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INTRODUCTION

INTERNATIONAL ASSOCIATION OF BUILDING PHYSICS (IABP)

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20/Aug/2024

To Whom It May Concern

Dear Sir or Madam,

We confirm that **Ibrahim Agah Tastemir** participated at IBPC 2024.

Ibrahim Agah Tastemir is author/co-author of the following accepted contribution(s):

A decomposition method for energy prediction metamodels and surrogate models in early design stage of buildings
Author(s): Tastemir, Ibrahim Agah; Koymen, Erdem; Yasa, Enes
Presenting Author: Tastemir, Ibrahim Agah
Submission Type / Conference Track: Building Physics for Energy saving and ZEBs

Daylight and energy performance relationship of classroom and office spaces : Comparative Study of Istanbul Commerce University Küçükyalı Campus Building.
Author(s): Yalçın Koçak, Nur Sümeyye; Taştemir, İbrahim Agah; Köymen, Erdem; Yaşa, Enes
Presenting Author: Yalçın Koçak, Nur Sümeyye
Submission Type / Conference Track: Ligthing in Building Physics

With best regards,

Organizing Committee of the conference
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A Decomposition Method for Energy Prediction Metamodels and Surrogate Models in Early Design Stage of Buildings

| Conference paper | First Online: 19 December 2024

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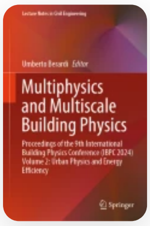

Multiphysics and Multiscale Building Physics

(IABP 2024)

İbrahim Agah Taştemir, Erdem Köymen & Enes Yaşa

Part of the book series: Lecture Notes in Civil Engineering ((LNCE,volume 553))

Included in the following conference series: International Association of Building Physics

Abstract

Early design is an important design phase for energy efficient design, as decisions about buildings have the highest impact on final performance at the lowest cost. A judicious selection of building form and variables in the early stages of design, especially in the conceptual design phase, can help to improve design performance early in the design

Daylight and Energy Performance Relationship of Classrooms and Office Spaces: Comparative Study of Istanbul Ticaret University Kucukyali Campus Building

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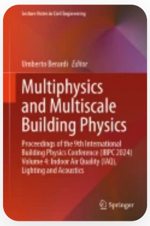

Multiphysics and Multiscale Building Physics

(IABP 2024)

Nur Sumeyye Yalçin Koçak ✉, Ibrahim Agah Tastemir, Erdem Koymen & Enes Yasa

Part of the book series: Lecture Notes in Civil Engineering ((LNCE,volume 555))

Included in the following conference series:
International Association of Building Physics

Abstract

Natural lighting is important for human comfort and should not be ignored in architectural design. Natural light allows students and instructors to establish healthy visual communication with each other and their surroundings and is known to affect physiological and psychological health. In this study, the architectural design workshops of the Istanbul Ticaret University Kucukyali Campus Building, which was transformed from a leather factory into an educational building, and the office spaces used by the lecturers of the architecture department are examined in the context of natural lighting. In the fall and spring semesters of the 2023–2024 academic year, measurements were made with a lux meter on December 21 and March 27, when suitable sky conditions were provided, and the radiation-based Designbuilder program was used for daylight simulation analysis. In four different interior spaces, illuminance level measurements were made. The illuminance measurements of the volumes were calculated at 12:00, 14:00, and 16:00 for December 21, 2023, and at 10:00, 12:00, 14:00, and 16:00 for March 27, 2024. By evaluating the data obtained, the general lighting conditions of the space and the access status of the users to these conditions were revealed. It was determined that the presence of fixed horizontal shading devices placed in the building without paying attention to orientation significantly affects the amount of illumination in the volumes and increases energy consumption. It is recommended to increase the level of illumination by making the shading devices movable with an automation system according to the effect of sunlight on the facade and painting the volumes with materials with high reflection multipliers.

References

1. Kumar Maurya, A., Kumar, R., Kumar, A.: Evaluation of daylight performance in classrooms through retrofitting in the composite climate of Eastern India. Civ. Eng. Archit. **12**(2), 917–936 (2024). https://doi.org/10.13189/cea.2024.120218

Article Google Scholar

2. Küçük, S.: Aydınlatma ve Işığın İnsan Yaşam ve Sağlığı Üzerindeki Etkileri. Yeni Yüzyıl J. Med. Sci. **4**(3), 95–102 (2023)

Google Scholar

3. Kiliç, Z.A., Yener, A.K.: Determining proper daylighting design solution for visual comfort and lighting energy efficiency: a case study for high-rise residential building. In: Journal of Physics: Conference Series, vol. 2069, no. 1, p. 012156. IOP Publishing (2021)

Google Scholar

4. Ahadi, A.A., Hanmohammadi, M.K., Masoudinejad, M., Alirezaie, B.: Improving student performance by proper utilization of daylight in educational environments (case study: IUST1 school of architecture). Acta Tech. Napocensis: Civ. Eng. Archit. **59**(1), 1–21 (2016)

Google Scholar

5. Yildirim, B., Yüksek, D.: Eğitim Yapılarında Doğal Aydınlatma: Kuveyt Üniversitesi Örneği. Online J. Art Des. **12**(2) (2024).

