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The Comparative Study on the Influence of Early Architectural Design Decisions on Energy Demand: A Case Study in Turkey

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Abstract

The early design process has the most salient design decisions for architects. It is crucial to observe the impact of these design decisions in terms of performance-based design. However, because of the large amount of variance of the performance criteria in the early design parameters, the decision-making is highly arduous. The current study proposes a method to quantify output uncertainty and presents the relationship between independent and dependent variables for providing insight into the decision-making process. The energy simulations for hypothetical office building based on TS-825 requirements were executed with cooling and heating demand (kWh/m^2-year) outputs for two different regions, i.e., Erzurum as a cold climate and Izmir as a hot-humid climate. Researchers computed the input parameters' impact on building performance with quasi-random statistical sampling and filtering techniques. Respectively, ineffective parameters eliminated with factor fixing and factor prioritization (i.e., first-order) was realized to sort the most effective parameters with Morris Local Sensitivity Analysis. The interaction (i.e., second-order) between independent variables was analyzed using Global Sensitivity Analysis of Sobol'. The output weighting process was applied for rating each result combining the performance based on output variables for the factor mapping. It is the presentation of 100 best solutions in the aspect of the effective range of the input parameters for the most significant reduction in the variance of the output variables. The results were presented with Parallel Coordinate Plot (PCP) for each climate as a comparison. Consequently, the study showed how climate conditions are essential for building energy demand, and design options could be analyzed based on the impact of design decisions.

Keywords: early architectural design, performance-based design, global sensitivity analysis, decision-making support

Introduction

In recent years, there has been a trend towards environmental design in building planning and construction under the influence of climate change. In particular, the increase in energy demand has been accelerated due to industrialization and the growth of urban areas, and this has reached critical levels (Mumovic, 2009). In parallel with this situation, there was a need for analytical observation for efficient energy management for designers. Although many stakeholders are involved in the design process, architects have the greatest impact on determining the energy performance of buildings. Especially for the performance-oriented parameters for energy usage, etc., geometric volume dimensions, and surface properties (Granadeiro et al., 2013).

Many designers try to design the building entirely at once, without including performance analysis and simulations in the design process (C.A. Morbitzer, 2003). However, as the project's design progresses, the need for change arises, and these changes lead to loss of money and time in the project. Because most of the time, the initial stages of the design process are returned (Hien et al., 2000). Figure 1 points out that the most significant influence on energy performance for buildings comes from the decisions in the early design process (Attia et al., 2012). For instance, the energy demand of the building could decrease approximately 30-40% without any additional cost, only determining reasonable envelope design and orientation of the openings (Wang et al., 2005). The focus on the early design is to search and evaluate design alternatives in the first place to preventing the design limitations for final stages. Therefore, the importance given to the first design phase should be increased, and the performance-related design should be used to analyze the impact of the design decisions on energy usage.

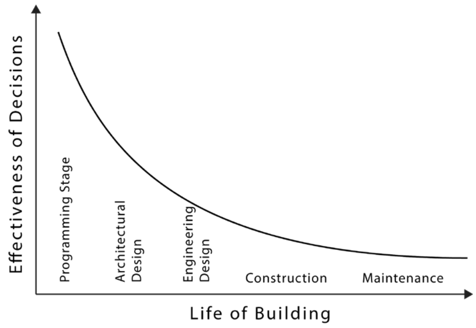


Figure 1. Representation of the process of construction and effectiveness of the decisions

The simulations are not only as supporting tool for the decision-making process. The simulation-based workflow in early design can lead to producing quantitative outcomes for the energy usage of the design as a feedback tool, and designers can use these results for the more realistic decision-making process (Christoph Andreas Morbitzer, 2003). Unfortunately, most of the energy simulation tools cannot investigate the overall energy performance of building influenced by design variables (Yildiz et al., 2012). Energy simulations should be proactive in the aspect of giving feedback about design variations by ranking the chosen parameters (Attia et al., 2012; Kanters & Horvat, 2012; Rights, 2016). Consequently, designers could have the possibility to manage multiple input factors and define effective performance outputs. For some studies, statistical sensitivity analysis could be the answer as a technique that measures the output uncertainty and demonstrate the impact of the independent variables on the dependent variable for unbiased decision-making procedures (De Wit & Augenbroe, 2002; O'Neill & Niu, 2017; Østergård et al., 2015; Ruiz Flores et al., 2012).

The performance-based design allows the designer to reach better energy and environmental performance by using design variables and constraints. In literature, point-estimation methodologies are popular among designers (Kämpf et al., 2010; Konis et al., 2016). The optimization works following the design automation philosophy: the executor who can be a designer or someone else, arrange the boundary values and constraints, and the generative tool forms the desired design solutions knowledge. The designer achieves just limited insight into the reasons behind the established design solution. Therefore, this limited approach could not present enough alternative evaluation for early architectural design. On the contrary, statistical sampling methods can provide a wide range of alternative production by analyzing the uncertainty of the process, and demonstrate the relationship between independent and dependent variables (Hemsath & Alagheband Bandhosseini, 2015).

The uncertainty for the decision-making process at the early design is a known fact (Macdonald, 2002). As a solution, the Sensitivity Analysis (SA) can derive reliable knowledge for the non-linear relation between independent and dependent variables, which can be characterized as 'Garbage-in, Garbage-out' (Coakley et al., 2014). The framework of SA proposes useful computational ability to decrease problem complexity with ranking each parameter influence on defined model outputs (Firth et al., 2010). Sensitivity analysis is capable of in-depth exploration of the model attitude following quantifying the influence scanning for all variations of inputs (Iooss & Lemaître, 2015). In various studies, researchers tested several methods to compute uncertainty of the dependent variables, i.e., screening/decreasing inputs (Alam et al., 2004), meta-modeling by reducing the complexity of the energy model (Topcu & Ulengin, 2004), robustness framework (Burhenne et al., 2011).

Sensitivity analysis (SA) has the capability to identify a-priori influence and to rank the sensitivity of the variables. It is a response to the "What-if" question by measuring the regressions or correlations of particular inputs (Struck et al., 2009). Therefore, it is common among designers for observational works of architectural analysis (Kristensen & Petersen, 2016; Sun, 2015). SA methods are classified into two ways, which called local sensitivity analysis (LSA) or global sensitivity analysis (GSA) (Hemsath & Alagheband Bandhosseini, 2015). LSA performs better for the detection of the uncertainty of the input parameters around a specified point. On the other hand, GSA could scan the whole input set in terms of output activity, which contains an explanation for binary input interactions and non-linearity (Saltelli et al., 2007). Various studies have implemented LSA for building energy modeling to observe the local attitude of the input parameters with regards to static energy modeling, net-zero energy building design, thermal comfort, ventilation, and lastly, building design (Rasouli et al., 2013). Global Sensitivity Analysis frequently is used for early design building energy models, which scores the direct and total impacts of input parameters on the defined outputs (Menberg et al., 2016). The main differences from the local sensitivity analysis, all the chosen parameters get involved in the analysis process simultaneously (Kristensen & Petersen, 2016). In literature, GSA was utilized by researchers for different studies of building energy performance analysis (Ruiz Flores et al., 2012; Yang et al., 2016). In this study, Morris Method as screening techniques of LSA and Sobol' Method as variance-based of GSA were used for different steps.

