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MASTER THESIS

THE INFLUENCE OF EARLY DESIGN DECISIONS ON ENERGY DEMAND: A QUANTITATIVE ASSESSMENT USING SENSITIVITY ANALYSIS

ORÇUN KORAL İŞERİ

THESIS ADVISOR: ASST. PROF. DR.-ING. ONUR DURSUN

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We certify that we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science

Jury Members: **Signature:**

Prof. Dr. Zehra Tugce KAZANASMAZ ....
Izmir Institute of Technology

Asst. Prof. Dr. Eray Bozkurt ....
Yasar University

Asst. Prof. Dr.-Ing. Onur DURSUN ....
Yasar University

Prof. Dr. Cuneyt Guzelis
Director of the Graduate School

ABSTRACT

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İşeri, Orçun Koral
M.Sc. in Architecture
Advisor: Asst. Prof. Dr.-Ing. Onur Dursun
May 2018

Architectural design is a complex problem which contains multiple design parameters and constraints. Particularly, early architectural design includes all the major decision-making process that defines the framework of yearly energy demand of the unit. Due to time constraints and uncertainty of the energy demand at early design it is important to analyze the process starting from the early design. To reduce the complexity of model, quantify output uncertainty and lastly understand the relation between independent and dependent variables, in the current study, Morris and Sobol' global sensitivity analysis have applied for one zone office building to support a decision-making guidance for designers with regards to specified quasi random sampling methods. As energy modelling composes from physical properties of the building and weather type, procedure has been conducted for cold climate of Erzurum and hot-humid climate of Izmir. Firstly, ineffective parameters factor fixing is implied than factor prioritization is illustrated with Morris analysis. Afterwards, by using variance based Sobol' sensitivity analysis, first and total order effects are investigated for each climate. Thirdly, a performance filtering process has been executed for 100 best high energy performances of samples to illustrate each of them by presenting the valuable range values of parameters with Parallel Coordinate Plot (PCP). Lastly, a comparison has been implemented for how input parameter and its values are changing according to climate type. For further works, it is aiming to apply all the process for specified design of building by adding Monte Carlo filtering applications.

Key Words: early architectural design, performance-based design, energy modelling, global sensitivity analysis, decision-making support

ÖZ

ÖN TASARIM AŞAMASI KARARLARININ ENERJİ KULLANIMI ÜZERİNE ETKİSİ: DUYARLIKLIK ANALİZİ İLE KANTİTATİF DEĞERLENDİRME

İşeri, Orçun Koral
Yüksek Lisans, Mimarlık
Danışman: Dr. Öğretim Üyesi Onur Dursun
Mayıs 2018

Mimari tasarım, çoklu tasarım parametreleri ve kısıtlamaları içeren karmaşık bir sorundur. Özellikle, erken mimari tasarım, yapı yıllık enerji talebini büyük oranda tanımlayan önemli karar verme süreçlerini içerir. Zaman kısıtlamaları ve erken tasarımda enerji talebinin belirsizliği nedeniyle, erken tasarımdan başlayarak süreci analiz etmek önemlidir. Modelin karmaşıklığını azaltmak, çıktı belirsizliğini ölçmek ve son olarak bağımsız ve bağımlı değişkenler arasındaki ilişkiyi anlamak için, tek bölüm ofis binası için tasarımcılar için bir karar verme rehberliğini desteklemek üzere belirtilen rastgele örnekleme yöntemlerine göre uygulanan Morris ve Sobol' geniş duyarlılık analizini içerir. Enerji modellemesi, binanın fiziksel özelliklerinden ve hava koşullarından oluştuğundan, Erzurum'un soğuk iklimi ve İzmir'in sıcak-nemli iklimi için süreç yürütülmüştür. Öncelikle, etkisiz parametrelerin faktör tespitinin, Morris analiziyle faktör önceliklerinin daha fazla olduğu anlaşılmaktadır. Daha sonra, değişiklik tabanlı Sobol' duyarlılık analizi kullanılarak, her iklim için birinci ve yüksek dereceden etkileri araştırıldı. Üçüncüsü, 100 en iyi yüksek enerji performansının görselleştirildiği Paralel Koordinat Çizimi (PCP) ile parametrelerin değerli aralık değerlerini sunarak bir performans süzme işlemi gerçekleştirilmiştir. Son olarak, girdi parametresinin ve değerlerinin iklim türüne göre nasıl değiştiğine ilişkin bir karşılaştırma yapılmıştır. Daha ileri çalışmalar için, edilen carlo filtering uygulamalarını ekleyerek, belirtilen binanın tasarımına yönelik tüm sürecin uygulanması hedeflenmektedir.

Anahtar Kelimeler: ön mimari tasarım, performans tabanlı tasarım, enerji modellemesi, genel duyarlılık analizi, karar verme desteği

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Orçun Koral İŞERİ

Izmir, 2018

TEXT OF OATH

I declare and honestly confirm that my study, titled “THE INFLUENCE OF EARLY ARCHITECTURAL DESIGN DECISIONS ON ENERGY DEMAND: A QUANTITATIVE ASSESSMENT USING SENSITIVITY ANALYSIS” presented as a Master of Science Thesis, has been written without applying to any assistance inconsistent with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn directly or indirectly from external sources are indicated in the text and listed in the list of references.

Iseri, Orcun Koral

Signature

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June 20, 2018

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SYMBOLS AND ABBREVIATIONS

ABBREVIATIONS:

EUI	Energy Use Intensity
OAT	One at a Time
PCP	Parallel Coordinate Plot
S1	First Order
ST	Total Order
WWR	Window to Wall Ratio
IDF	Input Data File
IDD	Input Data Dictionary
EPW	EnergyPlus Weather Data
TMY	Typical Meteorological Year
HVAC	Heating, Ventilation, and Air Conditioning
EE	Elementary Effect
E+	EnergyPlus simulation engine
m	meter
K	Kelvin
kWh	Kilowatt hour
sqm	Square meter
cbm	Cubic meter
wwr_north	North facade window to wall ratio
wwr_east	East facade window to wall ratio
wwr_south	South facade window to wall ratio
wwr_west	West facade window to wall ratio

SYMBOLS:

Δ	Difference - Delta
%	Percentage
mu*	Individual importance
σ	Interaction between parameters
^{0}C	Centigrade Degree

CHAPTER ONE
INTRODUCTION

1.1. BACKGROUND

"Energy is a design topic, not a technology topic, but there are few of us who have always believed this."

Donald Watson, FAIA

In recent years, there has been tendency towards environmental and sustainable design for building design and construction due to climate change. The motivation has driven for increasing energy demand for occupants and responsibility for the environment. Hence, assessing the building's total energy demand and preparing new schedule for usage habits are very crucial for future and current management of the society. To gain and continue these practices, building design and construction must focus on passive strategies and reach optimal solutions (Konis, Gamas, & Kensek, 2016). Raising the awareness of indirect and direct carbon emissions which comes from building energy cycle is increasing concern between designers and engineers who are responsible for building production from early design to construction. This sustainable conscious supported with the energy code compliance and simulations to reaching the optimal energy demand for controlling of indoor occupant comfort by predefined threshold values and implicitly, codes and low energy researches become guidance for designers to orient the design more energy efficient framework (Joe Clarke, 2001; Østergård, Jensen, & Maagaard, 2017)

The growth of urban communities has been encountered by sustained augmentation of energy demand which creates the need for analytical frameworks of a multi-objective and holistic approach from the initial phase of architectural design. Holistic design methodology in the early design where input and output uncertainties are varied and determinations of the design has radical implications on performance (Chen, Yang, & Sun, 2016; Jradi, Veje, & Jørgensen, 2017; Østergård, Jensen, & Maagaard, 2016a). For this reason, that issue is highly related with designers who are the generators of the urban environment therefore they have this strain to create more sustainable urban growth (Mumovic, 2009; Pacheco, Ordóñez, & Martínez, 2012).

Usually, energy considerations become substantial at the late design stages for evaluation of the building specifications whether fulfil the requirements of building regulations or certificates. During organization of building design, designers have more responsibility than other participants in terms of satisfy the client anticipations and balance the cost of environmental design. For near future, this harmony between cost and environmental requirements will not be difficult as today, by the time of progress the designers persuade clients and constructors for energy performance importance and positive impact on cost in a long-term. Unfortunately, environmental requirements are not highly concerned by current design procedure (Lechner, 2014). Besides, these efforts can support with individual interest by designers. In the contemporary design practice, there many important design considerations that some of them is highly regulated such as fire escape strategies and some of them take shape based on client or designer expectations such as project cost, aesthetically and functionally. In addition, architects, in practice, find it difficult to cope with the technical complexity required to enable them to evaluate different design options with an advanced simulation tool (Robinson, 1996; Y. Yildiz, Korkmaz, Göksal özbalta, & Durmus Arsan, 2012)

Many designers are attended for design process who are architects, civil engineers, structural engineers, etc. The defining of design decisions made by the different team members on the energy performance, with architects and engineers having the biggest impact: architects who arrange parameters that influence the energy and environmental performance of the building such as envelope design and building services engineers because they design the systems that building provides adequate indoor conditions such as plug-loads (Granadeiro, Duarte, Correia, & Leal, 2013; Morbitzer, 2003). According to some researches, analysis opportunities, for example for passive energy strategies, are mostly explored during early design development (Konis et al., 2016; Østergård et al., 2017).

1.2. PROBLEM STATEMENT

According to various researches, building envelope design is counted as the main factor of energy use of the facility and directly, the decisions are related with early design depends on architectural management (Allen, E., & Iano, 2006) Addressing the issue, for many years, several guidelines have been established for how building form determines the total energy performance (Y. Yildiz et al., 2012). Several studies pointed out that compactness of the building is one of the most prominent measurement to evaluate as low energy use indeed, as building design compose from multiple variables, energy usage differs according to climate (Depecker, Menezo, Virgone, & Lepers, 2001; Gratia & De Herde, 2003). Extra, there are studies examining the building volume to surface ratio with regards of energy production from the sunlight (Kampf & Robinson, 2010; Kanters, Dubois, & Wall, 2013).

In current situation, mostly, energy simulation tools have no complete feature investigation of overall performance of building influenced by decision variables. It is specifically hard process to execute in early design phase due to lack of time, technicality and uncertainty of the defined objectives for reaching the desired results (Østergård et al., 2016a). On the other hand, simulations has capability of serving as an evaluative tool in the place of proactive design (Attia, Gratia, Herde, & Hensen, 2012; Kanters, Horvat, & Dubois, 2014). Especially, for the designers, energy analysis should be suitable to give feedback about design variations by ranking, fixing and filtering the chosen parameters (Attia et al., 2012; Rights, 2016). Before detailed modeling process, designers should deal multiple input factors and to define right output selection that would shape the end architectural design for this reason. In literature, sensitivity analysis could be the answer as a technique that searches the impaction of parameters for the output and interaction between decision variables. Simultaneously, it could work as an intelligent feedback tool for the architects while they are designing the facility (Østergård et al., 2016a; Ruiz Flores et al., 2012).

Sensitivity and uncertainty analysis frameworks are useful computational power to decrease model complexity and demonstrate the parameters impact on output for unbiased decision-making procedure (De Wit & Augenbroe, 2002). Uncertainty of the model is affecting the architectural process and building performance even after construction phase and users of the building becomes the victim of the inadequate design organization. To understand usage patterns of the building form, construction materials, climate properties, sensitivity analysis approach has been observed from previous scientific studies (Sanguinetti, Eastman, & Augenbroe, 2009; Struck & Hensen, 2007)

In particularly, sensitivity analysis (SA) has been increasingly used in a practical approach or as a step in more structured procedures, to investigate how model parameter uncertainties influence model attitude and to address the following issues:

- Determine most effective input parameters,
- Measurement of output uncertainty,
- Comprehend the relations between design parameters and objectives,
- Supportive decision-making assessment,
- Offering solution definable problems.

Any prominent change happens in design process which brings about the alternation throughout the end-product that contains detailed decisions. This practice was more visible before mass-production periods. Therefore, contemporary building production has pulled away from manual craft-based style. It is the design methodology which composed by several generation of transformation based on experience and thoroughly unified with environmental response such as building the structure according to climatic conditions of the house with local material (Lawson, 1990). Design experience transforms and grows from generation to generation as current situation adapts the method to generate new solutions and alternative. The technique was a suitable solution for climate but could not response for fast population and urbanization increasing. On the other hand, experience-based design continues among architects but, mostly impersonal way, and linear workflow has adapted for decades which is led to architect to start project by initial drawings afterwards, simulation includes the process for analyzing the building in accordance with environmental performance. But, methodology startle because of the lack of collaborative working and evaluation of the multiple alternatives that environmental observation could not change architectural artifact as it should be. If change is crucial that occurs lots of effort to implement in it (Anton & TĂnase, 2016).

The anticipations of customer or production tackles when authorizing the design revises several times. Even building function can expect a building without mechanical interference for ventilation. At the time, designer can struggle to compose sufficient air change rate to balance indoor environment in terms of cooling and refreshing occupants breathing zone. In addition, building should stand out against extreme temperature levels throughout all year (Morbitzer, 2003). So far, simulation adaptive performance based design is a promising technique which can be useful linking the whole design process and preventing the problems before it happened hence decreasing the alterations in similar way (Strømann-Andersen & Sattrup, 2011).

Instead of simulation usage at early design process, many designers endeavor to reach holistic building design from the start, personally. But, while project design advances, trade-offs come up and designers confront with alterations multiple times and sometimes they should turn back initial process to change it which cost time and expenses of the process. Besides, as project continues from pre-design to construction, any intervention’s cost rise and it is influence decrease (Hien, Poh, & Feriadi, 2000). The importance about simulations that they are not just design support elements that their impact depends on the judge of designer, they are one of the key elements of performative design: (1) For detailed design stages of architectural design process just few design variables are still adjustable; so, ways of solving any highlighted problems are restricted. (2) Using building simulation in the detail design process supplies information at a design phase when it can make the least effective change upon the quality of the architectural design. Using simulation at an early design stage could provide the designer with insight into the characteristics of a proposed building design at a time when it would be better used and therefore having a much more significant potential for the improvement of the building design (Morbitzer, 2003).

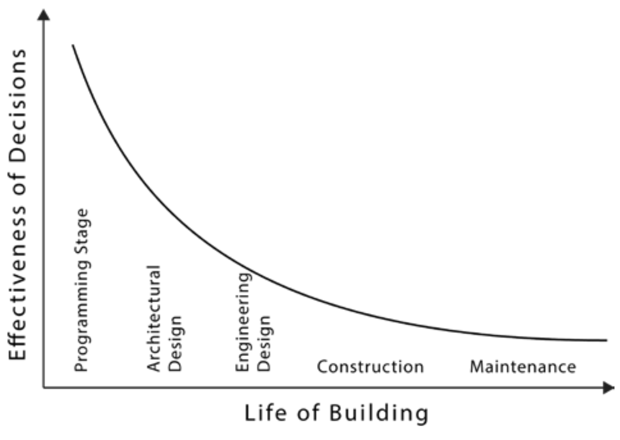


Figure 1.1. Representation of connection between life of building and effectiveness of decision (Lechner, 2014)

Moreover in Figure 1.1, most of existing methods and operations incline the figuring out design alternatives after decision making process, however, valuable and highest influence on energy performance for buildings comes from the decisions at early design process (Attia et al., 2012). Instead of evaluating energy character of building solely with compliance obligations at detailed design stages, designers and operating systems are focusing to get sudden and iterative energy performance feedbacks in early design stages where decisions have biggest effect on building achievements and highest cost efficiency (Yohanis & Norton, 2000). To reach effective energy performance targets by analyzing building geometry, location, positioning, thermal and visual performance and indoor environment quality must collide with the whole building energy concept which compose multiple elements and time-consuming activity for design phases. On the other hand, it is not impossible goal to obtain. For various researches, designers ought to construct collaborative and interdisciplinary working atmosphere, adapt environmental aims and comparative performance analyses for design phases (Konis et al., 2016).

Energy simulations provide strong computational outcomes that lead to understand complex thermal transfers between outdoor and indoor environments (Morbitzer, 2003). Instead of limiting the decision-making process with insufficient past experiences or inadequate alternative production, simulation-based workflow converts the design to more transparent model that decisions can be seen easily. Another advantage is by implementing the analysis into design phase, can decrease the uncertainty of the building performance for the designers while in the decision-making process especially at the early stages. According to quantitative outcomes of the performance analysis, designer can compare several design schemes with the direction of predefined parametrized building form features.

1.3. RESERCH AIMS

Addressing the previous sections, the current research aims to observe the early design architectural parameters with regards to energy demand of the building. Related with this, a genuine method has been presented to analyze design parameters influence on the pre-defined output parameters due to factor prioritization thus design teams can recognize how to focus on important decision parameters at the early design stage which could lead to give it more specific design result.

In addition, another aim is the work is to produce many alternatives by using statistical sampling methods and simulation tools to scan the global design space in the sense of design team. That is, designers and stakeholders can evaluate global design solutions and during the ongoing process it is beneficial to comprehend design parameters impact for the subsequent stages of design.

Another aim of the research is to detect and fix the design some of the impotent design parameters for the energy demand of the unit. Building design is a complex task to execute, due to many alternations that cause by the design parameters, it is crucial to stabilize some of the unimportant parameters for the performance-based design to increase the attention for the influential design parameters. By using that kind of a technique, it is possible to reduce complexity of the energy model.

Lastly, one of the main goals of the process is to define valuable range values of the design parameters to provide effective performance for the energy usage. Due to uncertainty of early design, instead of presenting of point estimation framework for the energy performance of the building, this research aims to provide alternatives of design space for designers by decreasing the range values of the effective design parameters into more secure zone which has the effect to produce low energy performance outcomes and adaptation of a design process as a supportive guidance tool.

1.4. METHODOLOGY

The current research focuses on the architectural decision-making process of early design in terms of low energy performance with regards to physical and functional design parameters influence on the output which are yearly heating and cooling demand (kWh/sqm-year). The main idea of the process has derived from the idea of the early design decisions designate common framework of the design process therefore it is important the observe the initial design process to lead the high-performance energy usage for the buildings. Related with this issue, in the ongoing process, from among the many input factors, it is aimed of which of them are highly provides uncertainty of the energy demand. On the other hand, which of them are relatively ineffective in terms of energy performance. Finally, with statistical sampling and filtering techniques, researched searched to map input vector range values according to probabilities to generate model realizations close to target measurements in which low heating and cooling demand usage, for the context of the work. It is the essence of calibration of the model. Generally, design solutions differentiate with the environment and weather properties, to form better case for the scientific perspective, there are two other cases prepared to compare climate impact on the early design energy modelling, one case is from Izmir (Hot-Humid) and second one is from Erzurum (Cold), Turkey. Izmir locates western and Erzurum locates eastern part of the Turkey (Figure 1.2.)

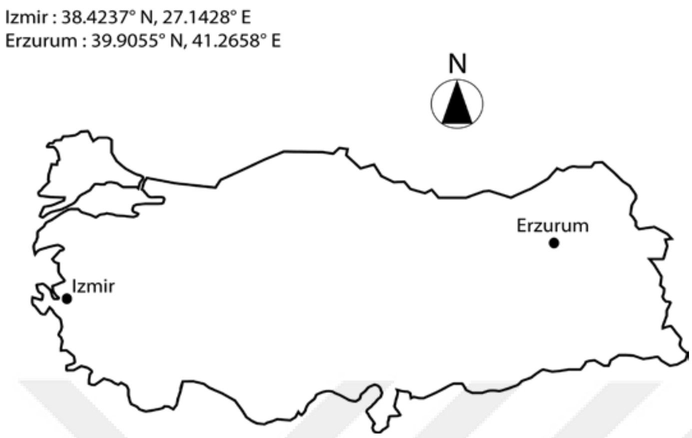


Figure 1.2. Location of the current investigation: Izmir and Erzurum

In the frame of the work, energy model has been analyzed with the energy simulation engine (EnergyPlus) which is highly popular to build architectural energy model in attempt to assess building energy performance (US Department of Energy). Due to produce many alternation of the design process, it is crucial to organize the system in automated structure therefore code-based system has been chosen for the content of the research (Fehily, 2002). In the Python community, for energy simulations executed with Eppy (scripting language for E+ IDF files, and E+ output files) and Geomeppy (Geometry editing for E+ IDF files) libraries. Besides that, early design process has lack of certainty in terms of input and output parameters and to compensate this tackle and it is possible to generate many design alternatives either understand the input and output factor relations and to prevent to stick around narrow local solutions. Correspondingly, a statistical library of Python has been preferred to execute sampling, analyze and filtering process which is the SALib (sensitivity analysis tool).

Firstly, to assess the energy performance of the unit, input data file that compose the physical and functional properties of the digital model, is prepared before the simulation in the scripting language. In the broad extent, input data file contains physical properties of the model, mechanical ventilation and climatization parameters and related with it scheduling, occupant density and building function, etc. As many decision variables exist in the early design process, the variables have come under several categories, i.e. heat transmission by conduction, heat transmission by convection, air changes and lastly, internal gain. For the progressing time, a box model is conducted according to standards of energy simulation, related with this issue, all the input factors have been decided according to ASHRAE (The American Society of Heating, Refrigerating and Air-Conditioning Engineers) standards to compose a scientific and quantitative environment in the purpose of generate and compare design alternatives. In the context of the research, heating and cooling loads has been chosen as objectives of the model, based upon the lack of the cooling map of Turkey, global energy standards have been implemented to organize input files. In addition, input data dictionary (thermo-physical function library) added in the process to execute energy simulations and energy simulations has two main input cluster one of them as mentioned above, input file and secondly, EnergyPlus weather data (climate properties of the location) used before the simulation stage.

Secondly, to produce design alternatives by changing the instant values of the input factors, some sampling strategies has been utilized which are quasi-random sampling methods, in the Monte Carlo framework. Input factor values has been changed with respect of a pattern to scale all the alternative design space and with sampling, many distributions are produced with specifically relative to chosen input factors. With this structure, it is aimed to evaluate input parameter influence on the output. Afterwards, with the generated data input prioritization which is the visual classification of the impact for the heating and cooling demand. Some of the inputs has come to the forefront rather than ineffective ones. At this point, factor fixing method has been applied to convert the some of the decision variables with default values. As result for factor fixing, it is aimed to reduce model complexity. For this process, Morris Sensitivity analysis showed input importance with box plotting which was the main reason that it is chosen to show the outcomes in an easier way due to lack of technical knowledge of design team.

Out of the reduce complexity of the energy model, two main objectives have added into one equation. As two pre-defined outputs is evaluated with same units this method derives the possible outcomes in one frame. Basically, it is the summation of two energy demand unit by assign weighting function. Each of them multiplied with 0.5 and as a result energy demand metric composed with the value of one. Of course, there would be differentiation between the values according to climate and site location, but this concern has been excluded from the content of the research.

As Morris sensitivity analysis is used to decrease input cluster another sensitivity analysis has been used to observe total effect of the all variables with 95 percent confidence interval, such as Sobol' sensitivity analysis. Sobol' method is formed based on the variance of output parameters due to input parameter variation, so the method is suitable to explain individual importance of the decision variables, relation with two independent variables and finally the total impact of the all included decision variables. With this method, it is aimed to analyze input factor effectiveness with several alternatives. Especially, it is valuable in the design process to comprehend the input behaviors in the aspect of the design team.

In the ongoing process of study, to observe most effective range values in terms of the high energy performance output distribution, Monte Carlo filtering statistical technique has been chosen to define positive behavior input parameter distribution with the intent of the provide range estimation for the design team. The method is helpful to identify both input and output relation in the aspect of the high-performance tendency and to supply a guide for the design team to manage the design alternatives through performance metrics. Instead of to solve the problem for the later stages, it provides instant feedback to prevent the problem before it is happened.

Lastly, at the validation stage, it is aimed to observe how architectural design changes in the different situations therefore, input factor types and its valuable range values are compared in the sense of climate and site selection. All results are drawn parallel between each other by illustration of the plotting outcomes.

1.5. SCOPE AND LIMITATIONS

The current researched has been conducted to analysis early design decision variable influence on the combined heating and cooling demand output in the sense of how decision variables shape the performance of the building according to their relations with each other and related design outcomes with regards to different climate selection. Therefore, a code based automated workflow has been formed with energy simulations firstly, to produce design alternatives by quasi-random sampling strategies and secondly, to analyze the sensitivity measurements both individually and totally for the decision variables. Finally, determination of the related input factor distribution range values towards high energy performance outcome.

