Sensitivity analysis of energy consumption of Integrated Façade Systems: system and sub-system variables of a base case model for Building Energy Simulation

Yahya Ibraheem[1,2], Poorang Piroozfar[1], Eric R. P. Farr[3], Neil Ravenscroft[1,4]

[1] School of Environment and Technology, University of Brighton, Brighton, BN2 4GJ, United Kingdom

[2] Department of Architectural Engineering, University of Technology, Baghdad, P.O.Box: 18310, IRAQ

[3] NONAMES Design Research Foundation, 1249 F Street, San Diego, CA 92101, USA

[4] Brighton Doctoral College, University of Brighton, Brighton, BN2 4GJ, United Kingdom

ABSTRACT

Buildings Energy Simulation (BES) has been used as a substitute for more time- and cost-intensive physical modelling methods such as test cells, environmental chambers and real building monitoring. Their flexibility, ease of use and broader coverage are also very strong advantages they have over mathematical modelling for energy studies. Development of a benchmark model for BES is the first step in this methodology and bares high importance on methodological reliability and validity of the study. This paper uses a unique methodology to develop a base case model as a benchmark model for BES of highly- to fully-glazed office buildings in hot and arid climates to test the robustness of the results of the model developed. Using the base case and the variables at the system and sub-system level – as set out through the methodology developed for this study – the paper will conduct energy simulation of different scenarios and will carry out the sensitivity analysis to test out the robustness of the results. The results form part of the analysis of the research, which has been designed to provide a full account of how different combinations of a set of variables can and will influence energy generation/use, indoor comfort, and daylighting of highly- to fully-glazed office buildings in hot and arid climates.

Keywords: Sensitivity analysis, base case model, benchmarking, Building Energy Simulation (BES).

INTRODUCTION AND BACKGROUND

Integrated Façade Systems (IFS) in which different technological solutions are incorporated to improve the building performance and to lower its environmental impacts can not only offer many positive impacts on the environment but they can also play as a part in more recent strategies for integrated and holistic building design. Better control of heat gain, thereby air-conditioning loads can be administered and glare control while the use of natural light are maximised are some of the advantages of IFSs (Ibraheem et al., 2017). Incorporating High-Performance Glazing (HPG), Shading Devices (SD), and Integrated Photovoltaics (IPV) are some of the most effective strategies in designing IFSs. Despite its growing importance, the research in this area is still relatively limited. It is even more so for non-residential buildings with fully- or highly-glazed façades in hot and arid climates. Moreover, lack of systemic studies on such systems with customisable parametric characteristics which makes them flexible and accommodating for different geographical, site, building and component factors to suit other contextual conditions indicates a major gap in the knowledge in this specific area.

An established and tested methodology to carry out studies of this nature is building energy simulation (BES). BES provides a reliable, affordable and time efficient alternative to physical mock-ups, and real building testing (Hui, 1998, Anderson, 2014), and is more user-friendly, more agile, more flexible and faster than mathematical modelling. Energy performance of a

building can be analysed dynamically through BES to help understand the relationship between the design parameters and energy use in a building. BES is widely used in building performance assessment and design (Ayyad, 2011, Kim et al., 2012, Awadh and Abuhijleh, 2013, Namini et al., 2014, Lamnatou et al., 2015) both by researchers and practitioners.

Various simulation tools can be utilised to predict the energy performance of a building. 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 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, links to other programs, and availability. On the other hand, another analysis carried out by Attia et al. (2009) and Attia (2010) used more intuitive ('Architect-friendly') analysis of the BES tools. Both studies ranked IES-VE at the top of their list as a powerful dynamic simulation tool which has been widely used by different researchers (Ayyad, 2011, Kim et al., 2012, El Sherif, 2012, Awadh and Abuhijleh, 2013) just to name a few. Moreover, the modular construct and new capabilities of IES-VE allows for parametrisation of the thermal, day-lighting, artificial-lighting as well as PV generated electricity under one full suite of a software application which ensures consistency, reduces the risk of double-counting and any other discrepancies or problems which may arise as a result of software interoperability issues.