Google Scholar

6. Ma'bdeh, S., Matar, H.: Designing a dynamic fenestration to improve visual performance in educational spaces using daylight. Periodicals Eng. Nat. Scie. **8**(3), 1898-1910 (2020)

Google Scholar

7. Djalilova, L., Şahin, B.E.: Sürdürülebilir Okul Tasarımında Gün Işığı Kullanımına Yönelik Uygulamalar Üzerine Bir İnceleme. Artium **8**(1), 44–60 (2020)

Google Scholar

8. Natalia, S., Suharjanto, G.: The openings and lighting design strategies of primary school in Jakarta. In: IOP Conference Series: Earth and Environmental Science, vol. 998, no. 1, p. 012036. IOP Publishing (2022)

Google Scholar

9. Ekici, B.B., Orhan, G., Yüksel, E.N.: Pencere Ve Gölgeleme Elemanlarının Bina Enerji İhtiyaçlarına Etkisinin Değerlendirilmesi

Google Scholar

10. Liu, G., Qu, G., Ren, L., Zhang, Y., Zang, X., Dang, R.: The influence mechanism of daylight visual evaluation in college classrooms under visual field physiological characteristics of student group: case study. Build. Environ. **209**, 108655 (2022)

Article Google Scholar

11. Piparsania, K.R., Vaidya, P., Kalita, P.C.: Evaluation of daylight performance of classroom spaces in Ahmedabad, in NordDesign, pp. 1–12. Denmark (2020)

Google Scholar

12. Heschong, L.: Daylighting in schools an investigation into the relationship between daylighting and human performance condensed report, california board for energy efficiency (1999)

Google Scholar

13. Abdelhamid, Y.M.S., Wahba, S.M., ElHusseiny, M.: The Effect of parametric patterned façade variations on daylight quality, visual comfort, and daylight performance in architecture studio-based tutoring. J. Daylighting **10**(2), 173–191 (2023)

Article Google Scholar

14. Mehta, D.: A review on challenges of daylight-based-classroom-studies and their methodology regarding architectural-design-process. Int. J. Innovative Res. Sci. Eng. Technol. **9**(10), 10–15680 (2020)

Google Scholar

15. Ashrafian, T., Moazzen, N.: The impact of glazing ratio and window configuration on occupants' comfort and energy demand: the case study of a school building in Eskisehir. Turk. Sustain. Cities Soc. **47**, 101483 (2019)

Article Google Scholar

16. Acosta, I., Campano, M.Á., Molina, J.F.: Window design in architecture: analysis of energy savings for lighting and visual comfort in residential spaces. Appl. Energy **168**, 493–506 (2016)

Google Scholar

17. Ngarambe, J., Adilkhanova, I., Uwiragiye, B., Yun, G.Y.: A review on the current usage of machine learning tools for daylighting design and control. Build. Environ. **223**, 109507 (2022)

Article Google Scholar

18. Erlalelitepe, İ, Aral, D., Kazanasmaz, T.: Eğitim yapılarının doğal aydınlatma performansı açısından incelenmesi. Megaron Yıldız Teknik Üniversitesi Mimarlık Dergisi **6**, 39–51 (2011)

Google Scholar

19. Bayram, G., Kazanasmaz, T.: Simulation-based retrofitting of an educational building in terms of optimum shading device and energy efficient artificial lighting criteria. Light Eng. **24**(2) (2016)

Google Scholar

20. Lee, K.S., Han, K.J., Lee, J.W.: The impact of shading type and azimuth orientation on the daylighting in a classroom–focusing on effectiveness of façade shading, comparing the results of DA and UDI. Energies **10**(5), 635 (2017)

Article Google Scholar

21. Çelik, K.: Eğitim yapılarında sürdürülebilir aydınlatma tasarımı için bütüncül bir yaklaşım (Doctoral dissertation) (2018)

Google Scholar

22. Bayram, İ, Kale, Ö.A., Baradan, S.: Eğitim binalarinin aydinlatma performansi açisindan değerlendirilmesi. Dicle Üniversitesi Mühendislik Fakültesi Mühendislik Dergisi **11**(2), 783–798 (2020)

Google Scholar

23. Onak, B., Yıldıran, N.: Eğitim yapilarinda aydinlatma türü ve kullanimi önerileri: kocaeli üniversitesi mimarlik fakültesi binası. Mimarlık ve Yaşam **5**(2), 361–380 (2020)

Google Scholar

24. Ishac, M., Nadim, W.: Standardization of optimization methodology of daylighting and shading strategy: a case study of an architectural design studio—the German University in Cairo. Egypt. J. Build. Perform. Simul. **14**(1), 52–77 (2021)

Article Google Scholar

25. Salomón, D., Avalos Ambroggio, S.: Optimización del diseño de aulas: aprovechamiento de la luz natural para confort visual en Villa María. Argent. Rev. Hábitat Sustentable **12**(1), 74–89 (2022)

Article Google Scholar

26. Nocera, F., Lo Faro, A., Costanzo, V., Raciti, C.: Daylight performance of classrooms in a mediterranean school heritage building. Sustainability **10**(10), 3705 (2018)

Article Google Scholar

27. Kutlu Güvenkaya, R., Küçükdoğu, M.Ş.: İlköğretim dersliklerinde aydınlatma enerjisi yönetiminde yönlere göre uygun cephe seçeneklerinin belirlenmesi. İTÜDERGİSİ/a, **8**(2) (2009)

Google Scholar

28. TS EN 12464–1 Light and Lighting-Lighting of Workplaces (2021)

Google Scholar

29. Licht, U.B.: Lighting design, detail practice. Birkhauser, Munich (2006)

Google Scholar

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Ethics declarations

The authors have no competing interests to declare that are relevant to the content of this article.