The current research aims to observe the impact of the early design architectural design decisions on the energy demand of the building. A statistical methodology consists of the factor prioritization by evaluating the effect of the independent variables. Thus, design teams can recognize how to focus on essential decision parameters at the early design stage. As the method consists of quasi-random sampling, designers can evaluate global design solutions based on generated building energy simulations.

In this study, the aim was to form a prognostic law-driven model by combining the building energy simulation with the statistical sensitivity analysis to evaluate design alternatives on a broader scale. Preparing simulation-based statistical models can provide a high degree of valuable information about understanding the insight of the models with defining constraints by comparing the decisions by the results.

Methodology

The current study focuses on the early architectural design decision-making process in terms of analyzing energy performance with regards to physical and functional design parameters relation with annual heating and cooling demand (kWh/m^2-year). The main idea of the process has derived from the concept of the early design decisions designate a common framework of the design process (Figure 2), therefore, the methodology aimed to select important input parameters with regards to providing low uncertainty level for the dependent variables.

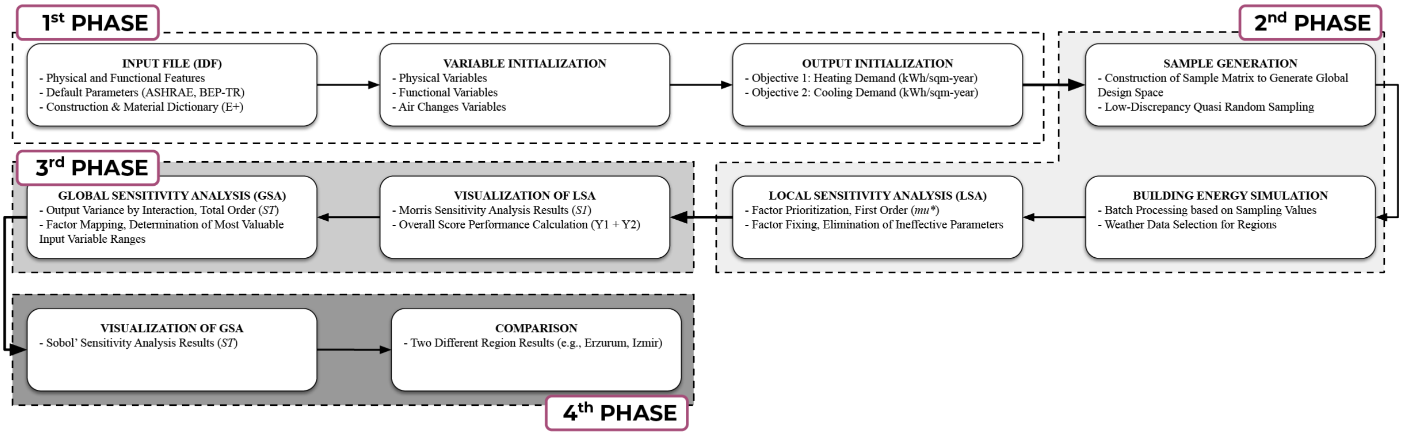


Figure 2. Flowchart of the proposed model

Model Description

The analysis geometry is a digital box model to observe the variables with less possible physical constraints. The test model (Figure 3) is a rectangular single-zone office building. Its dimensions are 8 meters x 6 meters x 2.7 meters. Even there are the physical design variables that change the dimensions of the model, the interior volume of the building has taken as constant value as 129.6 cubic meters (Szewczuk & Conradie, 2014). Because of the design solutions differentiate according to the environment and weather, the simulations were produced in two different locations to additionally compare climate difference impact on the early design energy modeling, e.g., Izmir is in ASHRAE climate zone 3A (2500 < Cooling Degree Days 10°C < 3500) and Erzurum is in ASHRAE climate zone 6B (4000 < Heating Degree Days 18°C ≤ 5000) (ASHRAE, 2009).

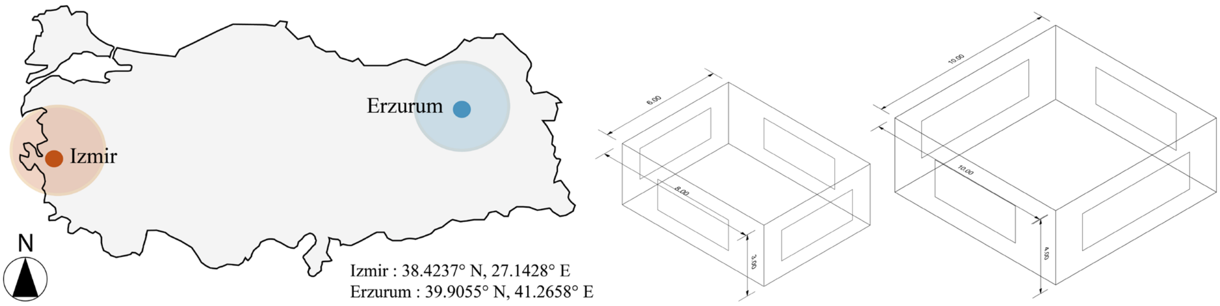


Figure 3. (a) Location of Izmir and Erzurum; (b) Digital building model physical variation

The construction material organization consists of basic EnergyPlus basic definitions, e.g., thickness, thermal resistance, and thermal mass features. The EnergyPlus of medium construction was adjusted between light and heavy constructions for the digital model to meet the requirements of both climates. The symbols before the material name identify the material type and the layer of the constructions (Table 1). *NoMass* materials are responsible for varying thermal transmittance of u-value (kWh/m2-K) of the construction for variables, and They do not have any thermo-physical properties in terms of conductivity, density, etc. For each surface, there are different *NoMass* materials. The setpoint temperature values are different based on two different climate specifications. Setpoint temperature values refer to values that under which degree heating should be activated or above the which degree cooling should be activated; thus, the pre-defined values have a direct influence on energy demand (I. Yildiz & Sosaoglu, 2007). For Izmir, the setpoint temperature of heating is 22.0 °C and cooling is 26.0 °C. For Erzurum, the setpoint temperature of heating is 18.0 °C and cooling is 22.0 °C.