To be able to devise and carry out a systemic study on IFSs using BES, the first step is to develop a base-case scenario; what is also known as a benchmark or a building prototype. It should be flexible and customisable enough to be used as to develop different combinations of the façade components considering the unique set of possibilities and limitations as set within the study. The use of office prototypes dates back to 1990 to investigate the effect of shading devices on energy performance (Leighton and Pinney, 1990), which allows for detailed analysis of energy measures at building scale (Torcellini et al., 2008). Leading research institutions, such as U.S. Department of Energy (DoE), Lawrence Berkeley National Laboratory (LBNL), Pacific Northwest National Laboratory (PNNL), and National Renewable Energy Laboratory (NREL) have developed such models to represent 70% of offices in the United States (EWC, 2012) which have been used to investigate thermal and visual performance of fenestration systems (Haglund, 2010, Carmody, 2004). However, those models cannot be applied to similar studies in other contexts and therefore a context-specific representative model is always needed in order to represent real practices in a certain context. 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). Earlier attempts used standardised offices to provide details about the building envelop (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). In places where data or precedent studies are not available or accessible, generating benchmarks could be achieved by conducting a questionnaire survey on buildings in order to realise a prototype model to represent the buildings (Hernandez et al., 2008).

The approach developed for this study builds on comprehensiveness and inclusiveness of a wide variety of parameters where the methodology aims to develop a full parametric combination of such variables. As a result, the complexity of this study grows exponentially and requires a proportionate statistical method to gauge the impact of those changes on output variables. Sensitivity Analysis (SA) helps assess the significance of various input parameters, provides a robust tool to quantify the effect of different design parameters, and can be categorised in different ways (Hamby, 1994, Frey et al., 2003, Tian, 2013, Nguyen and Reiter, 2015). SA have been divided into mathematical approach, statistical (or probabilistic) approach or graphical assessment (Frey et al., 2003), or Local, Global or Screening (Heiselberg et al., 2009). The latter classification is the most commonly adopted in BES studies (See for instance Tian (2013) and Nguyen and Reiter (2015). Others have coupled both Sobol index and Morris's SA method with uncertainty to compensate for input parameters variation where they were not available (Hopfe and Hensen, 2011, McLeod et al., 2013). 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. Standardized Rank Regression Coefficient (SRRC), by contrast, has been used as a quantitative measure of sensitivity where the data variation range is known. 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. To address this gap, this paper seeks to achieve two different aims:

1. To devise a base-case model 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 establish and test out a statistical method by which the impact of change of those parameters can be measures and weighed against the others' so that evidence-base decisions can be formulated and design solutions can be proposed using a systemic and comprehensive approach.

RESEARCH DESIGN AND METHODOLOGY

This research utilises a methodology which is derived from modern systems theory and the application of building science to building performance (Kesik, 2014). Others investigated the building envelope as 'the system', the building as 'the super-system' and the façade components as 'the sub-system' to study customisation in AEC industry (Piroozfar, 2008) and for application of BIM to facilitate a fully customisable façade system (Farr et al., 2014). This methodological approach has benefits for both theory and practice. The study of the literature can be conducted using this methodology in a comprehensive manner. Moreover, this methodology can help classify the impacts of change of parameters at different system levels. It further enables the decision support for design and technical interventions, and practical applications of IFSs. As the first implication of this methodology, the body of literature about PV as shading devices were classified under: performance aspects, assessment methods and design considerations/configurations which are not mutually exclusive (Figure 1). With this vision at its core, this study takes the building level as 'the system'. The upper level, 'the super-system', includes the context in which building exists such as site, geographical location, climate (micro and macro), etc. and the lower level, 'the sub-system', involves the façade and its associated compartments and elements (Figure 2).

This methodological approach has then been used to develop a base case and to determine the variables at the system and sub-system levels as defined in the methodology. To validate and test the base case, energy simulation of different scenarios will be conducted.