Related with the project a digital box model has been formed with several decision variables. To analyze the envelope design with energy performance, volume of the box model has changed from 300 cbm to 124 cbm. All the input factors related with architectural decision-making process are varied around the box model. The model is prepared with the peripheral structures to embed the constructed environment influence of the centered box model. As most of the building stock is situated in or around the cities, this situation has been preferred to adapt the current human city development. Rather than implementing specified environment around test model, a one unit has been positioned in front of each façade of the unit. In addition to this, periphery building heights are valued between 6 meters to 3 meters about typical urban neighborhood.

Box model of the unit has been cleared of any specific architectural interference related with structure and visual performance. Main reason behind this intervention was to analyze all the energy related envelope architectural parameters in a clear way. This gives an opportunity to evaluate all the outcomes in an objective way. For further works, the methodology of the thesis will be implemented for specific architectural design project to test in a practical approach.

One of the most important buildings are office units where during day time, human activation is existed. Besides, especially for ease of use and to prevent the unnecessary intervention for the energy performance comparison, single zone office unit has been arranged as observation model of the current study.

As the content of the research is shaped for the observe and analysis energy performance of the unit with regards to decision variable variation, all aesthetical aims of the architecture excluded from the design process. It is aimed to solely focus on the input connections and relatively output relation with quantitative approach.

Another important point of the frameworks is to adapting u value of calculation of the building envelope instead of choosing specific construction materials for surfaces of the unit. Especially, for early design stage of architectural design due to uncertainty of the energy demand, it is hard to propose defined materials therefore, in the current study u value properties of the construction materials has been implemented in order to observe heat transfer by transmission. Subsequently, construction material selection has been arranged according to ASHRAE 90.1 standards which contains medium type envelope construction design suitable for both hot-humid and cold climate.

Especially for the simulation and validation process all the workflow repeated two times for two different climates. Weather properties has been included into simulations with EnergyPlus weather data (EPW). As weather data is one of the most important inputs of the energy modelling, it is important to use as current as possible, thus 2014 dated EPW files are used in the process.

1.6. OUTLINE OF THE MANUSCRIPT

The current work composes from six other chapters. As first chapter is introduction, in the following content, literature review is conducted in Chapter 2. In the frame of the literature review, current applications of the energy modellings are surveyed with several approaches. Besides that, there are several researches related with the uncertainty of the input and output parameters at early design. Afterwards, sensitivity analysis has observed in the aspect of the architectural energy modelling, especially for the current developments and concerning this research.

In Chapter 3, the methodological approach of the workflow presented in sequential way. The part of the script aims to explain for observing the decision variable influence on the combined heating and output demand in the sense of energy performance by using sensitivity analysis techniques and there are some related demonstrations for the sampling and filtering process for input factor valuable range values.

In Chapter 4, an outcome and comparison are illustrated for cold climate of Erzurum and hot-humid climate of Izmir by the sense of sensitivity analysis. At first, Morris sensitivity analysis and second variance based Sobol' sensitivity analysis. Lastly, there is an implication of performance filtering by implying Parallel Coordinate Plot (PCP) to illustrate all the selected input valuable ranges in one chart.

In Chapter 5, the commentary explanation of the result is written in the way of evaluation for the results that it has been executed in the process.

Last, in Chapter 6, a summary of the study process and projections for future research are presented.

CHAPTER TWO
LITERATURE REVIEW

Architects are encountering several economical and technical restrictions, such as energy analysis, cost management, project design, therefore energy demand arrangement policy should be take into consideration from the earliest architectural design phases. Different researches have been executed that physical features of the buildings are the most important factors for the energy use of the facility (Allen, 2011; Olgyay, 2015). Particularly, passive environmental decisions are useful to set course for decreasing the energy performance. From the historical perspective, several keynotes are presented about how building form shapes total energy usage. As a primarily approach, to quantify the overall performance of the building, there is the method where external surface ratio divided by interior volume of the unit which is called the shape coefficient (Depecker et al., 2001). Afterwards, several studies pointed out that compactness of the building is one of the main measure to use as energy decreasing strategy. While several researches continue to enter the issue, it has been proven that influence of compactness about energy usage differs according to weather conditions (Gratia & De Herde, 2003; Ourghi, Al-Anzi, & Krarti, 2007). Immediately in the ongoing process, there are wider researches has examined for building volume to surface ratio by adding energy production from the sunlight and ventilation (Hachem, Athienitis, & Fazio, 2011; Kämpf, Montavon, Bunyesc, Bolliger, & Robinson, 2010) While observations were increasing for design process, energy simulation software have been involved as a full package for performance measuring, consequently, process has evolved in a way of detail investigation (US Department of Energy).

Energy simulations are generally stepped in the architectural design process at the detailed design stages by the help of engineers. Software has mostly developed in accordance with the usage of technical stakeholders who produce the results as a specified point-based results. In addition, simulations serve as evaluative tools in the place of proactive (Kanters & Horvat, 2012). For this reason, current energy simulations have not completely fill up for features of focusing on investigation of overall performance of building by taking range-based impact of decision variables into account. On the other hand, due to lack of time and technical knowledge, it is difficult to perform a search for uncertainty of pre-arranged objectives, notedly initial stages (Østergård, Jensen, & Maagaard, 2016b). Because there are many parameters that changes the outcome simultaneously and these links between inputs and outputs could not detect instantly. So, to apply the methodology in a right manner, designers could get a chance to deal many changeable parameters and define right objectives that would shape the end architectural design. Hereby, it is crucial to practice beneficial decision-making process for initial design phases. Most particularly, from the point of designers, energy analysis should be suitable to give feedback about design variations by ranking, fixing and filtering the chosen parameters (Batueva & Mahdavi, 2014). It could help both designers while decreasing their workload and transform the model to a clear way. In literature, i.e. Østergård, Maagaard, & Jensen, (2015), sensitivity analysis could be the answer as a technique that searches the impaction of parameters for the output and interaction between decision variables. Simultaneously, it could work as an intelligent feedback tool for the architects while they are designing the facility.

Each building design forms from lots of elements, and therefore, pretty much special according to environmental parameters. The decisions about building form are belong to early design arrangements thus, it is the totally focus zone of the architect as a designer (Aksamija, 2015; Stumpf, Kim, & Jenicek, 2011) That is beneficial to illustrate the global design space for the designers. It is extremely significant that researches and techniques should provide the information about the design parameters from the rational perspective. In time, while energy simulation tools are adapted to extend and expand the search area, amount of the parameters has been increased exponentially and investigation for the energy performance became multi-layered. There are several techniques has been applied to deal with this complexity, such as sensitivity and certainty analysis (Hughes, Palmer, Cheng, & Shipworth, 2013; O’Neill & Niu, 2017).

2.1. ENERGY EFFICIENCY AND ARCHITECTURAL DESIGN

Basically, an energy model works as a computing engine which includes inputs which are building geometry, location information, system and maintenance specifications, building and operation schedules and outputs which are performance comparison and compliance reports (Porwal & Hewage, 2013). Therefore, building energy modelling (BEM) anticipates the building total energy demand and preserving in accordance with threshold values which predefined by energy compliance codes using typical meteorological year data in which climate data of the site location (TMY).

Building total energy demand contains building operation and maintenance activities. Due to lack of technical knowledge as compared to engineers, architects use building energy modelling tools with front-end interfaces (Porwal & Hewage, 2013). Besides, designers enter energy related inputs through engine and they do not know the calculation process works at the background of the interfaces. At this point, if designers can comprehend the decisions influence for the energy demand of the building, design can evaluate towards to low energy usage. Consequently, in practice, users of the energy software procure results, as graphical display to compare the alternatives of existed designs if they involve into generative design process. Addressing the issue, methodology will discuss at forthcoming sections in detail. For some situations, there are more than one interface that developers, engineers and designers can attribute in accordance with their technical acknowledge. But, generally operation units have one integrated suite for everyone and as many of the software presents complex user interface, designers especially the architects are struggling the adapt the usage (Porwal & Hewage, 2013; Yohanis & Norton, 2000). For adaptation process, there has been many researches about statistical and mathematical solutions to point out the relation between design elements and the energy performance, thus for the perspective of architects, it is possible to form a guide method to reach the energy performance-based design at early design process.

Previous studies made by Association of Collegiate Schools of Architecture stated that nearly all architects could not cooperate with energy use and performative design, even they know the importance of it (Yohanis & Norton, 2000). Especially, the building expenses related with energy usage are highly correlated with design physical decisions and functional design decisions, such as orientation, building envelope, occupancy, indoor environment quality etc. On the contrary, architects have advantages of directing the building design towards low energy usage and encourage that buildings achievements through the high standards, as they are the leader of the design process. Therefore, architects should adapt new technologies, terms and strategies into early design process and increase the ratio of energy awareness into decision-making. This comes with the learning of energy as acknowledge, calculation and modelling. In current situations, there are some misunderstandings which comes from the past and architects still believe these in practices, as follows (American Institute of Architects, & Publishing, 2013):

“Energy modelling is too detailed in practice.”

This claim can be counted true to a certain degree, on the other hand design process is starts with building envelope forming which has the most influential process that identify end usage. The first focus point of the energy modelling is the prevent the problem before it is occurred therefore, instead of spending the valuable time to improve or fix the problems, it could be helpful to avoid them by observing at initial phase of design.

“Energy modelling takes time and resources.”

Statistical analysis shows that an effort that gave at the early design process is more effective than the effort that supplied for later stages. Besides, design team can deduce relations from these investigations which process can be arranged as fluent route.

“Energy considerations and integrated design teams will limit design decisions?”

Instead of modifying the design to make it close to low energy framework for the later stages it is beneficial to manage all the parameters and constraints by initial stages. That could provide many advantages to designers to screen the whole process in one scheme.

Due to many elements involved to finalize the result and resources endeavor to arrange confirmed simulation-based thermo-physical energy investigations, commitment for energy performance expanded outside the discipline of architecture to Heating, Ventilation and Air Conditioning (HVAC) engineering consultants, where the main logic founded improvements in building construction and systems efficiency in accordance with energy standards (Thornton et al., 2013). The focus of the energy modelling at early design is to search and evaluate design alternatives in the first place to preventing the design limitations for final stages of the design. The fragmented approach of final design energy improvement restricts the potential to discover design strategies (e.g. building geometry, window to wall ratio (WWR, shading elements, etc.) to minimize heating and cooling system energy demand and the application of passive strategies such as natural ventilation, exposed thermal mass, and daylighting (Asadi, Amiri, & Mottahedi, 2014; Elbeltagi, Wefki, Abdrabou, Dawood, & Ramzy, 2017; Picco, Lollini, & Marengo, 2014).

Building performance are defined by the conceptual phase judgements. For example, energy demand can be decreased by 30–40% without any additional cost just by determining reasonable envelope design and right orientation for the building (Wang, Zmeureanu, & Rivard, 2005). Building energy modelling is the one side of energy application into design process form earlier stages. There are many other requirements to reach certain achievements for building energy performance. It contains building energy modelling, inter-disciplinary collaborative working, performance-based comparison, etc. To fulfil the all requirements for efficient energy policy for building production, overall methodology of the performance models are quite alternatives to consider, as indicated below (American Institute of Architects, & Publishing, 2013):

- Simplification of the model: Decrease model complexity as much as possible. At the conceptual phases of design, when there are not exist detailed system components. This simple model with separation or specific schedule with default materials. This simple model is suitable to test passive and active design strategies for limiting energy demand. This simplification saves an enormous amount of model-development time. As the project continues, the energy model also could have modelled detailed, gradually.

- Comparison of alternatives: Comparative graphical representation of the efficient design alternatives that contains all related performance pointers is exceptionally useful.

- Balance performance indicators: To compensate efficient usage between the performance indicators specific for the specific system in question; e.g., for the building envelope, energy efficiency must be arranged with thermal and visual comfort, natural daylight obtainment, etc.

- Identify constraints: At conceptual design phase, designer should understand that code, planning, sociological, programming, and other constraints related subject exist which are relevant alongside the optimization of site, orientation, massing, and envelope energy efficiency.

Parameters which is effective for energy performance that designer must be aware of it and increase the attention on them to emphasize possible alterations of design for preventing the problem before happened (Athienitis & O'Brien, 2015; Joseph Clarke, 2007). For instance, ventilation can lead to the heat loss and even it could have more impact than conductive heat loss by envelope. This could create advantage and cost-effective result for indoor air quality but could cause inefficiency about thermal performance of indoor environment. Even though, mechanical assistance of later stages can't redeem energy loss. So, before the problem occurred with simulation tools and energy models this fault can be detect and adaptation mechanical of mechanical ventilation can be a solution. In addition, performance based design could support of comprehend of daylight usage for interior spaces in terms of how daylight pass from the glazing and circulate indoor area and how daylight can decrease artificial lightning cost in short-term and how can create enlightened atmosphere which balance visual comfort threshold values as compared to compliance reports (Li, Williams, & Guo, 2016).

As the last part of the chapter, by the technological and mathematical improvements during recent years, energy simulation tools became the most important partner for the performance-based building design. The benefit of a simulation-based working methodology for a designer depends on the rightness of the performance estimations, which is based on two prominent measurement: (1) the simulation method of simulation software, which executes all calculations and (2) the correctness and detail of the model that was used in the simulation (Attia et al., 2012; Morbitzer, 2003; Rezaee, Brown, & Augenbroe, 2014). Besides, there are many other aspects that make it easier the process for stakeholders, as follows (American Institute of Architects, & Publishing, 2013):

- Increased Satisfaction: The ability to use energy modelling presumably for design and construction process has possibility to promote more relationships between design squad, which can increase both client and project team satisfaction.

- Reduced First Cost: Energy modelling and performance-based design lead to decline of the higher initial cost and alterations throughout design and construction process because of the graphical and comparative working in early design process.
- Reduced Maintenance Expenses: Energy and cost effective and confirmed material and right-sizing systems decrease long-term maintenance costs after construction phase until demolition.
- Higher Predictability of Operating Costs: The ability of collaborative energy and construction modelling through lower operation cost during life-cycle of building and helps to facilitate financial decision-making.
- Enhancement for Occupants Comfort: Occupancy surveys for indoor environment demonstrated about a correlation between energy efficient design and occupant comfort, due to enhancement of envelope radiant losses and gains and reduced infiltration that predefined by integration of energy modelling (Edwards & Torcellini, 2002; Heerwagen, 2000).
- Improved Environmental Performance: Meeting with energy modelling allows the team members measurement for possible decreasing in energy demand and generation and associated with greenhouse gas emissions, conclusively decreasing infrastructure and utility demands and the depletion of the limited resources.

2.2. PERFORMANCE BASED DESIGN

Every Architectural Design drives from unique design choices, functions. Addressing to this issue, each design formation serves according to its parameters and constraints cooperation to supply sufficient comfort requirements for occupants. Concordantly, many different specifications convert the design process in the complex framework hence, multi-objective solutions as informed as possible. For several functions and aims, designers can follow same patterns to achieve well-defined energy performance by applying the simulation in combination with rule or optimization-oriented techniques. While targeting the operation tool as assistant for designer for decision making process and leaving the final decision to designer’s own architectural perspective which contains experience and personal aesthetic approach. The main function is to define all the inputs of algorithm and tool achieve and present optimum solutions in accordance with objectives that predetermined by function, location and design aspects.

Generally, all types of performance-based design solutions include same aim that is allowing the designer to reach better energy and environmental performance by generating design solutions iteratively or not. But in practice, they have different techniques to accessing the satisfied results. For optimization methodology, determine the best design solutions according to chosen objectives that results can change according to problem definition and workflow of algorithm. On the contrary, it could be offered that give more options associated with design directions for designer and pre-arrange design parameters. In conclusion for this statement, as researches pointed out that there are two essential design philosophies exist and they define boundaries of parameters and objectives but take different into account the process (Duffy & Duffy, 1996):

> *"The 'design assistant' philosophy considers a computer aided design (CAD) system as a designer's colleague, whereas the 'design automation' philosophy considers it as a designer's substitute".*

The function of optimization works in accordance with on the design automation philosophy: the executor who can be designer or someone else, arrange the boundary values and constraints and the tool generative form the acknowledgement in the sense of the desirable design solution. The input of the designer in the design process is finite. The designer achieves just limited insight into reasons behind the established design solution. However, this limited approach could not present enough alternative evaluation due to point estimation-based techniques. As an answer of this solution, statistical sampling methods should provide alternative production and demonstrate the relation between input parameters and output parameters, such as screening based, variance-based ad metamodel construction frameworks. Providing designers with an comprehension of the performance of the unit by alternative design parameter values, likewise, reasons for this conduction makes it easier to adapt the performance predictions into the overall design process, gradually (Hemsath & Alagheband Bandhosseini, 2015).

2.3. BUILDING ENERGY SIMULATION

From the mid 50’s until these days, there have been a consistent search about buildings thermo-physical performance in keeping with the peripheral properties of the site location and climate issues due to get under control of energy performance of the units. The requirement of study has started with the fast urbanization phase, as consequence of industrial revolution which led to increase the usable floor areas for both residential and non-residential buildings and it is caused to augment the stand for energy sources. As all the resources are limited, there has been shown a tendency to either investigating how to reduce energy demand and using renewable energy. For the pre-computer ages, there was simplified methods are executed manually about thermodynamic transfers from exterior to interior areas, but after the innovation of the computers, many technical and statistical models have been formed by the scientists and facilitate for convergence of the automation.

Energy simulations is one of the most popular scientific models that contains many parameters about building properties and weather conditions. To comprehend better the simulation of building performance, it is better to check the classification of the scientific models (Coakley, Raftery, & Keane, 2014). As Coakley et al., (2014) and Saltelli et al., (2007) pointed out that, there are two major model types which are called diagnostic or prognostic and law-driven or data driven.

- Diagnostic or Prognostic: Diagnostic types of models represent the models that search for the cause of the incident or incidents. In other respects, prognostic model can be defined as for the models that foresee the patterns of system with pre-defined laws.

- Law-Driven or Data-Driven: Law- Driven model observe the conduct of the system with suitable laws which is related with the model itself. Data-Driven models are identified as the models create a solution about constructed system from pre-arranged data set. Rather than Law-Driven models, Data-Driven models are parsimonious. They are restricted to the data that they have given. For these issues, Law-Driven models can be more trustable to predict the attitude of the model.

According to this discrete gradation, it can be said that building energy simulations are more suitable to called as prognostic law-driven models which they try to estimate the main direction of complex systems with a given a set of well-instructed laws, i.e. energy transfer, mass balance, reflection, transmission, etc. In addition, as a detail modelling of the unit, energy simulations works as time-step based thermos-physical models about active and passive designs. The measuring process is mainly performed a fully-year(Coakley et al., 2014). There are various important energy simulation tools in the community such as EnergyPlus (US Department of Energy), DOE-2 (Hong, Chou, & Bong, 2000), TRNSYS (Klein, 1988).

Energy simulation helps to produce quantitative outcomes about complete configurations of building by observing the thermal interactions of units (Hygh, DeCarolis, Hill, & Ranji Ranjithan, 2012; Morbitzer, 2003). Extra, with the implementing into the methodology, building performance tracking turns out to be more sensitive and detailed (Hobbs, Morbitzer, Spires, Strachan, & Webster, 2003). For these purposes and simplified methods, energy simulations could serve as a feedback organ at early design stage, in the way of comparing the alternatives, analyzing the deficient points for the evaluation of architectural design., Lam, Chun Huang, & Zhai, (2004) proposes that behalf of the rule-of-thumbs or past experiences, ‘first principle-based engineering algorithms’ must be applied due to reach reasonable results (Hygh et al., 2012).

Even there are many alternatives of simulation tools, a main challenge of simulation software is how to manage with unexpected parameter variations and difficulty of components, especially for complex models, i.e. nonlinear actions, anomaly lastly, uncertainty of input and output parameters (Attia et al., 2012). There are many parameters associate with high performance and energy efficiency that can conflict each other, therefore, it impacts the anticipation of output information (Aksamija, 2015; Roudsari, Pak, & Smith, 2013; Wetter, 2011). Attia et al., (2012), aimed to refer that issue by preparing benchmark model that gets the results from energy simulation program (EnergyPlus) with the help of sensitivity and uncertainty analysis. Generally, energy simulation tools could not answer about giving the feedback regarding the potential of passive and active design, nor the comfort regulations which depends on environmental considerations (Crawley, Hand, Kummert, & Griffith, 2008). Besides, out of the 392 Building Performance Simulation (BPS) tools listed on the Department of Energy (DOE) website in 2011, less than 40 tools are aiming direct collaborations with architects for initial phases of design (Hong et al., 2000). Most of the simulation programs are divided into two main aspects: (1) Simplified tools which organized for rough estimation for early stages. (2) Parametric tools that has the capability bend the parameters easily for concept design.

The integration of simulation-based method into the building design process led to understand how design decisions impact the energy and environmental performance of design, hence raising the attention for integration during the complex decision-making process. Previous researches showed that how designer utilize simulation separately for different design stages (Joseph Clarke, 2007; Morbitzer, 2003). At the starting point of the design process they will use simulation to determine benchmark figures of the building performance, however for detailed design stages the simulation focus on services systems of building. Therefore, simulation tools should thus be capable to supply information towards design team at every design stage with relevant analysis(Joe Clarke, 2001; Halliday, 2007; Morbitzer, 2003).

2.4. INTEGRATED DESIGN PROCESS &IMPORTANCE OF FEEDBACK

The adaptation of simulation into the building design process led to understand how design decisions impact the energy performance of building, hence raising the attention for integration during the complex decision-making process (Morbitzer, 2003). Previous researches showed that how designer utilize simulation separately for different design stages. At the beginning of the design process they will use simulation to determine comparison models of the building energy demand, whereas for detailed design stages the simulation works on services systems of building. For this reason, simulation tools should works as a guidance for designers from earliest phases of design (Joe Clarke, 2001; Halliday, 2007).

The literature offers several techniques for adaptation of simulation tools into design process. Previous researches suggests two possible approaches: (1) Simple and easy understandable interface simulation tools could be useful for early stages and more technical ones could serve at detailed stages and more sophisticated one could be suitable for throughout all design process (CIBSE, 1998). (2) Managing all the thermo-physical calculations into one program (Joseph Clarke, 2007). For instance, by adapting simulation-based technique to generate envelope of the unit simultaneously with energy efficiency concern from conceptual phases could be an answer. It could prevent the repetitive modeling for design and energy calculations, separately (Granadeiro et al., 2013).

Due to mass production strategy and fast incremental population augmentation of urban development is decreased building construction quality. Therefore, indoor environment air and environment quality are decreased dramatically that has caused unhealthy indoor air quality and contaminant production which reduces indoor occupant comfort. In this respect, pre-modern building designs were more suitable for human health. Lechner, (2014) thanks to economic and technological new outcomes and designers started to adapt new techniques and acknowledgment into design process.

Multiple stakeholders are participating into design process but especially, as an head of the design team architects who are the decision-maker about all design and construction problems, are more responsible for the design. Therefore, it is important to give feedback to them during design process in terms of energy efficiency (Morbitzer, 2003). Analysis opportunities, for example for passive energy strategies, are thus best explored during schematic and early design development (Konis et al., 2016).

To bring together the different participants who involved in the building design process because of the robust quality of the building. Various researches present that collaboration among design professionals who are involved in the design process will represent convergence for an important goal which is increasing building performance. In addition, communication can be existed when the different design parties (especially architects and building services engineers) use the same simulation engine (Kalay, 1999).

2.5. UNCERTAINTY ANALYSIS

As previously mentioned, energy simulations as a complex design models are constituted by multiple parameters, batch of construction materials, occupancy editing, equipment scheduling such as, HVAC and plant, thus, it produces unsteady relations in terms of pre-defined objectives. Several researches have been conducted either highlight and compass the issue (De Wit & Augenbroe, 2002; Macdonald, 2002). Due to model complications, there are multiplicity about the interactions between inputs and outputs, to hand on these patterns it is needed to decrease the output uncertainty as much as possible. According to (Franklin, n.d.), about multi-layered models, "the portion of the world captured by the model is an arbitrary enclosure of an otherwise open, interconnected system". Even simulations compose from mathematical definitions, it is possible to yield non-linear and partially illogical outcomes, for instance the model maker can wrongfully organize the input importance because decision-making variation of the model outputs are not obvious. As a result, the aim can be more defined if statistical model analysis can promote inner vision for the non-observable sections of the energy design model (Coakley et al., 2014).