Table 1. Construction materials of the testing 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

Each alternative solutions were produced by sampling techniques by using EnergyPlus building energy simulation software (Reference & Calculations, 2015). EnergyPlus works with text-based file mode, e.g., IDF (Input Data File). Researchers modified IDF to composed thermal and geometrical design variables using eppy.py python libraries (Philip et al., 2011). For statistical calculations, SALib.py statistical sensitivity analysis was chosen (Jon, Herman, Will, 2019). Due to the time constraints of early architectural design, it is difficult to handle the process manually. Therefore, researchers aimed to take automated serial simulations with batch-processing (Python Software Foundation, 2020).

The Parameter Initiation and Output Score Weighting

The proposed model leads to the search for design variable behaviors and their interactions between each other under different climate types conditions. The chosen variables are the ones that are finalized at the early design process, e.g., building shape design and construction material. Thus, during the ongoing process, all design process follows these initial decisions. For various studies, researchers executed analysis for the impact of the design variables at the initial steps (Depecker et al., 2001; Østergård et al., 2017).

Table 2. Design variables of the model

Type	Physical	Physical	Physical	Physical	Physical	Physical	Physical	Physical	Physical
Group	HTT	HTT	HTT	HTT	HTT	HTT	HTT	SG	SG
Decision Variable	Width (x_1)	Length (x_2)	Height (x_3)	WWR North (x_4)	WWR East (x_5)	WWR South (x_6)	WWR West (x_7)	SHD North (x_8)	SHD East (x_9)
Range	[6-10], *meter*	[8-10], *meter*	[3-4], *meter*	[0.1-1.0]	[0.1-1.0]	[0.1-1.0]	[0.1-1.0]	[0.1-1.0]	[0.1-1.0]
Type	Physical	Physical	Functional	Functional	Functional	Physical	Physical	Physical	Physical
Group	SG	SG	AC	IG	SG	HTT	HTT	HTT	SG
Decision Variable	SHD South (x_{10})	SHD West (x_{11})	Natural Ventilation (x_{12})	Occupancy (x_{13})	SHGC (x_{14})	U Value of Roof (x_{15})	U Value of Floor (x_{16})	U Value of Wall (x_{17})	Height of Context (x_{18})
Range	[0.1-1.0]	[0.1-1.0]	[0.5-4.0], m^3/s	[4-8], *ppl*	[0.40-0.904]	[1.41-1.69], *W/m2-K*	[1.47-1.85], *W/m2-K*	[0.45-1.77], *W/m2-K*	[0.0-6.0], *meter*

**Heat transfer by transmission: HTT, Solar Gain: SG, Internal Gain: IG, Air Changes: AC, WWR: Window-to-Wall-Ratio, SHD: Shading Depth, SHGC: Solar Heat Gain Coefficient*

The values of the prepared energy model properties are selected according to BEP-TR standards, ASHRAE 90.1, ASHRAE 62.1, and the EnergyPlus input data dictionary were taken as default as thermo-physical function library (American Society of Heating, 2013; ASHRAE, 2004; Bakanlığı, n.d.). The variables for generating alternative states of the building modeled were arranged as functions to modify the IDF file. The parameters are based on four different groups (Table 2), i.e., heat transmission by conduction, heat transmission by convection, air changes, and internal gain.

The heating and cooling (kWh/m^2-year) demand of dependent variables were chosen to visualize the impact of the climate conditions for different regions in detail, etc. Izmir and Erzurum. They were unified with the linear calculation by forming the total energy demand (kWh/m^2-year) as a single score function (1). This modification can be beneficial to decrease the run-time process and give the fast results, and the holistic score approach facilitates comparison when seizing on large numbers of design options (Østergård et al., 2015). Furthermore, it supports the rendition of sensitivity analysis and provides more salient filtering for quasi-random sampling.

$$0.5 \times (\text{heating demand} + \text{cooling demand}) = \text{total energy demand} \tag{1}$$

Data Generation and Sampling

Monte Carlo simulation techniques work based on pseudo-random sampling methodology with a low discrepancy to visualize the multivariate global design space (Figure 4-a). In this workflow, the researcher first defines input distributions and sampling strategies. Next, simulations are run with respect to outputs, i.e., energy demand. The methodology is highly popular in the field of building energy modeling to complete the deficiency of point estimated based energy simulations, e.g., optimization. They provide a global screening approach for the output variance (Haarhoff & Mathews, 2006).

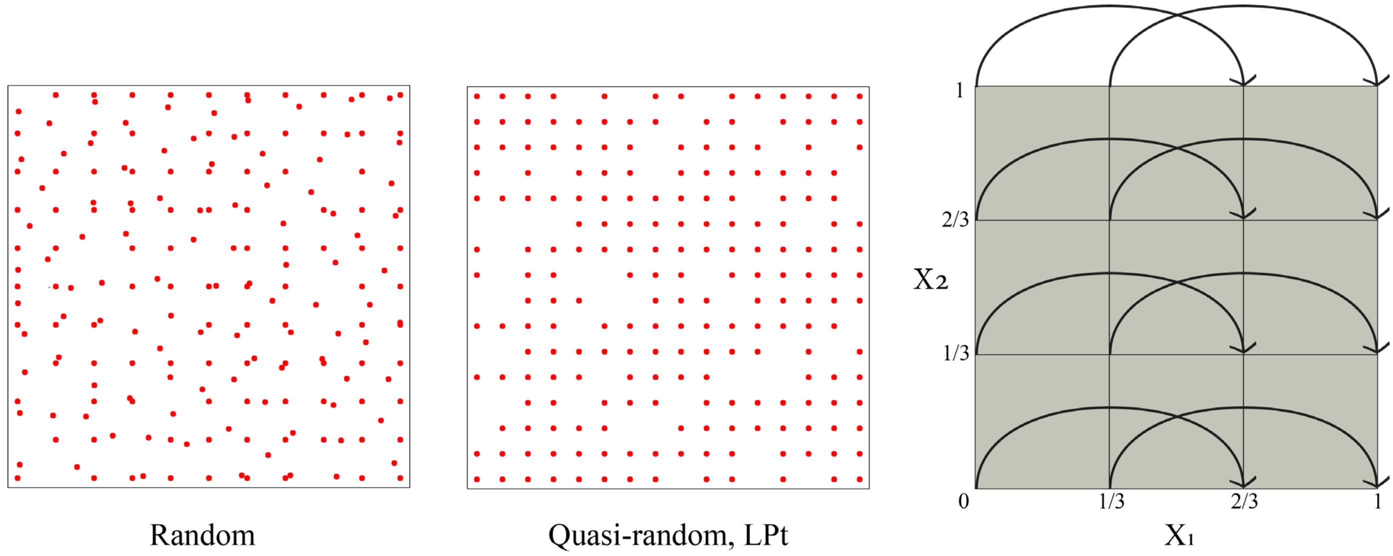


Figure 4. (a) Sampling Types; (b) Demonstration of the four-level grid, the arrows identify the eight points needed to estimate the elementary effects relative to factor X_1

The ranges of design variables were arranged as uniform distribution either discrete [*0, 1, 2, …*] or continuous [*0-1*] range values. The discrepancy of the variable shows the global design space, which represents the variation of output parameters. Therefore, the sampling technique provides independent variable sampling in terms of the probability distribution. The established parameter ranges were interpreted as central *95%* confidence intervals.