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A Decomposition Method for Energy Prediction Metamodels and Surrogate Models in Early Design Stage of Buildings

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Abstract. Early design is an important design phase for energy efficient design, as decisions about buildings have the highest impact on final performance at the lowest cost. A judicious selection of building form and variables in the early stages of design, especially in the conceptual design phase, can help to improve design performance early in the design process at minimal cost. In this study, a decomposition method is developed that can be used in building energy performance evaluation by converting the building form into simple basic forms. The aim of the study is to develop a geometry-based energy estimation method for surrogate and metamodels to be used in the early design phase of buildings. The developed method is applied to certain cases of design variation under specified boundary conditions and the accuracy of heating and cooling energy loads are calculated with simulated energy models of these cases. As a result of the calculation, accuracy rates between 92.64% and 99.74% founded. This paper proposes a prediction model with geometric identification method for an innovative geometry-based surrogate modelling method. This method also provides a way for artificial intelligence-based prediction models used in surrogate models to create a data set and can be used in the training in future works.

Keywords: Decomposition · Building Form · Building Energy Efficiency · Energy Prediction

1 Introduction

Architectural designers are crucial for providing appropriate indoor comfort conditions for user actions in building spaces The early design is an important design phase for energy-efficient design, as decisions about buildings have the highest impact on final performance at the lowest cost. In the architectural design process, building mass design is a fundamental step to determine the aesthetic and functional context of the building and to investigate the appropriate functionality of the three-dimensional external shaping (form, size, or orientation) and structural states. However, many studies show that the building form determined in the early design phase of building mass-form design greatly impacts energy efficiency [1, 2].

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Building energy performance simulation tools (such as Energy Plus) are used in the design phase for building energy performance assessment. Despite the achievements of recent research and technical developments in building energy simulation tools, there are several limitations due to the complexity of the algorithms inherent in the interfaces of these tools, the need for theoretical knowledge in different subdisciplines (such as HVAC settings), the cost of the tools, and difficulties in time management. Data-driven surrogate modelling of building performance simulation method is an efficient option for a fast and effective way for building mass-energy consumption assessment because it is time-efficient comparative energy assessment rather than accuracy in early design implementation.

1.1 Building Design Performance in Early Design Stage

Building design is an iterative and evolutionary process in which designers try various design variations with different design processes in the light of many factors [3]. Building early design stage refers to the process before the detailed design phase. Therefore, decisions such as building geometry, building mass, area/volume decisions, orientation are made in the early design phase [4]. Improvements in the direction of the building opening and building envelope design can reduce the energy demand of the building by 40% [5]. Therefore, to better understand the relationship between design decisions and building performance, technical investigations such as building energy simulations and statistical data analysis should be carried out to increase the importance given to early design phases.

Building performance optimization and prediction studies are critical in the early design phase. Due to the time cost of the calculation process in building performance and customized parameter settings, environmental performance assessment is usually evaluated in the late design phase and the assessment is performed by professionals from different disciplines. Performance-based architectural design enables the designer to achieve better energy use and environmental performance as building performance can be measured and visualized [6]. Designers should receive rapid and iterative performance feedback on decisions at early design stages when the most significant impacts on building performance and occupant comfort are identified, rather than analyzing whether a predetermined building design exceeds a compliance requirement at late stages of design development [7]. Building geometry, orientation, ventilation configurations, and thermal comfort management strategies should become supporting parts of the building concept to achieve energy efficiency and climatic comfort conditions. To achieve this, designers should optimize the environmental services provided by natural systems beyond incremental improvement in the efficiency of mechanical systems. Therefore, workflows need to enable designers to examine and optimize the implementation of passive environmental strategies in early-stage design [8].

The increasing use of machine learning algorithms in various professional fields has led to the use of these methods in the field of architecture. Building energy prediction models with machine learning method, also called the black box approach, has become more widely used recently in building energy performance assessment [9]. The main purpose of building a forecasting model is to find mathematical relationships between independent parameters and target variables based on historical data [10]. The common objective of black box models is to determine the effect of variables on building energy consumption [11]. Due to the increasing availability of building energy consumption datasets and lower building parameter requirements, data-driven energy performance models have become one of the effective methods to predict energy use.

Pittarello et al. developed an artificial intelligence-based tool for fast and comparable building energy assessment on energy efficient design in the early design phase of a building, which does not directly use a building energy simulation tool. They obtained an automatic analysis and evaluation tool using energy models' outputs in which different design criteria are processed using deep feed-forward artificial neural networks. The obtained tool was tested on an accurate building model, and the data obtained were compared with the data obtained with the building energy simulation tool [12].

Oluj-Ajayi et al. emphasized the necessity of creating a machine learning based performance evaluation model that designers can use in energy efficient and climatic comfort conditions based design at the early design stage of buildings. The study investigates the use and efficiency of various machine learning techniques such as Artificial Neural Network (ANN), Gradient Boosting (GB), Deep Neural Network (DNN), Random Forest (RF), Stacking, K Nearest Neighbour (KNN) in energy prediction and performance evaluation. As a result of the analyses, the Deep Neural Network (DNN) method gave more efficient results than other methods [13]. Singh developed a web-based decision support model using CNN (Conventional Artificial Neural Networks), which uses building shapes and geometric features. The model, which predicts building energy consumption from 2D images, has a high validation rate [3].

Li et al. proposed a fast building energy consumption prediction method based on Artificial Neural Networks for complex architectural forms for early design phase. Within the scope of this method, they proposed an architectural form decomposition methodology to eradicate the complex geometry of the building shape in the early design stage and transform to the energy consumption prediction problem of complex architectural form into several energy consumption prediction problems of multiple simple blocks with used characterization decomposition method (MCD) and spatial homogenization decomposition method (MSHD). They found to accuracy deviation rate of the model $+-10\%$ [14].

