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EXPERIMENTATION OF PARAMETRICISM FOR DESIGN OPTIMISATION IN PREDICTING BUILDING PERFORMANCE

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ABSTRACT

When a parameter is changed, it does have a corresponding effect on the functional outputanalytic in output through a chain reaction. Several studies have emphasised the influence of shading devices and window openings concerning the regulation of indoor thermal comfort within regular building forms. However, a relatively small body of research is concerned with the shape optimisation of free-form buildings in the control of solar radiation for the benefit of thermal comfort and building performance. This study explores the use of parametric design principles at the preliminary stage of the building design to enhance its optimisation by manipulating shading devices to reduce direct solar heat gains. This study was approached as a quantitative simulation study linked to the environmental factors (temperature, humidity, carbon dioxide, solar radiation, and humidity ratio) that can influence a buildings' performance. The study proposed a machine learning linear regression model for environmental factor prediction and design of a project comprising irregular forms reproduced in Rhinoceros software and simulated based on on-site responses to radiation was utilised. Rhinoceros was used with its graphical algorithm editor, Grasshopper, which allows the freedom to create algorithmic relationships for design processes visually. Data returned from the analysis using Rhinoceros software and plugins was analysed using Microsoft's Excel. Results obtained revealed that the simulation technique generates shading systems that counter excessive radiation of the building envelope and enhance thermal comfort from the design stage. It was evident from the data that shows that the amount of radiation exposure on the building façade reduced by 60% in all the months of the year after the introduction of the shading device system. The adoption of parametric design methods to optimise building performance leads to the choice of solutions that ensure considerable thermal comfort level whilst maintaining the aesthetical and visual quality of the building.

INTRODUCTION

The optimisation is usually done after a building has been constructed. However, early design stages programming and building specifications can identify up to 80% of environmental pollutant contributions and building operating expenses (Aliero, Qureshi, Pasha, Ghani, & Yauri, 2021). The scope of increasing building performance has shrunk as design procedures have advanced, while the expenses of building optimisation have risen (Aliero, Qureshi, Pasha, & Jeon, 2021). Several studies like Acquaah, Steele, Gokaraju, Tesiero, & Monty (2020); Aliero, Qureshi, Pasha, Ghani, et al. (2021); Okafor, Ali, Modi, Duku, and Dodo (2020); Syed Ariffin, Dodo, Nafida & Kamarulzaman (2015) have underlined the relevance of decisions taken at the early design stage. 80% of a building project's expenses would have been established by the conclusion of the conceptual design stage (Okafor Christian Izuchukwu & Pitya Peter Marino Modi 2020). In many ways, the decisions taken at the designing phase greatly influence the building's efficiency. A building constructed to high-quality, for example, can spend 40% less energy than a structure planned to low-quality by altering design factors such as form, orientation, and envelope configuration (Mahmoud, Ahmad, Yatim, & Dodo, 2020). The design process initiates the narrative of the design by following a set of requirements needed to achieve design objectives (Van Langen & Brazier, 2006). During the preliminary design process, understanding design requirements depends on the designer's intuition, who is focused on a limited scope of performances like functionality and aesthetics (Turrin, Von Buelow, & Stouffs, 2011). Modern buildings comprise complex products comprising several fragments meant to perform various functions (Eltaweel & Yuehong, 2017). To mitigate errors in building construction emanating from the complexities involved in the building design process and ensure that buildings perform at their best, the building design process is often accompanied by evolutionary decision-making from the beginning of the design to the final stages. Complexities involved in the design process are associated with the quest to initiate new forms, design strategies, structural concepts, technical and environmental considerations (Alalouch, 2018). However, traditional design approaches are still being employed in projects despite the challenges encountered with complex designs.

Transition

EnergyPlus, Virtual Environment, Trnsys, eQuest, Esp-r, IES, and DeST are examples of building simulation software that can do dynamic energy consumption simulations. The fact that large volumes of data are required during modeling is something that all of these programs have in common, even if most aspects aren't completed until later in the design process.