Global Sensitivity Analysis & Performance Filtering

The building energy demand composes of multiple design parameters, e.g., building envelope design, building energy system design and performance, the operational building systems, occupant density and activities, and finally, indoor air and environment quality measurement. All of the parameters distinguish from each other in terms of their impact on different performance criteria. It is better to analyze holistically for improving the performance of the building. By analyzing the total influence and individual impact of the input factors, global sensitivity analysis has a huge role by determining the relative importance of the inputs while they all change at the same time in accordance with a basic sampling rule (Ruiz Flores et al., 2012). The process of this research has been divided into two parts in terms of methodological attitude. Firstly, Morris sensitivity analysis that depends 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.

Morris sensitivity analysis is the screening method that visualizes the performance of the input influences. It decreases the model size by extracting the inefficient parameters according to sequencing the independent variables activity. Morris sensitivity analysis has been realized with the *Elementary-Effect* method (Figure 4-b), which is the finite distribution of the decision variables. The analysis supplies significant representation by generating a large sample of input parameters to find which parameters are ineffective or to quantify the interaction between parameters. Lastly, it is suitable to show linear and non-linear relations(Waqas et al., 2017). The idea is to create r different trajectories in the *N*-dimensional design space (Figure 4-b). The *N*-dimensional input space was normalized to [0,1] and was divided into *p*-levels by distinguished *p*-quantiles. Each trajectory includes *N + 1* calculations for a reason one-parameter-changes (*OAT*) by defined equal steps at a time. Thus, each input parameter relates to the elementary effects method (*EE*) by determining the output value variation at *r* separate values. Input factor of *Elementary Effect (EE)* (2) is represented with the mathematical equation as follows (Saltelli et al., 2007):

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

where $\Delta \in [1/(p-1), \cdots, 1-1/(p-1)]$. Input factor distributions were produced globally, which discretized the input area with the trajectories. The local sensitivity analysis works as a one-parameter-changes (*OAT*). When input parameters change, at the background, Morris sensitivity measures the absolute mean value (μ*) and standard deviation (σ^2) of the distributions as (3,4):

$$\mu^* = \frac{1}{r}\sum_{j=1}^{r} \left|EE_i^j\right| \tag{3}$$

$$\sigma^2 = \frac{1}{r}\sum_{j=1}^{r} (EE_i^j)^{\,2} \tag{4}$$

wherein 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). If μ* of an input is high, which means the input factor has an interactive relation with output in which is not negligible. If σ^2 has a bigger value than the mean; consequently, the computation of *EE* is highly impacted by the sample point. Basically, it means the input factor based on the values of other inputs, or the input has a non-linear relation with the specified output.

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

Secondly, Sobol' sensitivity analysis applied in which is one of the variance-based methods. It indicates the individual input influence on the output, interactions between input parameters, and total impact for the output parameters. Sobol' sensitivity analysis has been performed with Sobol' sequences low discrepancy method to screen the global design space. Its computing cost is more than Morris sensitivity analysis, but in terms of explanation of the interaction between two variables or total input variable influence on the output, it provides quite substantial outcomes. A pseudo-Random sampling of *k*-dimensional points has a high discrepancy. However, there are infinite sequences of *k*-dimensional points that act much confident with respect to this measure. They have the specification that as the sizes length *N* gets very large, the discrepancy reduces the size into the optimal rate. As a result, an estimated mean for a function $Y(X_1, X_2, X_3, \cdots, X_k)$ were evaluated on points $\{X_{i1}, \cdots, X_{ik}\}_{i=1,N}$ from such a sequence can converge much more quickly than an estimated mean based on the same number of random points.

The Sobol' sequence sampling returns a matrix that includes model input values. The pre-defined Saltelli sampling preferred, which is the basic extension of Sobol' sequence. For each sampling strategy, with respect to procedure $N \times (D + 2)$ times, rows are produced in which *N* is the 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 converted $N \times (2D + 2)$, and it seen to computing cost increases.

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, 2015). First-order (S_i), the main effect of the index separately for each parameter without interactions, the higher value of S_i, the bigger the influence on the i^{th} factor for the variance of the output. Second-order measures the contribution of the output variance by the interaction of two model inputs. 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 variance-based model function is $Y = f(X)$ where Y is the output and $Y = (x_1, x_2, ... x_k)$ 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 the high dimensional model (5) when the input parameters are independent of each other.

$$V_y = \sum_{i=1}^{k} V_i + \sum_{i>j}^{k} V_{ij} + \cdots + V_{12\cdots k} \tag{5}$$

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 $V_{i1....is}$ and is to define collaborative fractional variance induced by $\{X_{i1,.....}X_{is}\}$. Therefore (6):

$$\sum_{i=1}^{k} S_i + \sum_{i>j}^{k} S_{ij} + \cdots + S_{12\cdots k} = 1 \tag{6}$$

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 equal to *1*. While the measurements of the sensitivity indices are in the linear relation with the 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 (7):

$$S_{Ti} = S_i + \sum_{i \neq j}^{k} S_{ij} + \cdots + S_{12\cdots k} \tag{7}$$

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, the input factor can be counted as a default value by the implementation of factor fixing.

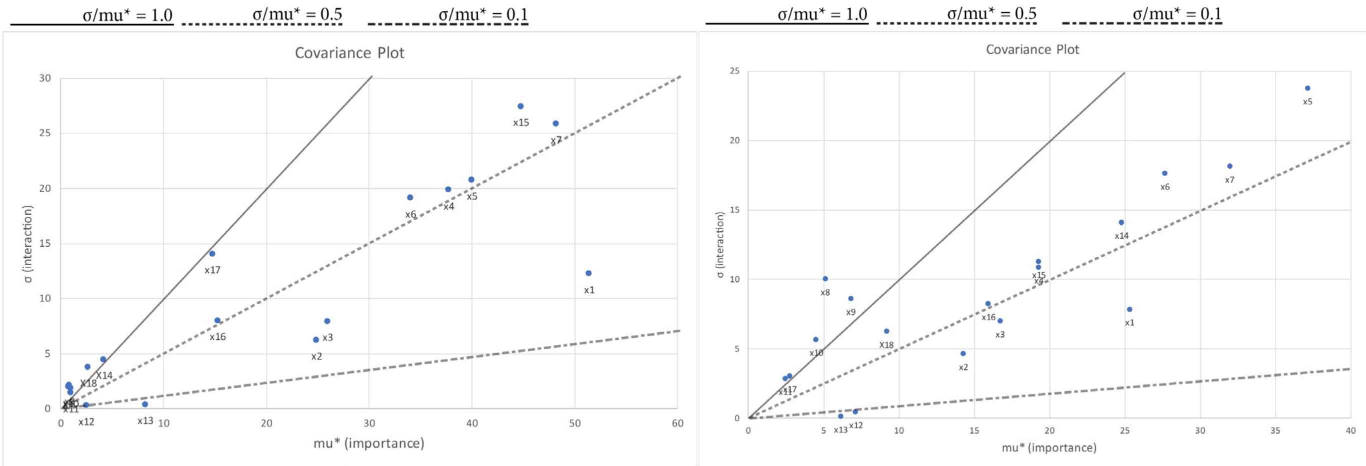
Finally, the factor mapping is the extension of a sensitivity analysis to support the process by which parameter and parameter range can provide a valuable solution due to the definition of the problem. After applying quasi-random sampling with Sobol' variance-based analysis, from the wide global design 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.