Ciardiello et al. attempted multi-objective optimization of buildings with I, L, O C, Y H, X and T regular plan shapes by considering shape parameters such as window wall ratio and orientation. In the mass decomposition method, a complex building form can be divided into several basic blocks and the whole thermal comfort energy consumption data can be estimated by summing the partial energy uses of the divided form geometries [15]. Zhu et al. studied different building forms and geometries with the meta-modelling method (meta-model) to predict the heating and cooling energy loads expressing the energy use intensity by considering the building mass. In the study, they not just consider only at the building scale but also, they consider to neighborhood scale that include the radiation effect of other buildings affecting the main building [16].

The literature review shows that most of the studies on building form and shape optimization with metamodels and surrogate models are for rectangular, L, U, T, H and courtyard-based building forms; the aim of this study is to present an evaluation method that covers not only common prototype form examples as in previous studies but also complex form and shape alternatives of architectural form that cannot be classified into common prototypes in a universal geometric scope [17]. The complexity of architectural geometry greatly increases the difficulty of geometric parameter extraction. With the developed geometric identification method based on simple forms, it is aimed to create a geometry-energy prediction method that will be used in future artificial intelligence-based surrogate and metamodel studies.

1.2 Aim of Research

Building energy simulation method is widely used to measure the energy consumption value of the building form under thermal comfort conditions at the early design stage of the building. Some of the difficulties of building energy simulation can be explained as uncertainty in design data and high calculation time. Building form and geometry are one of the most important design variables affecting the energy performance of buildings. A sensible selection of building form and variables in the early stages of design, particularly at the conceptual design stage, can help improve the design performance at the early stages of the design process at minimum cost. Repetitive modeling of different variations of the building form and geometry in the early design phase of the building leads to loss of time and effort for the designer in the process. In addition, the lack of technical data in the energy simulation tool makes it difficult to reach the correct result.

The aim of this research is to create a more effective and faster workflow model for designers in the energy simulation phase of building form and geometry design in the early design phase. As a result of this study, it is aimed to present a method that can be a reference for machine learning (black box) based building energy prediction models. The method created because of this study can be used as a geometric definition method for future artificial intelligence-based surrogate and metamodels.

2 Methodology of the Study

Many studies in the literature have categorized buildings into various building archetypes. However, in practice buildings can be complex shapes. Referred to other studies (Li et al., Zhu et al., Mehrotra et al., Ciardiello et al.) building decomposition method is introduced to better describe complex building forms using box units. This method is based on the theory that the adjacent surfaces of box units can be regarded as adiabatic boundaries for simplification and that internal wall heat conduction has an insignificant effect on the total building energy demand. In this context, the energy demand of a box unit in a building is considered equivalent to an isolated thermal zone with the same boundary conditions and environment [17, 18].

The literature review shows that most of the studies on optimization are on prototype buildings such as rectangular, L-form, T-form, h-form and u-form, where the architectural form is commonly used and limited. The decomposition method developed in this study enables the analysis of buildings with different and complex plan geometries. In this study, BTUD (Basic Triangle and Unit Box Decomposition Method) decomposition method of architectural form decomposition is proposed. The purpose of method is to decompose complex architectural forms for energy prediction. This method consists of dividing the geometry into triangular and rectangular-square forms by using long and short parts of the geometry of any structure. (see Fig. 1).

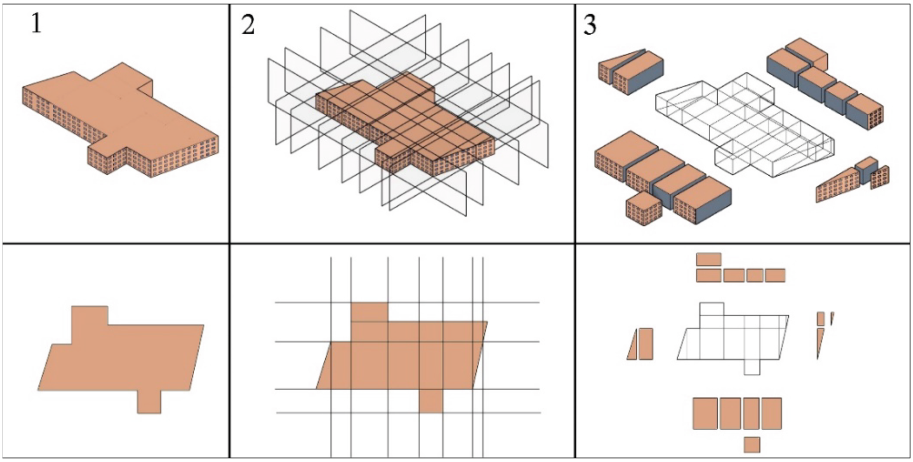


Fig. 1. 1. Decomposition plan geometry, 2. Decomposition process, 3. Decomposition result and units.

The BTUD method is developed in Rhinoceros Grasshopper, a parametric design and modelling tool. The decomposition of a building geometry with the method shown in Fig. 2 consists of the following steps.

Step 1: Separation pf plan geometry with vertical and horizontal direction.

Step 2: Cutting of plan geometry in vertical and horizontal direction with long edge side.

Step 3: Decomposition of triangle units.

Step 4: Decomposition of box-rectangle units.

