Methodological evaluation of Integrated Façade Systems: Sensitivity analysis of net-energy in a base-case model

Structured Abstract

Purpose: To develop a methodology to test the robustness of energy performance of highly- to fully-glazed office buildings in hot and arid climates using the net-energy figures.

Design/Methodology/Approach: The paper uses a methodology to develop a base-case model for building energy simulation (BES) of highly- to fully-glazed office buildings followed by Sensitivity Analysis (Linear Regression Model) to test the robustness of the results.

Findings: Net-energy is best achieved on south, followed by south-east, and south-west façades, the increase in d/l ratio has a diverse effect while there is a significant influence from glazing systems on the resultant net-energy figures.

Research Limitations/Implications (If applicable): The lack of experimental data for IFS with its various applications in existing body of knowledge forms the main limitation of this research.

Practical Implications (If applicable): Findings can be of practical use to practitioners and academics to assist them as a decision tool when working on energy performance of integrated façade systems (IFS).

Social Implications (If applicable): The research contributes to energy consumption reduction in office building stock at peak times, lowering the consequent energy shortage and blackouts for non-office buildings with clear positive social impacts.

Originality/Value: Adopting a systemic approach in BES studies will help further the understanding the impact of some phenomena and justify how the contributory parameters would behave when combined effects are under investigations.

Keywords: Sensitivity Analysis; Base-case Model; Benchmarking; Building Energy Simulation (BES); Net-energy; Integrated Façade Systems; Highly- to Fully-glazed Buildings; Office Buildings; Hot and Arid Climate.

Paper Type: Research Paper

1. Introduction

Improving the building performance and lowering their environmental impacts have recently attracted substantial attention in energy and environmental research. Integrated and holistic design solutions are major areas in which potential contribution can be made to this agenda. One effective strategy in integrated design is what is known as “Integrated Façade System” (IFS); façades where different technological solutions are incorporated to improve the performance. Some of the strategies in designing IFSs include incorporating: 1) High-performance Glazing (HPG); 2) Shading Devices (SD) and; 3) Integrated Photovoltaics (IPV). Reducing heat gain, cutting back on the need for air conditioning and decreasing glare while maximising the use of natural light are just to name a few of the advantages which can be achieved through IFSs (Ibraheem et al., 2017a). Despite the growing importance of research in this area, the literature and precedent studies are still few and far between. This is more so when the focus is on fully- to highly-glazed buildings and more specifically for non-residential buildings and buildings in hot and arid climates. There is some scattered research on IFS. However, the lack of a systemic study on IFS is pointing out a major gap in this field. A systemic study of IFS can help bridge the gap in a comprehensive examination of parametric combination of different variations of façade components while providing a customisable platform which can be adjusted and deployed in different contextual conditions.

In doing so, the first step in this study is to develop a base-case model. This model needs to be flexible and customisable enough to be used as a benchmark to produce the worst-case scenario outputs. The base-case will also be used to apply different variations of façade components and run quick building energy simulations (BES) to be able to compare the outcomes of each intervention to the worst-case scenario and to help quantify the impacts, or balance the consequences, of resulted trade-offs.

To address this gap, following aims will be pursued:

1. Developing a base-case to be used as a benchmark and for possible different combinations of parameters to test the impact of change of façade elements on the output variables.
2. To investigate and find a statistical method to establish, measure and weigh the impact of change of each of those parameters compared the others’ so that decisions can be informed, and design solutions can be prepared backed up by evidence.

2. Literature Review

2.1. Building Energy Simulation (BES)

BES is deployed to analyse the energy performance of a building dynamically and to understand the relationships between the design parameters and energy use characteristics of the building. It is the most commonly used method in building performance assessment and design (Ayyad, 2011, Kim et al., 2012, Awadh and Abuhijleh, 2013, Namini et al., 2014, Lamnatou et al., 2015). The effects of change can be simulated and observed in a fraction of time and for a fraction of cost it would take to study in real life (Hui, 1998, Anderson, 2014).

2.2. Simulation tools

There are various simulation tools which can be utilized to predict the energy performance of a building in the initial stage of design. Almost all of these tools have been improved continuously (Anderson, 2014). Using these tools, variations such as different types and forms of shading devices can be studied and analysed in details as a key design factor to determine and assess energy consumption (Kim et al., 2012). Energy flows can be modelled with flexibility for a combination of

different variables such as construction systems, materials, thermal characteristics, use profiles and weather data files for different geographical locations (Ayyad, 2011). Crawley et al. (2008) carried out analysis of major BES tools such as BLAST, BSim, DeST, DOE-2.1E, ECOTECT, Ener-Win, Energy Express, Energy-10, EnergyPlus, eQUEST, ESP-r, IDA ICE, IES-VE, HAP, HEED, PowerDomus, SUNREL, Tas, TRACE and TRNSYS. The features which were studied included modelling features, zone loads, building envelope, daylighting and solar gain, infiltration, ventilation and multi-zone airflow, renewable energy systems, electrical systems, HVAC systems, emissions, economic evaluation, climate data availability, results reporting, validation, user interface, interoperability, and availability and access. Attia et al. (2009) performed another analysis based on what they called criteria of 'architect friendly', consisting of 1) usability and information management of the interface; 2) integration of intelligent design knowledge base. IES-VE (Integrated Environmental Solutions-Virtual Environment) was ranked, by both studies, as high on their list. It has the capability to integrate valid weather data, benefits from a user-friendly interface, and the flexibility to perform different types of simulations. It can also perform different calculations for the same model using the software in-build modules and with specific data inputs. As such it is gaining momentum and claiming a growing share in the market (Anderson, 2014). It has been used as a powerful dynamic simulation tool which has been widely used around the globe (As some more recent examples see Ayyad, 2011, Kim et al., 2012, El Sherif, 2012, Awadh and Abuhijleh, 2013, Pomponi et al., 2015, Aksamija, 2016, Lau et al., 2016, Shen et al., 2016, Pomponi et al., 2017). More importantly, the most recent modular construct, novel capabilities and new features of IES-VE makes it a perfect solution for carrying out a full parametric analysis of the thermal performance, day-lighting, artificial-lighting as well as PV generated electricity. This can all be performed in IES-VE which eradicates the need to use different BES applications thereby eliminating possibilities of discrepancies or problems arising as a result of software interoperability, reduces the risk of double-counting and ensures consistency.