Results & Discussion

For Morris Sensitivity Analysis, 21000 simulations, and for the Sobol' Sensitivity Analysis, 42000 simulations have been generated. There are 18 different decision variables that have named next to the covariance plot with their units. The plot presents all design variables and outputs in one chart and provides opportunity detail analyzes with brushing techniques.

Factor Prioritization & Fixing

The Morris sensitivity analysis is beneficial to illustrate the individual influence of the design parameters during the architectural design process. It could be a useful tool as a guide for architects, particularly for the early design process. All implications are implemented on the covariance plot with regards to their interaction (*σ*) and influence (*mu**) on the output, which is the values of the weighted sum of heating and cooling demand (Figure 5). Eighteen different parameters were introduced in the model for the Morris sensitivity analysis with 1000 iteration, 18999 simulations have been executed for two different climates, separately. As a result, ten different parameters were evaluated effectively for the output parameter uncertainty for two regions.



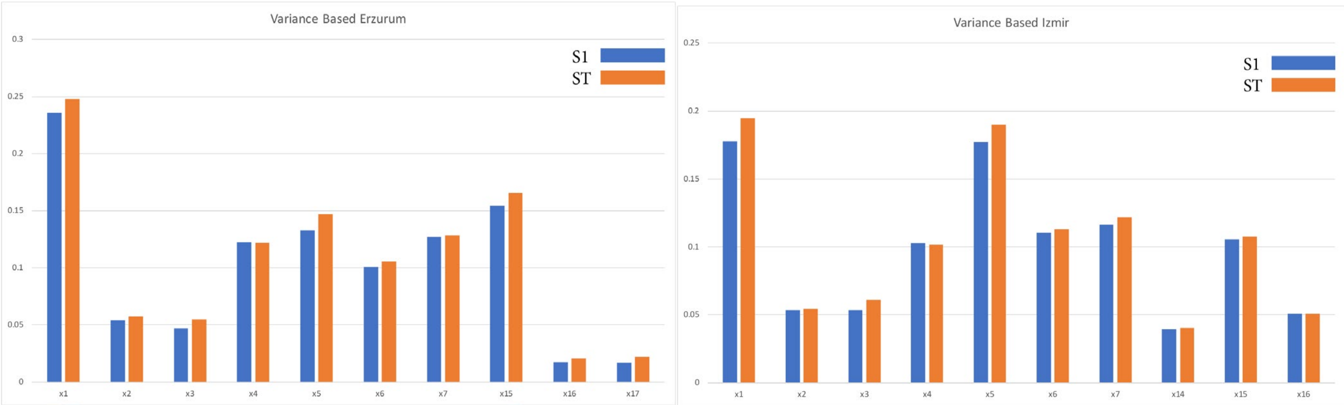
x_1 = width (m), x_2 = length (m), x_3 = height (m), x_4 = north wwr, x_5 = east wwr, x_6 = south wwr, x_7 = west wwr, x_8 = north shading (m), x_9 = east shading (m), x_{10} = south shading(m), x_{11} = west shading (m), x_{12} = natural ventilation (m3/s), x_{13} = occupancy, x_{14} = SHGC, x_{15} = u_value roof (m2-K/kWh), x_{16} = u_value floor (m2-K/kWh), x_{17} = u_value wall (m2-K/kWh), x_{18} = height of context buildings (m)

Figure 5. (a) Erzurum Covariance Plot; (b) Izmir Covariance Plot

Based on the Erzurum sensitivity analysis results (Figure 5), x_1, x_{15}, x_7, x_5, x_4, x_6, x_3, x_2, x_{16}, x_{17}, were evaluated as effective, and highly interactive with other variables. Respectively, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{18} are the variables that performed a low degree of importance for the output. Namely, they are the least essential parameters that should be ignored or grouped as one design variable. As a result of the Izmir, x_5, x_7, x_6, x_1, x_{14}, x_4, x_{15}, x_3, x_{16}, x_2 were both effective for the output parameters and interactive with other design variables. For the reason of long sunlight hours of Izmir, decision variables of WWR provide more variation than other variables. Respectively, x_{18}, x_{11}, x_{17}, x_{10}, x_8, x_{13}, x_9, x_{12} have performed low importance for the influence of the output. Therefore, these are the variables that are applied factor fixing and excluded from the second step detailed global sensitivity analysis. Consequently, envelope and construction-related parameters have performed a highly effective performance for the output distributions; therefore, their *mu** ratio is strictly higher than the other types of design variables. In conclusion, it was decided to analyze the interactions and the effect of design variables on the energy demand outputs in detail.

Variance-Based Individual and Total Effect

The Sobol' sensitivity analysis provides variance-based observation with regards to individual and interaction on the outputs. 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. In Figure 6, 10 different essential parameters were analyzed in terms of the distribution of the model of the output. Blue vertical bars stand for the individual influence of an input parameter, and the orange vertical bars were used for the total effect of an independent variable due to the variance of the aggregated energy demand. Generally, the total index gives higher results than the first order (*S1*), whereas for some variables, it is lower than the first order. Ten different parameters were introduced in the model for the Sobol' sensitivity analysis with 1000 iteration, 21999 simulations have been executed for each region.