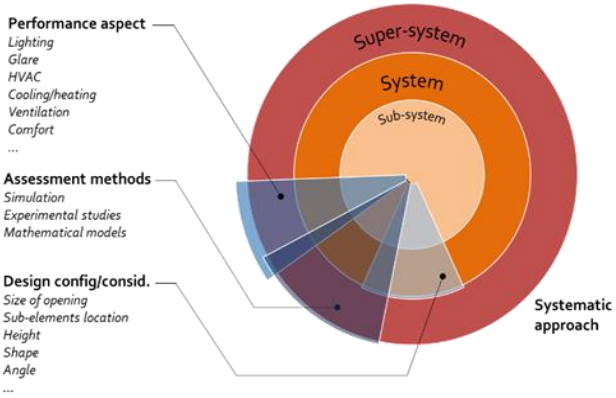

Figure 1: The identified scopes of literature superimposed on the systemic approach

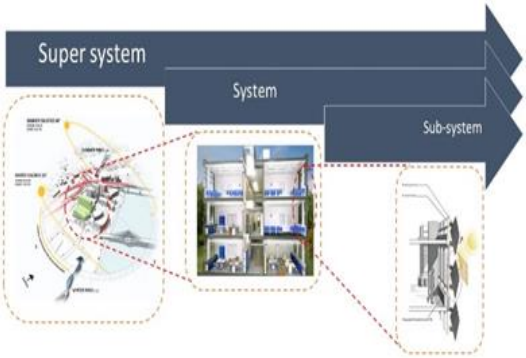

Figure 2: Systemic approach developed and deployed for this research

SA will then be carried out to demonstrate the impact of changes in input variables on output variables e.g. energy generation, energy consumption, and daylighting. In this paper, only energy consumption has been chosen as the representative indicator to demonstrate the sensitivity analysis. The model development will be elaborated on as a part of research instrument development in the data generation section.

In SA, the interdependency of the input and output variables is of paramount importance to ensure that all the variables are taken into account and no variable is unduly represented. Figure 3 demonstrates the interdependency of the variables in this study.