Design builder is one of the common building performance optimisation software that supports machine learning models to predict the building performance's potential outcome during the design stage. Therefore, this study employed building simulation and machine learning to aid the design process and prediction outcome in the design stages leading to decisions that have a major influence on the outcome of the building in terms of performance (Østergård, Jensen, & Maagaard, 2016). The application of computer simulations during building optimisation at the design stage requires that the different parameters about the building are tested and accounted. A systematic process of optimisation at the design stage includes establishing parameters, determining constraints, identifying goals, selecting the optimisation algorithm, conducting simulations, and displaying the final results (Østergård et al., 2016). Hence, parametric design involves manipulating building parameters through the utilisation of digital technology based on computer hardware and software.

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The organisation of the study is as follows: Section II described a literature review related work. Section III describes the methodology. Section IV presents the experiment, and finally, Section V concludes the study.

LITERATURE REVIEW

Parametric design is a process based on algorithmic thinking that enables the expression of parameters and rules that combine to define the relationships between the design intent and design response (Oxman & Gu, 2015). Implementation of these optimisation tools and techniques from the initial stages of the design to the final stages will ensure that the building will perform close to the digital model or exceed the expectations of the design intent. It also ensures that all the constraints that may negatively affect the project will be accounted for and lead to a wholesome design in thought, process, and execution. Parametric designs are approached from two broad perspectives. The first approach regards all designs as parametric due to considering parameters such as orientation, solar radiation, and wind (Gerber, 2007; Hudson, 2010).

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The second approach regards parametric design as dependent on the use of tools such as Revit, Grasshopper, Maya MEL, Rhino Scripting to enhance design by the simultaneous interconnection and coordination of design components (Woodbury, 2010). According to Hudson (2010), Parametric design entails the examination of multifarious solutions to architectural design challenges through the utilisation of parametric models. In parametric design, parameters in the parametric model are often manipulated to explore alternative solutions to challenges (Hernandez, 2006). It implies that available parameters are used to define a form by interchanging values of the parameters without having to erase or redraw.

Several methods cutting across disciplines have been employed to generate parametric models to enhance building design optimisation. Some techniques used in applying parametric design for building optimisation involve two phases; simple (preliminary) optimisation and detailed optimisation to investigate various situations (Eisenhower, 2012). Current research involving parametric design for building optimisation has focused on optimisation of façade to enhance indoor quality. Lee, Han presented significant analysis and discussion, and Lee (2016) compared the conventional approach with genetic algorithms to create optimal indoor lighting situations by adjusting louvre shapes and window patterns. Their study revealed that Computer-assisted daylight simulation could aid the design of shading devices, especially when dealing with a large amount of data and non-linear relationships. Daylighting provides lofty quality light while reducing energy consumption when fenestrations are properly designed for glare control and reduced solar heat gain (Munaaim, Al-Obaidi, Ismail, & Rahman, 2014; Reinhart, Mardaljevic, Consequently, several studies have emphasised the & Rogers, 2006). influence of shading devices and window openings regarding the regulation of indoor thermal comfort within regular building forms (Al-Masrani, Al-Obaidi, Zalin, & Isma, 2018; Lee et al., 2016; Tzempelikos & Shen, 2013).

Transition

However, a relatively small body of research is concerned with shape optimisation of free form buildings in the control of solar radiation for the benefit of thermal comfort and energy performance (Zhang, Zhang, & Wang, 2016). It seems possible that the lack of research utilising parametric design principles for the optimisation of free-form buildings is due to the complexities involved in deriving algorithmic formulas to describe shapes and volumes. Therefore, this study explores the use of parametric design principles at the preliminary stage of the building design to enhance its optimisation by manipulating shading devices to reduce direct solar heat gains.

METHODOLOGY

Unit of Analysis and Location

This study was approached as a quantitative simulation study linked to the environmental factors that can influence the performance of a building, particularly solar radiation. To this end, the design of a project comprising irregular forms was reproduced in Rhinoceros version 6 software and simulated based on on-site responses to radiation. The proposed research centre is located in the Federal Capital Territory (FCT) Abuja; hence, environmental data of the FCT was used for the simulation. The climate of Abuja is tropical, with an average annual temperature of 25.7°C. With latitude 9°3'28" N and 7°29'42" E, the city lies 477m above sea level.