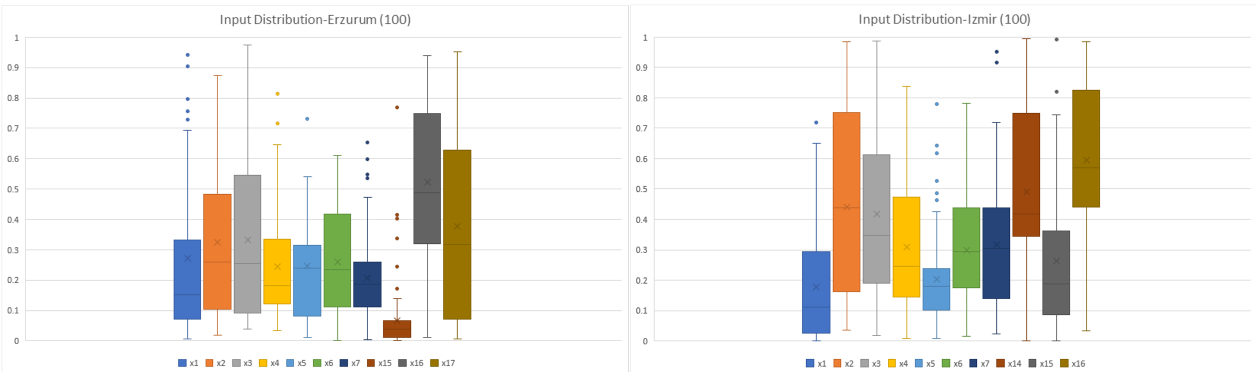
x_1 = width (m), x_2 = length (m), x_3 = height (m), x_4 = north wwr, x_5 = east wwr, x_6 = south wwr, x_7 = west wwr, x_8 = north shading (m), x_9 = east shading (m), x_{10} = south shading(m), x_{11} = west shading (m), x_{12} = natural ventilation (m3/s), x_{13} = occupancy, x_{14} = SHGC, x_{15} = u_value roof (m2-K/kWh), x_{16} = u_value floor (m2-K/kWh), x_{17} = u_value wall (m2-K/kWh), x_{18} = height of context buildings (m)

Figure 6. (a) Sobol' Vertical Bar Plot for Erzurum; (b) Sobol' Vertical Bar Plot for Izmir

For Erzurum results, x_1, x_{15}, x_5, x_4, x_7, x_6 became more effective than the other parameters. Except for u value of the roof (x_{15}), u value related construction parameters have provided less influential results on the output. The same pattern happened in terms of envelope parameters of the geometry; only the width of the geometry has given effective results. However, all the window to wall ratio independent variables caused a wide variance on the selective output. For results of Izmir, x_1, x_5, x_7, x_6, x_{15}, x_4 design variables performed more than others in terms of first-order (S_i) and total order (S_T). Similar variables listed as necessary among all effective ten variables. On the other hand, the order of importance is different. In conclusion, envelope related parameters presented a dominant tendency for cold climate compares to other design variables. On the other hand, envelope and solar gain related parameters resulted in high importance and interaction for the hot-humid environment.

Design Variable Range Filtering

The filtering process was applied to drive the valuable ranges of effective design variables by extracting the 100 most effective results. A quasi-random sampling strategy leads to analyze all the global design space. It gives highly dependable results on how design variables have relations with each other and which variable range drives the most valuable outcomes for outputs, i.e., the effective range of a yearly weighted sum of heating and cooling demand (kWh/m^2-year).



x_1 = width (m), x_2 = length (m), x_3 = height (m), x_4 = north wwr, x_5 = east wwr, x_6 = south wwr, x_7 = west wwr, x_8 = north shading (m), x_9 = east shading (m), x_{10} = south shading(m), x_{11} = west shading (m), x_{12} = natural ventilation (m3/s), x_{13} = occupancy, x_{14} = SHGC, x_{15} = u_value roof (m2-K/kWh), x_{16} = u_value floor (m2-K/kWh), x_{17} = u_value wall (m2-K/kWh), x_{18} = height of context buildings (m)

Figure 7. (a) The Distribution of 100 Best Performances of Erzurum; (b) Izmir

The design variable valuable range values were extracted by using the generated data of Sobol' analysis (Iseri, 2020). Ten uniformly distributed design variables got some valuable ranges based on the lowest energy demand. Figure 7 points out the 100 best most effective variable distributions of Erzurum. Total energy demand values are between 56.53 to 81.31 (kWh/m^2-year). The valuable ranges of each independent variable are positioned with respect to their first and third quartile values by the filled color of the values in Figure 7. For the Izmir Sobol' analysis results, the yearly weighted sum of cooling and heating demand is between 32.33 to 55.47 (kWh/m^2-year).

Depicting the results of energy analysis with multiple variables is crucial to the easier interpretation of the complicated relations among design variables and outputs. Hence, Parallel Coordinate Plot (PCP) is a useful solution to demonstrate global design space with multiple parameters at the same plotting (Tomasetti, 2019). 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. The vertical axes classify the values from worse to best. For the early architectural decision-making, designers can categorize the results according to the energy performance of the unit and which parameter corresponds to the selected output value to present design alternatives.

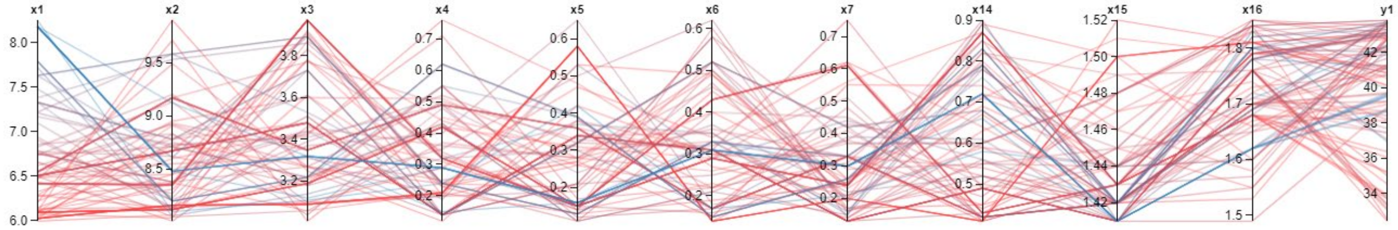
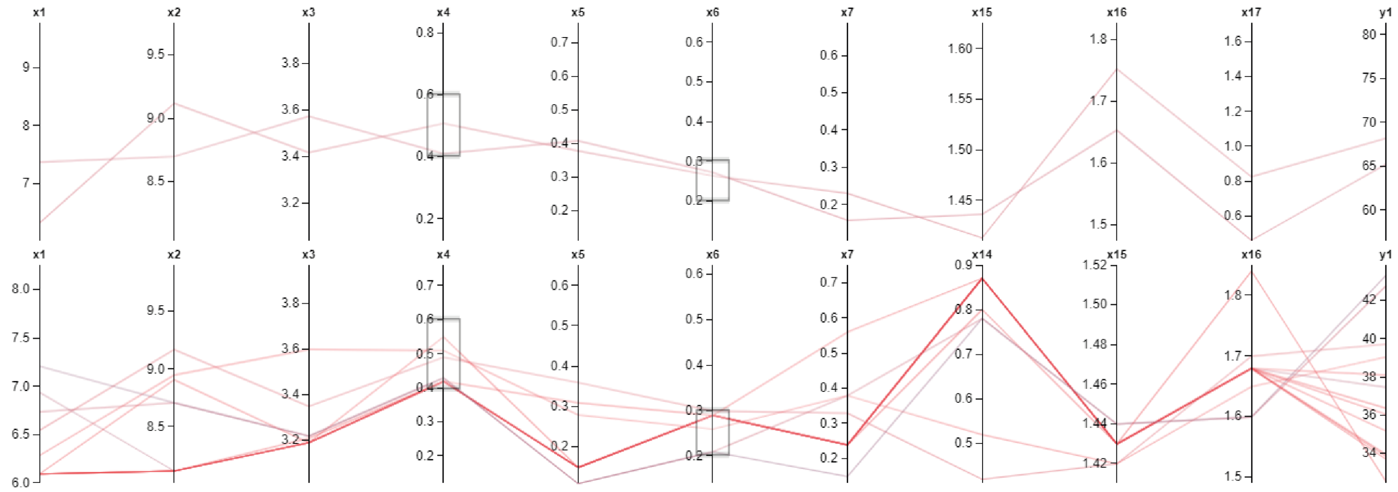