2.3. Building prototypes and benchmarks

The benchmark building models represent a starting point for analysis, especially for those focusing on the effect of energy efficiency technologies on specific building types in different climates (Torcellini et al., 2008). Back in 1990 when office prototypes were first utilised, building envelopes and their geometric characteristics were used to investigate the effect of shading devices on energy performance (Leighton and Pinney, 1990). Such prototypes allow for detailed analysis when studying the influence of energy measures at building scale (Torcellini et al., 2008). Attempts on developing such models have been recorded in previous work by leading research institutions. U.S. Department of Energy (DoE), Lawrence Berkeley National Laboratory (LBNL), Pacific Northwest National Laboratory (PNNL), and National Renewable Energy Laboratory (NREL) have developed standardised benchmark models for simulation purposes, which have widely been used by researchers to investigate thermal and visual performance of fenestration systems (Haglund, 2010, Carmody, 2004). Those models represent 70% of offices in the United States (EWC, 2012) and may not be easily and justifiably applicable to similar studies in other contexts. Therefore, a context-specific representative model – a prototype or a benchmark – is always needed in order to represent real practices in a certain context.

Therefore, the models should be formulated based on the characteristics of its geographical, urban and architectural contexts. Meantime, representing significant part of the building stock with a small set of building models is crucial but difficult to achieve because of the diversity of buildings and the limited data on existing buildings to draw from (Torcellini et al., 2008). Development approaches of

representative buildings have been devised and applied. A comprehensive review of the literature on developing benchmarks for energy simulation purposes has been carried out by Pomponi and Piroozfar (2015), which has then been used to develop a benchmark office building to investigate the application of double skin façades as a strategy for refurbishment of office buildings in the UK. Earlier attempts used standardised offices to provide details about the building envelope (Leighton and Pinney, 1990), whereas others focused on grouping benchmarks based on their ventilation type and layout (EEBPP, 2000), or into five categories based on urban context, structure, construction materials, envelope systems or internal layout (Dascalaki and Santamouris, 2002).

Where data or precedent studies are not easily accessible or available, creating benchmarks is another alternative option. This can be done through conducting a questionnaire survey on buildings specifications in order to formulate a prototype model to represent the buildings (Hernandez et al., 2008). Alternatively, to avoid low representativeness of the majority of buildings, parametric archetype benchmarks could be developed based on archived data and historical review of buildings' characteristics. Parameters such as elements' U-values, layout, glazing ratio and building types have been defined to lead to development of the models (Korolija et al., 2013).

2.4. Sensitivity Analysis (SA)

If the change in an input parameter (X) results in a change in an output parameter (Y) and these changes can be measured, then the sensitivity of Y with respect to X can be determined (Lam and Hui (1996) in Nguyen and Reiter (2015)). Sensitivity Analysis (SA) is defined as a measure of the effect of a given input on a given output (Saltelli et al., 2004). Another definition of SA is that it is a technique that aims at estimating how the uncertainty in the independent variables of a mathematical model affects a particular dependent variable, given a predefined set of assumptions (Eggebo, 2017). SA can be categorised in different ways (Hamby, 1994, Frey et al., 2003, Tian, 2013, Nguyen and Reiter, 2015). Such classifications have been used to help evaluate the output of one variable at a time, a sample of input vectors and their associated outputs or a partitioning of a particular input vector based on resulting output vectors (Hamby, 1994). Alternatively approaches to SA have been divided into mathematical approach, statistical (or probabilistic) approach or graphical assessment (Frey et al., 2003), or based on the number of inputs and the interactions between them accordingly i.e. Local, Global or Screening (Heiselberg et al., 2009). The last categorisation (Local, Global, Screening) is the most commonly adopted one in BES studies by many researchers such as Tian (2013) and Nguyen and Reiter (2015). While Tian (2013) uses SA categories of Local, Global, Screening-based, variance-based and meta-model methods, Nguyen and Reiter (2015) review previous research and classify them under nine SA methods (i.e. PEAR, SRC, PCC, SPEA, SRRC, PRCC, Sobol index, FAST, and Morris's SA method) as mainly developed by Frey et al. (2003) and others.