To approach the situation in a clear way, it is useful to classify the model uncertainties. According to, De Wit & Augenbroe, (2002), there is no specific point that converts the model attitude to unsteady position:

- Specification Uncertainty: The problem can form from the deficient model arrangement, such as, building form, construction material types, equipment design etc.
- Modelling Uncertainty: Over-simplification of thermo-physical properties which can cause by algorithm calculation or stochastic scheme positioning.
- Numerical Uncertainty: False assumption can occur the reason of dis-integration of the model or simulation inner design.
- Scenario Uncertainty: Peripheral circumstances on building, inner climate and occupant can create the error.

The influential implementation of uncertainty analysis (UA) also, referred to as uncertainty quantification, with building simulations to supply design information and satisfied quality arrangement is highly significant to early design architectural process (C. J. Hopfe & Hensen, 2011). As an instant response, UA can derive the reliable knowledge for interactions and impacts of design parameters for whole model, such as, minimum or maximum boundaries of heating or cooling demand, costs or illumination ratios etc. On the contrary, building performance analysis directs the decision-making process according to point estimation (Burhenne, Tsvetkova, Jacob, Henze, & Wagner, 2013). Whether to stay with definitive predictions or to ignore the uncertainties of the model, it could cause the false suppositions which could reduce end user life quality. Addressing the issue, multiple studies has been executed: screening/decreasing inputs (Alam, McNaught, & Ringrose, 2004), meta-modeling which reduce the complexity of the energy model (Leung, Tam, & Liu, 2001; Topcu & Ulengin, 2004), robustness framework (Burhenne, Jacob, & Henze, 2011).

Due to parameters amount and unclear relations between inputs and outputs, UA can be the complementary factor because it supplies the assignation of valuable input parameters and produce very large response space that ambiguous actions can be easily detected (C. J. Hopfe & Hensen, 2011). Notedly, researches experimented and presented the influence of UA with effective energy models, in terms of perturbation study of sensitivity errors, thermal comfort, instability of weather parameters, ventilation, passive systems (Marques et al., 2005; Verbeeck & Hens, 2007).

2.6. SENSITIVITY ANALYSIS

Architectural design composes from multiple factors where each factor contains many input parameters and to handle the design equation easily, it is crucial to determine most effective parameters in terms of time and effort efficiency. For this reason, sensitivity analysis (SA) could be a key method to strive this issue with collaboration of building energy simulations. The framework of sensitivity analysis proposes useful computational ability to decrease problem complexity due to ranking each parameter influence on defined model objectives such as, heating demand, lightning demand etc.(Firth, Lomas, & Wright, 2010). There are many parameters, associated with high performance and energy efficiency, conflicting each other that impacts the anticipation of output information While sorting the input elements by their influence, it could be easier to focus most effective parameters in the early design process. It can be characterized as ‘Garbage-in, Garbage-out’. It also demonstrates the input-output relation for unbiased decision-making procedure. As Iooss & Lemaître, (2015), sensitivity analysis is capable of deep exploration for the model attitude in accordance with quantifying the influence scanning for all variations of inputs.

Uncertainty of the model outputs are affecting building performance and users of the building becomes responsible of the inadequate design organization after construction phase (Sanguinetti et al., 2009). Due to point estimation based working process of building energy simulations, designers can pass over chance to see alternatives, for instance design variability (Y. Yildiz et al., 2012), user attitude and weather scenarios (C. J. Hopfe & Hensen, 2011), input and energy demand relation (Heiselberg et al., 2009). To understand energy usage patterns of the building form, construction materials, climate properties, many scientific researches has been devised (C. Hopfe, Hensen, & Plokker, 2007; Struck & Hensen, 2007)

Sensitivity analysis has capability to identify a-priori influence and to rank the sensitivity of the parameters. It could has seen as a response to ’What-if’ question by measuring the regressions or correlations of particular inputs (Struck, de Wilde, Hopfe, & Hensen, 2009). Therefore, it is popular technique for observational works of architectural analysis (Campolongo & Braddock, 1999; Kristensen & Petersen, 2016; Sun, 2015). Firstly, it categorizes the parameters according to effectivity. Secondly, it rates them according to feedbacks that returns from output objectives. Lastly, it extracts the valuable range of the variables for both to decrease the computing power and to elaborate the complexity of the model with the help of statistical methods, for instance Monte-Carlo Filtering (Østergård et al., 2015). From a technical aspect, SA methods are classified into two ways which called local sensitivity analysis (LSA) or global sensitivity analysis (GSA) (Hemsath & Alagheband Bandhosseini, 2015; Mara & Tarantola, 2008). Local sensitivity analysis performs better for detection of the uncertainty of the input parameters around a specified point, on the other hand, rather than the LSA, GSA could scan the whole input set in terms of output activity which contains explanation for binary input interactions and non-linearity (Saltelli et al., 2007).

Mostly, for the implementation of sensitivity analysis, there is certain manner while using for building energy analysis at early design process. Typically, it begins with determination of variable variance, while constructing the energy model and performing the runs of simulations. Then, it proceeds with gathering the results of simulations, application of the sensitivity analysis and presentation of the results with several plot graphics (Alam et al., 2004; Østergård et al., 2016b; Tian, 2013). Due to problem type or research aim, the structure can change with small percentages in terms of evaluation of the input factors more efficiently. For example, climatic properties behave as normal distribution whereas, physical design elements can be arranged as uniform distribution. Statistically, to reach satisfied solutions for energy models, this organization must be applied before the range of the parameters are organized.

2.6.1. LOCAL SENSITIVITY ANALYSIS (LSA)

Local sensitivity analysis (or differential sensitivity analysis) is a technique that has been used for building energy simulations to calculate the input parameters efficiency and impacts on outputs. Basically, it leans on one-parameter-at-a-time (OAT) methodology where the variance of a single parameter can be calculated while the other variables stay stable at their initial rate (Coakley et al., 2014; Lomas & Eppel, 1992; Petersen & Svendsen, 2010). Collaboratively, range of the parameters are enabled by building energy modeling (Cammarata, Fichera, & Marletta, 1993; Jensen, 1995; Kristensen & Petersen, 2016) Despite of the technical absences, there are several reasons for the researches apply LSA for building performance simulations, mostly for the reasons of easy customization and it can procures less computing power which is fundamental because sensitivity analysis usually occurs numbers of simulation evaluations (Firth et al., 2010; Petersen & Svendsen, 2010). As the other side of the coin, analysis occurs without evaluating the total effect of the probability density function of parameters where interactions between inputs and non-linear relations can be detected also, this technique can not approve the self-verification which is substantial for the robustness of the building energy model. In the meantime, global sensitivity analysis can response for these features(Hamby, 1994; Tian, 2013). Therefore, usage area of the LSA method is mainly seen limited (Kristensen & Petersen, 2016). Consequently, choosing the case according to conditions is crucial. For instance, Several researches about validation techniques of thermal models by implementing LSA are actualized for thermal models of building units in terms of direct effect parameter validation (Judkoff, Wortman, O'doherty, & Burch, 2008), residential energy monitoring (Butch., 1984), investigation for dynamic thermal models (Establishment B. R. & Science & Council, 1988; Lomas, 1991), etc.

Moreover, various studies has implemented LSA for the building energy modeling to observe the local attitude of the input parameters with regards of static energy modeling, net zero energy building design, thermal comfort, ventilation and lastly, building design (J. C. Lam & Hui, 1996; Rasouli, Ge, Simonson, & Besant, 2013). In addition, LSA is suitable to decrease the model complexity by dividing the parameters for effective or least effective by classifying the parameters property before evaluation of the complex non-linear models. (Alam et al., 2004; Bourges, 1992). To reach more detailed information and base logic of LSA, it can be observed (Lomas & Eppel, 1992).

2.6.2. GLOBAL SENSITIVITY ANALYSIS (GSA)

Global Sensitivity Analysis frequently are used for early design building energy models which scores the direct and total impacts of input parameters on the defined objectives (Lomas & Eppel, 1992; Saltelli et al., 2007). The main differences from the local sensitivity analysis, all the chosen parameters get involved the analysis process simultaneously (Kristensen & Petersen, 2016). Fundamentally, GSA produces all input parameters ranges and movements with the based on probabilistic approach, such as probability density function. To impose the probability outcomes for the whole input space which is based on input sampling, it needs to be generated multiple times (Saltelli et al., 2007). For instance, Monte-Carlo based evaluations execute the sampling methodology in sequence, according to quasi-random design. As building energy simulations computation cost is highly expensive, execution process can be continued long rather than LSA. In addition, Hygh et al., (2012), used EnergyPlus simulation engine with GSA to examine building form parameters by using Monte Carlo framework multivariate linear regression model to compare different climate types. Addressing this issue, from quasi-random sampling to Latin Hypercube Sampling, there are many other strategies can be applied for sampling phase according to problem and the sensitivity analyses type (Sallaberry, Helton, & Hora, 2008; Saltelli et al., 2010; Sobol & Kucherenko, 2005).

GSA can be performed with many different methods, but mainly there are three main techniques are popular for the building performance analysis. These are variance-based techniques (Saltelli et al., 2010), meta-model based methods (Eisenhower, O’Neill, Fonoberov, & Mezi, 2012), screening techniques (Alam et al., 2004). Screening technique is one of the most popular technique for the building energy modelling, significantly for early design process (McCulloch, 2005; Sallaberry et al., 2008). The method mostly aims to define non-significant input parameters which can be converted to constant value exempting the effect to chosen objective variance. Therefore, model complexity and the computing cost can be reduced. Screening methods, such as the most common one is Morris Method has been considerably used to identify the most and least design parameters for the building design in the sense of sustainable improvement, retrofitting, HVAC design and initial geometry parameters (Booth, Choudhary, & Spiegelhalter, 2012; Østergård et al., 2015). Screening methods are suitable for the designers for the reason of effective presentation and nonprofessionals could adapt this method while in the early decision-making process (Alam et al., 2004).

According to model properties, GSA can be changed, as an alternative method for variance-based methods are such as, Sobol and FAST are used for non-linear multiple output energy models. Main logic of the design comes from the decomposition of the output variety, in short, they are also called ANOVA (analysis of variance). The sampling strategy is generally depends on the method that has been chosen, such as Sobol, Saltelli sampling (Herman & Usher, 2017).The computational cost comes as expensive rather than local sensitivity and screening methods. For the reason of energy and daylight observation which depends on input parameters, there are several researches conducted with variance-based sensitivity analysis (Shen & Tzempelikos, 2013; Spitz, Mora, Wurtz, & Jay, 2012).

Last of all, meta-models are another type of technique which could have seen as simplified version of models. This method transforms the energy model to less complex form that gives chance to evaluate to process faster (Østergård et al., 2016b). It is basically focus on the variable and output correlation. There are many other recipes differs for the model dependency, such as Support Vector Machines, Multivariate Linear Regression and Artificial Neural Network and there is no one-for-all technique (Asadi et al., 2014; Eisenhower et al., 2012; Gorissen, Dhaene, & Turck, 2009). Meta-model design can be produced from multiple building energy simulation outcome or data (Cheng & Cao, 2014; Manfren, Aste, & Moshksar, 2013). As a simplification of the model and fast method, meta-model is preferred for early design in terms of calculation building loads, thermal comfort, indoor air quality, cost and daylight researches (Eisenhower et al., 2012; Manfren et al., 2013; Mavromatidis, Marsault, & Lequay, 2014; Saltelli et al., 2007).

2.7. SUMMARY AND DISCUSSION

Architectural design could have seen as one of the major complex disciplines that contains aesthetical, technical, social, energy-based study acknowledgements. Due to uncertainty of the end design of architecture, in particularly, from the initial phases to end phases it occurs some challenges how the energy performance of the unit can be reached towards high level. Addressing the issue, various studies are aimed to observe to find most important factors that determines the annual use of energy demand in terms of heating, cooling and lightning (Allen, E., & Iano, 2006). With this motivation, early design mostly in control of the designers, therefore generally there has been some investigations and improvements for the passive performance of the building with regards to envelope ratios, construction materials, natural lightning performances and natural ventilation (Depecker et al., 2001; Hachem et al., 2011).

As a support element to assess and design energy performance of the building, energy simulations have become highly popular in the field. On the contrary, due to complicated user interfaces and lack of the technical information for energy control, designers mainly postpone the important decisions related energy design to engineers during the detailed stages where the decision effect are strictly lower than initial phases. Proactive approach, could drive the energy assessment in the first place and direct the all design process according to this principle where the uncertainty of the performance is relatively high (Østergård et al., 2016b, 2017). In addition, energy models that has been composed by simulations are not capable of to evaluate alternative design solution. Hence it depends on experience or limited variations. As a response to these problems, statistical approaches could be effective by integrating in the design process. As this research are applied it, sensitivity analysis could perform suitable by generating multiple simulations to scan all the global design spaces. Basically, it is asking the what-if question through the problem and view the patterns between design parameters. In the field of architectural design, many researches has been applied studies related with this (Østergård et al., 2015; Tian, 2013).

Performance based design is the core methodology for supporting the designer team towards high energy performance of unit. Because, every design of an architect form from many decisions that could shapes the process from the beginning (Stumpf et al., 2011). As decisions are based on design variables and some of environmental and comfort related constraints it is quite substantial process that needs to be analyzed. In parallel with, the study should be observed the design parameter influence in the terms of how could shape end-result and interactions between them. Thus, Sensitivity analysis presents many advantages for the design stakeholders in the sense of providing feedback about design elements, evaluating multiple alternatives that put the process in a rational path and decrease the problem complexity for the purpose of focusing important parts of the design instead of spending valuable time in the limited duration of early design (Firth et al., 2010; Y. Yildiz et al., 2012).

As features of analysis, factor fixing, factor prioritization and factor mapping serves to the design team by obtaining the information about how important the design elements which designers are playing, which parameters should be fixed with the intent of reducing the process complexity and focusing the valuable design elements and lastly, in which ranges the design parameters are capable of to define the most of the ratios for the variance of the energy demand (Hygh et al., 2012; Saltelli et al., 2007). Addressing the issue, several researches have been conducted by applying local sensitivity analysis which is based on changing one decision variables for each iteration and global sensitivity analysis where the sampling strategy lets to change multiple parameter’s value for each iteration (Lomas, 1991; McCulloch, 2005; Petersen & Svendsen, 2010; Spitz et al., 2012).

The review of the literature presented that early architectural design highly important decision-making process which needs to be observed with some statistical techniques by evaluating many alternative solutions. Therefore, implementing the statistical techniques such as, Morris and Sobol’ global sensitivity analysis in to process could provide suitable information for the design team (Booth et al., 2012; Kristensen & Petersen, 2016). According to these implementations, there will be details explanation and investigations about causality of the problem and how to solve by using sampling and statistically analysis techniques.

CHAPTER THREE
METHODOLOGY

Architecture discipline is responsible to address numerous questions on social, economic, aesthetical and performance-based issues; and generally, the topics are organized with same decisions by designers. On the other hand, some parameters can be more important than others as far as to site location, building function and weather properties. By courtesy of scientific models, many of them can be investigated by implementing quantitative approach, particularly, for measuring energy metrics of the units. Preparing simulation based statistical models can provide high degree of valuable information about understanding the insight of the models with defining constraints by comparing the decisions in accordance with the results.

Design ideas and conceptual programming of the architectural design are identified at the initial stages of design, and these actions are drawing the borders of the framework. Therefore, due to decisions of the early design process are the most salient design attributes, it is highly important to observe relations and interactions between independent and dependent parameters for the phase of the design by the help of mathematical and statistical methods. If the designers can not extend the duration of conceptual process, energy models should proceed as an automated process to test many alternatives and illustrate their motion area. Related with this issue, in this chapter, there will be detailed explanation for the model of early design automated energy demand forecasting with energy simulations in terms of physical and functional parameters of the building, for instance building interior volume dimensions, construction material properties, occupancy program, etc. Firstly, the decisions associated with early design, will be observed according to their impact for the energy performance outputs and will be designated most effective parameters where the architects can be focus on. Additionally, early design phase has limited time, thus, analysis needs to be instant and visual for the reason of lucidity. Secondly, there will be filtering implementation to extract the valuable ranges of the decision variables therefore, designers can take advantage for their design process to comprehend how their decisions affecting the outcomes and how they can play with the decisions to the extent to energy performance of the building. It could be beneficial to see alternatives from the point of quantitative view and could facilitate to define the main route of the architectural design without spending valuable time or effort.

3.1. RESEARCH QUESTIONS, HYPOTHESIS, AND OBJECTIVES

The major aims of the current work are to visualize how physical and functional architectural design parameters are changing building energy performance; and to drive the valuable range values from the attitudes of input parameters. To achieve, a quantitative research design that is outlined in Figure 3.1 was adopted. As this research was constructed based on scientific language, couple of research questions shall be addressed to indicate the general approach of the work and right after, it was required to determine the hypothesis to steer the research on a logical path.

To understand and furthermore examine a topic, from these earliest phases, asking the adequate questions is crucial. Regarding this, this study pursuits about early energy demand forecasting, automation of the design process and performance-based design for architecture. Accordingly, the main research questions of the current work are formulated as follows:

- What are the physical design and function-based parameters that are relatively more significant to energy demand and therefore should be focused by the designers at the early design stage?
- Does the impact of these parameters differ between cold climate of Erzurum and hot-humid climate of Izmir?
- Is it possible to quantify the influence of climate properties on energy demand using sensitivity analysis?

All questions can be addressed using quantitative techniques which capsulate digital modelling and simulation techniques in the case of current work. Therefore, this study presents rational results that provide comparison between two different climate type and parameter interactions. To reach reasonable solutions, the current work prepared an energy modelling algorithm using a script language, i.e., Python 3.6 (Zelle, 2004).

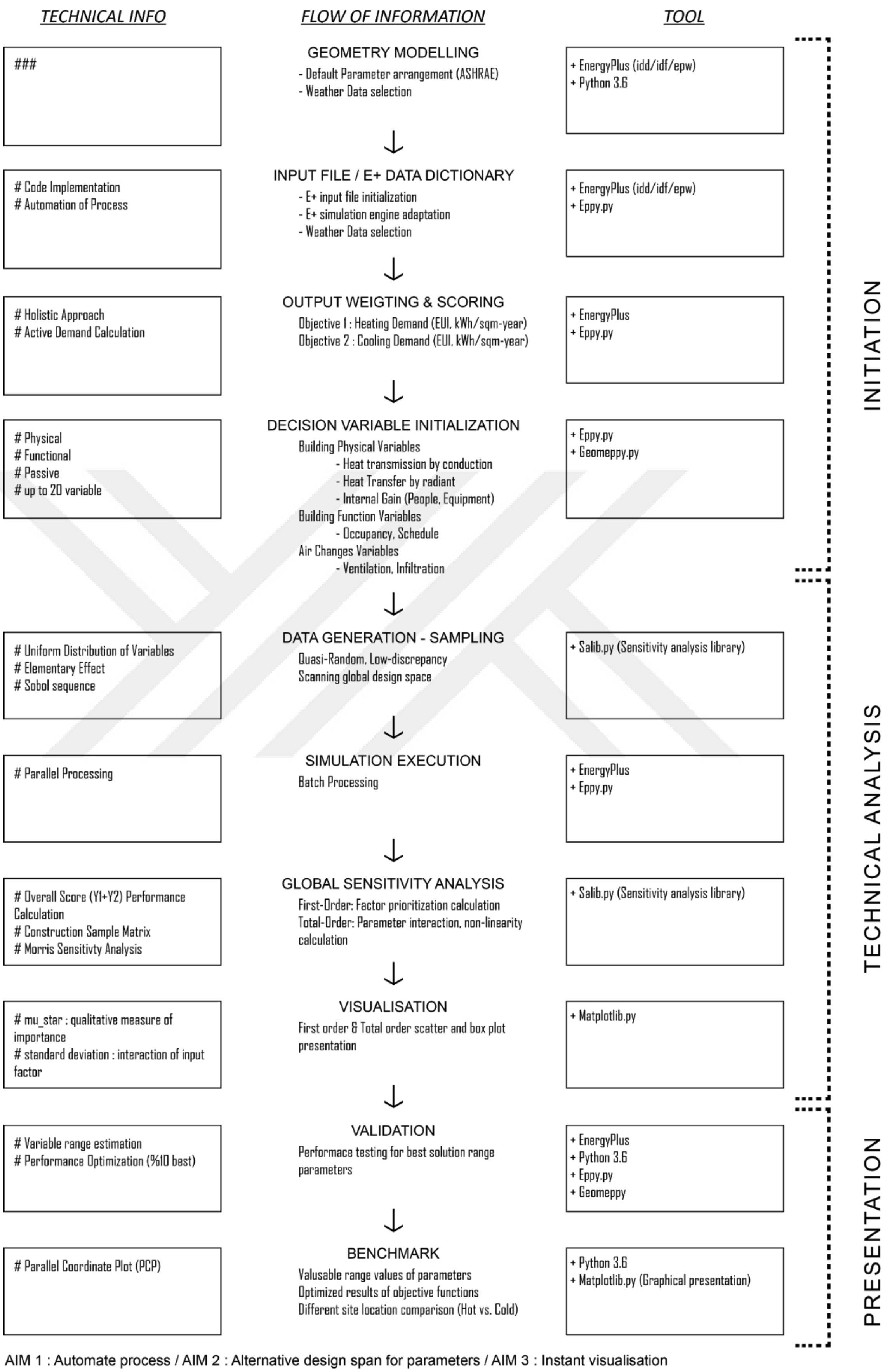


Figure 3.1. The flowchart of the research process

In general term, aims of research studies can be different as far as to focus point and subjects that they examined. Accordingly, methodological path of the researches can be varied, even they are investigating same subject. In line with the research questions, the main methodology of this research can be classified as quasi-experimental study. Due to observing technique differs from the experimental research, this research does not contain high degree control over all variables and objectives. Variable zone is limited with the most popular physical and functional building parameters based on heating and cooling demand at early design. Other inputs parameters are taken as default value on the purpose of reducing the computing cost of the model. As all the quasi-experimental studies are composed for understanding the causality, this research aims to find relations based on comparison, statistical outcomes and visual presentation (Alam et al., 2004).

Quasi-experimental research is an organized investigation of a defined problem in which it is an essay for reaching solution for a problem with controlling some of the variables and objectives. The right technique can be achieved by unambiguously identified objectives where route of the research has designated both for lightning the path that researcher should proceed and facilitating the reading for the viewers of the script. Addressing the issue, for the current thesis, objectives are composed with an intent for identification of the relationship between independent variables and output parameters and interactions among independent variables where comprising of the decision variables.

To summarize the whole study in specific measurable manners, there has been six objectives are prepared for the reason of formation of timeframe boundaries and available resources of the early design energy modelling. This research has been formed:

- To assert how early design decisions are directing the architectural process furthermore how is it possible to control global design space from the initial phases.
- To analyze the influence of the input decision variables in accordance with the variation of the energy related output parameters.

- To verify the early architectural design can be performed as an experimental study both the help of scripting and statistical methods such as sensitivity and uncertainty analysis.
- To find out the precious range values of decision variables concerning the building physical and functional properties for the reason of assisting the designer.
- To calculate the influence area of the climatic environment in which cold and hot, on output parameters such as heating and cooling demand, moreover how the climate can change and form the significant range values of decision variables.
- To visualize the early design decisions with the help of plotting techniques thus, designers can get feedbacks from it.

3.2. GEOMETRY MODELLING & MODEL DESCRIPTION

The focus of the study is to provide a proactive guidance for the early architectural design with respect to energy performance of the building. To start a research for concerning performance-based design, there has been prepared a digital building model with scripting language which is Python 3.6 (Zelle, 2004). Due to purpose of extracting the sole influence of climatic environment according to variance of physical input parameters, digital model has constructed as a surrogate model because, if a real case has involved into process, physical decision variables conduction could not observe in a transparent way, hence, in practice there are many other input parameters must be taken care of such as, code of practice, false construction process, depreciation of construction materials etc.