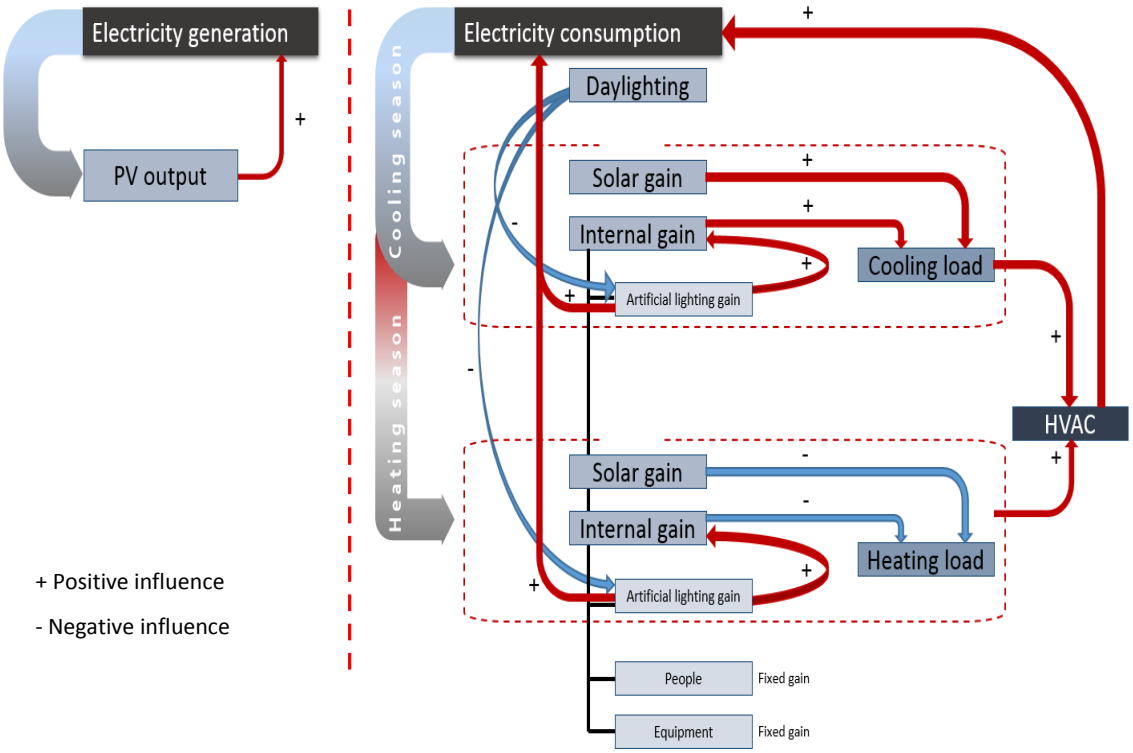

Figure 3: Interdependency of variables

DATA GENERATION

The building is a mid-sized office building with an internal cellular layout, separated by a central hallway of 2.0m wide. Dimensions of each office (or 'thermal zone' in BES) are 4mX6m. The story height is 4m. The built 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 facing the main street. This model was developed based on the results of a remote survey carried out between Nov 2016 and Feb 2017, distributed via email, social and professional media and local PSRBs to 88 professionals. 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. 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.

Few simplifications had to be applied to the final model in order to increase the accuracy of the intended results of the simulations (Figure 4). This helped eliminate variations that did not have any implications on the thermal performance of the building or where reaching consensus in the survey was not possible, such as the location of the services (wet zones) and the vertical access. The vertical access and the services (wet zones) were not included in the model due to the variation they may have from one design to another. This makes it hard to represent one identical occurrence with any reasonable frequency. Similar