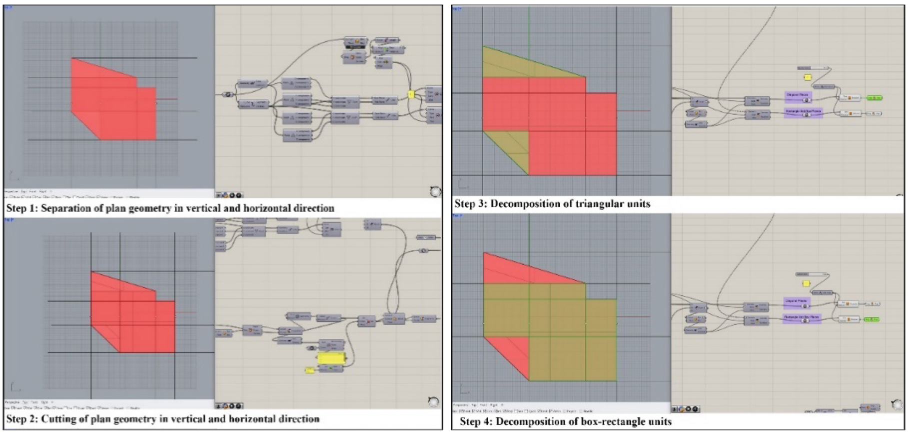


Fig. 2. The decomposition of a building geometry with the method, Rhino Grasshopper.

2.1 Prediction Workflow

In this study, an energy prediction method is developed using a data set generated by decomposing a complex structure using the BTUD method and defining the shape and geometric properties of triangular and box-rectangular units regarding energy consumption. The workflow of this prediction method is shown in Fig. 3. The application steps of the workflow consist of the following stages.

1. Creating Basic Forms Energy Consumption Dataset: In this section, firstly, the length and width, orientation, and surface boundary values of the rectangular and triangular form variants to be used in the BTUD method will be defined. After the defined values are defined, energy consumption simulations of the form variants will be performed to create the data set.
2. Decomposition of Design Variable with BTUD method: The energy analysis creates a dataset by linking the energy consumption values of the form variants to the limit values.
3. Data Matching Decompose Basic Forms: By breaking down the design variant into simple form parts, the decomposition method transforms it into a form compatible with the BTUD dataset.
4. Energy Prediction Results: The energy consumption values of the relevant simple form parts in the database are matched to the decomposed design variant and energy consumption values are generated according to the ASHRAE 90.1 thermal zoning rule [19].

As presented in the workflow of the study, it is aimed to estimate energy by creating a data set, decomposing the design variation with the BTUD method, and matching it with the created data set. The first part of the results section consists of the data set. In this section, energy simulations of simple form geometries under certain boundary conditions were performed, and a data set was created for the prediction model. In the second part of the results section, the validation of the BTUD model is analyzed.

2.2 BTUD Method Energy Simulation for Dataset

According to the workflow presented in the method section of the study, building heating and cooling energy loads were calculated based on the thermal comfort condition of the simple forms, which is the first stage of the BTUD decomposition method, and the dataset for the energy prediction model is created. The formation and boundary values of geometric part variations consisting of triangular and square-rectangular units are shown in Fig. 4. The data related to the variable boundary values of the simulation are shown in Table 1, and the data related to the fixed boundary values are shown in Table 2.

The energy simulations of the study is simulated with Energy Plus energy simulation engine. Energy simulations were carried out using Istanbul climate data in the energy model. The data set is created with 32.00 variations together with dynamic and static variable data. The data set was created using the EnergyPlus calculation technique, which is based on the ASHRAE 90.1 standard. Therefore, the computation approach is in sync with the standards set by ASHRAE 90.1. The data related to the basic variables in the energy simulation are shown in Table 1.