Figure 8. PCP representation of 100 best performances of Izmir

Figure 8 demonstrates the most valuable ranges of most effective ten design variables and with total energy demand (Y_1). The missing point of the PCP 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 the user. The interactive *brushing* technique can be used to organize only values that are important for the designer at the specified point of the design. The implication of the brushing highlights a selected line or collection of lines to isolate sections of the plot that the designer is interested in while filtering out of the noise or dense data cluster. Designers compare design alternatives by using the brushing process for focused values of design variables.



x_1 = width (m), x_2 = length (m), x_3 = height (m), x_4 = north wwr, x_5 = east wwr, x_6 = south wwr, x_7 = west wwr, x_8 = north shading (m), x_9 = east shading (m), x_{10} = south shading(m), x_{11} = west shading (m), x_{12} = natural ventilation (m3/s), x_{13} = occupancy, x_{14} = SHGC, x_{15} = u_value roof (m2-K/kWh), x_{16} = u_value floor (m2-K/kWh), x_{17} = u_value wall (m2-K/kWh), x_{18} = height of context buildings (m)

Figure 9. (a) Brushing on PCP for Erzurum; (b) Izmir

The early architectural design decision is highly interactive with the weather conditions, and the brushing implications presented that the brushing execution are the same for two regions. However, the number of alternatives is different for the two regions. Figure 9 shows the brushing implication of the 100 best design results. For the representation, designers applied filtering to x4 between 0.4 to 0.6 and x6 between 0.2 to 0.3. The used selection criteria for Izmir present more alternatives than the results of Izmir. If the Brushing implication consists of different variables, the number of alternatives for the desired conditions could result in different.

Conclusion

The architectural design contains multiple design parameters that designers should focus on in a short time. Due to the uncertainty of the total energy demand of the unit at early architectural design, it is supposed to analyze how architectural design elements identify the energy demand (kWh/m^2-year). Therefore, this research proposes a technique to observe the impact of the design variables in terms of energy demand in early architectural design. The methodology is the combination of two-step sensitivity analysis, energy simulations, and statistical filtering visualization. The process could be classified as a quasi-experimental study. Due to the observing technique differs from the experimental research, this research does not contain high degree control over all design variables and output parameters. The simulations were taken for two different types of climates, such as Izmir and Erzurum. The range of design variables is limited to the most popular physical and functional building parameters, i.e., heat transfer by transmission, solar gain, ventilation rate, and internal gains. Both Morris and Sobol' sensitivity analysis has used to improve model calibration for identifying important parameters and interactions between design variables. Consequently, ten different design variables were selected for each region. Their interactions with each other and two outputs were illustrated with Parallel Coordinate Plot by selecting 100 best performances based on outputs. The designers can analyze and illustrate alternations at early design with interactive brushing techniques that users can instantly choose valuable range intervals according to result.

References

Alam, F. M., McNaught, K. R., & Ringrose, T. J. (2004). Using Morris' randomized OAT design as a factor screening method for developing simulation metamodels. *Proceedings of the 36th Conference on Winter Simulation*, 949–957. Winter Simulation Conference.

American Society of Heating, R. and A.-C. E. (2013). *2013 ASHRAE handbook : fundamentals.* Retrieved from http://app.knovel.com/hotlink/toc/id:kpASHRAEC1/2013-ashrae-handbook

ASHRAE. (2004). *ASHRAE Standard 55-2004 -- Thermal Comfort* (Vol. 2004). https://doi.org/10.1007/s11926-011-0203-9

ASHRAE. (2009). ASHRAE climatic design conditions 2009/2013/2017. Retrieved February 4, 2020, from http://ashrae-meteo.info/

Attia, S., Gratia, E., Herde, A. De, & Hensen, J. L. M. (2012). Simulation-based decision support tool for early stages of zero-energy building design. *Energy & Buildings*, *49*, 2–15. https://doi.org/10.1016/j.enbuild.2012.01.028

Bakanlığı, Ç. ve Ş. (n.d.). BepTR. Retrieved July 4, 2020, from https://beptr.csb.gov.tr/bep-web/#/

Burhenne, S., Jacob, D., & Henze, G. P. (2011). Sampling based on Sobol'sequences for Monte Carlo techniques applied to building simulations. *Proc. Int. Conf. Build. Simulat*, 1816–1823.

Coakley, D., Raftery, P., & Keane, M. (2014). A review of methods to match building energy simulation models to measured data. *Renewable and Sustainable Energy Reviews*, *37*, 123–141. https://doi.org/10.1016/j.rser.2014.05.007

De Wit, S., & Augenbroe, G. (2002). Analysis of uncertainty in building design evaluations and its implications. *Energy and Buildings*, *34*(9), 951–958. https://doi.org/10.1016/S0378-7788(02)00070-1

Depecker, P., Menezo, C., Virgone, J., & Lepers, S. (2001). Design of buildings shape and energetic consumption. *Building and Environment*, *36*(5), 627–635. https://doi.org/10.1016/S0360-1323(00)00044-5

Firth, S. K., Lomas, K. J., & Wright, A. J. (2010). Targeting household energy-efficiency measures using sensitivity analysis. *Building Research & Information*, *38*(1), 25–41.

Granadeiro, V., Duarte, J. P., Correia, J. R., & Leal, V. M. S. (2013). Building envelope shape design in early stages of the design process: Integrating architectural design systems and energy simulation. *Automation in Construction*, *32*(September), 196–209. https://doi.org/10.1016/j.autcon.2012.12.003

Haarhoff, J., & Mathews, E. H. (2006). A Monte Carlo method for thermal building simulation. *Energy and Buildings*, *38*(12), 1395–1399.