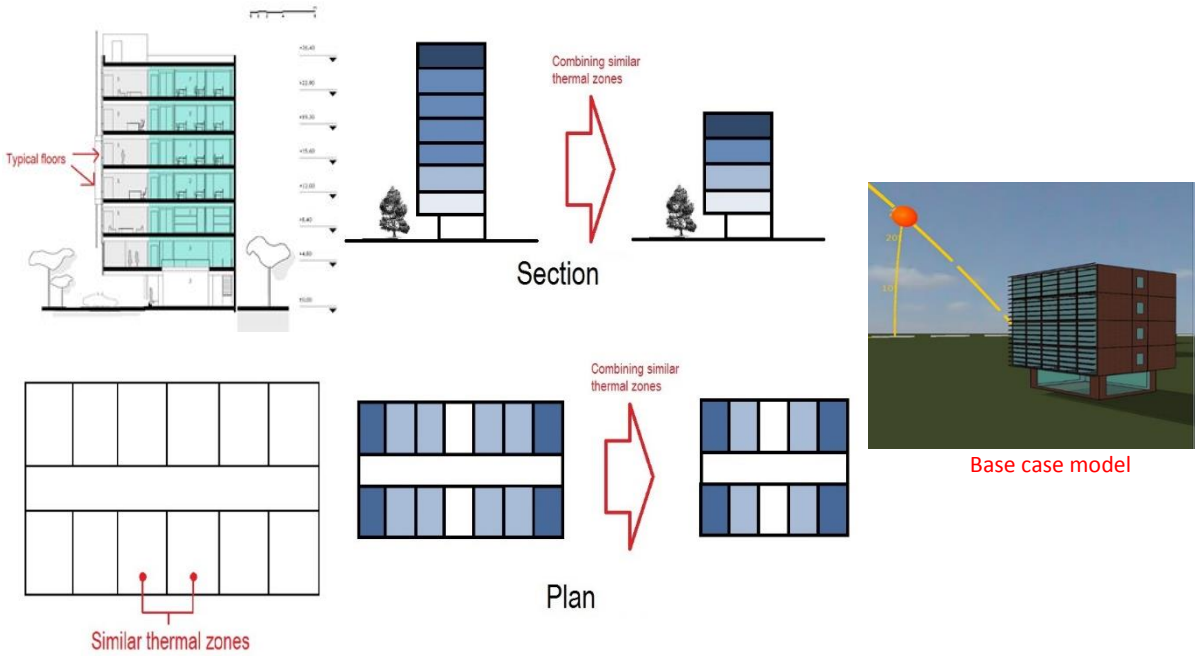

Figure 4: Interdependency of variables

approaches have been utilised for developing benchmark models, by other researchers such as Pomponi and Piroozfar (2015). From the thermal zoning point of view, in the layout, the number of the thermal zone variations should cover all the possible unique zone characteristics to facilitate a comprehensive, accurate and detailed analysis. Therefore, the common practice in building physics is to omit similar zones (vertically and horizontally) to the extent that the model includes only one of each particular thermal zone. Therefore,

another round of simplification was made to the model on both the number of the floors and the plan layout.

The model geometry was created in ModelIT-IES. The glazing systems created in LBNL Window 7.5, were imported to APcd-IES to be added to the model. Other construction materials of external walls and internal partitions were set up in APcd-IES. The model uses Baghdad weather file is set up in APLocate-IES for feeding into Apache, Radiance and SunCast. The optical properties of the glazing systems were set up in Radiance-IES. Occupancy profiles, internal gains, HVAC systems, dimming profiles, weekly and daily profiles were also set up in APpro-IES. Subsequently the simulation file is set up to run SunCast for solar shading calculations and Radiance illuminance calculations whose output would then be used to integrate within the thermal calculations in Apache. All simulations are organised in Tasks-IES[1]. Simulations were run in batches on six computers and the results were organised in VistaPro-IES to be used for analysis in Microsoft Excel™. Subsequently a database was prepared for IBM SPSS™ to run sensitivity analysis.

DATA ANALYSIS AND RESULTS

The detailed analysis of all the assessment indicators under investigation were conducted in three phases, starting with inferential data analysis as phase one, followed by decisional synopses (phase two) and finally Sensitivity Analysis SA as phase three, which is the main focus of this paper (Figure 5).

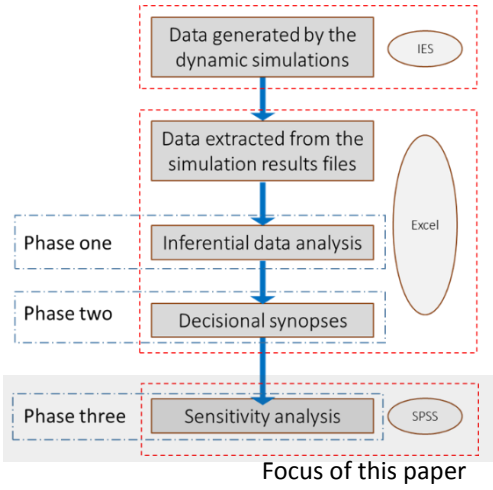

Figure 5: Analysis stages of the study and the focus of this paper

Classification of all the variables under investigation was carried out based on the systemic approach. Variables at system level were clustered separately as Orientation and Window to Wall Ratio (WWR). Sub-system variables were clustered into sub-groups. Those are depth of panels, d/l (d=depth of the PVSD and l=distance between the PVSDs), angle of inclination and glazing systems. This is summarised in Figure 6.

The same steps are followed for each of the output parameter in this phase; 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 i.e. $UDI_{300\text{-}3000\ lux}$ for the daylight sensitivity analysis. In this paper, only electricity consumption will be presented. The data was prepared for the analysis in SPSS by setting up the type of variables. The variable interdependencies were applied. The 'measure level' of each variable was also specified. In this study the independent variables are Nominal variables while the dependent variables are all Scale variables. The input variables represent the predictors for which importance graph is generated. This is calculated to account for the sensitivity of the output when the input variables change, taking into account changing of other inputs at the same time.