Instruments

To simulate environmental and weather-related analysis by creating visual algorithmic relationships between necessary information to create visual feedback of the weather data, the ladybug plugin was utilised (Roudsari, Pak, & Smith, 2013). It ascertains the radiation analysis and introduces shading devices as intervening variables in the study model. The Rhinoceros tool was used due to its ability to rapidly compose, adjust and evaluate discrete design alternatives and provide feedback on the impact of a given design choice (Elbeltagi, Wefki, Abdrabou, Dawood, & Ramzy, 2017). However, the software-generated data presents the radiation on the building geometry and colour-coded the effect of the radiation from blue (good/ acceptable) to red (bad/not optimum).

Data Collection Process

In the simulation, the massing of the building envelope was needed, so the first step was to produce a simple massing of the building envelope, as shown in Figure 1. It is important to note that a simplified massing is needed to generate the required result except in specific cases, where a higher level of detail is necessary for the analysis like interior designs (Suyoto, Indraprastha, & Purbo, 2015). An overly detailed massing will cause the algorithm to take an unnecessarily long to compute, and the information obtained will not make much of a difference. After the massing has been produced, the environmental simulation is the next process; this is done using the ladybug plugin for Grasshopper. The simulation carried out was the radiation analysis to check for solar exposure on the building. The building mass is used as the reference geometry, after which the analysis is carried out, and the result is displayed with the building geometry showing the building envelope radiation exposure, with a colour gradient from blue to red attached to it (red for really hot areas and blue for cool areas) as shown in Figure 2. The analysis is based on the weather information for January.



Figure 1: Image showing the level of detail of the building mass used for the analysis.



Figure 2: Image showing the results of the radiation analysis on the building mass (for January)

After the radiation analysis is carried out, the parts of the building mass that will be more exposed the most to direct sun rays are revealed. This information is then used to locate functional spaces, openings and specifically design the shading devices for this study. To create the shading devices, multiple variations were tested. Since multiple iterations will be made and tested, remodeling these variations will take an ample amount of time. Hence, an algorithm was designed for the entire design process of the shading device to avoid painstakingly remodeling different variations.

The result obtained from the radiation analysis of the building mass is then used to model the shading devices on the building façade, as shown in Figure 3. After the shading device has been modeled, another analysis is run with shading as a "context" to check the effect of the shading system with specific parameters on the building mass. The parameters included the size and shape of the shading devices. This process is repeated until the desired result is acquired. It is evident from the outcome, as shown in Figure 4 that the shading system has reduced the amount of radiation on the building envelope. The blue surface of the model shows the level of cooling on the façade.



Figure 3: Image showing the shading device on the mass model



Figure 4: Image showing the result of the radiation analysis after the shading device has been applied (for January)

Pre-Processing

The dataset normality probability test is a statistical data pre-processing test that provides useful information about the structure of the raw dataset and is an appropriate approach for creating a model that fits the dataset and accurately predicts the target variable. Several mathematical approaches for data processing, such as regression, correlation, t-tests, and variance analysis, are utilised to establish inferences regarding the dataset's normalcy. Based on the current total probability theorem, violation of normality is not a major concern if the number of observations in the sample selection is 200 or more.

Normality Test

The statistical analysis summary of the dataset is provided by the normalcy test result using a parametric test presented in Table 1 to convey as much

detail as feasible in the simplest way possible. To explain the fundamental features of the data in a dataset sample, this statistical summary is presented in a few terms: mean and standard deviation, skewness, kurtosis, and so on. To guarantee a constant dataset sampling rate, unwanted records were removed (with more than three missing columns and the same number of data streams on consecutive days). The dataset was presented in the study.

| | Da | ate | Humio | lity | Humi | dity Ratio | Temperatu | re | CO2 | Light | Occ | cupancy |
|-----------------------|------|------|-------|------|------|------------|-----------|------|-----|--------|-----|---------|
| Count | 4 | 2564 | 1 | 2564 | ŀ | 2564 | 2564 | 256 | 4 | 2564 | | 2564 |
| Average | 4 | 2.3E | 24 | 311 | | 193.8 | 25.35 | 193 | .8 | 25.35 | | 2.394 |
| Standard deviation | 4 | 2.1E | 23 | 2.03 | | 292.7 | 21.7 | 2.03 | 3 | 292.7 | | 21.7 |
| Coeff. c variation | of : | 5.31 | % | 5.1% |) | 8.10% | 135% | 5.3 | ۱% | 5.1% | | 8.10% |
| Minimum | 4 | 2.4E | 24 | 4.1 | | 193.8 | 25.35 | 193 | .8 | 25.35 | | 2.394 |
| Maximum | 4 | 4.4E | 24 | 8.1 | | 123.8 | 26.35 | 193 | .8 | 25.35 | | 2.394 |
| Range | | 7.1E | 22 | 6.10 | | 7.1E2 | 6.10 | 6.10 |) | 7.1E2 | | 9.0 |
| Stnd. skewness | - | -108 | 9.21 | 17.8 | | 14.1 | 16.01 | 16.5 | 56 | 13.64 | 3 | 18.63 |
| Stnd. kurtosis | 4 | 2813 | 30.2 | -6.4 | | -2.85 | -5.70 | -7.7 | 1 | -7.743 | 3 | -5.77 |