An important issue in detailed design is how to quantify and qualify the information obtained from a simulation study and to translate it into aggregated performance measures that are easily understood by the design team and support rational decisions (Hopfe, 2009). The relationship between simulation inputs and outputs is often unknown or uncertain due to complexity of building energy models (Nguyen and Reiter, 2015). Various applications of SA methods have been found in the literature. Hopfe and Hensen (2011) and McLeod et al. (2013) coupled both Sobol index and Morris's SA method with uncertainty to compensate for input parameters variation where they were not available. Uncertainty analysis was used as a pre-processing stage to conduct sensitivity analysis of three groups of input parameters of office buildings, i.e. physical, design and scenario parameters (Hopfe and

Hensen, 2011), for which the basic features were adapted from Morris method (1991) and Sobol method (1993) (Hamby, 1994, Frey et al., 2003, Saltelli et al., 2004). In the absence of the ranges of variation of input parameters, Latin Hypercube Sampling (LHS) method has also been used to generate the input data variation ranges. Standardised Rank Regression Coefficient (SRRC), by contrast, has been used as a quantitative measure of sensitivity where the data variation range is known.

Direct or indirect approaches can be followed to measure the sensitivity which can be computed using the following formula (Saltelli et al., 2004):

$$S_{x1} = \delta Y / \delta X_j$$

where Y is the output of interest and X_j is the input factor [variables].

Once the SA is measured and determined, the relationships and the relative importance of design parameters can be understood, and the building performance can be improved most effectively and most efficiently by focusing on the more important design parameters. Other areas of building performance analysis where SA can also be applied to, include where the aim is to:

- Provide a robust tool to quantify the effect of different design parameters.
- Identify sources of uncertainty.
- Assess the significance of various input parameters.

To summarise, the literature review of this study helps firstly, with the choice of the most appropriate simulation tool that is IES-VE. Secondly it assists in taking full account of all contributing factors for developing a methodology to devise the base-case model to specifically serve the purpose of this study. In doing so, and in light of lack of archival data and historic evidence, a remote questionnaire survey was administered to collect data to assist with developing the base-case model. Last but not least, the review literature also facilitates the choice of the most relevant SA methods for testing the validity and reliability of the findings of this study. It suggests that Global Sensitivity Analysis methods are the most applicable ones for quantifying the sensitivity of the output against variations of each of the parameters under the investigation in this study. Moreover, considering that the variation range of each of the parameters is fully controlled and no element of randomness is involved, linear regression modelling is the most appropriate technique for this study amongst Global Sensitivity Analysis methods. In addition to that, several other assumptions that the data must satisfy have also been fully verified in order to qualify for linear regression. This has been presented in details in the main research project.

3. Research Design and Methodology

A systemic methodology has been developed to study parametric combination of different variations of components in IFS. This can be used to develop a customisable platform for IFS in the context of this study which due to its modular structure can be adopted and adapted to the specifics of such façade systems in other contextual conditions.

As a more affordable, more time-efficient alternative to scaled physical modelling, real building testing and building test cells, and also a more user-friendly, more agile, more flexible and faster alternative to mathematical building modelling, BES has been used as a tested, established and reliable methodology to carry out studies of this nature.

Systems Theory has been used as underlying philosophy for the methodology devised for this study. The idea of the building as a system was originated in modern systems theory (Piroozfar, 2008) and in application of building science to building performance (Kesik, 2014). Piroozfar (2008) investigates the building envelope as ‘the system’, the building as ‘the super-system’ and the façade components as ‘the sub-system’ to investigate the trade-offs in mass customisation of envelope systems using off-site production methods; what has then been further developed to investigate the application of BIM for a fully customisable façade system by Farr et al. (2014). This methodological approach has twofold benefits both for theory and practice. It can facilitate not only the study of the literature on the topics related to that of this research but can also help classify their impacts and further enable the decision support for the course of propositions, interventions, and practical applications for building façade solutions. Within this systemic approach, the body of literature about PV as shading devices in buildings were mainly found under three main categories: performance aspects, assessment methods and design considerations/configurations with clear overlaps (Figure 1).

Figure 1 The identified scopes of literature superimposed on the systemic approach

With this underlying theoretical frame of reference, and with an aim to help classify impacts and to further enable and/or support decisions, this study takes the building level as ‘the system’. The upper level, ‘the super-system’, includes the context – such as site, geographical location, climate (micro and macro), etc. – in which the building exists and the lower level, ‘the sub-system’, involves the façade and its associated components and elements (Figure 2).

Figure 2 Systemic approach developed and deployed for this research

This study uses this methodological approach to develop a base-case and to determine the variables at the system and sub-system levels as defined here. To validate and test the base-case, energy

simulation of different scenarios will be conducted and used to carry out the sensitivity analysis to demonstrate the impact of changes in different input variables on output variables e.g. energy generation, energy consumption, and daylighting. Net-energy has been chosen as the representative indicator to demonstrate the sensitivity analysis in this paper. The model development will be elaborated on as a part of research instrument development in the data generation section.

What is of imperative importance is to determine the interdependency of the variables – both input and output – to ensure that all the variables are taken account for and no variable is double-counted. Figure 3 demonstrates the interdependency of the variables in this study.

Figure 3: Interdependency of variables

4. Data Generation

4.1. Model development

A remote questionnaire survey was developed and distributed via email, social and professional media and local PSRBs to 88 professionals between November 2016 and February 2017. 72 responses were received and the final number of valid responses was 65, bringing the response rate to 74% due to purposive snowball sampling strategy utilised. The authors' professional experience, expertise and local knowledge were used to develop the initial questionnaire and used as expert witness to factor out the invalid responses and as a point of reference where inferences were needed to help make decisions.

The modelling phase started when all results from the remote questionnaire survey were collected and decisions had been made as to what variables should be included. In addition to the survey

outcomes, findings from the literature related to modelling of a representative or benchmark model were also used for the development of the representative model.