[1] "Tasks-IES" is an IES-VE parallel simulation tool which allows for multiple simulation runs 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.

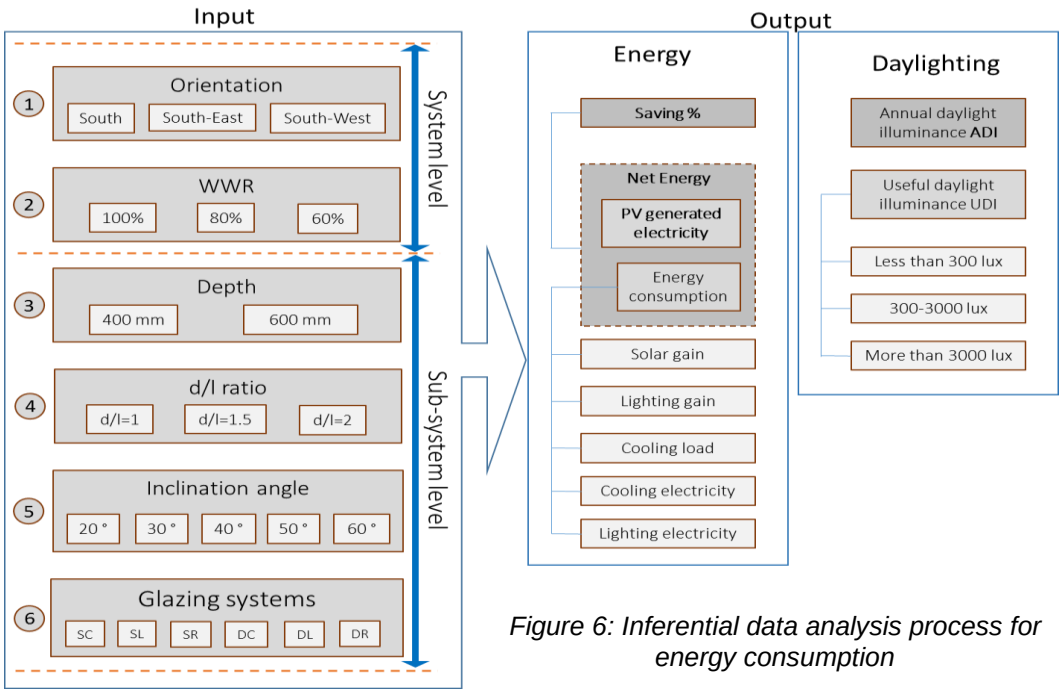

Figure 6: Inferential data analysis process for energy consumption

The predictor importance view is then plotted. This view shows the predictors in the final model in rank order of importance. The results were analysed using a linear regression modelling with 95% confidence interval. For linear models, 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). To check that the assumption of linearity is correct and the model can predict the output, a plot of the predicted results (based on the regression model) vs. observed results (extracted from the simulations) was generated. The closer the scatter plot is to 45°, the more accurate the model will be (Norušis, 2012).

In order to account for the reliability and validity of the models and results in this study, a verification process needs to be followed to ensure that the method of analysis can accurately predict the results and the models are accurate to satisfactory levels. This was followed within the SA by examining the model accuracy which is deemed to be a high-level summary of the model and its fit. The value of the displayed accuracy on the model summary chart is 100 × the adjusted R^2. Models with R^2 of less than 0.5 indicate no better than random occurrences.

Finally, One-At-A-Time (OAAT) analysis of the mean values of variations of each parameter were analysed in order to zoom-in on each of the parameters and to demonstrate the changes that correspond to each of their variations.

The results of energy consumption from all the 1620 dynamic simulation models were analysed in SPSS using a linear regression modelling with 95% confidence interval. Figure 7 shows the predicted vs. observed graph, indicating a high accuracy of the model, verified by the model summary in Figure 8 where the adjusted R^2 coefficient is 0.972. The level of impact of variations in each of the parameters on energy consumption is shown in Figure 9

where the importance of the parameters are quantified and ranked. It is evident that glazing system (HPG) is the most important parameter because its variation has the highest influence on energy consumption figures (more than 80%), followed by d/l ratio in the second place, with significantly lower impact of nearly 13%. The least influential parameters are WWR, angle of inclination and orientation scoring at 3%, 2% and 1% respectively. It can be noted that the depth of the PVSDs has no effect on energy consumption as it did not score in the sensitivity analysis.