Digital construction of the energy model does not require detailed modelling thereby, to just observe the thermo-physical transmissions, model has been prepared as box model however, it is needed to be arranged according to regulations to compare and present in a scientific manner (Creswell & Creswell, 2017). As global standards offer, physical test model (Figure 3.2) is a rectangular single zone where the dimensions are 8 meters x 6 meters x 2.7 meters (Szewczuk & Conradie, 2014). For the surrogate model, building height, width and length has been determined as decision variables and for observing the building shape with respect to energy performance, interior volume of the building has taken as constant value which is equalized to 129.6 cubic meter (Szewczuk & Conradie, 2014). This is especially suitable for early design while designers are evaluating the building shape according to environmental and peripheral circumstances (Hemsath & Alagheband Bandhosseini, 2015).

As regulation offers, there are multiple building design alternative to search for energy performance of unit but for this study, each building facade has an opening which control separately by decision variables es from 0.0 to 1.0. For the opening of facade, there is a architectural term that is called Window-to-wall-ratio which is the ratio of window surface area to wall surface area. Natural lighting is one of the key parameters that has influence on energy performance in terms of both heating and cooling demand therefore, for each facade of the building, a window-to-wall-ratio(WWR) has been defined where their ranges between total area of the exterior façade to ten times smaller the area. To observe how sunlight affecting from each facade separately, each facade's WWR is different decision variable.

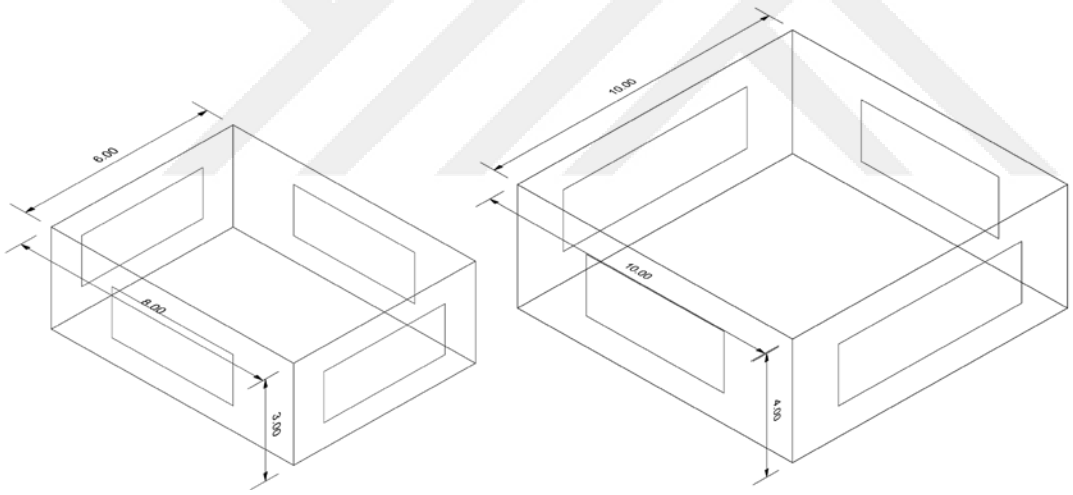


Figure 3.2. Digital building visualization of physical geometry

From initial phases to detailed phases, architectural design composes from many steps and each phase occurs many decisions that must be decided according to project requirements, for instance geometry planning and conceptual drawings for early design. As it is said at previous sections, decisions are effectuating the building energy performance starting from early paces of design. While decisions are defining, the energy modelling of the unit's complexity are increasing exponentially, eventually, they are augmenting the volume of the global design space. Consequently, due to time constraints of early design, it is difficult to handle manually therefore, either decrease the computing cost and take serial simulations, model should be organized with automated design. In addition, to make an investigation to identify the conduction of both independent and dependent variables by producing alternative design schemes, energy modeling should perform with batch processing. To procure that settings, surrogate energy models are constructed in the Python scripting language with the help of eppy and geomeppy, EnergyPlus modification libraries. These libraries can create an access to EnergyPlus simulation engine from python environment (Bull, 2016; Philip, Tran, & Tanjuatco, 2011).

3.3. INPUT FILE OF ENERGY PLUS & DATA DICTIONARY

This study aims to search building energy performance with detailed energy simulation engine. To meet the basic requirements of thermal calculations, EnergyPlus has chosen to execute the performance-based design logic at early design. EnergyPlus is an energy simulation engine about thermal load simulations which has the complete capability to execute thermal transmissions in terms of transmission (wall, roof, floor geometry and materials, thermal bridge calculation), solar gain (glazing geometry and materials), internal gain (occupancy, scheduling, maintenance etc.) and air changes (natural and mechanical ventilation, infiltration) (Hong, 2009b). The simulation engine is one of the product of the U.S. Department of Energy where text-based inputs and outputs are integrated with an automated workflow in FORTRAN scripting language.

EnergyPlus are composed from both the BLAST and DOE–2 programs. On BLAST (Building Loads Analysis and System Thermodynamics) and DOE–2 programs are commenced as energy and load simulation tools. The main working methodology is to manage proper HVAC equipment, study for life cycling cost analyses, optimize energy performance of the units, etc. Same as its predecessor, EnergyPlus is text-based energy analysis software which measures the heating and cooling loads according to thermal control setpoints, to validate that the simulation is performing close to actual building energy performance (Energy, n.d.). EnergyPlus has some specified features:

- Simultaneous simulation execution
- Sub-hourly, user-definable time steps (yearly to hourly)
- ASCII text-based data management (.idf files)
- Heat balance-based report productions (closed models)

- Transient heat conduction
- Thermal comfort models
- Daylighting controls

For the early design energy performance, there are many techniques has been studied by simplifying thermal calculations(Hemsath & Alagheband Bandhosseini, 2015). On the contrary, in this study should be preferred as complete energy simulation engine. Because, there are many input values identifies the thermal comfort models and heat transfers, as this study is based on quasi-experimental research methodology, instead of evaluating the whole input space, some values are chosen as default value but still, these parameters should be detected. That is the major logic about choosing the complete simulation engine. To observe these independent variables and obtain output values after performing simulations, there are some file formats that EnergyPlus contains. There are three different parts that they are input data dictionary (IDD), input data file (IDF) and EnergyPlus weather file (EPW).

Firstly, IDD file contains about the thermal calculation functions that gives the results as objectives. This is the basic function library that simulation input values are taken and after a calculation output values are produced. As pointed out previously, eppy and geomeppy python libraries provide parsing of and programmatic access to Input Data Dictionary (IDD) files. Whole simulation preparation starts from this phase.

Secondly, IDF files are preparing for the script. IDF files contains thermal properties about digital model to reach thermal comfort and heat balance calculation results. It is the phase that physical features, HVAC design, scheduling, construction types are introduced. For this part, there has been formed a digital box model, and building function has been identified as office. Because, there has been decided that one thermal zone observed. It is suitable for office structures.

EnergyPlus has predefined material library and this library is called as ‘ASHRAE_2005_HOF_Materials’. As it seen from the name, construction materials have been chosen with the direction of The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) standards. All the construction material organization has been prepared with respect to this material library. Besides, to array these materials IDF file has another specification which are construction part that is separating in three sections according to performance in which light, medium and heavy construction exist. This is the place that all the materials are organize in sequence in terms of their thickness, thermal resistance and thermal mass features. In this study, surrogate model is observed for two climate types which are cold and hot. To meet the requirements of the different climates, medium construction is adjusted for the digital model (Table 3.1). The symbols before the material name is identifying the material type.

Table 3.1. Construction materials of the test box

Construction	Outside Layer	Layer 2	Layer 3	Layer 4	Layer 5
Medium Roof Construction	*M14a* 100mm heavyweight concrete	*F05* Ceiling air space resistance	*F16* Acoustic tile	-	Material: No Mass: Roof
Medium Exterior Wall	*M01* 100mm brick	*I02* 50mm insulation board	*F04* Wall air space resistance	*01a* 19mm gypsum board	Material: No Mass: Wall
Medium Floor	*F16* Acoustic tile	*F05* Ceiling air space resistance	*M14a* 100mm heavyweight concrete	-	Material: No Mass: Floor

In the model, a default construction has been formed to arrange u-values of the building envelope constructions. As Table 3.1 present the layer of the constructions, Material: No mass materials are responsible to vary u-value (kWh/m^2-K) of the construction. For roof, wall and floor, there is specific no mass material which has not any thermo-physical properties in terms of conductivity, density, etc. Only u value modification is possible by controlling thermal transmittance value.

3.4. WEATHER DATA SELECTION

Energy simulation initializes with two major components. The first one is Input Data File (IDF) file which includes thermal and geometric properties of the digital model and the second one is EnergyPlus weather data (EPW). EPW is a data file that has produced by EnergyPlus which contains more than 80 meteorological properties such as wet-bulb temperature, wind direction, barometric pressure, solar gain etc. The data comes from the meteorological recordings by hourly values. Yet, all the parameters have not vital importance to compose weather data, and according to location, course density of data can be changed but actuality of the data is important to follow the current meteorological air movements. Weather data is the one of the most important parameters set for the building energy simulations therefore, it is better to be close to current year. For Izmir and Erzurum, EPW file has taken from 2014 that has produced after the research study of Pusat, Ekmekçi, & Akkoyunlu, (2015).

About the formation of the weather data, building simulation users have used a single typical year or a constructed typical meteorological year for climatic conditions of examined zone. This choice of action is directly related with computing cost and precision of results. Due to importance of catching the parameter conductions and interactions this study has chosen the constructed typical meteorological year method which is EPW is in that division. As a content of area, EPW file contains all year hourly values therefore it is counted as typical meteorological year data. Typical meteorological year (TMY) are generally preferred in building simulations to predict the annual energy performance of buildings (Xu & Zang, 2011). Due to reply to the exact computation, currently, more than 20 building simulation programs now read and use the EPW format. (Crawley, Hand, & Lawrie, 1999; Hui & Cheung, 1997). By the help of generalization EPW file is deemed as standards in energy simulation programs, such as Open Studio, Design Builder, Seferia etc. (Anderson, 2014; Garg, Mathur, Tetali, & Bhatia, 2017; Xu & Zang, 2011).

Table 3.2. Content of the EnergyPlus Weather Data

Content Variable	Unit
Date	
Hour	
Dry Bulb Temperature	^{0}C
Relative Humidity	%
Atmospheric Pressure	Pascal
Direct Normal Radiation	Watt*hour/m2
Wind Direction	Degree
Wind Speed	m/s
Liquid Precipitation Quantity	hour

EPW is capable of to give more exact outcomes about the energy performance of the unit due to hourly calculation and its content capacity (Table 3.2). According to program protocol and efficiency, calculation time can change. In this study each all year simulation process has been executed less than 2 seconds. This is all related with the process of the EPW file. For this study, there are two different climate types has been initialized for the building energy model. İzmir has taken as hot-humid climate and Erzurum has taken as cold-dry climate. To observe the independent variable behaviors under the different climate types, this procedure has been chosen based upon comparison issues.

3.5. PARAMETER INITIATION

In this chapter, study is searching for input parameter behaviors and interactions under condition of different climate types. The chosen input parameters are related mainly with the early design process and most of the time, the values that they are taken finalized at this phase of design thus, during the ongoing process, all design direction follows these initial decisions. As these parameters compose the most significant decisions that shapes the building performance it is highly substantial to comprehend their reflections on the output from the perspective of the designer. Addressing this issue, for various researches, building shape and construction material related searches has been executed to analysis the design parameters from the initial steps (Depecker et al., 2001; Østergård et al., 2017).

This study aims to produce scientific outcomes and for this purpose, decision variables of the search model has been arranged with respect to The American Society of Heating, Refrigerating and Air-Conditioning Engineers Association (ASHRAE) arrangements. In addition, ASHRAE (Thornton et al., 2013) divides the observation into two parts, such as residential and non-residential. Building function of the energy model is chosen as office building therefore it is evaluated in the non-residential category. ASHRAE standards offer different range values for residential and non-residential units. For this reason, for all the physical and functional decision variables, minimum ranges has been determined to the extent to ASHRAE 90.1 and ASHRAE 62.1 standards (Calm et al., 2007; Standard, 2010). ASHRAE 90.1 is all about energy standards for buildings without taking the residential units on the other hand, ASHRAE 62.1 is includes from ventilation standards for reasonable indoor air quality but residential buildings.

Building design composes from many other inputs. For the decision-making process, the parameters should have evaluated according to their influence on the building performance. As the scope of this thesis and to point out clear explanation, input parameters are divided into 4 groups in terms of their specifications, i.e. thermal transfer by transmission, solar gain, internal gain, air changes, and building function related parameters. Some of them are relevant with building geometry and the others related with functional features. In practice, the values that belongs to the parameters are identified depending on the past-experience of architect or subjective decisions. On the contrary, with scientific approach, it is possible to observe these decisions during the early design process. To analysis with respect to their properties and screen the all global design space, these parameters are counted as decision variables. In Table 3.3, their groups and ranges can be observed

Table 3.3. Decision variables

Type	Group	Decision variable	Range	Unit
Physical	Heat transfer by transmission	Width of the geometry	[6-10]	meter
Physical	Heat transfer by transmission/Solar Gain	Length of the geometry	[8-10]	meter
Physical	Heat transfer by transmission/Solar Gain	Height of the geometry	[3-4]	meter
Physical	Heat transfer by transmission	Window-to-wall- ratio South	[0.1-1.0]	-
Physical	Heat transfer by transmission	Window-to-wall- ratio West	[0.1-1.0]	-
Physical	Heat transfer by transmission	Window-to-wall- ratio North	[0.1-1.0]	-
Physical	Heat transfer by transmission	Window-to-wall- ratio East	[0.1-1.0]	-
Physical	Heat transfer by transmission	U value Roof Construction	[0.044-0.117]	(W/m^2K)

Table 3.3. (*contd.*) Decision variables

Type	Group	Decision variable	Range	Unit
Physical	Heat transfer by transmission	Wall Insulation	[0.04-0.12]	(m^2K/W)
Physical	Heat transfer by transmission	Floor Insulation	[-]	(m^2K/W)
Physical	Heat transfer by transmission / Solar Gain	Window Material	[-]	(W/m^2K)
Physical	Solar Gain	Shading Depth South	[0.1-1.0]	meter
Physical	Solar Gain	Solar Heat Gain Coefficient	[0.40-0.904]	-
Physical	Solar Gain	Shading Depth West	[0.1-1.0]	meter
Physical	Solar Gain	Shading Depth North	[0.1-1.0]	meter
Physical	Solar Gain	Shading Depth East	[0.1-1.0]	meter
Physical	Solar Gain	Height of the surrounding buildings	[0.0-6.0]	meter
Functional	Internal Gain	Occupancy	[4-8]	person
Functional	Air Changes	Ventilation Rate	[0.5-4.0]	m^3/s
Functional	Air Changes	Infiltration Rate	[0.5-2.0]	liter/hour

Architectural design normally starts with drawing the borders and arranging the volumes of the unit therefore one of the first decisions are taken for these phases. Especially, openings on the facade and building envelope design belongs to conceptual phase. For the reason of observing the building shape and compare for the alternatives, total interior volume is taken constant which is 300 meters cubic. Only decision variable is width of the geometry about a building envelope that its ranges are changing between 5 meters to 10 meters. As the base surrogate model digitally formed box shape, this decision changing one parameter about the shape was enough to investigate building shape influence for the results. To not assign the value between 5 meter, was the one of the primary decisions for the purpose of placing suitable inner zones (Albatici & Passerini, 2011).

Facade design one of the focus areas for the architectural design, to measure the effects of it, opening design decisions has been incorporated into model, furthermore shading design also is adapted into design in which correlated with solar gain of the building energy model. Because natural daylight is crucial for the architectural design. Either for the indoor visual performance or for the energy efficiency, openings on the facade are one of the most important architectural elements. While designer evaluating the building dimensions at early design, also facade design alternatives should consider from the designer. Especially, for window material, window to wall ratio and shading positions (vertical or horizontal) as decision variables. For this study, to observe each facade separately, window to wall ratio, shading depth are considered individually. For the practicality and indicate ensemble thermal zone, window construction is observed completely same for each facade of the unit.

Building energy requirements is complex task to accomplish because both for building physical parameters and weather features are in interaction with the unit. Particularly, weather decision variables specify the heating and cooling demand. To the extent to climate features there are classifications that is pre-defined by ASHRAE in which to manage construction material selection. They are called climate zone classification. According the heating or cooling based requirement hours by yearly, a climate type can be specified. The classification of the climate type is identified with degree day practice. Degree day method which are the difference between average temperature and the base temperature (I. Yildiz & Sosaoglu, 2007). Degree day method are applied with all the hours of the year to specify how many hours are heating degree day or cooling degree day. After the classification, with respect to ASHRAE International Climate Zone Definitions guideline, the climate zone can be found, therefore, construction materials minimum and maximum range values can be implemented into building energy model (Thornton et al., 2013).

Besides observation for the building envelope with physical variables, construction material investigation is implicated in the energy model of the building. Especially, insulation materials and glazing parameters are one of the most substantial and preferred decisions has taken at early design so it is worthwhile to evaluate within the context of the study (Attia et al., 2012; Y. Yildiz et al., 2012). Both building envelope design and construction materials are affecting the heat transfer by transmission, so they nominated under this category. To control the building construction design, u value of construction is identified for building envelope, such as floor, wall and roof. In the chapter 3, there was wider explanation for the arrangement of the constructions. The range values of the u values are organized according to EnergyPlus data set, in-order-to, determine maximum and minimum values of the u value construction. There are 3 different possible construction types in the data library, i.e., heavy construction, medium construction and light construction. Therefore, u value of the construction has varied between heavy and light construction values for each type of the envelope. As a default construction, medium construction is chosen to adapt the design both hot and cold climate.

As ASHRAE separated non-residential units from residentials, in the scope of the study, occupancy is taken consideration for the energy model due the density of the user is linear with the energy demand of the unit (Carpino, Mora, Arcuri, & De Simone, 2017; Guerra-Santin, 2017). On the other hand, designer is a generator of the building function due to constraints and variables and therefore users are shaping their life comfort with these decisions but in time, for some cases, the number of people who use the unit can be varied so as functional design options, it is crucial to observe the alternatives about occupancy to compose a guidance for the user. Therefore, as decision variable, between 4 to 8 persons variation adapted in the model as divided by total floor area, it is basically the ratio that is equal per square meter. Averagely, values are valued for 6 to 10 square meters per person.

For building energy models, solar gain comes from the outside is included hence it is the one of the major influential metrics that drives the total energy demand of the unit. On the other hand, EnergyPlus does not calculate the common metrics such as u value construction or material, to analyze the solar gain reaction for the model solar heat gain coefficient value has been chosen as EnergyPlus is considered as parameter. Namely, it is considered as solar transmittance at normal incidence which is the 90 degrees vector sunlight that enters from the glazing to indoor environment. The ranges of the varies [0.04-0.904] that has been arranged according to EnergyPlus data set, i.e., window glass material library.

Architectural design particularly have related with physical parameters but, as natural ventilation is an passive solution to manage indoor thermal comfort, it is highly concerned subject which has observed by designers (Konis et al., 2016). In the current framework, natural ventilation is provided by openings according to working schedule hours hence it is identified as decision variable. Ventilation rate (m3/s) of the digital model also is depend on the maximum and minimum indoor temperature values which are defined as [22.0-28.0] ^{0}C. As when the instant indoor temperature values go out of from these values, natural ventilation has converted to be active. In addition, outdoor temperature values should be provided to reach a set of reasonable observation due to adapt the energy model for the practice. Ventilation is opened when the outdoor temperature is valued as [17.0-28.0] ^{0}C.

Finally, due to global warming and non-stop increasing trend of energy demand, in recent years, there is an inclination towards passive design (Klimowicz, 2018). Within this scope, designers are trying to offer passive solutions especially for indoor air quality such as natural ventilation and infiltration rate. It is highly considerable for hot and humid climates to adapt that kind of design options, for this reason this study has investigated about the effects of natural ventilation under the concept of climate type and infiltration rate also.

3.6. SETTING DEFAULT PARAMETERS

Building energy simulations offer many input parameters to analyze the energy performance of the units and particularly, as EnergyPlus simulation engine is one of the detailed simulation tools, it presents more than thousand parameter for the designers and engineers (Hong, 2009a). Some of the parameters do not encapsulate the decisions of early design besides. Due to output uncertainty for the design, it is not suitable to predict point estimation values during the initial phases, therefore, for this study most preferred design parameters by designers has been taken consideration (Østergård et al., 2017; Y. Yildiz et al., 2012). Because of the complexity of the energy modelling, estimation of the variance of output parameters are hardly compelling.

Therefore, remained parameters has been determined as default values according to ASHRAE 90.1 and ASHRAE 62.1 standards.

For building energy modelling, there are several parameters are directly in an interaction with the total energy demand of unit, for instance, setting point temperature for cooling or heating one of the most interacted ones. Set point is the temperature that you have “set” your thermostat to maintain for indoor thermal comfort and at the above and below values HVAC system turns on to procure the indoor thermal comfort which causes to energy use. For this study, surrogate model is observed for hot-humid climate, that is Izmir and cold-dry climate, Erzurum. As this study aims to evaluate early design decisions under the condition of two different climate types, set point temperature values should be different as far as to climate specifications. For Izmir, set point temperature of heating are indicated 22 ^{0}C and of cooling is 26 ^{0}C. For Erzurum, set point temperature of heating are defined 18 ^{0}C and of cooling is 22 ^{0}C. Set point temperature values are basically refers to values that under which degree heating should be activated or above the which degree cooling should be activated thus, the pre-defined values has direct influence on energy demand (I. Yildiz & Sosaoglu, 2007).

3.7. OUTPUT WEIGHTING SCORING

The area of architectural design is outfaced from tight demands in accordance with energy use and cost management which becomes a target to reach for building performance arrangement. Further, for the design process, design firm comprise of many partners and each of them could have different opinions by the virtue of their professionalism. In case of conflict, decisions at the early stages are formed due to extensive variance, it matters most to find right metrics to follow and converge stakeholders on building performance. Therefore, with the building energy performance, design team can reach objective outcomes by defining the output parameters

In this study, building energy performance are investigating in terms of influence of decision variables that output parameters are identified as cooling and heating demand. Because of these are the outcomes that mostly defines yearly the building energy demand (Pardo, Vatopoulos, Krook-Riekkola, Moya, & Perez, 2012). In addition, artificial lightning can be counted in total energy demands but it is excluded from this investigation to focus on HVAC parameters on the building performance. Besides, energy demand prediction is volatile measurement for early design, in terms of false construction applications or detail design solutions. However, to direct the design towards the performance-based methodology, it can give the insight view for the energy use for the lifetime of the unit.

This research contains two different output and to decrease the complexity and computing cost of the energy model, two result outcomes unified with linear calculation and each of them has multiplied with 0.5 to form the total energy demand by gathering up in a single score function (1). This modification can be beneficial to decrease the run-time process and give the fast results and holistic score approach facilitates for comparison when seize on large numbers of design options. Furthermore, it supports the rendition of sensitivity analysis and provides more salient filtering for quasi-random sampling. This methodology has been applied as scoring function for the output parameters for building energy performance to encapsulate all the metrics in one term and asses the overall energy demand, in literature, there can be found similar examples (Østergård et al., 2015).

$$0.5 \times (heating\ demand + cooling\ demand) = total\ energy\ demand$$

Score function organize the multiple output parameters in one equation according their importance but as for this work refers to analyze heating and cooling demand that can be varied from location to location in terms of their importance for the total energy use, coefficient ratio for each of them was taken 0.5 to reach 1 at the end calculation. Also, the study aims to focus on the input parameters influence for the total energy demand, therefore for this framework can be satisfied the results (Bjørn & Brohus, 2006).

Total energy demand output parameters have been driven from the tool of EnergyPlus and simulation engine gives the parameters unit as gigajoule but as for energy use is calculated as kWh/sqm in the field of energy modelling, with simple conversion ratio total use value are converted from gigajoule to kWh and divided with total floor area to find the energy use per sqm in which is called energy-use intensity (American Institute of Architects, & Publishing, 2013). Building function or occupancy in the indoor are can effect on energy total yearly energy demand and in some cases, results can be unclear to comprehend, herewith, energy use intensity (kWh/sqm) eases the understanding of result and comparison between alternatives.