Table: 1 Statistical analysis result of the dataset

The pre-processing applies forward fill and reverse fill on the original streams. Table 1 contains 2564 measurements for each selected data variable from the whole stream. It also provides standardised skewness and standardised kurtosis, which are used to determine if the sample is from a normal distribution. The dataset's standardised skewness and kurtosis values, on the other hand, are not in the -2 to +2 range, suggesting substantial deviations from normality, which would likely contradict the normally distributed data theory assumption.

Q-Q Plot Normality Test

Since the computed kurtosis of the sample dataset in data analysis in Table 1 is outside the range of -2 to +2, the graphic representation of normality of the sample dataset is performed using the Q-Q plot to verify. Outliers in the dataset sample might occasionally cause this to happen. Outliers are values in a dataset sample that are out of the norm, and they can distort statistical modeling and contradict hypotheses. They can occur due to erroneous reading. As a result, the observer must decide how to proceed when such values are noticed. Outliers are thought to lead to incorrect predictions in many situations; therefore, it's better to remove them from the dataset.



Figure 5: Humidity and Temperature Normality Distribution



Figure 6: Occupancy and Humidity Ratio Normality Distribution

EXPERIMENT

When machine learning algorithms are used to generate predictions on data to assess their prediction accuracy, data is divided into ratios during model training. The approach aids in evaluating the output of machine learning algorithms and selecting the best technique for the model prediction issue. The method is shuffling and dividing the original information into training and test ratios, such as 50:50, which is part of the method. The training dataset is the first part of the process, and it is used to match the model. The test dataset is utilised as input to the variables dataset, which feeds the model and tests and quantifies prediction outputs.

To better understand the variables in machine learning architecture for estimate, linear regression models were chosen for investigation. This model is less complicated and exciting than many more recent advancements in this field, but it is well-known and frequently used as a performance benchmark. Aside from performance prediction, this model can make solid predictions in various other applications, all of which are well served by machine learning libraries. Both algorithms in this paper use the scikit-learn Python library, and the archive documentation contains information on the default algorithm parameters.

Prediction Result

To construct and test a model, environmental data were gathered utilising statistical and machine learning techniques. The study results of the five indoor environmental factors for model training and testing displayed in Table 2 show that the probability confidence score for both mean and standard deviation has attained a minimum of 0.75. As the number of individuals in the room grows, so does the number of prediction mistakes. An interactive learning technique was utilised to collect indoor environmental data to communicate information with users.

Table 2: Result of linear regression prediction on indoor environmental variables