The developed model is a mid-sized office building with office modules aligned to two main façades with an internal cellular layout, separated by a central hallway of 2.0m wide. Dimensions of each office (also known as ‘thermal zones’ in BES applications) are 4mx6mx4m (WxLxH). The shape is near-rectangle. The building footprint (built area to land plot area ratio) is between 40% and 60%. The ground floor layout is sitting back off the edges of land plot unlike the rest of the above floors which fill the layout. The entrance of the building is at the middle of the front façade that faces the main street providing access to the building.

4.2. Simplification of the model

Some simplifications were applied to the final model in order to increase the accuracy of the intended results of the simulations. This helped eradicate redundant variations with no implications on thermal performance of the building or where reaching consensus in the survey was not possible and had no significant impact on the outcomes e.g. location of staircases (vertical access) and the wet zones (services). Those were not included in the model due to the variation they may have from one design to another. This was because representing one identical occurrence with a reasonable frequency was difficult if not impossible altogether. Similar approach has been utilised by other researchers (See for instance Pomponi and Piroozfar, 2015 amongst others).

Furthermore, carrying out simulation of a building model with similar thermal zones (both vertically and horizontally) serves no purpose but to only increase the simulation time and the possibilities of errors to occur. Therefore, from the thermal zoning point of view, the number of the thermal zone variations should cover the minimum of all the possible unique zone characteristics to facilitate a comprehensive, accurate and detailed analysis. This makes omission of similar zones (vertically and horizontally) to the extent that the model includes only one of each particular thermal zone, a common practice in building physics.

Figure 4: Model simplification stages

Figure 4 shows the layout of the developed base-case model showing all possible unique thermal zones characteristics, where similarly treated floors and zones have been omitted or combined to include only one representative thermal zone vertically and horizontally to include any specific unique thermal characteristics.

4.3. Setting up the 3D virtual model in IES-VE

The modelling procedure starts with creating the geometry of the model in ModelIT-IES, followed by creating the glazing systems in LBNL Window 7.5; the tool widely used to create reports of the desired input, containing all the optical and thermal properties of glazing systems. Those reports are then imported to APcd-IES to be added to the construction database of the model. In addition to the glazing input via LBNL Window 7.5, other construction materials of external walls and internal partitions – e.g. external and internal finishes, in-fill layers and insulations – have been inputted to the library directly using APcd-IES. The materials and glazing systems are then assigned to the model in Apache-IES in the base-case model geometry as shown in Figure 5. The model uses Baghdad weather file. This file will feed into the thermal simulation, Radiance analysis and SunCast analysis. The glazing systems created in Window 7.5 are also set up in Radiance-IES to account for the optical properties of the glazing systems. Profiles of occupancy, internal gains, HVAC systems, dimming profiles, weekly and daily use profiles are set up in APro-IES. The geographical location is set up in APLocate-IES to be used in thermal, SunCast and Radiance analyses. Subsequently the simulation file is set up to run SunCast for solar shading calculations and Radiance illuminance calculations.

Figure 5: Base-case model geometry setup materials

4.4. Simulations

In the simulations, the assessed dependent variables include total electricity consumption, solar gain, artificial lighting gain, cooling loads, PV generated electricity, and UDI_{300-3000 lux}. In addition, net-energy and savings figures are also included to facilitate the decisions about the optimum solutions/combinations with different functions of IFS (for further explanation about variable interdependencies, refer to ‘Research Design and Methodology’ section and Figure 3).

All simulations are organised in *Tasks-IES*¹ so that for each of the models, SunCast solar energy and shading calculations are run first, followed by Radiance simulation for full year-long daylight simulation. The output files of SunCast and Radiance simulation result files are then fed back into the Apache thermal simulation as a last run to integrate their impact into the thermal simulation.

Figure 6 Modelling and simulation processes

Having run all the simulations in the queues on six computers in parallel, extraction of the results was conducted via VistaPro-IES to prepare the data for the analysis in Microsoft Excel™. Excel was then used to analyse the data and to provide the database for IBM Statistical Package for the Social Sciences (SPSS™) using which the sensitivity analysis was conducted. To summarise the simulation procedure from start to end, Figure 6 shows the modelling and simulation procedure, the tools used, and the inputs and outputs of each stage.

5. Data Analysis

This paper focuses on Sensitivity Analysis (SA) as the third phase of the second stage of data analysis of this research project. The study's analysis is divided into two stages, a proof-of-concept analysis and detailed simulation analysis. In the first stage, preliminary results of two rounds of simulation were presented as a proof-of-concept. A discussion about the preliminary results of simulation of one parameter was also provided with observations (Ibraheem et al., 2017b). The strategy that was proven to be reliable in the proof-of-concept stage was then adopted and rolled out to the other combinations of different variables at system and sub-system levels. The second stage of the analysis includes the detailed analysis of all the assessment indicators under investigation and was conducted in three phases, starting with inferential data analysis as phase one, followed by decisional synopses as phase two, and finally Sensitivity Analysis (SA) as phase three, which is the main focus of this paper (Figure 7).

Figure 7 Analysis stages of the study and the focus of this paper

Using the systemic approach, classification of all the variables under investigation was carried out. Variables at system level are clustered separately to form the main groups as Orientation and Window to Wall Ratio (WWR). Then sub-system variables are included and clustered into sub-groups within the system level's main groups. Those are depth of panels, d/l ratio², angle of inclination of the Photovoltaic Shading Devices (PVSDs) and the HPG systems. This is summarised in Figure 8.

