01
17	4.45	3.59	3.20	2.96	2.81	2.70	2.61	2.55	2.49	2.45	2.38	2.31	2.23	2.19	2.15	2.10	2.06	2.01	1.96
18	4.41	3.55	3.16	2.93	2.77	2.66	2.58	2.51	2.46	2.41	2.34	2.27	2.19	2.15	2.11	2.06	2.02	1.97	1.92
19	4.38	3.52	3.13	2.90	2.74	2.63	2.54	2.48	2.42	2.38	2.31	2.23	2.16	2.11	2.07	2.03	1.98	1.93	1.88
20	4.35	3.49	3.10	2.87	2.71	2.60	2.51	2.45	2.39	2.35	2.28	2.20	2.12	2.08	2.04	1.99	1.95	1.90	1.84
21	4.32	3.47	3.07	2.84	2.68	2.57	2.49	2.42	2.37	2.32	2.25	2.18	2.10	2.05	2.01	1.96	1.92	1.87	1.81
22	4.30	3.44	3.05	2.82	2.66	2.55	2.46	2.40	2.34	2.30	2.23	2.15	2.07	2.03	1.98	1.94	1.89	1.84	1.78
23	4.28	3.42	3.03	2.80	2.64	2.53	2.44	2.37	2.32	2.27	2.20	2.13	2.05	2.01	1.96	1.91	1.86	1.81	1.76
24	4.26	3.40	3.01	2.78	2.62	2.51	2.42	2.36	2.30	2.25	2.18	2.11	2.03	1.98	1.94	1.89	1.84	1.79	1.73
25	4.24	3.39	2.99	2.76	2.60	2.49	2.40	2.34	2.28	2.24	2.16	2.09	2.01	1.96	1.92	1.87	1.82	1.77	1.71
26	4.23	3.37	2.98	2.74	2.59	2.47	2.39	2.32	2.27	2.22	2.15	2.07	1.99	1.95	1.90	1.85	1.80	1.75	1.69
27	4.21	3.35	2.96	2.73	2.57	2.46	2.37	2.31	2.25	2.20	2.13	2.06	1.97	1.93	1.88	1.84	1.79	1.73	1.67
28	4.20	3.34	2.95	2.71	2.56	2.45	2.36	2.29	2.24	2.19	2.12	2.04	1.96	1.91	1.87	1.82	1.77	1.71	1.65
29	4.18	3.33	2.93	2.70	2.55	2.43	2.35	2.28	2.22	2.18	2.10	2.03	1.94	1.90	1.85	1.81	1.75	1.70	1.64
30	4.17	3.32	2.92	2.69	2.53	2.42	2.33	2.27	2.21	2.16	2.09	2.01	1.93	1.89	1.84	1.79	1.74	1.68	1.62
40	4.08	3.23	2.84	2.61	2.45	2.34	2.25	2.18	2.12	2.08	2.00	1.92	1.84	1.79	1.74	1.69	1.64	1.58	1.51
60	4.00	3.15	2.76	2.53	2.37	2.25	2.17	2.10	2.04	1.99	1.92	1.84	1.75	1.70	1.65	1.59	1.53	1.47	1.39
120	3.92	3.07	2.68	2.45	2.29	2.17	2.09	2.02	1.96	1.91	1.83	1.75	1.66	1.61	1.55	1.55	1.43	1.35	1.25
∞	3.84	3.00	2.60	2.37	2.21	2.10	2.01	1.94	1.88	1.83	1.75	1.67	1.57	1.52	1.46	1.39	1.32	1.22	1.00

Appendix C: Minitab FFD effect table

In the following table, results of performing DOE in Minitab are presented. Response variable is delivered energy for heating. Effects column from this table are used for developing mathematical model. T-value and p-value are used for testing factor effect statistical significance and VIF provides information about variation.

Term	**Effect**	**Coef**	**SE Coef**	**T-Value**	**P-Value**	**VIF**
Constant		64.0077	0.0334	1916.29	0.000	
A	-46.9959	-23.4980	0.0334	-703.49	0.001	1.00
B	-41.5480	-20.7740	0.0334	-621.94	0.001	1.00
C	-10.4141	-5.2070	0.0334	-155.89	0.004	1.00
D	-7.1120	-3.5560	0.0334	-106.46	0.006	1.00
A*B	-4.0664	-2.0332	0.0334	-60.87	0.010	1.00
A*C	1.0054	0.5027	0.0334	15.05	0.042	1.00
A*D	2.6109	1.3054	0.0334	39.08	0.016	1.00
B*C	1.4800	0.7400	0.0334	22.15	0.029	1.00
B*D	2.3082	1.1541	0.0334	34.55	0.018	1.00
C*D	0.5786	0.2893	0.0334	8.66	0.073	1.00
A*B*C	-1.2025	-0.6012	0.0334	-18.00	0.035	1.00
A*B*D	0.2259	0.1130	0.0334	3.38	0.183	1.00
A*C*D	-0.0559	-0.0279	0.0334	-0.84	0.557	1.00
B*C*D	-0.0822	-0.0411	0.0334	-1.23	0.434	1.00