| Temperatu | r e E | Iumi | dit | уL | i g | ; h | t | С | 0 | 2 | H u | mid | lity | R a | t i o | 0 c c u | pai | ı c y | Scor | e M | e a n | Score | Standa | rd Devi | iation |
|-----------|-------|-------|-----|-----|-----|-----|----|-------|-------------|-------|-----|-----|------|-----|-------|---------|-----|-------|-------|-----|-------|-------|--------|---------|------------|
| 0.44148 | 21 | . 5 7 | 8 | 9-0 | .77 | 25 | 51 | .01 | 752 | 224 | 1 | . 1 | 75 | 59 |) 7 | 0.92 | 282 | 59 | 1.0 | 626 | 578 | 0. | 3 2 3 | 53 | 71 |
| -0.8117 | 8- | 1.27 | 05 | 5-0 | .77 | 25 | 5- | 0.9 | 912 | 285 | | ι. | 13 | 4 8 | 34 | - 0 . | 85 | 28 | -0. | 876 | 18 | 0. | 324 | 43 | 92 |
| -0.2612 | 5- | 0.20 | 37 | 21. | 001 | 194 | 20 |).09 | 948 | 861 | - (| 0. | 2 | 75 | 6 | 0.21 | 58 | 37 | 0.0 | 850 | 26 | 0. | 324 | 45 | 94 |
| 1.31584 | 82 | .352 | 16 | 61. | 001 | 194 | 22 | 2.22 | 259 | 912 | 2 | . 1 | 50 | 8 4 | - 5 | 2.35 | 531 | 03 | 2.2 | 431 | 78 | 0. | 3 2 : | 54 | 56 |
| 0.72322 | 21 | .110 | 83 | 51. | 445 | 556 | 41 | . 5 (| 576 | 527 | 1 | . 0 | 04 | 14 | 17 | 1.64 | 06 | 81 | 1.5 | 631 | 31 | 0. | 3 2 : | 50 | 44 |
| -0.5300 | 4- | 0.19 | 07 | 1-0 | .77 | 25 | 5- | 0.5 | 582 | 273 | - (|). | 37 | 4 8 | 3 5 | -0.4 | 96 | 59 | -0. | 59 | 3 5 | 0. | 324 | 40 | 69 |
| 1.54415 | 50 | 0.025 | 86 | 82. | 018 | 807 | 80 |).9 | 177 | 717 | 0 | . 6 | 48 | 29 |) 5 | 0.92 | 282 | 59 | 0.8 | 926 | i 4 7 | 0. | 3 2 3 | 52 | 64 |
| 1.41 | 32 | 2.262 | 52 | 21. | 086 | 586 | 92 | 2.23 | 361 | 165 | 2 | . 1 | 42 | 1 2 | 2 8 | 2.35 | 531 | 03 | 2.2 | 568 | 66 | 0. | 3 2 3 | 54 | 06 |
| 1.05839 | 6- | 0.19 | 07 | 10. | 93(| 000 | 30 |).32 | 298 | 341 | 0 | . 2 | 83 | 62 | 24 | 0.21 | 58 | 37 | 0.3 | 009 | 02 | 0. | 324 | 46 | 66 |
| -1.1129 | 5- | 1.05 | 29 | 4-0 | .77 | 25 | 5- | 0.9 | 947 | 759 | | Ι. | 1 1 | 0.6 | 55 | - 0 . | 85 | 28 | -0. | 908 | 73 | 0. | 324 | 43 | 04 |
| 0.46819 | 81 | .615 | 85 | 3-0 | .77 | 25 | 51 | 1.1 | 38 | 17 | 1 | . 2 | 1 2 | 93 | 34 | 1.2 | 84 | 47 | 1.1 | 276 | i 3 8 | 0. | 3 2 : | 54 | 68 |
| 2.25239 | 10 | .408 | 73 | 71. | 129 | 983 | 30 |).29 | 920 |)73 | 1 | . 2 | 56 | 57 | 1 | 0.21 | 58 | 37 | 0.2 | 474 | 4 6 | 0. | 32 | 82 | 18 |
| 0.3443 | 31 | .151 | 07 | 21. | 188 | 818 | 31 | .4(|) 1 5 | 518 | 0 | . 8 | 5 0 | 2 4 | 8 | 1.2 | 84 | 47 | 1.3 | 914 | 6 2 | 0. | 32 | 5 | 17 |
| -0.176 | 40 | 0.091 | 76 | 71. | 032 | 231 | 60 |).25 | 537 | 793 | - (|). | 0 5 | 6 2 | 2 4 | 0.21 | 58 | 37 | 0.2 | 367 | 97 | 0. | 324 | 4 5 | 63 |
| -0.2288 | 7- | 0.07 | 16 | 51. | 041 | 190 | 80 |).07 | 767 | 746 | - (|). | 18 | 0 0 |) 9 | -0.1 | 40 | 37 | 0.0 | 593 | 56 | 0. | 324 | 4 5 | 94 |
| -0.7146 | 3- | 0.16 | 06 | 1-0 | .77 | 25 | 5- | 0.7 | 68 | 315 | - (|). | 4 2 | 94 | 1 | - 0 . | 85 | 28 | - 0 . | 782 | 86 | 0. | 324 | 43 | 51 |
| 1.77246 | 10 | 0.206 | 18 | 30. | 579 | 963 | 4(|).95 | 555 | 598 | 0 | . 8 | 8 0 | 64 | 1 | 0.92 | 282 | 59 | 0.9 | 476 | i 6 5 | 0. | 3 2 : | 55 | 18 |
| -1.1129 | 5- | 1.08 | 98 | 9-0 | .77 | 25 | 5- | 0.9 | 961 | 27 | - 1 | ι. | 13 | 2 4 | 4 | - 0 . | 85 | 28 | - 0 . | 921 | 03 | 0. | 324 | 43 | 28 |
| -0.9089 | 3- | 1.22 | 74 | 4-0 | .77 | 25 | 5- | 0.9 | 941 | 61 | - 1 | Ι. | 14 | 2 8 | 6 | - 0 . | 85 | 28 | - 0 . | 903 | 52 | 0. | 324 | 43 | 39 |
| 0.3443 | 31 | .496 | 78 | 3-0 | .77 | 25 | 50 |).97 | 758 | 321 | 1 | . 0 | 74 | 6 (|) 9 | 0.92 | 282 | 59 | 0.9 | 606 | i 1 5 | 0. | 3 2 : | 52 | 58 |
| 1.7141 | 71 | .517 | 31 | 31. | 081 | 187 | 41 | . 5 4 | 49 1 | 171 | 1 | . 7 | 8 1 | 0 4 | 4 | 1.64 | 06 | 81 | 1.5 | 530 | 31 | 0. | 324 | 47 | 85 |
| 0.92724 | 11 | .948 | 42 | 5-0 | .77 | 25 | 51 | . 58 | 824 | 195 | 1 | . 6 | 66 | 9 5 | 53 | 1.64 | 06 | 81 | 1.5 | 901 | 67 | 0. | 32 | 61 | 98 |
| -0.8603 | 5- | 0.47 | 40 | 2-0 | .77 | 25 | 5- | 0.8 | 357 | 0 2 | - (|). | 67 | 4 4 | 4 | - 0 . | 85 | 28 | -0. | 855 | 28 | 0. | 324 | 41 | 16 |
| 1.22841 | 12 | 2.22 | 24 | 90. | 93(| 000 | 31 | . 90 | 544 | 4 4 3 | 2 | . 0 | 13 | 67 | 7 | 1.99 | 968 | 92 | 1.9 | 700 | 56 | 0. | 3 | 2 5 | ; 1 |