3.8. DATA GENERATION AND SAMPLING

As architectural design is facing with multiple tasks that comprise of energy performance, it is significance act for design team to screen global design space while output variance is large. Besides, building energy simulations are giving the results as point estimation which do not have a capability evaluate alternatives. To support the energy modellings with feature of production of alternatives, statistical analysis tools can be as solution to solve it. Especially, Monte Carlo simulation techniques which is pseudo random sampling (see Figure 3.3) and several low discrepancy sampling methods are organized for that reason to analyze the influence of the input parameters on the output and interactions between input parameters. It is highly popular in the field of building energy modelling to complete the deficiency of point estimated based energy simulations by providing global screening approach for the output variance (Haarhoff & Mathews, 2006).

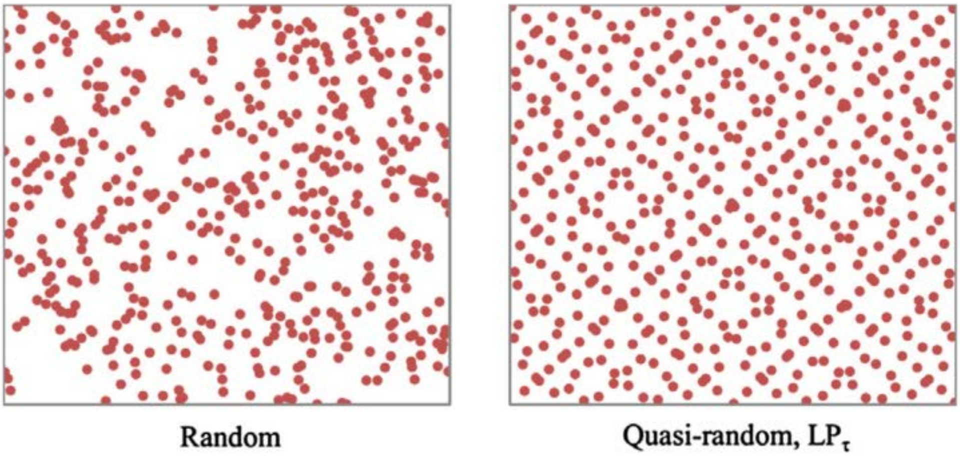


Figure 3.3. Random vs Quasi Sampling

The process of this research has been divided into two parts in terms of methodological attitude. Firstly, Morris sensitivity analysis has been applied that is one of the screening methods of, to visually perform the input influences for the reason to decrease the model size by extracting the inefficient parameters and sequencing the independent variables activity. Morris sensitivity analysis has been realized with elementary effect method which is the finite distribution of the decision variables. As Morris sensitivity analysis particularly beneficial to visualize the parameter impacts on output, the method can be implemented in the early design architectural process. Morris sensitivity analysis is computationally effective rather than other low discrepancy sampling methods. For the latter part of the process, Sobol' sensitivity analysis applied in which is one of the variance-based methods to indicate both input influence for the dependent variables, interactions and total impact for the output parameters in which includes all the input parameters activity. Sobol' sensitivity analysis has been performed with Sobol' sequences low discrepancy method to screen the global design space and its computing cost is more than Morris sensitivity analysis but in terms of explanation of interaction between two variable or total input variable influence on the output, it provides quite substantial outcomes. Therefore, for two different part of the study, has been applied different sampling techniques.

Decision variable variation can be arranged as uniform distribution either discrete [0, 1, 2, …] or continuous [0 - 1] range values. Due statistical compatibility, the range values have varied as uniform distribution. The discrepancy of the independent variable shows the global design space which represent the variation of output parameters. While scanning the all the design space, stakeholders can test and observe insignificant design solutions at the early design. Therefore, as methodological approach, sampling technique provides independent variable sampling by which probability distribution. On the other hand, sampling strategy is special subject to the specific analysis thus, the method of Morris works with Elementary Effect sampling strategy. Morris analysis supply significant representation to scan large sample of input parameters in order to find which parameter is without effect or quantification of interaction between parameters, in addition it is suitable to show linear and non-linear relations (Waqas, Melati, & Melloni, 2017). Studying with Elementary Effect technique offers a model $Y(X_1, X_2, X_3, \cdots, X_k)$ with $\boldsymbol{k}$ inputs. The k-dimensional input space is divided by $\boldsymbol{p}$ levels by distinguishing into $\boldsymbol{p}$ quantiles. Input factor of Elementary Effect is represented with mathematical equation as follows (Saltelli et al., 2007):

$$EE_i = \frac{\left[Y(X_1,\, X_{2,}\ldots\ldots, X_{i-1}, X_i\, +\, \Delta, \ldots\ldots, X_N\, -\, Y(X_1, X_2, \ldots\ldots X_N)\,)\right]}{\Delta}$$

where $\Delta \in [1/(p-1), \cdots, 1 - 1/(p-1)]$. Input factor distributions are produced as globally which discretized at input area as came after from the trajectories. As local sensitivity analysis, one factor changes at a time (OAT). While input parameters are changing, at the background Morris sensitivity are measuring the absolute mean value (μ^*) and standard deviation (σ^2) of the distributions as:

$$\mu^* = \frac{1}{r}\sum_{j=1}^{r} |EE_i^j|$$

$$\sigma^2 = \mu_i^* = \frac{1}{r}\sum_{j=1}^{r} (EE_i^j)2$$

where in both equations ***r*** represents the number of samples. The absolute mean value (μ*) points out the total influence input (X_i) on the output (Y). Therefore, absolute mean of an input is high, that means the input factor has interactive relation with output in which is not negligible. If the standard deviation (σ^2) has bigger value than the mean, consequently, the computation of EE is highly impacted from the sample point. Basically, it means the input factor based on the values of other inputs, or the input has non-linear relation with the specified output.

For Sobol' sensitivity analysis, to scan the whole design space equally, Sobol' sequence sampling strategy has been chosen to generate input parameter values. Basically, the sampling is producing quasi-random variable production with low discrepancy sequence on the global design space to decrease the discrepancy which is the feature of the global sensitivity analysis. Pseudo-Random sampling of k-dimensional points have a high discrepancy but there are infinite sequences of k-dimensional points that act much confident with respect to this measure. They have basically provided equal distribution on the global design space, as shown above (Figure 3.3). They have the specification that as the sizes length N gets very large, the discrepancy reduce the size into optimal rate. As a result, an estimated mean for a function $Y(X_1, X_2, X_3, \cdots, X_k)$ evaluated on points $\{X_{i1}, \cdots, X_{ik}\}_{i=1,N}$ from such a sequence will converge much more quickly than would an estimated mean based on the same number of random points. On the contrary of local sensitivity analysis which has the methodology to change one input parameter at a time (OAT), with Sobol' sequence sampling there is adopted a global methodology to change some parameters at the same time to grab the influence for the output parameters and interactions between each other. The Sobol' sequence sampling returns a matrix which includes model input values and the process has been executed with python sensitivity analysis library, SALib (Herman & Usher, 2017). In the library predefined Saltelli sampling preferred which is the basically extension of Sobol' sequence. For each sampling strategy, with respect to procedure $N \times (D + 2)$ times rows are produced in which N is number of samples to generate and D is the number of decision variables. In addition, if second order calculation is implicated in the process which is the value defining the total influence of all parameters on the output, the equation is converts $N \times (2D + 2)$ and it seen to computing cost increases.

3.9. EXECUTION OF SIMULATION

As energy modelling have importance for early design process, for this study each alternative that produced by sampling techniques are generated with specific energy design system program which is called EnergyPlus (*Empirical Validation of Building Energy Simulation Software: EnergyPlus*, 2011). EnergyPlus is whole building energy performance simulation software which is suitable for estimation performance with statistical sampling methods at early design even output variance is much than expected and consequently, it is used for building energy demand predictions (Granadeiro, Duarte, & Palensky, 2011). EnergyPlus works with three different type text file mode, respectively; IDD file that contains all the thermo-physical equations to produce yearly, monthly and hourly outcomes. IDF file in which includes base case's geometrical parameters that is the related with heat transfer by transmission, solar gain, such as window-to-wall ratio, glazing specifications, air changes such as, natural ventilation, infiltration rate, and finally internal gains that occurs for the reason of occupancy, building function. Besides that, HVAC, building daily and yearly scheduling has introduced into file that works as input for the thermo-dynamical equations. Lastly, EnergyPlus Weather Data (EPW) is comprise of the yearly climatic data of the site location that is another important input value for the energy simulation.

As explained above, about the scope of this study, except for some independent variables, there are many default values such as set point and set back temperatures, active ventilation strategies, ventilation schedule of the building, has been encoded as constant values into base IDF file according to ASHRAE 62.1, non-residential ventilation for acceptable indoor air quality and ASHRAE 90.1, energy standard for buildings except low-rise residential buildings regulations. Pre-generated sample values are introduced for the independent variable and for each generation, base file has compiled with sample values and has been created new file with new file name that is the number of iteration of the simulation. For Morris Sensitivity Analysis, 21000 simulations and for Sobol' Sensitivity Analysis, 42000 simulations have been generated by using the python and its libraries such as, eppy.py, geomeppy.py, SALib.py, etc. These numbers of simulations are derived from sampling techniques. After making of the new IDF file, IDD file are simulated with the file then as resulting file many file formats produced such as, ‘csv.’ (comma-separated values), ‘htm’ (hypertext markup language) which this study embarks on the ‘htm.’ file format by reading the results.

As EnergyPlus text files are coded with the old FORTRAN scripting language, due to technical issues about adaptation to old scripting language to Python scripting language, one energy plus simulation models period can get at up to 10 seconds and especially with multiple file generation at early design, it is the difficult task that should solve it and as number of simulations are reached huge amount of values, to compensate the time constraint and increase the efficiency of the simulations, parallel processing has been preferred during the simulations. For the procedure, 6 threads have been used and as an average value, one simulation execution time has been reduced below two seconds and to run all EnergyPlus simulations, 6th gen. I7, 16gb ram windows 10 operating system based a laptop pc has been used. Therefore, total duration of reaching the results changed between 10 hours to 20 hours.

3.10. GLOBAL SENSITIVITY ANALYSIS

From the first steps of the energy modeling, detecting the factors that sizes the energy performance of the unit was challenging because of the ignorance about the parameter attitudes and how they contribute the definition of energy demand by applying with high confidence interval as a statistical approach. That is probably has occurred due to lack of understanding the relation between design process and actual use of energy for the buildings. In a nutshell, building energy demand has affected by six main parameters in which are climate selection, building envelope design, building energy system design and performance, building operational system and its attendance, occupant density and activities and finally indoor air and environment quality measurement. All the parameters should have not distinguished each other and should prevent from local focusing to improve the performance. By analyzing the total influence and individual impact of the input factors, global sensitivity analysis has huge role by determining the relative importance of the inputs while they all changes at the same time in accordance with a basic sampling rule (Ruiz et al, 2012). Based on the relative importance calculation, several indices are measuring the values according to sensitivity analysis techniques therefore, in this study, there are two method are adopted to in the process which are firstly, Morris sensitivity analysis that is depend on the degradation of the individual factor variance and visualization, secondly, Sobol' sensitivity analysis that is based on disaggregation of the total variance of the inputs and individual change by all the independent variables varied, simultaneously. Consequently, with the help of analysis, when variance of the inputs have been detected, it is possible to rank the factors according to their importance, extract the non-influence parameters and define the valuable range values for independent variables. Addressing the issue, a thermo-physical model has been prepared and simulated at EnergyPlus energy software to the extent to standards and regulations to analyze the building energy performance in accordance with input parameters at early design process to form a guidance for the design team.

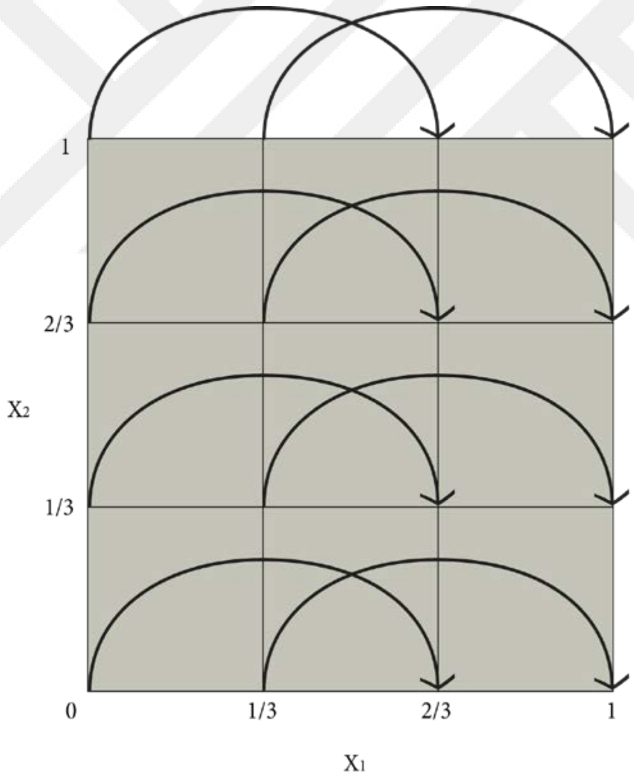


Figure 3.4. Demonstration of the four-level grid. The arrows identify the eight points needed to estimate the elementary effects relative to factor X_1

The process has been started with Morris sensitivity analysis to rank the input factors relative importance in accordance with the influence of the output parameters. Especially for early design, input and output are highly varied to evaluate the production of alternative design solutions and comparison therefore, it is beneficial to apply a screening method of sensitivity analysis. Due to lack of technical and statistical knowledge of the design team, visual outputs can help to comprehend the factor importance in terms of design procedure. The aim of the method is basically besides to rank the importance of the input parameters, it is helpful to identify negligible parameters to reduce the input size with regards to ease the computing cost. Particularly, in the terminology method is called factor fixing (Saltelli et al., 2007). Method of Morris is popular for the building energy simulations because of this technical capacity (Alam et al., 2004). The idea is to create *r* different trajectories in the N-dimensional design space (Figure 3.4). This space is normalized to [0,1] and divided into p levels by distinguished p quantiles and each trajectory includes N + 1 calculations for the reason one parameter changes (OAT) by defined equal steps at a time. Thus, each input parameter relates with the elementary effects method (EE) by determining the output value variation at *r* separate values. The formula of Elementary Effect defines the i^{th} values of X (1):

$$EE_i = \frac{\left[Y(X_1,\ X_{2,}\ldots\ldots,X_{i-1},X_i\ +\ \Delta,\ldots\ldots,X_N\ -\ Y(X_1,X_2,\ldots\ldots X_N)\ )\right]}{\Delta}$$

where $\Delta \in [1/(p-1), \cdots, 1-1/(p-1)]$ denotes the change in the input. For each input i, we obtain the following three sensitivity measures:

- Mean of elementary effects:

$$\mu_i = \frac{1}{r}\sum_{j=1}^{r} EE_i^j$$

- Mean of elementary effects absolute values:

$$\mu_i{}^* = \frac{1}{r}\sum_{j=1}^{r} |EE_i^j|$$

- Standard deviation of EE's:

$$\sigma^2 = \mu_i{}^* = \frac{1}{r}\sum_{j=1}^{r} (EE_i^j)^2$$

In the situation of the mean of the absolute values (μ*) of the EE's is large for the i^{th} input, that means the i^{th} input has high influence on output or same situation when μ* is small, i^{th} input has low influence then it could be neglected. On the other hand, If the EE's for the i^{th} input has a large standard deviation (σ) then the model is whether non-linear or the influence of the i^{th} input is related with the interactions of other input factors. The mean value, denoted as μ*, is capable of the estimate total sensitivity calculation which is the total influence of all the independent variables and interactions between them on the output. As method of Morris performs at early design energy modeling, it could be highly effective in terms of designers to neglect non-influential parameters then set sight on the most influential parameters.

Especially, for initial phase of the proposed methodology, this phase is the extension of the qualitative presentation of the analyzing values. It is special to by quantifying the total output variance for each model decision variables. Current method supplies the effective scale for determining which variable or variables is inefficient to define model output variance. On the other hand, by identifying the most influential parameters on the output, it is possible the deduce output variance with quantized technique (Rights, 2016).

Second phase of the process continues with the Method of Sobol that is one of the variance-based methods of sensitivity analysis. Variance-based sensitivity analysis concentrate on some questions (Schwieger, 2004):

- Which decision variable must investigate in the sense of how impacts the output value inefficient way?
- Which of the decision variables changes the output value in an important way?

Variance-based model function is $Y = f(X)$ where Y is the output and $Y=(X_1, X_2, \ldots.. X_k)$ are k independent variables that each parameter changes in accordance with their probability density. As the Sobol' demonstrate that (Sobol, 2001), any square integrable mathematical function can be solved by a unique figuration of high dimensional model, when the input parameters are independent from each other.

$$V_y = \sum_{i=1}^{k} V_i + \sum_{i>j}^{k} V_{ij} + \cdots + V_{12\cdots k}$$

Where V_y is the total variance of the output parameters and V_i is the residual variance that has produced by X_i and $V_{i1\ldots is}$ and is to define collaborative fractional variance induced by $\{X_{i1,\ldots\ldots}X_{is}\}$. Therefore:

$$\sum_{i=1}^{k} S_i + \sum_{i>j}^{k} S_{ij} + \cdots + S_{12\cdots k} = 1$$

Where $S_i = V_i / V_y$ is the first order index about sensitivity that calculates the variance of Y induced by X_i. $S_{ij} = V_{ij} / V_y$ is the second order index that calculates the variance of Y explained by the interaction of two input parameters, i.e. X_i and X_j. For all the individual variances and interactions are scaled into [0,1] and all equals to 1.

While the measurements of the sensitivity indices are in the linear relation with number of inputs (i.e., 2^{k-1}) the computing cost of the calculation increases therefore in many cases, first order (S_i) and total order (S_T) of the sensitivity indices are summarized in the one formula as follows:

$$S_{Ti} = S_i + \sum_{i \neq j}^{k} S_{ij} + \cdots + S_{12\cdots k}$$

The total sensitivity index includes all the contributions of X_i (residual and collaborative) to the variance of Y thus, when its value is close to zero, X_i can be determined as non-significant. At that time, input factor can be counted as default value by implementation of factor fixing.

As Method of Morris computes sampling and observe the input attitude on the output one at a time input variable changing, Sobol' sensitivity analysis is computationally cost method and number of indices growth in an exponential way with the number of dimensions and total cost measures as N * (2D + 2). Where N is the number of iterations and D is the size of the input values. Because of the calculation of the second order at the same time which is the total sensitivity index for contribution to the output variance caused by the interaction of two model inputs. Basically, Method of Sobol' is suitable when the model is non-linear, and decomposition of the output can be explained by Sobol' indices. Sobol sensitivity analysis has three indices that analyze the input conduction (Iooss & Lemaître, n.d.):

- First-Order (S_i), main effect of the index separately for each parameter without interactions. When the higher value of S_i, the higher the influence on the i^{th} factor for the variance of the output. As S_i value is specific for each parameter, for all the sum of S_i is always equal or lower than 1, and if any case, the sum is equal to 1, that means there is no interaction between independent variables which is one of the rare situations to happen. The equation of the first order sensitivity indices is, as follows:

$$S_i = \frac{V_{Xi}\,(E_{X\sim i}\;(Y|X_{\sim i}))}{V(Y)}$$

- Second-Order measures the contribution of the output variance caused by the interaction of two model inputs. As it is related with just two input factors, the area of utilization is smaller than other indices.

- Total order (or Total-effect) (S_T), this index measures the contribution to the output variance of X_i including all variance caused by its interactions, of any order, with any other input variables. The equation of the first order sensitivity indices is, as follows:

$$S_{Ti} = \frac{E_{X\sim i}\;(V_{Xi}(Y|X_{\sim i}))}{V(Y)}$$

As the Global sensitivity analysis behaves the model as black-box model statistical outcomes and sensitivity indices of analysis techniques gives insight for the interior structure of the model by inducing the variation for the input parameters. For this study sensitivity analysis procedure proceed, as follows:

- Define model and objectives that is related to interest area,

- Determine most effective design variables (k) and determine their probability density functions,

- Produce a sample of the model input space size with specified sampling techniques,

- Run the model for each sample point and collect output and input data values,

- Execute sensitivity and uncertainty analysis in order to interpret outcomes by factor prioritization, factor fixing and factor mapping techniques.

3.11. PERFORMANCE FILTERING

Factor mapping is the extension of a sensitivity analysis to support process by which parameter and parameters range can be provide valuable solution due to definition of problem. By neglecting low influence parameters, focusing on the fit parameters. For factor screening, factor prioritization and factor fixing procedures, sensitivity calculation depends on the output of the model. The technique can present clearly the input and output model relation especially helps to integrate with previous phases of architectural design.

In the current study, after applying quasi random sampling with Sobol' variance-based analysis, from the wide global design cluster, 100 best values are filtered on Parallel Coordinate Plot. Best values have corresponded to low energy demand in terms of heating and cooling demand.

3.12. VISUALISATION OF THE RESULTS

Architectural design is highly related energy modelling due to late events related with climate concerned issues. Especially, for initial phases of the design evaluating the design alternatives supports the both precedent design ideas and later-on stages. Due to analyze the design parameters according to their influence and importance for the model it is highly important to use statistical approaches as uncertainty for the energy demand at early architectural design. In the current study, Morris and Sobol' sensitivity analysis has been used to observe which independent variables are responsible for the output variance. For Morris Sensitivity analysis, importance (mu*) and interaction values are the core the analyses, to present both metric in the same plot, scatter plotting has been used as it is possible to organize 2 dimensions data in terms of multiple input factor (Figure 3.5).

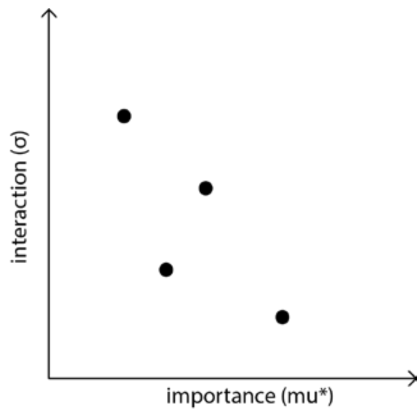


Figure 3.5. Morris Sensitivity Scatter Plot

In addition, to observe the individual influence for each decision variable with regards to output variance which is dependent to importance(mu*) horizontal bar plot are preferred (Figure 3.6). It is particularly provided reasonable outcome for factor prioritization. As general, Morris sensitivity analysis can manage the complex problems which contains multiple parameters. Specifically, it is susitable to use as a guidance.

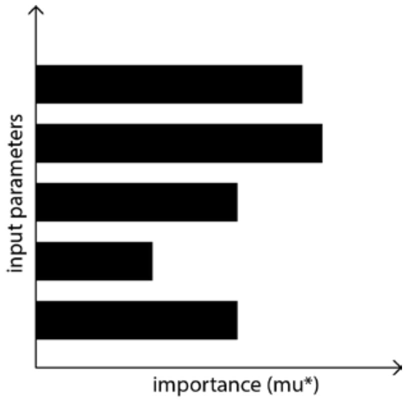


Figure 3.6. Morris Sensitivity - Horizontal Bar Plot

Sobol' is the one of the detailed analysis for variance calculation in terms of both independent and dependent variable distribution. It provides more detailed observation according to Morris sensitivity analysis hence it is preferred as a second step of the working flow the current study. Sobol' sensitivity analysis is focused on either the individual input parameter influence on the output and interaction with other parameters. To present and comprehend visually for two metric, box and whisker plotting are chosen. The plot is generally used for the sample distribution however for the study comparison of the multiple parameters with 2 dimensional frameworks, the technique supplies satisfied outcome (Figure 3.7)**.**

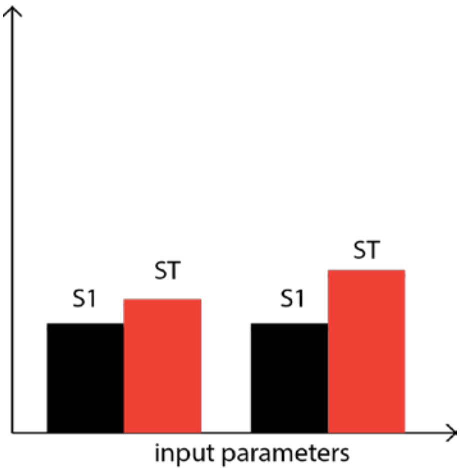


Figure 3.7. Sobol' Sensitivity - Vertical Bar Plot

To visualize multiple parameters in a single plot, a Parallel Coordinate Plots provides satisfied solutions Figure 3.8 illustrates the plot presentation in a simple way. A visual representation of the application of Parallel Coordinates Plots for two input parameters and one output as an example with focus on the Brushing (filtering capabilities). Due to performance clustering between solutions it is highly beneficial to apply particularly for early architectural design (Elbeltagi et al., 2017). Each attribute presented with interactive range selectors giving the following interaction possibilities:

- Depict the upper and lower boundary of the selection that can be either changed individually or simultaneously.
- User can drag the selection range up and down on the axis easily.
- The lower boundary of respective selection can be dragged individually or simultaneously.
- Mouse pointer will highlight spot only the data items satisfying the presently applied filtering criteria in visually.