Figure 8 Inferential data analysis process for net-energy

6. Results

Starting with energy performance indicators such as electricity consumption, solar gain, artificial lighting gain, cooling load, PV electricity generated, net-energy and energy saving, as well as daylight performance indicators such as $UDI_{300-3000 \text{ lux}}$ for the daylight sensitivity analysis, the same steps were followed for each of the output parameter in SA. In this paper, only net-energy will be presented. The net-energy is a useful measure as it comprises both the energy that could have been consumed if IFS integration had been excluded and the energy consumption as a result of including IFS. To prepare the data for analysis, the first step after inputting the data, was to specify the input variables as independent variables and the output variables as dependent variables. The variable interdependencies – as discussed in Research Design and Methodology section of this paper, and summarised in figure 3 – were instrumental in attributing the correct specifications to variables at this stage.

The 'measure level' of each variable should also be specified. In this study the independent variables are Nominal variables while the dependent variables are all Scale variables. The input variables are considered as 'predictors' and their importance graph has been generated where the sensitivity of the output will be probed when the input variables change, taking into account changes of other input variables simultaneously. The predictor importance graph (Figure 12) shows the input variables in the

final model in rank order of importance. The simulation outputs were analysed using a linear regression modelling with 95% confidence interval, where the importance of a predictor is the residual sum of squares with the predictor removed from the model, normalized so that the importance values sum up to 1 (Norušis, 2012). The assumption of linearity is then checked to verify if the regression model can predict the output. To do so, the predicted results (based on the regression model) were plotted against the observed results (extracted from the simulations) to examine the accuracy of the model as determined by how close the scatter plot is to 45°.

The reliability and the validity of the models and results in this study, were accounted for through a verification process to ensure that the method of analysis can accurately predict the results and the models are accurate to satisfactory levels. To do so, a high-level summary of the model was generated, where adjusted R^2 was examined (displayed accuracy value = $100 \times$ adjusted R^2 ; models with $R^2 < 0.5$ indicate random occurrences).

Last but not least, One-At-A-Time (OAAT) analysis of mean values for variations of each parameter was plotted and analysed. This helped investigate each parameter separately and demonstrate the range of change corresponding to variation of each parameter. Figure 9 shows the procedure followed for the sensitivity analysis.

Figure 9 Sensitivity analysis procedure

6.1. Net-energy

The total number of IFS combinations summed up to 1620 models for which dynamic simulations were run. The results were clustered based on their specifications and analysed using a linear regression model with 95% confidence interval in SPSS™. The model shows high accuracy which can be seen in Figure 10 where predicted³ vs. observed⁴ results were plotted, and verified by the model summary for which the adjusted R^2 coefficient is 0.967 as shown in Figure 11. The overall influence of variations in each of the parameters considered in this study on net-energy is shown in Figure 12 where the importance of the parameters is quantified and ranked.

Figure 10 Predicted vs. observed results (mean net-energy)

Figure 11 model summary

Figure 12 Predictor importance graph for net-energy

The HPG system scored the highest rank with 89%, indicating its variation has the highest impact on the net-energy. It was followed by the second important parameter that is building orientation, with only nearly 5% of impact, followed by WWR, angle of inclination, d/l ratio, and the depth with an influence of only 4%, 2%, 1% and 1% correspondingly. Interestingly enough, the depth of the panels showed the least effect on the net-energy.

Figure 13 shows OAAT graphs of the mean value of net-energy. The variations of each parameter are shown on the x-axis and their influence on net-energy on the y-axis. The findings from the analysis of the graphs confirm the findings from the sensitivity analysis. The line connecting the mean values of 400mm and 600mm depths is almost horizontal in comparison to other parameters which shows insignificant influence of this variable on the net-energy. HPG system, by contrast, is the most influential factor which is proven by the fluctuation observed in mean values of each glazing system. In addition, the figure shows that building orientation (system level variable), followed by WWR (system level variable), angle, d/l ratio and depth do have some influence but are significantly less impactful.

7. Discussion of Findings

Variation of different HPG systems was found to have the highest impact on the net-energy, as proven by the fluctuation in the OAAT graph and confirmed by the findings of sensitivity analysis. Single-clear (SC) and Single-reflective (SR) were shown to have been the most energy intensive glazing systems. This will have an immediate negative impact on the resultant net-energy for those HPG systems. This is because SC is a system with the least improved thermal properties while SR is the one with the poorest optical properties. In cooling-dominant climates, on the other hand, both double clear (DC) and double low-e (DL) were proven to be better options than single low-e (SL) for net-energy. All the combinations with DL were shown to be the best compared to other combinations for net-energy. The sensitivity analysis indicated that glazing system accounts for 89% of influence on electricity consumption.

Figure 13 One-At-A-Time parameter of net-energy mean values

South, South-east and South-west were the orientations studied in this research as they are orientations where PVDSs are naturally more likely expected to be found and may be relevant to the scope of this study. This is because they are where the PVDSs will be most effective. South orientation showed better net-energy results compared to south-east and south-west. Orientation was found the second most influential variable in the sensitivity analysis. This finding confirms what is generally found in the literature where modifications on the building envelopes are conducted with an aim to

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improve electricity consumption in addition to improved PV generated electricity due to excessive sunlight for this orientation.