RESULTS AND DISCUSSION

Data returned from the analysis using Rhinoceros software and plugins was analysed using Microsoft's Excel. The analysis was carried out by creating a table showing the range of values from the radiation per square meters values of each month before and after the introduction of the shading system; the amount of heat that was observed to have been reduced from the shading system showed its effectiveness in reducing heat gained by the building

This study's scope involves optimising the building envelope through the use of parametric tools to manipulate shading devices to reduce direct solar heat gains whilst maximising indoor thermal comfort. Consequently, the minimum and maximum solar radiation values on the building mass measured in kilowatt-hours per square meter (Kwh/m2) was measured before and after the shading device was introduced to the building. Table 1 reveals the difference in the minimum and maximum values, indicating the radiation or solar exposure level before and after the shading devices were introduced. The results are presented from January to December as obtained from the simulation analysis.

| Month | Minimum | Maximum | Minimum | Maximum | | |
|-----------|--------------------|--------------------|--------------------|--------------------|--|--|
| | (Before) | (Before) | (After) | (After) | | |
| | Kwh/m ² | Kwh/m ² | Kwh/m ² | Kwh/m ² | | |
| January | 19.27 | 192.67 | 19.27 | 77.07 | | |
| February | 18.81 | 188.1 | 18.81 | 75.24 | | |
| March | 21.85 | 218.5 | 21.85 | 87.4 | | |
| April | 20.66 | 206.57 | 20.66 | 82.63 | | |
| May | 18.8 | 188.03 | 18.8 | 75.21 | | |
| June | 16.21 | 162.14 | 16.21 | 64.86 | | |
| July | 16.2 | 161.98 | 16.2 | 64.79 | | |
| August | 16.4 | 164.03 | 16.4 | 65.03 | | |
| September | 15.91 | 159.08 | 15.91 | 63.63 | | |
| October | 17.58 | 175.8 | 17.56 | 70.32 | | |
| November | 17.31 | 173.08 | 17.31 | 69.23 | | |
| December | 17.65 | 176.55 | 17.65 | 70.62 | | |