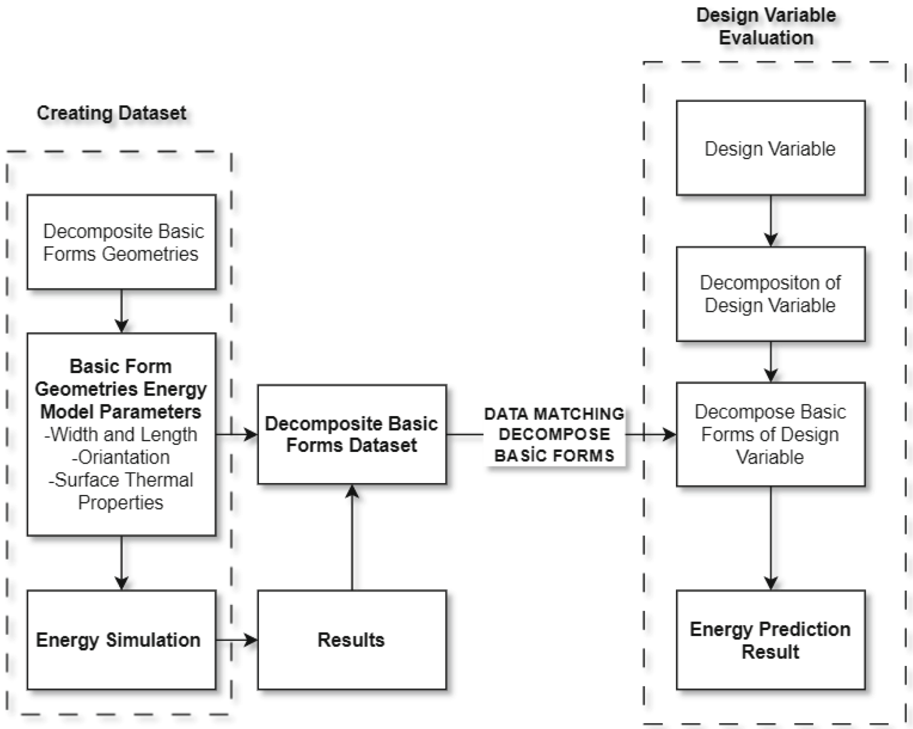


Fig. 3. Workflow of BTUD prediction method

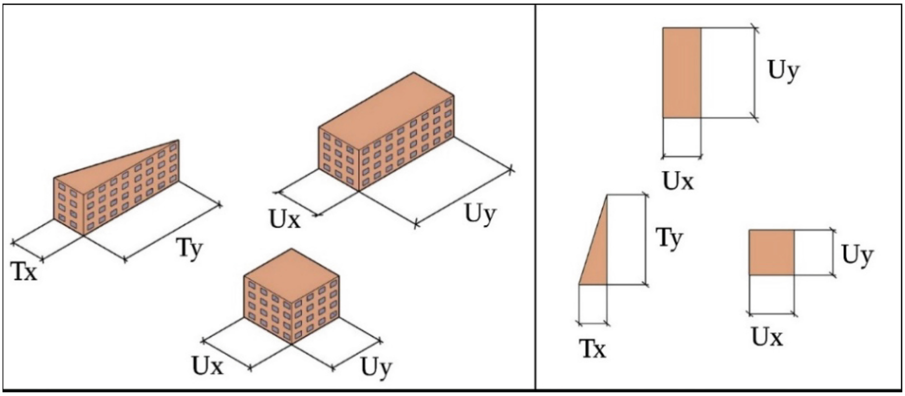


Fig. 4. Decomposition Method Geometric Properties

According to this table, for the geometric boundary values of "Tx", "Ty", "Ux" and "Uy", which are the edge boundary values of the units, a value range between 1 m and 10 m was used for each edge. As for the adiabatic surface ratio, the data set was created with 20 variables with a 5% increase in value between 0% and 100%. Rotation input was

Table 1. Basic variables in the energy simulation

Type	Description	Value Range	Value Range Change
Ux	Unit Box Plan Width	1–10 m	1 m
Uy	Unit Box Plan Length	1–10 m	1 m
Tx	Unit Triangle Plan Width	1–10 m	1 m
Ty	Unit Triangle Plan Width	1–10 m	1 m
Adiabatic Surface Ratio	Adiabatic Surface ratio of intersect units	%0–%100	%5
Rotation	Rotation of Units	0°–360°	45°

created with 8 different angles between 0°–360° with 45° degree value range change. Every basic shape and space has its own unique energy consumption estimate. All of the lowermost basic form spaces are in direct contact with the ground. The uppermost surfaces of the most basic form spaces are all exposed to the atmosphere. The inter story layer does not have grounded or roofed basic form spaces. Additionally, each basic form space in every layer is distinct when it comes to calculating energy consumption.

As shown in Fig. 1, the building geometry decomposed by BTUD decomposition method is divided into two surface types: exterior surface and adiabatic surface. According to whether the building geometry is flat or diagonal, it is divided into triangular and box-rectangle units. The edge boundary values of the units are shown as “Tx” and “Ty” for triangular units and “Ux” and “Uy” for box-rectangle units. The floor boundary values of the units are expressed as “U Ground” ground. Boundary for the floor in contact with the ground, “U Floor” for the floor boundary between the floors, and U Top for the floor boundary on the roof and the boundary values are given in Table 2.

3 Results and Discussion

A prediction model was created from 32.000 variations using the data-matching method for the energy prediction model. The data set created with simple building geometries separated by the BTUD method was matched, and the heating and cooling energy load was analyzed. Case studies were simulated to verify the results of this analysis. The simulation inputs in the energy simulation process used to same simulation inputs with data set simulation process. For the prediction validation of the BTUD method, building variation cases selected (Table 3).

The results of the energy simulation are presented in Table 4. The accuracy rate calculated to compare the predicted and simulated results as follows (1):

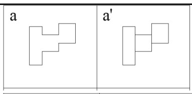
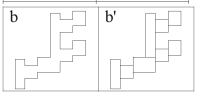
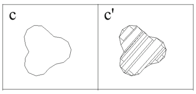
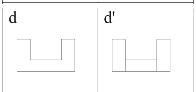
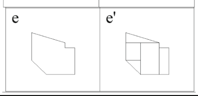
$$\text{Accuracy Rate} = 100\% - \left(\frac{\left|\mathrm{E_{predicted}} - \mathrm{E}_{simulated}\right|}{\mathrm{E}_{simulated}} x100\%\right) \tag{1}$$

As can be seen in Table 4 and Fig. 5, the form energy estimation rates of type a building are 98.57% for cooling energy load and 98.57% for heating energy load.

Table 2. Steady Conditions of Model

Parameter Name	Description	Value
U_wall	Conductivity of the walls	0,350 W/m^{2}K
U_win	Conductivity of the windows	1,96 W/m^{2}K
U_Top	Conductivity of the roof(top)	0,250 W/m^{2}K
U_Floor	Conductivity of the interior slabs	2,90 W/m^{2}K
U_Ground	Conductivity of the ground slab	0,250 W/m^{2}K
WWR	Window/Wall Ratio of Exterior Surface	%30
Adiabatic	The boundary conditions of adiabatic surfaces	0(full exterior)-1.0(full interior)
Activity: Generic Office	Activity Conditions of Building	Occupancy: 0,11 p/m2 Clo: 1,0, Met: 0,90 met
HVAC Settings	Building HVAC Conditions	Heating: Natural Gas Cooling: Electricity
Floor Properties	Building number of floors and story height	Number of floors:6 Story Height:3 m