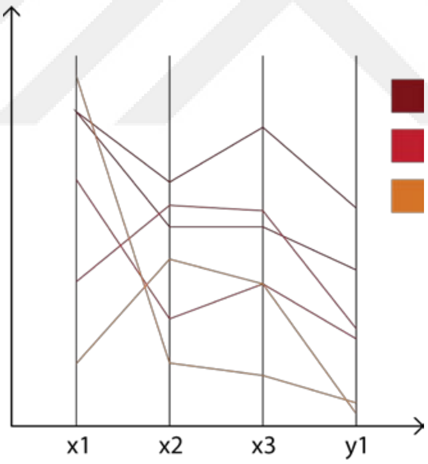


Figure 3.8. Parallel Coordinate Plot - Performance Filtering

3.13. VALIDATION

In this chapter, one of the main aims of the study, there is an application for comparing two climate results. Firstly, Morris sensitivity analysis investigations is the application for implying factor fixing and factor prioritization than for two climate type which independent variables can provide satisfied results to variation of the model of output. In the first part of the chapter, 18 different variables influence will be observed according to climate type, such as, cold climate type of Erzurum and hot-humid climate type of Izmir. As Morris sensitivity analysis is capable of the analyze for complex models and easily visualize the input parameter influence, two output plots have observed simultaneously. On the ongoing process of the Morris sensitivity analysis how parameters will be resulted according to specified quasi random sampling method. Afterwards, with selected outputs individual effect and total interaction effect of the selected parameters have analyzed and compared in accordance with cold and hot humid climate. S1 and ST are the metrics that is derived after decomposition of the output variance with global sensitivity analysis of Sobol'. According to outcomes, how are differentiated between weather types. Lastly, by applying performance filtering for 100 best performances to produce valuable ranges of the input parameters. Two Parallel Coordinate Plot values will be compared according to maximum, minimum and quartile values.

CHAPTER FOUR
RESULTS

This chapter includes investigation of the outcome in terms of input influence for the decomposition of the selected output for the methodology of the study. For this part, firstly, there will be presentation of result of Morris sensitivity analysis to visualize the energy modelling relations between input and output parameters for early architectural design. It is basically, factor fixing for the inefficient decision variables, visualization of the factor importance on the defined objectives by applying plotting. Secondly, it will continue with more detailed sensitivity analysis which is the Sobol' sensitivity analysis to observe individual input interaction and total effect of all parameters on the output variance. Thirdly, there will be a performative selection for the most intensive energy demand by applying factor mapping to decrease and determine valuable range values of the input parameters. Lastly, there will be a validation chapter for comparing valuable range distribution for two different climate which are hot-humid climate of Izmir and cold climate of Erzurum.

4.1. FACTOR FIXING & FACTOR GROUPING

For the initial step of the sensitivity analysis the elementary effect applied by Morris sensitivity analysis. Morris sensitivity analysis are beneficial to illustrate the individual influence of the design parameters during the architectural design process. Due to lack of technical knowledge for the energy modelling and statistical background, it could be useful tool to be a guidance for the architects particularly for early design process. It has been presented at methodology chapter (3.10) in terms of identification of input parameters influence on the output and eliminate inefficient parameters by fixing them as default values. All implications are implemented on the covariance plot with regards to their interaction (σ) and influence (mu*) on the output which is the weighted sum of heating and cooling demand.

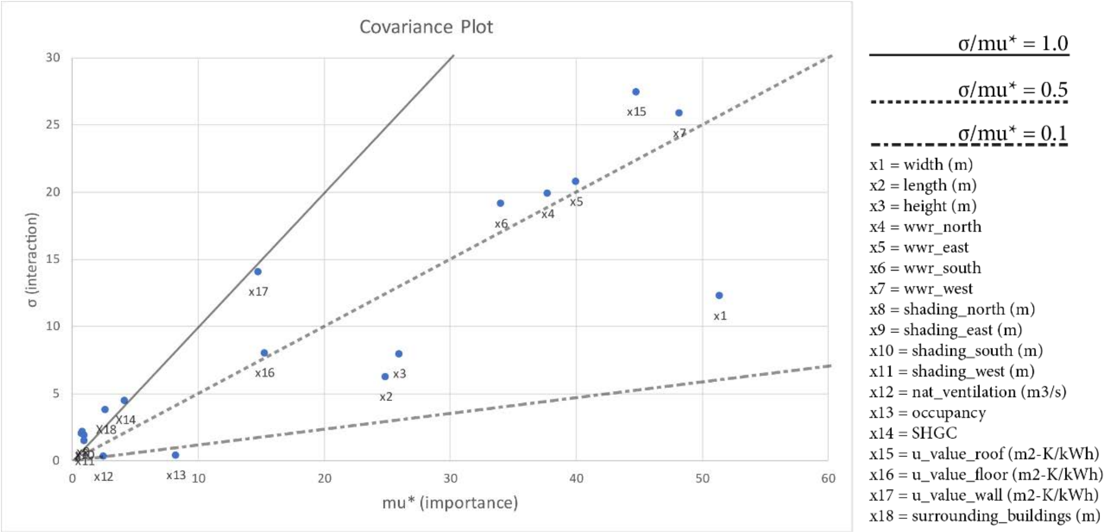


Figure 4.1. Erzurum Covariance Plot

As Figure 4.1 refers, Morris Sensitivity analysis has graded and depicted all the decision variables according to their impact on the total energy demand (total = 0.5 cooling demand + 0.5 heating demand) and interactions between other input parameters. There are 18 different decision variables which have named next to covariance plot with their units. The plot has been derived by using Eppy and Geomeppy libraries which are the scripting language to modify EnergyPlus and SALib library that is script implementation of sensitivity analysis at the Python 3.6 framework.

Morris sensitivity analysis uses some of the specified sampling methodologies based on quasi-random sampling that produce trajectories between input ranges by dividing six parts (0.0, 0.2, 0.4, 0.6, 0.8, 1.0) and jumps 2-step methodology (0.0,0.4,0.8, etc.) for each iteration and for each simulation one parameter changes (OAT). According to sampling strategy, 18999 different simulations have been executed in a parametric way in 5 hours 45 minutes. The number of the simulations has formed from the N*(D+1) formula that Morris sampling lean on, where N is the iteration number which has chosen 1000 to create 0.95 confidence interval distribution and where the D is the number of decision variables that were 18 different input parameters. The 18 independent variables are the once mostly preferred decision variables on the early architectural design. The sampling scans the global design in a homogeneous way and drives define complete output distribution. By applying the quasi-random sampling on the input variables, analyzed all interaction (σ) of parameters which there as it seems on the plot, i.e. x7(wwr_west), x15(u_value_roof), x5(wwr_east), x4(wwr_north), x6(wwr_south), x17(u_value_wall), x1(width of the geometry), x3(height of the geometry), x16(u_value_floor), x2(length) have highly performed interactive distribution with other input parameters. Because of this dominant interaction between parameters it is seen that it needs to be observed more detailed for the relation between input parameters. Therefore, after factor fixing implication for several parameters, methodology continued with Sobol' sensitivity analysis which is based on variance of the distribution for decision variables in terms of total, individual and secondary effect.

One of the major ability of the Morris sensitivity analysis, is to capability to observe how input value distribution provides the output variation due to specified sampling strategy. Particularly for complex models, there is an opportunity detect and decrease the variance for output of model. Figure 4.1. also points out the interaction level of each independent variable with other variables. According to left wing of the plot, x15(u_value_roof), x7(wwr_west), x5(wwr_east), x4(wwr_north), x6(wwr_south), x17(u_value_wall), x1(width of the geometry), x16(u_value_floor), x3(height of the geometry), x2(length of the geometry) have the most interaction with other design parameters.

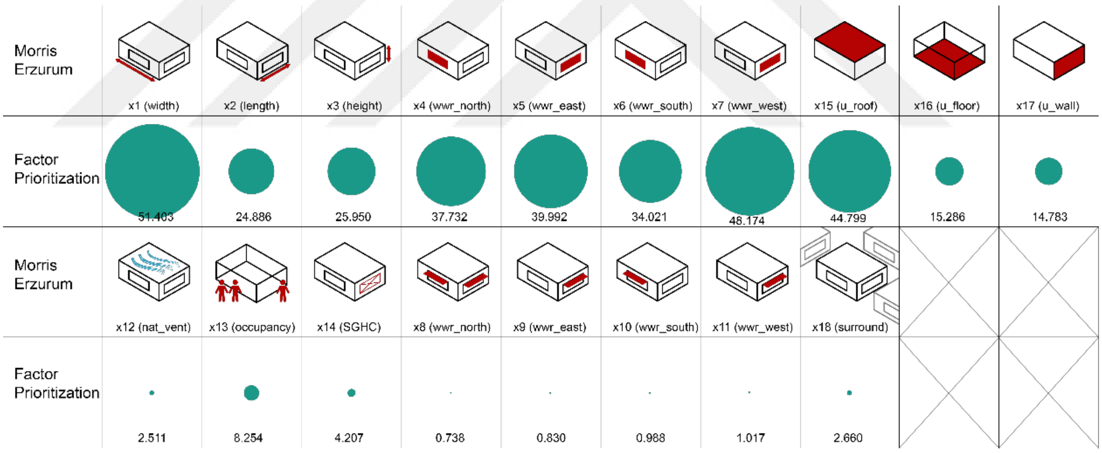


Figure 4.2. Morris Erzurum Results

To illustrate in detail, **Figure 4.2** points out the individual factor importance according to total energy demand. Each input parameters are shown with horizontal bars. This gives the how necessary are the input parameters by the technique of factor prioritization. **Figure 4.2** demonstrates the importance (mu*) of the input parameters in the sense of weighted sum of heating and cooling demand. Respectively, x8(north shading depth), x9(east shading depth), x10(south shading depth), x11(west shading depth), x12(natural ventilation), x13(occupancy), x14(solar heat gain coefficient of glazing), x18(height of the surrounding buildings) are the input parameters procure low degree of importance for the output. Namely, they are the least important parameters should be ignored on for the early architectural design of energy modelling.

Some of the parameters are behaved both interactive and importance in the with regards to yearly total energy demand of the unit. For instance, x7(wwr_west) effectuated the output either individually and interaction with other parameters. On the other hand, some of the parameters are positioned both ineffective and non-interactive with other parameters. Which are, x13(occupancy), x8(shading ratio north), x9(shading ratio east), x10(shading ratio south), x11(shading ratio west), x12(natural ventilation). Therefore, within the scope of the similarity, x8(north), x9(east), x10(south), x11(west), shading depth parameters are grouped according to their insufficient individual influence on the output and reduce the computing cost of the analysis. Additionally, x12(natural ventilation), x13 (occupancy) are fixed due to ineffective variation on the output parameters hence they are fixed as default value. In conclusion, each parameter has sampled with an equal sampling variation between 0.0 to 1.0 value ranges and some of the parameters have set as default value and shading parameters have grouped due to less influence on the energy demand in the climate of Erzurum which is included in the process mostly because of the cold climatic properties.

As sensitivity plotting for the Erzurum presented inefficient input parameters to provide variation on the total energy demand of the unit, for some parameters such as, x17(u_value_wall), x13(occupancy per square meter), x12(natural ventilation), x10(shading_south), x11(shading_west). Especially for u value of the roof has become inefficient because of the heating demand of the unit. For the buildings at warm and humid climate, it is expected result due to reason of the heat transmission from the interior to exterior in terms of internal gain and sun exposure. The parameter has behaved contrary for the Erzurum, which is cold climate, to preserve the heat in the indoor space.

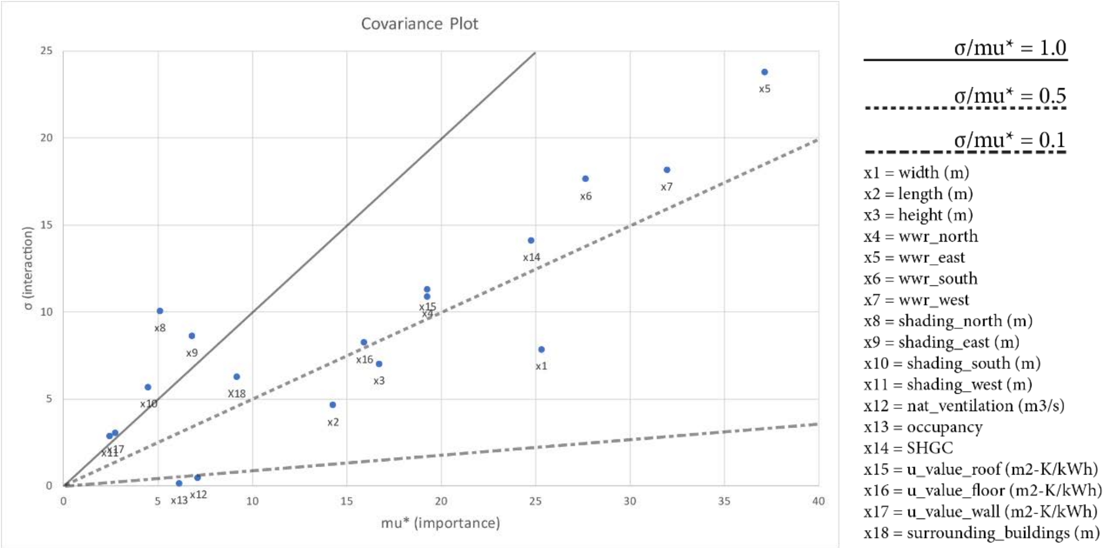


Figure 4.3. Izmir Covariance Plot

As **Figure 4.3** is the covariance plot of the Morris sensitivity analysis which points out the energy performance of the digital model, positioning of all input parameters has arranged according to their importance and interaction performance same as for observation for Erzurum. The same 18 different decision variables are implemented in the either sampling and analyzing process. On the contrary of Erzurum sensitivity analysis, input parameter conduction has shown different kind of awareness according to output variance. Obviously, this separate distribution is the main interest on the current study and it is caused due to different climate type of two location. Erzurum has mainly cold and dry climate but for Izmir, there is warm and humid climate is effective, therefore early design architectural decisions changes to compensate the impression of the climate.

About Morris sensitivity analysis for Izmir sampled and executed with 18999 different simulations and total duration were close to 6 hours. It is different from the value of Erzurum sensitivity analysis in consequence of different calculation in thermo-physical simulation engine, EnergyPlus. As a result, some of the input parameters has come up with effective results, respectively, x5(wwr_east), x7(wwr_west), x6(wwr_south), are both most effective and interactive with other parameters in terms of cumulative calculation. For the reason of long sunlight hours of Izmir, decision variables of window to wall ratio provide more variation than other parameters. Relatively, x4(wwr_north) has stayed less effective than other facades based upon exposure of the diffused sunlight of northern hemisphere. With regards importance measure (mu*), x14(solar heat gain coefficient), x15(u value of roof construction), x4(wwr_north), x1(width of the geometry), x3(height of the geometry), x2(length of the geometry), x16(u value of floor construction) follows the most important parameters in the sense of influence on the output. For the interaction performance of the input parameters, the situation changes and input parameters presentation situate as follows, x14(solar heat gain coefficient), x15(u value of roof construction), x4(wwr_north), x8(north shading depth), x9(east shading depth), x16(u value of floor construction), x1(width of the geometry), x18(height of the surrounding buildings), x3(height of the geometry). Even x8(north shading depth) is situated as least important in terms of output variance it is performed highly interactive with other parameters.

To compare the distribution of the parameters according to climate perspective, generally u value of the envelope has derived substantial role to conserve the heat at the interior space for Erzurum but on the contrary the parameters efficiency has reduced for Izmir to let the heat transmission from interior to exterior to ensure the indoor thermal comfort.

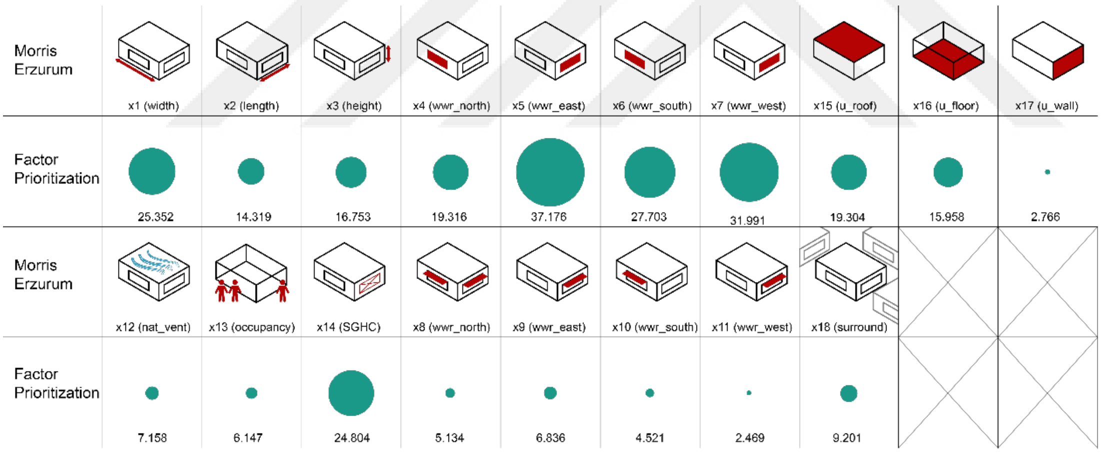


Figure 4.4. Morris Izmir Results

For detail observation, **Figure 4.4** indicates the input parameters influence on the output excluding the interaction with other decision variables. For each parameter, horizontal bars with their error ratio depicts individual importance as **Figure 4.4**. Mostly, envelope related parameters have performed highly effective performance for the output distribution therefore their mu* ratio is strictly higher than the other types of decision variables. Respectively, x11(west shading depth), x17(u value of wall construction), x10(south shading depth), x8(north shading depth), x13(occupancy), x9(east shading depth), x12(natural ventilation) have performed low importance for the influence of the output. Therefore, these are the parameters are applied factor fixing and excluded from the second step detailed sensitivity analysis.

4.2. VARIANCE-BASED INDIVIDUAL AND TOTAL EFFECT

Particularly the variance is decomposed into main effects which is the individual effect of the parameter and interaction effects or total effect. The main effect of a parameter quantifies the portion of the variance of the model output which is explained by that parameter. Especially, by allowing all parameters to be varied at the same time with a specific pattern, as it is mentioned in the previous chapters related for the working methodology of Global sensitivity analysis. The total effect of a design variable evaluates the residual variance of the model output that remains by removing the portion explained by all other parameters, i.e. quantifies the uncertainty in the model output that would be left by fixing any other factor. The Sobol' method is a Monte Carlo procedure that allows to compute any term of the variance decomposition, each at the cost of N model runs. For the cost of estimating the entire set of main and total effects is of N * (2D +2) model evaluations with respect to the original Sobol' algorithm. For the second step of the methodology, 21999 simulations have been executed in 6 hours 30 minutes to analyze input parameter efficiency in Erzurum.

Sobol' sensitivity analysis is based on variance-based observation with regards to individual and interaction related influence on the output. Therefore. S1 is the symbol for the individual effect for the output variance and the ST stands for the individual and total interaction effect of the output for the specified independent variable. It is the cumulative sum of all the secondary and the higher interactions between other input parameters. In the **Table 4.1**, there is the representation of the numerical results of the first and total order effects of the selected input parameters. As sensitivity analysis is driven with sampling and variance calculations, it is preferred to prove the outcomes with a statistical approach which is confidence interval of the input parameters. As it is seen in the table, each parameters confidence interval value is lower than %5 percent of the total distribution that is the frequency of possible confidence intervals that includes the true value of their corresponding parameter. It produced valid results in terms of the dependability of the analysis.

Table 4.1. Results of Sobol' Analyses for Erzurum

Parameters	S1	S1 Confidence	ST	ST Confidence
x1(width)	0.236017	0.04031	0.248034	0.024372
x2(length)	0.054069	0.02116	0.057284	0.007927
x3(height)	0.046867	0.019112	0.05451	0.010534
x4(wwr_north)	0.122642	0.029397	0.121887	0.012096
x5(wwr_east)	0.133089	0.031203	0.147262	0.018774
x6(wwr_south)	0.100909	0.029912	0.105421	0.015106
x7(wwr_west)	0.127189	0.025958	0.128175	0.014185
x15(u_value_roof)	0.154541	0.035241	0.165612	0.019928
x16(u_wall_floor)	0.01766	0.010611	0.02075	0.009209
x17(u_value_wall)	0.016814	0.010252	0.022324	0.010153

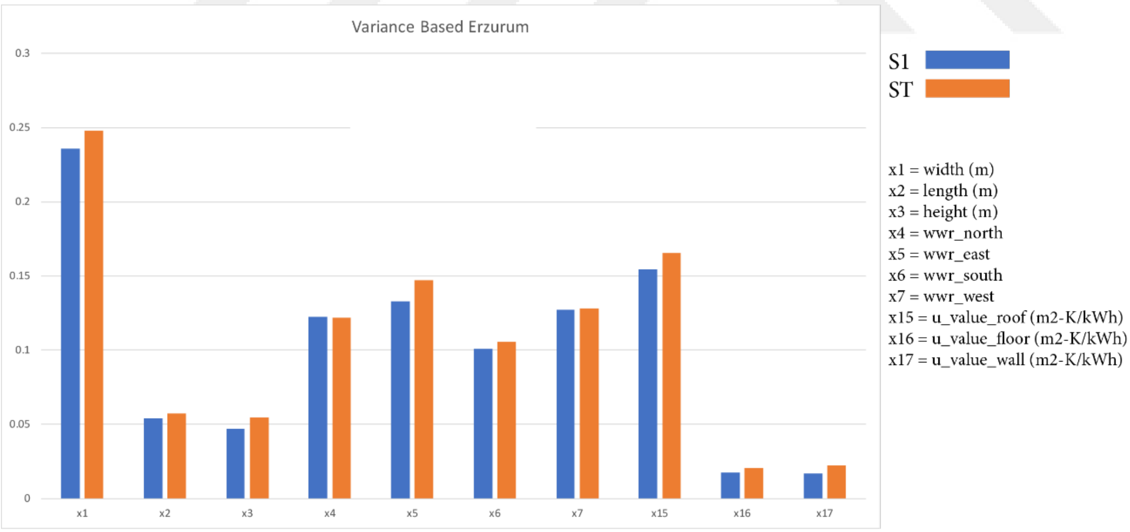


Figure 4.5. Sobol' Vertical Bar Plot for Erzurum

In the **Figure 4.5** there are 10 different important parameters are analyzed in terms of distribution of the model of the output. Generally, physical parameters and thermo-physical properties have come to the front. Respectively, x1(width of the geometry), x15(u value of the roof construction), x5(wwr_east), x4(wwr_north), x7(wwr_east), x6(wwr_south) has become more effective the other parameters. Except the u value of the roof (x15), u value related construction parameters have provided les influential results on the output. Same pattern happened in terms of envelope parameters of the geometry, only width of the geometry has given effective result. However, all the window to wall ratio independent variables has caused wide variance on the selective output.