Table 3: Radiation analysis showing before and after introduction of shading devices

The solar radiation measured in Kwh/m² is a measure of how much radiation a surface is exposed to. The higher the value of radiation per square meter, the more likely it is for that surface to be hot and consequently lead to high usage of energy for cooling the interior (Wankanapon & Mistrick, 2011). From the values in Table 1, it can be seen that March has the highest radiation exposure on the façade, with a minimum of 21.85 Kwh/m² and a maximum of 218.5 Kwh/m². The month of July has the lowest radiation exposure on the façade, with a minimum of 16.2 Kwh/m² and a maximum of 161.98 Kwh/m². However, the minimum value is not of much concern but the maximum, which indicates how much radiation the building will be exposed to, as illustrated in

Plate 2 with colour graded representation before introducing shading devices. The method of selecting the maximum values as critical periods to determine the level of radiation exposure of the building envelope is consistent with the shading period selection criteria of Sargent, Niemasz, and Reinhart (2011).

Transition

A louver shading system is introduced to the building envelope through the simulation process to counter excessive heating of the building envelope. Static exterior shading devices such as louvers and overhangs have been used as means of solar radiation control to improve indoor environmental conditions (Sargent et al., 2011). It could be seen from Table 1 that March with the highest radiation exposure value for the year (218.5 Kwh/m²) was reduced to 87.4 Kwh/m² after the introduction of the shading device system. According to E. S. Lee and Selkowitz (1994), the shades should close when the transmitted direct solar radiation is higher than 94.5 Kwh/m2. Therefore, 87.4 Kwh/m² radiation on the building façade is not expected to affect the indoor environmental conditions of the building occupants adversely.

On the other hand, the month of July with the lowest radiation exposure value for the year (161.98 Kwh/m2) was further reduced to 64.79 Kwh/m2 after introducing the shading device system. It could reduce drastically the energy demand for cooling induced by direct solar radiation. The shading system introduced mimics a wavelike pattern placed at differing angles on the building facade with equal spacing and repeated until a suitable range is obtained. In the case of this study, a spacing of 1200mm was chosen. Interestingly, the result obtained revealed that the amount of radiation exposure on the building façade reduced by 60% in all the months, as shown in Figure 7. This underscores the consequence of utilising shading devices to optimise the building's performance.



Figure 7: Change in radiation on the building façade after the introduction of shading devices

LIMITATIONS OF THE STUDY

This study explored the utilisation of parametric design tools in the process of building design to enhance its optimisation through manipulation of shading devices to reduce direct solar heat gains. This involves simulating environmental parameters by creating visual algorithmic relationships between necessary information to create visual feedback of the weather data to ascertain the radiation analysis and introduce shading devices as intervening variables in the study model. Results obtained revealed that introducing the louver shading system through the simulation process can counter excessive radiation of the building envelope. It was evident from the data that shows that the amount of radiation exposure on the building façade reduced by 60% in all the months after the introduction of the shading device system. This reduction in radiation on the building façade ultimately portends the enhancement of cooling for the building interior. Only solar radiation parameter was utilised

CONCLUSION

This study explored the utilisation of parametric design tools in the process of building design to enhance its optimisation through manipulation of shading devices to reduce direct solar heat gains. This involves simulating environmental parameters by creating visual algorithmic relationships between necessary information to create visual feedback of the weather data to ascertain the radiation analysis and introduce shading devices as intervening variables in the study model. Results obtained revealed that introducing the louver shading system through the simulation process can counter excessive radiation of the building envelope. It was evident from the data that shows that the amount of radiation exposure on the building façade reduced by 60% in all the months after the introduction of the shading device system. This reduction in radiation on the building façade ultimately portends the enhancement of cooling for the building interior. Only solar radiation parameter was utilised as the weather condition in predicting the building performance in this study; hence, future studies should extend the scope of the investigation to other conditions such as wind. The parametric design approach entails simultaneous design analysis, enabling designers to monitor changes during the design process, thereby enhancing performance in buildings and generating forms by integrating performance evaluation of particular design requirements.

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