Variations of 60%, 80% and 100% were tested for WWR as a representative of highly- to fully-glazed buildings as reported in the literature. It was shown that the bigger the WWR is, the more energy intensive the combinations will be, which will make it more difficult to counterbalance the energy consumption with energy generation and improve net-energy figures and/or achieve near-zero energy buildings, with a quite significant change in the range of mean values. As the third most impactful factor, the WWR was highlighted in SA, which conforms to the amount of the solar gain and its influence on cooling loads thereby increasing the electricity consumption with an adverse impact on achieving more desirable net-energy figures. However, the results of phase one inferential data analysis of this research project indicated that increasing WWR could reduce energy use (only if daylight potential is optimised). Therefore, it is not surprising to find some of the combinations with lower energy use and higher WWR when the impact of daylighting is considered. An example of this could be where a combination with DL glazing system with WWR=80% is found to be much more energy efficient compared to a same combination with lower WWR (e.g. 60%) but with single or double reflective glazing. Hence, trade-offs can be achieved within different WWR ranges. This may prove helpful as a decision support tool when, for instance, within a certain range of building performance requirements, other factors such as construction costs or building materials and components specifications may be added to design intent or client's brief.

The next influential variable was shown to be the angle of inclination as shown in Figure 12. Increasing the angle of inclination from 20° to 60° (with intervals of 10°) shows a nearly steady increase in the net-energy as also verified in Figure 13. While increasing the angle of inclination reduces the solar gain, it has a negative impact on dimming of internal artificial lights which results in additional load for increased need for artificial lighting as well as subsequent additional internal heat gain that contributes to higher cooling loads. This will, in return, increase the electricity consumption which will again have some detrimental impacts if best net-energy results are aimed at in a study or for a specific design intent. 20° was found to be the optimum angle of inclination across all cases, but only if the net-energy figures are considered in isolation, without any account for daylighting.

The distance between PVSDs, which is governed by the depth of the blades, was studied for $d/l=1, 1.5$ and 2. While the mean value of net-energy showed a negative correlation with d/l ratio (See Figure 13), d/l remained one of the least influential variables when it comes to net-energy. This is justifiable as increasing the distance between the PVSDs (in a fixed d/l ratio) will allow for more solar gain, introducing more cooling loads. Moreover, the mean artificial lighting gain is significantly reduced as a result of increasing d/l ratio. It is interesting to notice that the mean values of net-energy shows divers level of change as a result of change in d/l ratio. As seen in Figure 13, the increase in the d/l ratio from 1 to 1.5 will significantly reduce the net-energy; while increasing from 1.5 to 2 will not result in a significant change in the net-energy, suggesting that the net-energy is less influenced by this parameter within this particular interval (from 1.5 to 2). Therefore, it is no surprise to see that, in the SA, the d/l ratio scored as one of the least significant parameters compared to other parameters, such as HPG, orientation and angle of inclination.

It was shown that the depth has negligible effect on energy consumption, as indicated in the OAAT figure, and proven by the SA, although previous studies may have suggested otherwise. This is

probably because they mainly focused on the generated electricity by the PVSDs (and not net-energy), where excluding other aspects such as cooling loads or daylighting, have proven to have significant impacts on the net-energy figures.

8. Conclusion and Future Work

This paper highlighted the fact that adopting the systemic approach will further help deepen our understanding of some phenomena and justify how the contributory factors and elements would behave when combined effects are under investigations.

It was found that the most dominant parameter that influences the net-energy is HPG. This was due to its major influence on solar gain, cooling load, and artificial lighting gain, in addition to daylighting. With the help of sensitivity analysis, the effect of alteration of each input variable on net-energy was quantified to allow for a more accurate and conclusive decision to support optimum design solutions. Parameters at sub-system level showed higher influence on the outcome than those at the system level as suggested by the sensitivity analysis. These results help understand – given the existing restrictions and limitation in the contextual conditions – where design efforts should be concentrated to guarantee the best application of IFSs. For instance, under the assumption that the orientation may be a constraint and alteration of WWR is a complicated task, HPG, angle of inclination and d/l ratio are the elements on which to focus. Such results can be of great help in the design stage to narrow the possible number of configurations down to a meaningful level that can then be evaluated and decided upon.

Although the findings of this study conformed to some of the previous research findings, suffice to say that the research in this field seems to be restricted to one element at a time, missing out an important point which is the overall performance of IFS when the glazing systems, in actual settings, is combined with other elements of the building envelope, such as shading devices, especially when they are integrated with PV panels (i.e. PVSDs). To date, the absence of a holistic, comprehensive study and systemic analysis, is a major gap; what one of the major contributions of this study has managed to address. To serve this purpose, this paper laid the foundations by devising an instrument as a witness base-case to measure and monitor the impact of change in different input variables on selected output variables; in this case net-energy of the building.

Some previous research findings were challenged by findings of this study; for instance, the impact of the depth of panels on energy consumption. This was quite expected as a result of comprehensiveness of the current research project and the fact that due to various reasons previous studies had to choose a more limited scope and only focus on part of a problem. The difference also originates in the fact that despite the holistic approach of this research project, most of previous studies chose a deterministic approach and froze or factored out some of the influential input variables. As such, this research is unprecedented in its comprehensiveness and its exclusive methodological approach which is customisable, adaptable and usable in other contextual conditions and has the capability to take full parametric account of all different input variables on a selected output parameter.

The net-energy figures – which combine both electricity consumption and PV-generated electricity – can be used either separately (i.e. as an energy optimisation function), or in conjunction with other output variables in order to account for the ultimate functionalities of IFS and, for instance, to achieve

a trade-off between complexity of design, availability of products and technologies, access to specialised labour, on the one hand, and their associated costs, on the other.