Blue vertical bars are stand for individual influence of an input parameter and the orange vertical bars are used for the total effect of an independent variable due to variance of the total energy demand. Generally, total index gives higher result than the first order (S1) but for some parameters it is lower than the first order. Because of the compatibility of the mathematical workflow, if a parameter forms strictly lower interaction with other parameters, algorithm produce negative values that is decreasing the total index value. It is basically means that the parameter has highly important for the output variance but least interactive with other input parameters, such as x4(wwr_north). On the other hand, x2 (length of the geometry), x6(wwr_south), x16(u value of the roof) is also shares the same issue which is highly effective for the output but less interactive to compose an interaction with other parameters. As remainder, x1 (width of the geometry), x3(height of the geometry), x5(wwr_east), x6(wwr_south), x7(wwr_west), x15(u value of the roof), x17(u value of the wall) either provided highly effective result for the uncertainty of the model output and entered higher interaction with other parameters.

In the Sobol' sensitivity analysis for Izmir, there have been 21999 simulations are executed in a sequence with Saltelli sampling technique. As Sobol' is one of the global sensitivity analyses at the same time more than one parameters value has changed in to analyze decomposition of the output variance. Later, the Morris sensitivity analysis 10 parameters are evaluated as important to influence on energy demand of the unit. **Table 4.2** presents the individual influence (S1) and total effect (ST) of each parameter for the variance of the output. Each parameter has evaluated with higher confidence interval which is higher than 5 %. As dependability of the parameters are satisfied than first and total order effect of the independent variables are reasonable to observe (**Figure 4.6**)

Table 4.2. Results of Sobol' Analyses for Izmir

Parameters	S1	S1 Confidence	ST	ST Confidence
x1(width)	0.177696	0.037947	0.194879	0.017635
x2(length)	0.05357	0.020845	0.054324	0.005428
x3(height)	0.053574	0.020968	0.060732	0.006698
x4(wwr_north)	0.103008	0.025342	0.101809	0.009429
x5(wwr_east)	0.177314	0.034086	0.190147	0.020795
x6(wwr_south)	0.110272	0.026633	0.112957	0.01223
x7(wwr_west)	0.116595	0.029256	0.121876	0.012002
x14(SGHC)	0.039475	0.020912	0.040194	0.00617
x15(u_value_roof)	0.105439	0.031506	0.107541	0.010829
x16(u_wall_floor)	0.050735	0.019122	0.050922	0.004932

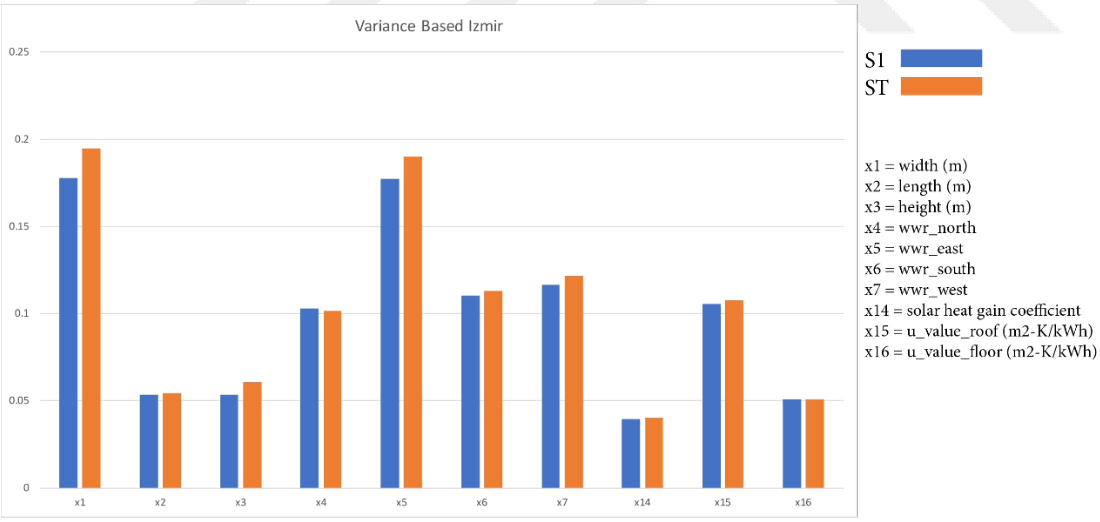


Figure 4.6. Sobol' Vertical Bar Plot for Izmir

4.3. PERFORMANCE FILTERING

To analyze the data more detailed and drive the valuable ranges of the input parameters, filtering process has been applied on the process by extracting the most effective results of the distribution to provide output variance. In the current part of the work, by executing sampling strategy for scanning the total global design, it gives highly dependable results on the how parameters have a relation with each other and which parameters range drives the most valuable outcomes with selected constraints. In conclusion, main aim was to reach the analyze extract the effective range values of the input parameters with regards to high performance energy demands, which was the yearly weighted sum of heating and cooling demand of the building.

Table 4.3. Input Parameters Distribution of Erzurum

	x1	x2	x3	x4	x5	x6	x7	x15	x16	x17
Min.	0.001	0.003	0.000	0.006	0.012	0.004	0.003	0.000	0.029	0.005
Q1	0.103	0.148	0.144	0.143	0.135	0.138	0.131	0.037	0.296	0.120
Med.	0.207	0.351	0.339	0.259	0.281	0.271	0.253	0.119	0.572	0.353
Q3	0.400	0.583	0.605	0.416	0.448	0.510	0.492	0.273	0.820	0.619
Max.	0.941	0.986	0.995	0.940	0.906	0.984	0.882	0.932	0.998	0.988
Mean	0.287	0.376	0.390	0.304	0.297	0.331	0.314	0.183	0.553	0.395
Range	0.940	0.982	0.994	0.934	0.894	0.979	0.879	0.932	0.969	0.982

For second analyses, the data sampled by Saltelli technique quasi random sampling and according to 21999 simulation data alternatives are evaluated for all global design space. Than 10 uniformly distributed input parameters get some valuable ranges to apply lowest energy demand. Addressing the filtering process **Figure 4.7**. points out the 100 best performances of input parameter distribution which is the lowest energy demand of the unit for Erzurum. Total energy demand values are varied between 56.53 (kWh/sqm) to 81.31 (kWh/sqm) for energy use intensity values which is the yearly energy demand per sqm. With regards to best performance of the units, valuable ranges of each independent variables are positioned respect to their first and third quartile values. By the filled color of the values are representing the range values between 1st and 3rd quartiles which is the dense data of sampling are composed. In detail, **Table 4.3** demonstrates the maximum, minimum and quartiers values of the input distributions of **Figure 4.7** values.

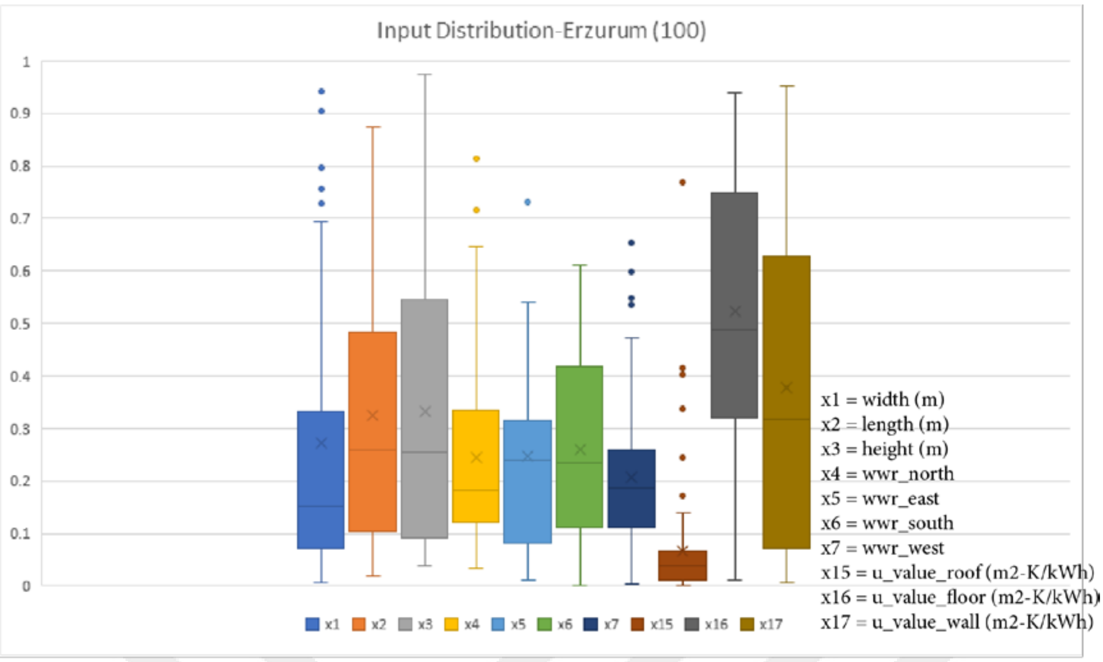


Figure 4.7. Best 100 Performances Distribution of Erzurum

As second step implied for Izmir distribution in accordance Sobol' sensitivity analysis, 10 different independent variables are uniformly distributed for the global design space. After executing 21999 simulations in sequence way, 100 best performance of simulation has chosen to illustrate with plotting. Whisker and box plotting is suitable to demonstrate how the ranges of dense data are composed which directs the yearly energy demand high performance. It is suitable to drive and represent the performative data in a way of guidance to designer at early architectural design.

Figure 4.8 demonstrates the 100 best performances of input parameter distribution which is the lowest energy demand of the unit for Izmir. Yearly weighted sum of cooling and heating demand are valued between 32.33 (kWh/sqm) to 55.47 (kWh/sqm) for energy use intensity values which is the yearly energy demand per sqm. Same methodology has been applied for Izmir Sobol' sensitivity analyses with 21999 simulations by sampling 10 uniformly distributed input parameters to reach high energy performance of the unit. **Table 4.4** demonstrates the maximum, minimum and quartiers values of the input distributions for each parameter. In addition, with regards to best performance of the units, valuable ranges of each independent variables are positioned respect to their first and third quartile values that is the distribution becomes more sensitive.

Table 4.4. Input Parameters Distribution of Izmir

	x1	x2	x3	x4	x5	x6	x7	x14	x15	x16
Min.	0.001	0.036	0.019	0.009	0.007	0.016	0.023	0.001	0.001	0.034
Q1	0.025	0.161	0.191	0.146	0.103	0.183	0.140	0.345	0.085	0.443
Med.	0.111	0.437	0.346	0.245	0.179	0.294	0.304	0.417	0.188	0.569
Q3	0.287	0.753	0.612	0.463	0.237	0.438	0.438	0.746	0.356	0.785
Max.	0.720	0.984	0.987	0.838	0.780	0.782	0.952	0.994	0.991	0.984
Mean	0.178	0.440	0.418	0.309	0.203	0.299	0.317	0.490	0.264	0.594
Range	0.719	0.948	0.969	0.830	0.773	0.766	0.929	0.993	0.990	0.950

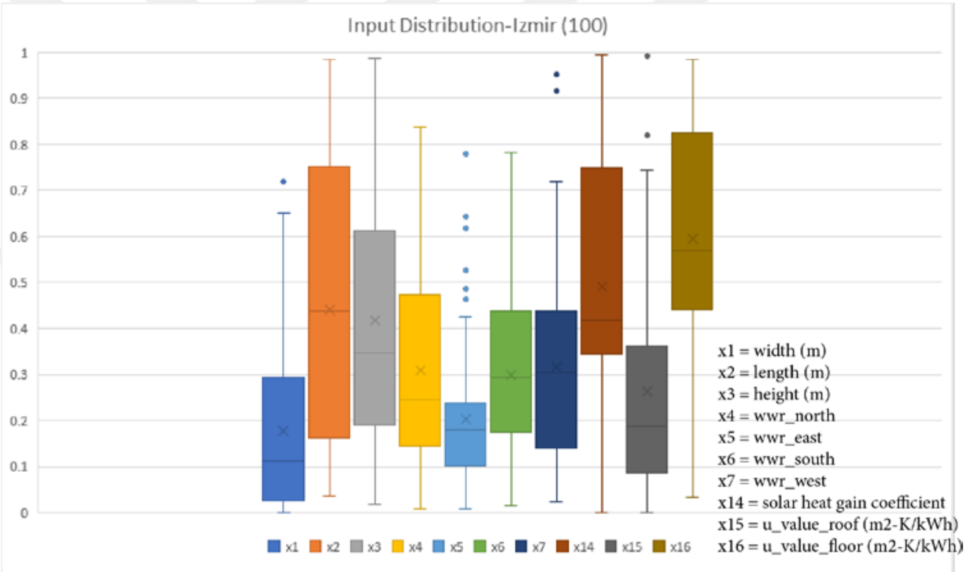


Figure 4.8. Best 100 Performances Distribution of Izmir

The benefit of depict strategy for energy analysis with multiple parameters is crucial because it would be complicated to interpret the many lines of value data, which represent the final input and output data for the whole simulation analysis process. Hence, a Parallel Coordinate Plot is a plotting type used to demonstrate many input and output parameters across many dimensions. Each dimension of data corresponds to a vertical axis on the plot and each data element is displayed as a series of connected polylines along the dimensions and vertical axes which can be classified from worse value to best value or in the sense of analysis focus, it could visualize confined spaces at global design. To further investigation and observe the multiple data relation with the best performances output and Parallel Coordinate Plot (PCP) has been composed from the 100 best solutions. It is suitable to all the parameters in one chart. Designers can categorize the results according the energy performance of the unit and which parameter corresponds the selected output value to present design alternatives. It is highly recommended for designers to be used as guidance in the early architectural design. In **Figure 4.9** points out the selected 10 parameter relations with total energy demand (kWh/sqm). PCP has been prepared by using data visualization strategy (DVS) web site which is constructed analyze multiple parameter results at the same time.

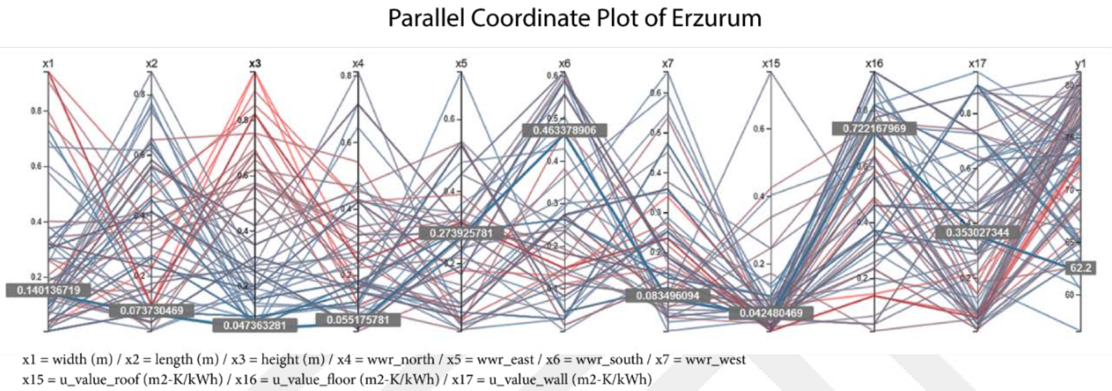
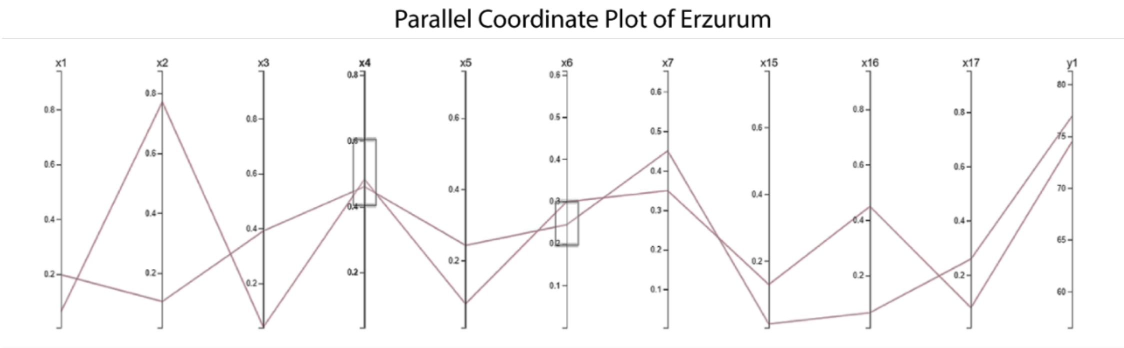


Figure 4.9. 100 best performances of Erzurum

The missing point of the Parallel Coordinates is that when the design alternatives are cumulated at very data-dense the plot area becomes over-cluttered therefore it is unreadable with regards to user. To overcome it, the interactive 'brushing' technique can be used to organize only values that are of researched for the designer at specified point of design. Brushing highlight a selected lines or collection of lines to isolate sections of plot that the designer is interested in, while filtering out of the noise or dense data cluster. **Figure 4.10** shows a plotting demonstration of the implementation of Parallel Coordinates Plots for two input parameters and one output. It is the depiction of Brushing technique. Each line depicts one row of a data from the selected output values which is satisfied point of energy demand of the building. The PCP of Erzurum composes from 10 different design parameters, respectively, x1(width of the geometry), x2(length of the geometry), x3(height of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_west), x15(u value of roof construction), x16(u value of floor construction), x17(u value of wall construction) and y1(weighted sum of cooling and heating demand).



x1 = width (m) / x2 = length (m) / x3 = height (m) / x4 = wwr_north / x5 = wwr_east / x6 = wwr_south / x7 = wwr_west
x15 = u_value_roof (m2-K/kWh) / x16 = u_value_floor (m2-K/kWh) / x17 = u_value_wall (m2-K/kWh) / y1 = total energy demand

Figure 4.10. Brushing implication on PCP for Erzurum

Table 4.5. Brushed values of Erzurum points out the values that has brushed on the Parallel Coordinate Plot for the x4(wwr_north) which is filtered between 0.4 to 0.6 and x6(wwr_south) values that is brushed between 0.2 to 0.3. Instantly, the other parameters values also filtered which is corresponds to at intersected line. **Table 4.5** represents numerical values of input parameters for PCP, in detail. As a result, by filtering two parameters at the same time, arranges the weighted sum of cooling demand and heating demand values for 74.5 (kWh/sqm) and 76.95.

Table 4.5. Brushed values of Erzurum

x1	x2	x3	x4	x5	x6	x7	x15	x16	x17	y1
0.065	0.772	0.042	0.484	0.079	0.299	0.350	0.129	0.450	0.080	74.50
0.199	0.105	0.391	0.461	0.243	0.245	0.451	0.011	0.066	0.259	76.95

All the filtering process applied for Izmir's best 100 high performance energy demand simulation data and as it seen it is resulted more distributed than Erzurum results (**Figure 4.11**). The PCP of Izmir contains 10 different design parameters, respectively, x1(width of the geometry), x2(length of the geometry), x3(height of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_west), x14(SGHC), x15(u value of roof construction), x16(u value of floor construction) and y1(weighted sum of cooling and heating demand). Nevertheless, still connections are highly illegible in terms of the users. Therefore, same brushing points for x4(wwr_north) and x6(wwr_south) are applied on Parallel Coordinate Plot.

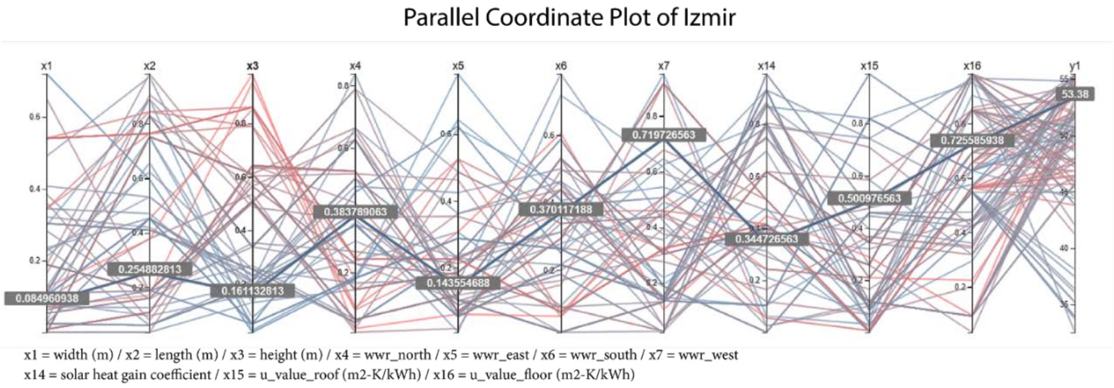


Figure 4.11. 100 best performances of Izmir

On the Parallel Coordinate Plot due to data density, it is hard to analyze all multiple lines of data at the same time. As Erzurum PCP, interactive brushing technique has been applied on the PCP with the same value range of x4(wwr_noth) and x6(wwr_south). To the contrary of Erzurum brushing, more 9 row lines of data satisfied the filtering implication. Due to climate differentiation between two climate design alternatives are varied as a diversified depiction. In **Figure 4.12**, one can see the relation between 10 parameters and one output parameters at the same time. If designer would like to focus these value ranges, there are 9 different solutions are expected to alternate during the early design architectural process.

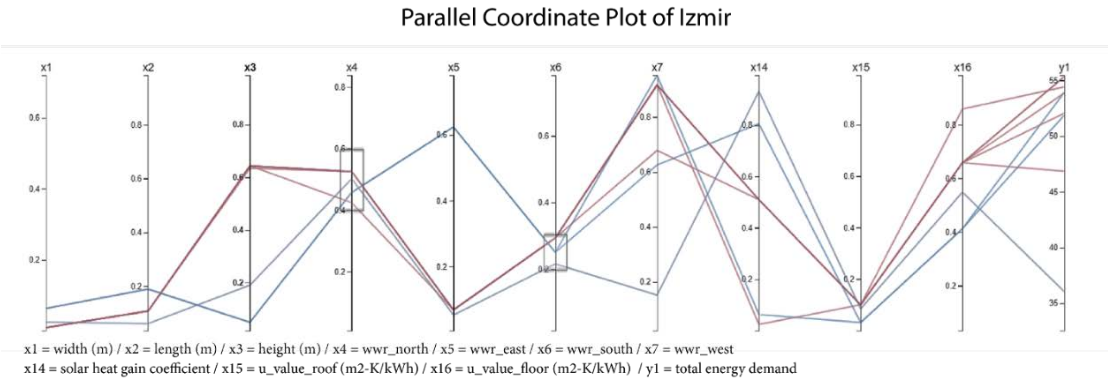


Figure 4.12. Brushing implication on PCP for Izmir

Table 4.6 points out detailed value presentation of the selected filtering interval in terms of the x4(wwr_north) and x6(parameters). In addition, **Table 4.6** shows all brushed values of Izmir.

Table 4.6. Brushed values of Izmir

x1	x2	x3	x4	x5	x6	x7	x14	x15	x16	y1
0.063	0.190	0.050	0.458	0.624	0.251	0.626	0.806	0.032	0.413	51.89
0.063	0.190	0.050	0.458	0.624	0.251	0.952	0.063	0.032	0.413	53.94
0.009	0.109	0.635	0.526	0.070	0.294	0.917	0.510	0.101	0.659	55.360
0.009	0.109	0.644	0.424	0.070	0.294	0.917	0.510	0.101	0.659	53.890
0.009	0.109	0.644	0.526	0.070	0.294	0.679	0.510	0.101	0.659	46.870
0.009	0.109	0.644	0.526	0.070	0.294	0.917	0.025	0.101	0.659	52.080
0.009	0.109	0.644	0.526	0.070	0.294	0.917	0.510	0.101	0.859	54.440
0.009	0.109	0.644	0.526	0.070	0.294	0.917	0.510	0.101	0.659	55.360
0.025	0.062	0.191	0.502	0.054	0.216	0.152	0.932	0.085	0.549	36.060

4.4. VALIDATION

One of the main aims of the research was how architectural design elements are changing for different climates. Weather properties and physical geometry of the building design are two major factor that determines the yearly energy demand of the unit. Office program is selected as building function in one zone and additionally, schedule and HVAC program of the unit identified according to function of unit as default values at the preparation phase of the energy model. Addressing the issue, there have been two different climates are selected, hot-humid climate of Izmir and cold climate of Erzurum.