Table 3. Case Design variables properties for energy prediction validation

Cases	Total Building Area	Decompose Basic Form Type	Number of Decompose Basic Form
	2000	Rectangle-Box Unit	3
	18400	Rectangle-Box Unit	8
	4900	Rectangle-Box Unit Triangle Unit	28
	2540	Rectangle-Box Unit	3
	22400	Rectangle-Box Unit Triangle Unit	5

92.64% was determined. Total energy consumption estimation rate It was analyzed as 97.50%. B-type building form energy estimation ratios were determined as 99.74% for cooling energy load and 99.18% for heating energy load. Total energy consumption

Table 4. Building Energy Simulation and BTUD Energy

Test Building Type		Cooling Energy (kWh/m^2)	Accuracy Rate	Heating Energy (kWh/m^2)	Accuracy Rate	Total Energy (kWh/m^2)	Accuracy Rate
a-a'	Predicted	72.88	98.57%	16.09	92.64%	88.97	97.50%
	Simulated	71.84		14.91		86.75	
b-b'	Predicted	89.08	99.74%	19.15	99.18%	108.23	99.93%
	Simulated	88.85		19.31		108.16	
c-c'	Predicted	60.52	99.49%	22.26	93.49%	82.78	98.63%
	Simulated	60.84		20.81		81.65	
d-d'	Predicted	99.61	99.58%	23.43	99.71%	123.04	98.90%
	Simulated	98.20		23.49		121.69	
e-e'	Predicted	73.98	99. 28%	20.35	99.44%	94.33	99.55%
	Simulated	74.51		20.23		94.74	

estimation rate was analyzed as 99.63%. C type building form energy estimation ratios were determined as 99.49% for cooling energy load and 93.49% for heating energy load. Total energy consumption estimation rate was analyzed as 98.63%. D type building form energy estimation rates were determined as 99.58% for cooling energy load and 99.71% for heating energy load. The total energy consumption estimation rate was analyzed as 98.90%. E type building form energy estimation rates are 99.28% for cooling energy load and 99.44% for heating energy load. The total energy consumption estimation rate was analyzed as 99.55%. (see Fig. 5).

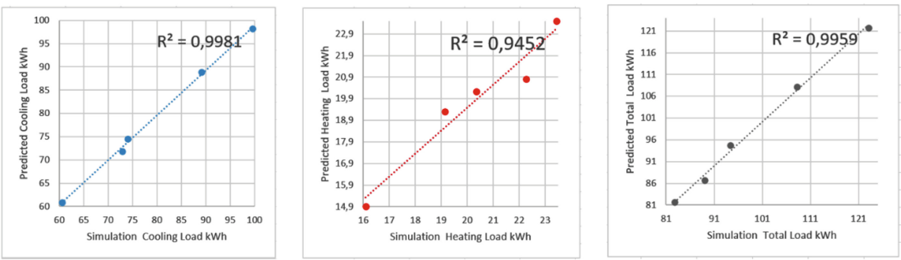


Fig. 5. Correlation analysis of cooling, heating and total energy loads.

As shown in Table 4 and Fig. 5, the design variations analyzed with the BTUD prediction model, and the energy simulation results of these design variations are compared. As a result of the comparison, the accuracy rate for cooling energy load is between 98.57% and 99.74%. Simulated and predicted design variation heating energy load results are analyzed the accuracy rate is between 92.64% and 99.71%. Correlation Analysis R^2 score is a statistical way of measuring and determining how close and cohesive the data are to the fitted regression line. Correlation analysis shown to Fig. 5 R^2 value for cooling energy load is 0,9981, R^2 for heating energy load is 0,9452 and R^2 for total energy load is 0,9959. When these results are analyzed, it is seen that the energy prediction model has a high prediction rate. The cooling energy load prediction rate is higher than the heating energy load prediction rate.

4 Conclusion

Early design is an important design phase for energy efficient design, as decisions about buildings have the highest impact on final performance at the lowest cost. A judicious selection of building form and variables in the early stages of design, especially in the conceptual design phase, can help to improve design performance early in the design process at minimal cost. This study proposes a decomposition method for defining a form geometry for building surrogate models for the early design phase. The decomposition method's accuracy, BTUD, is measured with design examples with different form geometries. As a result of the validation analyses, it was found that the decomposition method has a high accuracy between 92.64% and 99.71%. With these results,

- As an alternative to building energy simulation in measuring building comfort conditions-based energy performance prediction models built on the definition and decomposition of building geometry can give results with high accuracy.
- The difficulties of building energy simulation in the design phase of architectural design can be eliminated by using building energy prediction methods.
- The developed calculation and estimate approach is consistent with the ASHRAE 90.1 thermal zoning calculation method since it is based on the latter.

In future studies, the development of additional methods that can provide reference and data to machine learning models used in building energy prediction models can increase the accuracy of building energy performance prediction. Different decomposition methods, which are also used in the literature, can be used as a verification method and tool for the application and development of thermal comfort and building design principles for building energy prediction models.