The sensitivity analyses for net-energy may well reveal a significant influence of more parameters than those resulting from the same analysis of daylighting performance or energy consumption (as separately indicated in SA for those output variables, in other sections of this research project). Subject to further studies, such probable differences between net-energy and daylighting results are predicted to be caused by different roles that certain parameters play according to the assessment indicators under consideration. This means that a certain parameter could sometimes be significant under certain circumstances but less so in other occasions. These diverse findings once again confirm the need for a holistic and rather systemic approach to avoid making uninformed decisions, which, in turn, may negatively affect some other functionalities associated with IFS. This is what has been advocated for, evidenced, devised, applied, analysed and proven to be key to any all-inclusive research in this area if and when an ultimate conclusive and evidence-based outcome is intended.

Due to the set research boundaries for this study, the results are restricted to the net-energy only and this may be considered as one of the limitations of this study. Adopting a more holistic view (to include a whole lifecycle view of IFS or an optimisation strategy to strike a balance between different output variables as previously indicated in this research) could alter the results significantly. This is a very novel and under-researched area and can provide great potential for further research in the future. The fact that both the structure and the construct of this study, enabled through the systemic approach devised, potentially provides the opportunity to switch between different lifecycle views of the systems would potentially facilitate a rather effortless and straightforward path to further research in this area. Future research can also be conducted on how the systemic approach developed in this study can be built into a semi-automated or automated decision support system. It will also be interesting to investigate how artificial intelligence, machine and deep learning can be built into such a/an (semi-) automated decision support system to enhance the performance of the algorithm, and continuously improve the content of the decision process and the value of the proposed final decisions.

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References

- AKSAMIJA, A. 2016. Design methods for sustainable, high-performance building facades. *Advances in Building Energy Research*, 10, 240-262.
- ANDERSON, K., AUTHOR. 2014. *Design energy simulation for architects: guide to 3D graphics*, London, Routledge.
- ATTIA, S., BELTRÁN, L., DE HERDE, A. & HENSEN, J. 2009. "ARCHITECT FRIENDLY": A COMPARISON OF TEN DIFFERENT BUILDING PERFORMANCE SIMULATION TOOLS. *Eleventh International IBPSA Conference*. Glasgow, Scotland.
- AWADH, O. & ABUHIJLEH, B. 2013. The Impact of External Shading and Windows' Glazing and Frame on Thermal Performance of Residential House in Abu-Dhabi. *Sustainable Building conference 2013-SB13 Dubai*. Dubai, UAE.
- AYYAD, T. M. 2011. *The Impact of Building Orientation, Opening to Wall Ratio, Aspect Ratio and Envelope Materials on Buildings Energy Consumption in the Tropics*. MSc in Sustainable Design of the Built Environment, The British University in Dubai.

- CARMODY, J. 2004. *Window systems for high-performance buildings*, New York, Norton.
- CRAWLEY, D. B., HAND, J. W., KUMMERT, M. & GRIFFITH, B. T. 2008. Contrasting the capabilities of building energy performance simulation programs. *Building and Environment*, 43, 661-673.
- DASCALAKI, E. & SANTAMOURIS, M. 2002. On the potential of retrofitting scenarios for offices. *Building and Environment*, 37, 557-567.
- EEBPP 2000. Energy use in offices. Energy Consumption Guide 19. *Energy Efficiency Best Practice Programme*. London, UK.
- EGGEØ, H. 2017. *Sensitivity analysis for investigating the energy performance of a retrofitted kindergarten under different weather scenarios*. NTNU.
- EL SHERIF, S. K. 2012. *The Impact of Overhangs and Side-fins on Building Thermal Comfort, Visual Comfort and Energy Consumption in the Tropics*. MSc of Sustainable Design of Built Environment, The British University in Dubai.
- EWC 2012. FAÇADE DESIGN TOOL USER'S GUIDE. Regents of the University of Minnesota, Center for Sustainable Building Research.
- FARR, E. R., PIROOZFAR, P. A. & ROBINSON, D. 2014. BIM as a generic configurator for facilitation of customisation in the AEC industry. *Automation in Construction*, 45, 119-125.
- FREY, H. C., MOKHTARI, A. & DANISH, T. 2003. Evaluation of selected sensitivity analysis methods based upon applications to two food safety process risk models. *Prepared by North Carolina State University for Office of Risk Assessment and Cost-Benefit Analysis, US Department of Agriculture, Washington, DC*.
- HAGLUND, K. L. 2010. Decision-making Methodology & Selection Tools for High-performance Window Systems in U.S. Climates. *Building Enclosure Science & Technology Conference*. Portland, OR.
- HAMBY, D. M. 1994. A review of techniques for parameter sensitivity analysis of environmental models. *Environmental Monitoring and Assessment*, 32, 135-154.
- HEISELBERG, P., BROHUS, H., HESSELHOLT, A., RASMUSSEN, H., SEINRE, E. & THOMAS, S. 2009. Application of sensitivity analysis in design of sustainable buildings. *Renewable Energy*, 34, 2030-2036.
- HERNANDEZ, P., BURKE, K. & LEWIS, J. O. 2008. Development of energy performance benchmarks and building energy ratings for non-domestic buildings: An example for Irish primary schools. *Energy and Buildings*, 40, 249-254.
- HOPFE, C. J. 2009. *Uncertainty and sensitivity analysis in building performance simulation for decision support and design optimization*. PhD, Eindhoven University of Technology.
- HOPFE, C. J. & HENSEN, J. L. 2011. Uncertainty analysis in building performance simulation for design support. *Energy and Buildings*, 43, 2798-2805.
- HUI, S. C. M. 1998. Simulation based design tools for energy efficient buildings in Hong Kong. *Hong Kong Papers in Design and Development*, 1, 40-46.
- IBRAHEEM, Y., FARR, E. R. & PIROOZFAR, P. A. 2017a. Embedding passive intelligence into building envelopes: a review of the state-of-the-art in integrated photovoltaic shading devices. *Energy Procedia*, 111, 964-973.
- IBRAHEEM, Y., PIROOZFAR, P. A. E. & FARR, E. R. P. 2017b. Integrated Façade System for Office Buildings in Hot and Arid Climates: A Comparative Analysis. In: DASTBAZ, M., GORSE, C. & MONCASTER, A. (eds.) *Building Information Modelling, Building Performance, Design and Smart Construction*. UK: Springer International Publishing.
- IES-VE 2017. Parallel Simulations User Guide. Glasgow, UK: Integrated Environmental Solutions Ltd.
- KESIK, T. J. 2014. *Building Science Concepts* [Online]. National Institute of Building Sciences. Available: <https://www.wbdg.org/resources/buildingscienceconcepts.php> [Accessed 24/04/2016 2016].
- KIM, G., LIM, H. S., LIM, T. S., SCHAEFER, L. & KIM, J. T. 2012. Comparative advantage of an exterior shading device in thermal performance for residential buildings. *Energy and Buildings*, 46, 105-111.