From the first step to end of the methodology there has been differentiation between two climates in the sense of which parameter are performed efficient for the variance of total energy demand value and which parameters are suitable to neglect it. Table 5 compares the input parameters importance (mu*) values of two weather type. As a result of Erzurum analysis, x1(width of the geometry), x2(length of the geometry), x3(height of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_west), x15(u value of roof construction), x16(u value of floor construction), x17(u value of wall construction) are became highly resulted important in a way of evaluation of uncertainty of output. Besides, x1(width of the geometry), x15(u value of roof construction), x5(wwr_east), x4(wwr_north) are eluded from the other parameters in terms of importance. On the other hand, as a result of Izmir, x1(width of the geometry), x2(length of the geometry), x3(height of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_west), x14(solar heat gain coefficient), x15(u value of roof construction), x16(u value of floor construction) are performed significant value for output. For Izmir, there has been more distributed importance are happened between independent variables and x5(wwr_east) are became the dominant parameter between other parameters. For each climate type, 10 different decision variables are selected for second step which is variance based Sobol' sensitivity analysis, rest of them fixed as default value.

In the second step of the application, there has been variance-based sensitivity analysis has executed to observe individual importance (first order) and all the cumulative interactions between other parameters (total effects). Both Erzurum and Izmir analysis conducted exactly 21999 simulations with Saltelli sampling method to scan all the global design space in terms of alternations. In **Table 4.7**, Between two climates, previously some of the parameters are dissociated such as, for Erzurum 17(u value of wall) and for Izmir x14(solar heat gain). Nevertheless, the other 9 parameters were same it is possible to compare first and total order of the parameters. Either Izmir and Erzurum x1(width of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_west), x15(u value of wall construction) input parameters have holding high value of S1. However, for Erzurum, x1(width of the geometry) and x15(u value of construction) are resulted higher than other important parameters for Izmir, x1 and window to wall ratio (x4, x5, x6, x7) related parameters are came in the first place. On the other hand, for both location, x2(length of the geometry), x3(height of the geometry), x16(u value construction of floor) are became least important. In addition, x17(u value of wall construction) also has performed lower performance for Erzurum and x14(solar heat gain coefficient) has performed in the same manner for Izmir.

Table 4.7. Comparison for Morris Sensitivity Analysis of Erzurum and Izmir

Morris Erzurum	mu*(importance)	Morris Izmir	mu*(importance)
x1	51.403	x1	25.352
x2	24.886	x2	14.319
x3	25.95	x3	16.753

Table 4.7. (*contd.*) Comparison for Morris Sensitivity Analysis of Erzurum and Izmir

Morris Erzurum	mu*(importance)	Morris Izmir	mu*(importance)
x4	37.732	x4	19.316
x5	39.992	x5	37.176
x6	34.021	x6	27.703
x7	48.174	x7	31.991
x8	0.738	x8	5.134
x9	0.83	x9	6.836
x10	0.988	x10	4.521
x11	1.017	x11	2.469
x12	2.511	x12	7.158
x13	8.254	x13	6.147
X14	4.207	X14	24.804
x15	44.799	x15	19.304
x16	15.286	x16	15.958
x17	14.783	x17	2.766
X18	2.666	X18	9.201

To analyze total order effect that is the result of cumulative interaction with other parameters with selected input parameter of the independent variables for Erzurum and Izmir. In **Table 4.8**, for Erzurum analysis, x1(width of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_east), x15(u value of roof construction) have been valued with high number of total order effect. On the other hand, x4(wwr_north) has gotten lower value of ST rather than. In theory, it is not possible in the sense of Sensitivity analysis of Sobol' but in the implication if a parameter has close to zero interaction value it means it could some time get negative value of interaction. However, x1(width of the geometry), x5(wwr_east), x15(u value of roof construction) are performed higher level of interaction with other parameters. In **Table 4.8**, For Izmir analysis, x1(width of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_east), x16(u value of floor construction) have come in the first place with regards to interaction level with other parameters. In addition, x1(width of the geometry), x5(wwr_east), x16(u value of floor construction) has resulted dominant level of interaction, as a matter of fact there is very differentiation between S1 and ST for x16 value.

Table 4.8. Comparison of the first order for Erzurum and Izmir

Sobol' Erzurum	First Order (S1)	Sobol' Izmir	First Order (S1)
x1	0.236	x1	0.178
x2	0.054	x2	0.054
x3	0.047	x3	0.054
x4	0.123	x4	0.103
x5	0.133	x5	0.177
x6	0.101	x6	0.110
x7	0.127	x7	0.117
x15	0.155	x15	0.105
x16	0.018	x16	0.051

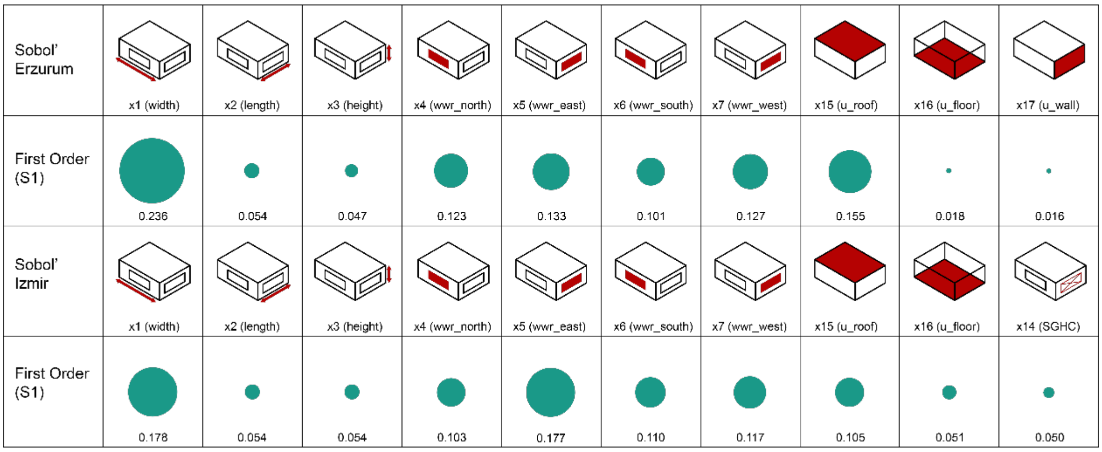


Figure 4.13. Visual Presentation of first-order

According to sampling results of Sobol' analysis there has been applied a performance filtering for related parameters. And it is aimed to analyze, range values of the independent variables. As **Table 4.9** depictions are observed the data in a way of sensitivity analysis formulations, in this chapter there are some value propositions to be serve as guidance to designers at early architectural design. In **Table 4.10**, there is information about how input parameters are changed in terms of maximum and minimum values. For performance filtering of Erzurum, x2(length of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_west) and x15(u value of roof construction) are varied lower than the difference between border values. On the other hand, x1(width of the geometry), x3(height of the geometry) and x16(u value of floor construction) are distributed in a wider interval. For Izmir performance filtering, x1(width of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south) are decreased their range values in terms of distribution.

Table 4.9. Comparison of total order between Erzurum and Izmir

Sobol' Erzurum	Total Order (ST)	Sobol' Izmir	Total Order (ST)
x1	0.248	x1	0.195
x2	0.057	x2	0.054
x3	0.055	x3	0.061
x4	0.122	x4	0.102
x5	0.147	x5	0.190

x6	0.105	x6	0.113
x7	0.128	x7	0.122
x15	0.166	x15	0.040
x16	0.021	x16	0.108

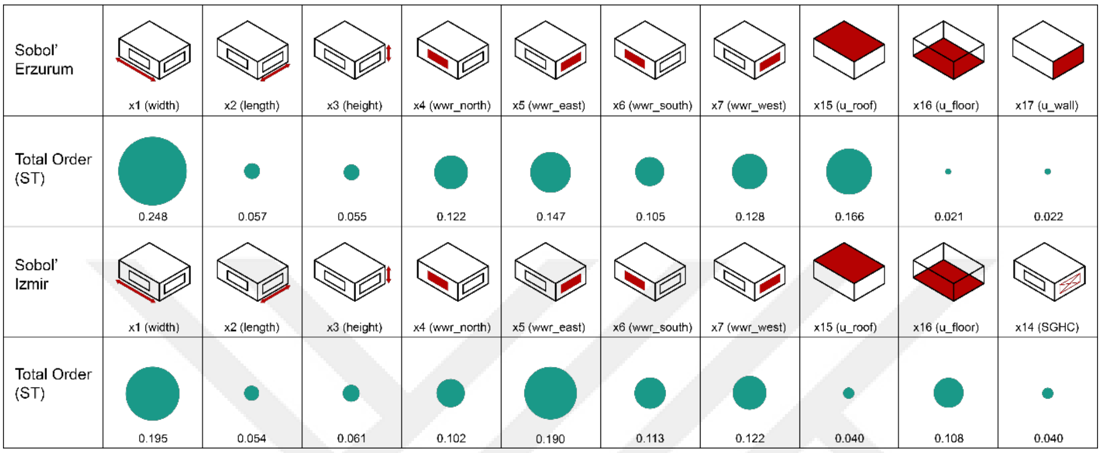


Figure 4.14. Visual Presentation of total-order

Table 4.10. Comparison of 100 best performances for Erzurum and Izmir

Erzurum	Maximum	Minimum	Izmir	Maximum	Minimum
x1	0.941	0.006	x1	0.720	0.001
x2	0.875	0.018	x2	0.984	0.036
x3	0.974	0.040	x3	0.987	0.019
x4	0.813	0.033	x4	0.838	0.009
x5	0.732	0.012	x5	0.780	0.007
x6	0.610	0.000	x6	0.782	0.016
x7	0.653	0.003	x7	0.952	0.023
x15	0.769	0.000	x15	0.994	0.001
x16	0.939	0.012	x16	0.991	0.001

Table 4.10. (*contd.*) Comparison of 100 best performances for Erzurum and Izmir

Erzurum	Maximum	Minimum	Izmir	Maximum	Minimum
x17	0.953	0.006	x17	0.984	0.034

CHAPTER FIVE
DISCUSSION

The current study aimed to reach reasonable explanation for energy modelling and analysis between input and output parameters at early architectural design within two different climates, such as hot-humid climate of Izmir and cold climate of Erzurum. Building function of the model has been chosen as office and single zone to analyze the physical and functional parameters at one zone. As architectural design is complex problem that compose from multiple parameters and constraints it has high importance to analyze from the early stages (Y. Yildiz et al., 2012). Related with this issue, climate is one of the major inputs that shapes the energy demand of the building. Besides, arrangements of the early design are generally the ones that determine most of the energy demand of the unit. It is highly important to focus on the decision-making process of early architectural design because the interventions at the later stages of the design process could not make any difference as the implications at the early design. Besides, conceptual phases of architectural design contain limited time interval that the design stakeholders could not concentrate each design alternative and elements. Therefore, they should to be renounce from the some of the parts of the design to complete and pass later stages.

The novel method has driven from the statistical analysis of the design alternatives due to observe how architectural design elements shapes and from the total energy demand of a building. Addressing the issue, decision making at initial phases is the driving properties that shapes and organize the energy policy of the buildings until detailed stages. In the framework of the research, a digital model has been constructed in the scripting language and an energy simulation which is EnergyPlus has been applied to analyze the architectural design element influence on the selected output that is the weighted sum of heating and cooling demand in a yearly timeline.

For the research, 18 different independent variables have been chosen to analyze the attitude and how they interact with each other that defines the yearly energy demand. Input parameters has been selected under 4 categories, i.e. heat transfer by transmission, solar gain, internal gain and ventilation. Mostly, the chosen parameters are related with envelope properties of the building such as, height, length, window to wall ratio, u value of constructions, etc. These classified elements are the most preferred and studied elements at the early architectural design (Depecker et al., 2001). Hence, in the extent of the work, they have been arranged as decision variables to detect the how they influence on the variance of the selected output and is there any interaction between each other that converts to problem more complex. Related with issue, in the literature there has been some statistical techniques that is suitable to analyze uncertainty of the output at early design by applying sampling methodology to scan the alternative design space. In the current study, sensitivity analysis has been applied for the 18 different parameters that influence the output variance.

Firstly, by applying quasi random sampling techniques Morris sensitivity analysis are executed to observe the which parameters has least important in terms of the weighted sum of energy demand and how they are in interaction with each other that transforms the problem in a complex situation. It is crucial to apply in the early design to reduce the complexity of the problem to focus on the most influential parameters. In addition, it is helpful method providing a guidance for the designers to observe the design decisions from the earliest stages (De Wit & Augenbroe, 2002). Morris sensitivity analysis applied for two different climates, Izmir which is hot-humid climate and Erzurum is the cold climate. For the analyses, there has been 18999 simulations applied in a parametric way by changing one parameter for each iteration is called one-at-time(OAT). For Erzurum the duration of the simulations has completed in 5 hours 45 minutes and for Izmir it took close to 6 hours.

The main objective for the application of Morris sensitivity analysis is to define which parameters are important in terms of variation of the output and reduce the model complexity by implying factor fixing which is converting some independent variables to default values. Both Erzurum and Izmir, analysis is started with 18 different parameters and reduced 10 important parameters in accordance with the mu*(importance) and σ(interaction) values. For Erzurum, x1(width of the geometry), x2(length of the geometry), x3(height of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_west), x15(u value of roof), x16(u value of floor), x17(u value of wall) input parameters are resulted either interactive and highly influential. Even solar gain is strictly lower for cold climate, it is still resulted as significant for cold climate of Erzurum. Besides, all the substantial design parameters are envelope design and construction related parameters for the cold climate of Erzurum. For Izmir, still same number of parameters are evaluated as significant performance for the output variance. However, there is alteration for selected parameters which is respectively, x1(width of the geometry), x2(length of the geometry), x3(height of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_west), x14(solar heat gain coefficient), x15(u value of roof), x16(u value of floor). On the contrary Erzurum, there is lack of importance u value of constructions and solar heat gain coefficient has displayed important performance due to extensive solar exposure. In accordance with results, for each location 10 parameters are analyzed elaboratively with Sobol' sensitivity analysis.

During the analysis, there has been some discrepancy between two climates. For instance, the design related envelope parameters, such as length(x1), width(x2) and height of the geometry(x3), are resulted highly important with regards to selected output. On the other hand, u value of constructions has performed different for two climates. In the cold climate of Erzurum, foremost u value of roof construction(x15) has got important value for the output variance same scenario has happened for u value of floor(x16) and wall construction. Particularly, for colder climate, to conserve the indoor temperature it is expected result. However, for hot-humid climate of Izmir, u value of construction parameters has strictly become least important by changing the output value. U value of wall construction(x17) has even stayed inefficient in terms of effect the selected output. It is resulted in that way for the reason of in the indoor temperature balance for hot climates. Due to higher outdoor temperatures and additionally indoor heat gains that caused by occupants, machines, there is a tendency towards from indoor to outdoor.

Solar gain is the one of the most important ingredients of the climate. As a result, there is another differentiation in terms of sunlight exposure related parameters. In the Morris sensitivity analysis for Izmir window to wall ratio of each facade are performed dominant importance rather than Morris analysis of Erzurum. Window to wall ratio independent variables has valued between as a percentage of the total area of the facade from 0.0 to 0.95. To investigate more in accordance with the direction, there has been identified separate independent variables for each vertical surface of the building. It is the result of the amount sunlight hour for Izmir. As solar gain is the driving force for yearly energy demand, by increasing the sunlight hour ratio impress the importance of the window to wall ratio of the building facade.

During the analysis, there are encountered some significant results especially related with ventilation design of the office unit for Izmir. Generally, for hot humid climate types natural ventilation and infiltration rates are accepted as driving force that can either reduce and increase the total energy demand of the unit. For the preparation of the script, while determining the natural ventilation as decision variables, it is seen that it is extensively influence the weighted sum of cooling and heating energy demand. Therefore, to reach compatible results natural ventilation rates, the implication of ventilation converts as per sqm than the total variance output and ventilation schedule are equalized to office working hours schedule to manage indoor temperature when the occupant density of the zone is increased. Generally, natural and mechanical ventilation design are belonging to later stages of architectural design hence strategy of ventilation is positioned lower than envelope design parameters which are the most focused variables in the early design.

In the second part of the study, with 10 most influenced parameters are analyzed with Sobol' sensitivity analysis in terms of decomposition of output of the model. As mentioned at previous paragraphs, different independent variables are evaluated with regards to Morris sensitivity analysis results. To scan global design space of the design alternatives, sensitivity analysis calculations use specific Monte Carlo sampling procedures. For Sobol' analysis N * (2D +2) model evaluations has been applied where D is the number of parameters which has resulted as 10 parameters. N is the iteration value of the simulations. As 10 parameters exist in the analysis 22 simulation has been executed for each iteration than roughly 21999 simulations are applied with quasi random sampling methodology. For Sobol' analysis contains more simulation number than Morris sensitivity analysis, individual and total effect analysis is basically convergence for better as a result. Sobol' analysis of Erzurum pointed out the individual(S1) and total effect(St) of parameters. Total effect contains cumulative interaction calculation between other parameters for selected input parameter.

As variance-based sensitivity analysis of Sobol' are investigating the input activity in a wider range, there is an extraordinary outcome has been seen during the process. For Erzurum analysis, x4(wwr_north) is performed strictly lower total order rather than other façades. Due to sunlight exposure faces with the north facade in a diffuse form, there was no high interaction of other parameters. For instance, for x5(wwr_east) has relatively higher interaction values because when the surface area of the face has increased the amount of the sunlight that will enters in the building will be increased also. For north facade, due to diffuse sunlight there will be less change for the total amount of sunlight. In the meantime, x1(width of the geometry) are resulted with higher interaction value. Particularly, it is important to conserve indoor temperature value so when the width of the geometry has increased all the other physical parameters are positioned according to envelope of the geometry. Same as, it is possible for x15(u value of roof construction) which is directly related with heat transfer by transmission. To support the idea, even for hot-humid climate of Izmir, envelope related construction parameters are also performed high value of interaction when the heat transfer by transmission plays important role of the energy demand.

Another important issue of the analysis process has illustrated that for Izmir sensitivity analysis, input parameters first and total order values are more uniformly distributed rather than Erzurum. Because Erzurum has cold dominant climate type but on the other hand climate of Izmir contains both huge amount of sunlight and cold temperature therefore each physical and functional parameter have entered in reaction according to temperature differences and solar exposure. In addition, for 100 best performances of Izmir total energy demand are varied between 32(kWh/sqm) and 50(kWh/sqm) however for the Erzurum cases energy demands of the unit could not reach lower than 50’s, i.e. 50(kWh/sqm) to 81(kWh/sqm)

In conclusion all the effective parameters are presented with Parallel Coordinate Plot(Plot) of 100 best performances and for some parameters it is reached to valuable range values, for Erzurum, x2(length of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_west), x15(u value of roof construction) and for Izmir, x1(width of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south). As Izmir contains more variety in terms of temperature level, less number of parameters are resulted as dominant rather than other parameter (Elbeltagi et al., 2017).

CHAPTER SIX
CONCLUSION

Architectural design contains multiple design parameters that designers should focus on in a short time. Therefore, to determine the important parameters to work on that will shapes most of the yearly energy demand of the unit. The research observes for the early architectural design of energy modelling for two different type of climates, such as hot-humid weather of Izmir and cold weather of Erzurum. Building energy demand are formed physical properties of the unit and weather specifications of the site location. Due to uncertainty of the total energy demand of the unit at early design, it is supposed to be analyze how architectural design elements identify the energy demand per sqm which is Energy Use Intensity (EUI). To overcome the specific problems iteratively, multiple simulations has been generated by using EnergyPlus engine simulation. Related with this issue, a scripting model has been prepared to analyze multiple alternatives in terms of decision variables influence on the weighted sum of heating and cooling demand. In-order-to analyze input parameter impact with regards of the output variance, statistical models have been applied by quasi random sampling techniques of sensitivity analysis. For the research, to observe all the global design space widely, both to reduce computing time and link the system in an automated way, all the energy model has been coded with Python 3.6.

In the beginning of the process, a digital model has been prepared as one zone of office building. Base model has been composed as a box model that the physical and functional properties are varied during the process. Basically, energy modelling has been composed from 4 selections, i.e. heat transfer by transmission, solar gain, ventilation rate and internal gains. For observation, 18 different decision variables are identified. All the decision variables are the ones related with early architectural design which designers are integrating the elements to drive the end design. To form the pre-model in the script language, eppy and geomeppy of EnergyPlus libraries have been used. Briefly, architectural energy model of the simulation has been comprised of input data file (IDF), input data dictionary (IDD) and EnergyPlus weather data (EPW) which is the yearly climate properties of the chosen site location. For the simulation model, occupant and HVAC scheduling are arranged according to building function and these are defined as default values.

Firstly, as early design architectural energy modelling is complex problem for the reason analyze the problem in a deeper way to detect the design elements interaction and driving power for the output, a global sensitivity analysis has been chosen at Morris global sensitivity analysis are executed to define both visually and in a numerical way to identify which parameters are negligible in order to influence of the output model and which design parameters are important to focus on at early architectural design. For the implication of the Morris sensitivity analysis, specific quasi random sampling method has been applied to analyze independent variable activity. The method has been applied as one parameter change at a time (OAT). When 18 different parameters have entered in the sensitivity calculation with 1000 iteration, 18999 simulations have been executed both two different climate, Erzurum and Izmir. As a result, 10 different parameters are evaluated important by the way of affecting the uncertainty of the output model. Which are x1 (width of the geometry), x2(length of the geometry), x3(height of the geometry), x5(wwr_east), x6 (wwr_south), x7(wwr_west), x15(u value of the roof), x16(u value of the floor), x17(u value of the wall) for analysis of Erzurum. At the same time, x1 (width of the geometry), x2(length of the geometry), x3(height of the geometry), x5(wwr_east), x6 (wwr_south), x7(wwr_west), x14(solar heat gain coefficient), x15(u value of the roof), x16(u value of the floor) are performed higher performance to determine variance of the output value. Especially, envelope design and construction related parameters are resulted as highly substantial according to architectural design. There are also interactions are observed between input parameters. Rest of the other parameters are seen as uninfluential with regards to change of the yearly energy demand of the unit per square meter, so they have been fixed as default values. In conclusion, it is decided to analyze deeply the importance of input parameters in the sense of output and understand the interactive actions of decision variables.

Secondly, another global sensitivity analysis has been implied for most selected 10 architectural design parameters to observe individual importance (first order) and cumulative interaction values between parameters (total effect). Sobol' sensitivity analysis is basically depends-on variance decomposition of the model output which uses specific quasi random sampling method of Saltelli sampling which changes the value of multiple input parameters at the same time with uniform distribution. To scan all the global design space in a homogenous way, 1000 times process has been iterated. Due to calculation technique 21999 simulations are executed both Erzurum and Izmir analysis. According to results of Erzurum analysis, x1(width of the geometry), x15(u value of the roof construction), x5(wwr_east), x4(wwr_north), x7(wwr_east), x6(wwr_south) has become more effective rather than other independent variables in terms of individual sensitivity of selected input parameters. Besides, x1(width of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_east), x15(u value of roof construction) of architectural design parameters have been valued with high number of total order effect that means they have high dependency of by defining output of the model. On the other hand, conclusion of the Izmir analysis, same as the cold climate results, x1(width of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_east), x15(u value of roof construction) has performed high value of importance for the reason of affecting the output variation. In addition, x1(width of the geometry), x4(wwr_north), x5(wwr_east), x6(wwr_south), x7(wwr_east), x16(u value of floor construction) are the ones that have entered high interaction levels. In addition, the design variables were more uniformly distributed in-order-to determine output value. In conclusion, for cold climate envelope related parameters are presented dominant tendency on the other hand for hot-humid climate either envelope and solar gain related parameters are resulted high importance and interaction during the analysis process.

Lastly, after applying multiple iterative simulations for sensitivity analysis, a performance filtering procedure has been applied for cold and hot-humid climate results to supports to early design process as a guidance element. For the performance filtering, 10 different parameters are selected and organized with specific range values that will quantify high performance energy demand of the unit for cold climate of Erzurum and hot-humid climate of Izmir. By using Parallel Coordinate Plot (PCP) 100 best performances are visualized at the same time and if the designers are aiming to analyze and illustrate alternations, and interactive brushing techniques are existing that user can instantly choose valuable range intervals according to design result. In conclusion, both Morris and Sobol’ sensitivity analysis has used to improve model calibration for identifying important parameters and interactions between input variables. For further investigation, it is aimed to applied Monte Carlo filtering process for performance filtering and comparison of multiple climate types to observe the process

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