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References

1. Mehrotra, A., Yi, H.: Effect of adaptive intelligent sampling and machine-learning emulators in surrogate energy modeling of architectural massing. J. Build. Eng. **72**, 106614 (2023). ISSN 2352-7102. https://doi.org/10.1016/j.jobe.2023.106614
2. Kahraman, Ö., Köymen, E.: The influence of building form compactness on energy efficiency in accommodation structures: the case of Türkiye. Sakarya Univ. J. Sci. **27**(5), 1055–1078 (2023). https://doi.org/10.16984/saufenbilder.1253136

3. Singh, M., Smith, I.: Convolutional neural network to learn building-shape representations for early-stage energy design. Energy AI **14**, 100293 (2023). https://doi.org/10.1016/j.egyai.2023.100293
4. İşeri, O.K, Dursun, O.: The impacts of early architectural design decisions on building performance. IJDIBE **11**(2), 1–21 (2022). https://doi.org/10.4018/IJDIBE.301245
5. Wang, W., Zmeureanu, R., Rivard, H.: Applying multi-objective genetic algorithms in green building design optimization. Build. Environ. **40**(11), 1512–1525 (2005). https://doi.org/10.1016/j.buildenv.2004.11.017
6. Yasa: Microclimatic comfort measurements evaluation of building physics: the effect of building form and building settled area, on pedestrian level comfort around buildings. J. Build. Phys. **2**, 1–29 (2016). https://doi.org/10.1177/1744259115621979
7. de Wilde, P.: Building performance analysis, first. Wiley, Chichester, UK (2018). https://doi.org/10.1002/9781119341901
8. Konis, K., Gamas, A., Kensek, K.: Passive performance and building form: an optimization framework for early-stage design support. Sol. Energy **125**, 161–179 (2016). https://doi.org/10.1016/j.solener.2015.12.020
9. Hamdaoui, M.-A., Benzaama, M.-H., El Mendili, Y., Chateigner, D.: A review on physical and data-driven modeling of buildings hygrothermal behavior: Models, approaches and simulation tools. Energy Build. **251**, 111343 (2021). https://doi.org/10.1016/j.enbuild.2021.111343
10. Zhang, L., Jin, G., Liu, T., Zhang, R.: Generalized hierarchical expected improvement method based on black-box functions of adaptive search strategy. Appl. Math. Model. **106**, 30–44 (2022). https://doi.org/10.1016/j.apm.2021.12.041
11. Sun, Y., Haghighat, F., Fung, B.C.M.: A review of the-state-of-the-art in data-driven approaches for building energy prediction. Energy Build. **221**, 110022 (2020). https://doi.org/10.1016/j.enbuild.2020.110022
12. Pittarello, M., Scarpa, M., Ruggeri, A.G., Gabrielli, L., Schibuola, L.: Artificial neural networks to optimize zero energy building (Zeb) projects from the early design stages. Appl. Sci. **11** (2021). https://doi.org/10.3390/app11125377
13. Olu-Ajayi, R., Alaka, H., Sulaimon, I., Sunmola, F., Ajayi, S.: Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques. J. Build. Eng. **45** (2021). https://doi.org/10.1016/j.jobe.2021.103406
14. Li, Z., Dai, J., Chen, H., Lin, B.: An ANN-based fast building energy consumption prediction method for complex architectural form at the early design stage. Build. Simul. (2019). https://doi.org/10.1007/s12273-019-0538-0
15. Ciardiello, A., Rosso, F., Dell'Olmo, J., Ciancio, V., Ferrero, M., Salata, F.: Multi-objective approach to the optimization of shape and envelope in building energy design. Appl. Energy **280**, 115984 (2020). https://doi.org/10.1016/J.APENERGY.2020.115984
16. Zhu, S., Ma, C., Zhang, Y., Xiang, K.: A hybrid metamodel-based method for quick energy prediction in the early design stage. J. Clean. Prod. **320**, 128825 (2021). https://doi.org/10.1016/J.JCLEPRO.2021.128825
17. Chen, Y., Hong, T., Piette, M.A.: Automatic generation and simulation of urban building energy models based on city datasets for city-scale building retrofit analysis. Appl. Energy (2017). https://doi.org/10.1016/j.apenergy.2017.07.128
18. Dogan, T., Reinhart, C., Michalatos, P.: Autozoner: an algorithm for automatic thermal zoning of buildings with unknown interior space definitions. J. Build. Perform. Simul. **9**, 176–189 (2016). https://doi.org/10.1080/19401493.2015.1006527
19. ANSI/ASHRAE/IES Standard 90.1–2013. Energy Standard for Buildings Except Low-Rise Residential Buildings, Appendix G. The American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, GA (2013)

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Abstract	Natural lighting is important for human comfort and should not be ignored in architectural design. Natural light allows students and instructors to establish healthy visual communication with each other and their surroundings and is known to affect physiological and psychological health. In this study, the architectural design workshops of the Istanbul Ticaret University Kucukyali Campus Building, which was transformed from a leather factory into an educational building, and the office spaces used by the lecturers of the architecture department are examined in the context of natural lighting. In the fall and spring semesters of the 2023–2024 academic year, measurements were made with a lux meter on December 21 and March 27, when suitable sky conditions were provided, and the radiation-based Designbuilder program was used for daylight simulation analysis. In four different interior spaces, illuminance level measurements were made. The illuminance measurements of the volumes were calculated at 12:00, 14:00, and 16:00 for December 21, 2023, and at 10:00, 12:00, 14:00, and 16:00 for March 27, 2024. By evaluating the data obtained, the general lighting conditions of the space and the access status of the users to these conditions were revealed. It was determined that the presence of fixed horizontal shading devices placed in the building without paying attention to orientation significantly affects the amount of illumination in the volumes and increases energy consumption. It is recommended to increase the level of illumination by making the shading devices movable with an automation system according to the effect of sunlight on the facade and painting the volumes with materials with high reflection multipliers.

Keywords (separated by '-')	Visual Comfort - Shading Device - Daylight - Illuminance