- KOROLIJA, I., MARJANOVIC-HALBURD, L., ZHANG, Y. & HANBY, V. I. 2013. UK office buildings archetypal model as methodological approach in development of regression models for predicting building energy consumption from heating and cooling demands. *Energy and Buildings*, 60, 152-162.
- LAM, J. C. & HUI, S. C. M. 1996. Sensitivity analysis of energy performance of office buildings. *Building and Environment*, 31, 27-39.
- LAMNATOU, C., MONDOL, J. D., CHEMISANA, D. & MAURER, C. 2015. Modelling and simulation of Building-Integrated solar thermal systems: Behaviour of the system. *Renewable and Sustainable Energy Reviews*, 45, 36-51.
- LAU, A. K. K., SALLEH, E., LIM, C. H. & SULAIMAN, M. Y. 2016. Potential of shading devices and glazing configurations on cooling energy savings for high-rise office buildings in hot-humid climates: The case of Malaysia. *International Journal of Sustainable Built Environment*, 5, 387-399.
- LEIGHTON, D. & PINNEY, A. 1990. *A set of standard office descriptions for use in modelling studies*, Building Environmental Performance Analysis Club.
- MCLEOD, R. S., HOPFE, C. J. & KWAN, A. 2013. An investigation into future performance and overheating risks in Passivhaus dwellings. *Building and Environment*, 70, 189-209.
- NAMINI, S. B., GOLIZADEH, H., DING, G. K. C. & SHAKOURI, M. 2014. Analysis of annual energy performance of double-glazed windows in different climates. *ENERGY EFFICIENCY*.
- NGUYEN, A. T. & REITER, S. 2015. A performance comparison of sensitivity analysis methods for building energy models. *Building Simulation: An International Journal*, 8, 651-664.
- NORUŠIS, M. J. 2012. *IBM SPSS statistics 19 statistical procedures companion*, Prentice Hall.
- PIROOZFAR, P. A. E. 2008. *Mass-customisation: The Application on Design, Fabrication and Implementation (DFI) Processes of Building Envelopes*. PhD, University of Sheffield.
- POMPONI, F., BARBOSA, S. & PIROOZFAR, P. A. E. 2017. On The Intrinsic Flexibility of the Double Skin Façade: A Comparative Thermal Comfort Investigation in Tropical and Temperate Climates. *Energy Procedia*, 111, 530-539.
- POMPONI, F., FARR, E. R. P., PIROOZFAR, P. & GATES, J. R. 2015. Façade refurbishment of existing office buildings: Do conventional energy-saving interventions always work? *Journal of Building Engineering*, 3, 135-143.
- POMPONI, F. & PIROOZFAR, P. A. 2015. Double skin façade (DSF) technologies for UK office refurbishments: A systemic matchmaking practice. *Structural Survey*, 33, 372-406.
- SALTELLI, A., TARANTOLA, S., CAMPOLONGO, F. & RATTO, M. 2004. *Sensitivity analysis in practice: a guide to assessing scientific models*, John Wiley & Sons.
- SHEN, J., ZHANG, X., YANG, T., TANG, L., WU, Y., PAN, S., WU, J. & XU, P. 2016. The Early Design Stage of a Novel Solar Thermal Façade (STF) for Building Integration: Energy Performance Simulation and Socio-Economic Analysis. *Energy Procedia*, 96, 55-66.
- TIAN, W. 2013. A review of sensitivity analysis methods in building energy analysis. *Renewable and Sustainable Energy Reviews*, 20, 411-419.
- TORCELLINI, P., DERU, M., GRIFFITH, B., BENNE, K., HALVERSON, M., WINIARSKI, D. & CRAWLEY, D. DOE commercial building benchmark models. *Proceeding of*, 2008. 17-22.

¹“Tasks-IES” is an IES-VE parallel simulation tool which allows users to run multiple simulations concurrently. It provides a single user interface for displaying and managing all of the user’s simulations IES-VE 2017. *Parallel Simulations User Guide*. Glasgow, UK: Integrated Environmental Solutions Ltd.

² The ratio between the depth of the PVSD (d) and the distance between the PVSD blades (l)

³ Predicted: Refers to the mean values calculated from the estimated regression model.

⁴ Observed: Refers to the results generated through the dynamic simulation modelling.