Hemsath, T. L., & Alagheband Bandhosseini, K. (2015). Sensitivity analysis evaluating basic building geometry's effect on energy use. *Renewable Energy*, *76*, 526–538. https://doi.org/10.1016/j.renene.2014.11.044

Hien, W. N., Poh, L. K., & Feriadi, H. (2000). The use of performance-based simulation tools for building design and evaluation: A Singapore perspective. *Building and Environment*, *35*(8), 709–736. https://doi.org/10.1016/S0360-1323(99)00059-1

Iooss, B., & Lemaître, P. (2015). A review on global sensitivity analysis methods. *Uncertainty Management in Simulation-Optimization of Complex Systems*, 101–122.

Iseri, O. K. (2020). orcunkoraliseri/ATI-2020-Conference-Data-Repository. Retrieved March 6, 2020, from https://github.com/orcunkoraliseri/ATI-2020-Conference-Data-Repository

Jon, Herman, Will, U. (2019). Concise API Reference — SALib 1.3.10 documentation. Retrieved from https://salib.readthedocs.io/en/latest/api.html#method-of-morris

Kämpf, J. H., Montavon, M., Bunyesc, J., Bolliger, R., & Robinson, D. (2010). Optimisation of buildings' solar irradiation availability. *Solar Energy*, *84*(4), 596–603.

Kanters, J., & Horvat, M. (2012). The design process known as IDP: a discussion. *Energy Procedia*, *30*, 1153–1162.

Konis, K., Gamas, A., & Kensek, K. (2016). Passive performance and building form: An optimization framework for early-stage design support. *Solar Energy*, *125*, 161–179. https://doi.org/10.1016/j.solener.2015.12.020

Kristensen, M. H., & Petersen, S. (2016). Choosing the appropriate sensitivity analysis method for building energy model-based investigations. *Energy and Buildings*, *130*, 166–176. https://doi.org/10.1016/j.enbuild.2016.08.038

Macdonald, I. A. (2002). *Quantifying the effects of uncertainty in building simulation*.

Menberg, K., Heo, Y., & Choudhary, R. (2016). Sensitivity analysis methods for building energy models: Comparing computational costs and extractable information. *Energy and Buildings*, *133*, 433–445. https://doi.org/10.1016/j.enbuild.2016.10.005

Morbitzer, C.A. (2003). *Towards the Integration of Simulation into the Building Design Process*. University of Strathclyde.

Morbitzer, Christoph Andreas. (2003). Towards the Integration of Simulation into the Building Design Process. *Regulation*, (January), 278. Retrieved from http://www.esru.strath.ac.uk/Documents/PhD/morbitzer_thesis.pdf

Mumovic, D. (2009). *A Handbook of Sustainable Building Design and Engineering: An Integrated Approach to Energy, Health and Operational Performance*.

O'Neill, Z., & Niu, F. (2017). Uncertainty and sensitivity analysis of spatio-temporal occupant behaviors on residential building energy usage utilizing Karhunen-Loève expansion. *Building and Environment*, *115*, 157–172.

Østergård, T., Jensen, R. L., & Maagaard, S. E. (2017). Early Building Design: Informed decision-making by exploring multidimensional design space using sensitivity analysis. *Energy and Buildings*, *142*, 8–22. https://doi.org/10.1016/j.enbuild.2017.02.059

Østergård, T., Maagaard, S. E., & Jensen, R. L. (2015). A stochastic and holistic method to support decision-making in early building design. *Proceedings of Building Simulation*, (Tian 2013), 1885–1892.

Philip, S., Tran, T., & Tanjuatco, L. (2011). eppy: scripting language for E+. *EnergyPlus (Version 0.46)[Software-GNU AFFERO GENERAL PUBLIC LICENSE] Avaliable From< Https://Pypi. Python. Org/Pypi/Eppy/0.4*, *6*.

Python Software Foundation. (2020). batch-processor · PyPI. Retrieved December 6, 2020, from https://pypi.org/project/batch-processor/

Rasouli, M., Ge, G., Simonson, C. J., & Besant, R. W. (2013). Uncertainties in energy and economic performance of HVAC systems and energy recovery ventilators due to uncertainties in building and HVAC parameters. *Applied Thermal Engineering*, *50*(1), 732–742.

Reference, T., & Calculations, E. (2015). *EnergyPlus TM Documentation Engineering Reference The Reference to EnergyPlus Calculations*. (c), 1996–2015.

Rights, M. (2016). Characterisation of an airflow network model by sensitivity analysis : Parameter screening , fixing , prioritising and mapping . Journal of Building Performance Simulation . This version is available at https: *Journal of Building Performance Simulation*. Retrieved from http://dx.doi.org/10.1080/19401493.2015.1110621

Ruiz Flores, R., Bertagnolio, S., Lemort, V., Ruiz, R., Bertagnolio, S., & Lemort, V. (2012). Global Sensitivity Analysis applied to Total Energy Use in Buildings. *… High Performance Buildings …*, (2004), 1–10. Retrieved from http://docs.lib.purdue.edu/ihpbc%5Cnhttp://docs.lib.purdue.edu/ihpbc/78%5Cnhttp://orbi.ulg.ac.be/handle/2268/129192

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., … Tarantola, S. (2007). Global Sensitivity Analysis. The Primer. In *Global Sensitivity Analysis. The Primer*. https://doi.org/10.1002/9780470725184

Sobol, I. M. (2001). Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Mathematics and Computers in Simulation*, *55*(1–3), 271–280.

Struck, C., de Wilde, P. J. C. J., Hopfe, C. J., & Hensen, J. L. M. (2009). An investigation of the option space in conceptual building design for advanced building simulation. *Advanced Engineering Informatics*, *23*(4), 386–395.

Sun, Y. (2015). Sensitivity analysis of macro-parameters in the system design of net zero energy building. *Energy and Buildings*, *86*, 464–477.

Tomasetti, T. (2019). Design Explorer 2. Retrieved January 6, 2020, from https://tt-acm.github.io/DesignExplorer/

Topcu, Y. I., & Ulengin, F. (2004). Energy for the future: An integrated decision aid for the case of Turkey. *Energy*, *29*(1), 137–154.

Wang, W., Zmeureanu, R., & Rivard, H. (2005). Applying multi-objective genetic algorithms in green building design optimization. *Building and Environment*, *40*(11), 1512–1525.

Waqas, A., Melati, D., & Melloni, A. (2017). Stochastic simulation and sensitivity analysis of photonic circuit through morris and sobol method. *Optical Fiber Communication Conference*, Th2A-3. Optical Society of America.

Yang, S., Tian, W., Cubi, E., Meng, Q., Liu, Y., & Wei, L. (2016). Comparison of Sensitivity Analysis Methods in Building Energy Assessment. *Procedia Engineering*, *146*, 174–181. https://doi.org/10.1016/j.proeng.2016.06.369

Yildiz, Y., Korkmaz, K., Göksal özbalta, T., & Durmus Arsan, Z. (2012). An approach for developing sensitive design parameter guidelines to reduce the energy requirements of low-rise apartment buildings. *Applied Energy*, *93*, 337–347. https://doi.org/10.1016/j.apenergy.2011.12.048