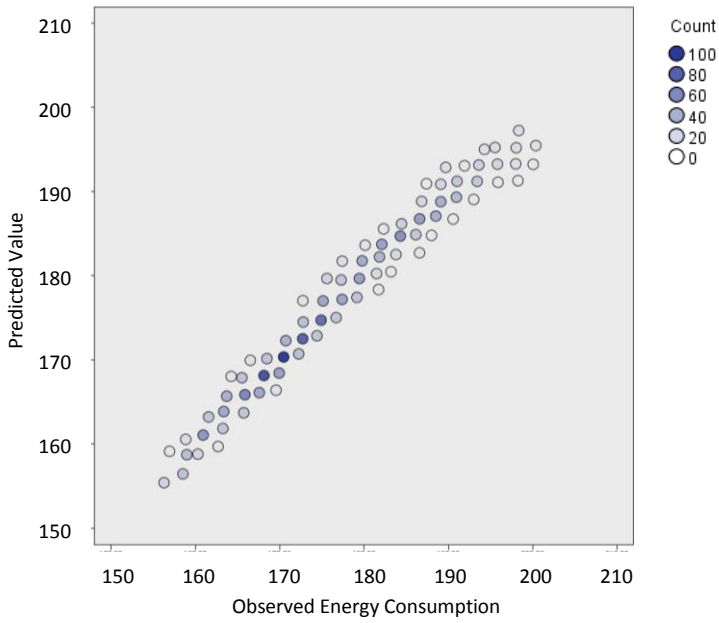

Figure7: Predicted by observed plot

Target	Electricity Consumption
Automatic Data Preparation	On
Model Selection Method	Forward Stepwise
Information Criterion	1,749.854

The information criterion is used to compare to models. Models with smaller information criterion values fit better.

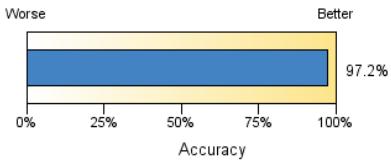

Figure 8: Model Summary

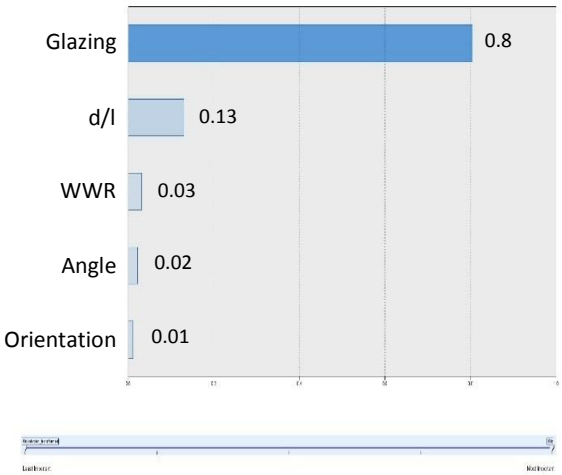

Figure 9: Predictor importance for Electricity Consumption

OAAT graphs of the influence of individual input variables on energy consumption are shown in Figure 10. On the x-axis, the variations of each parameter are plotted with their influence on the energy consumption shown on the y-axis. It can be seen that the depth has negligible influence where the red line that connects the mean values of the two different depths (400mm and 600mm) is almost horizontal. On the contrary, glazing is extremely influential. This is evident from the fluctuation of the mean values of each type of glazing system. In addition, the figure shows that d/l ratio, followed by angle, WWR and orientation do have some impact but definitely less of influence. The findings of the analysis of the graphs in the figure confirms the findings from the sensitivity analysis.

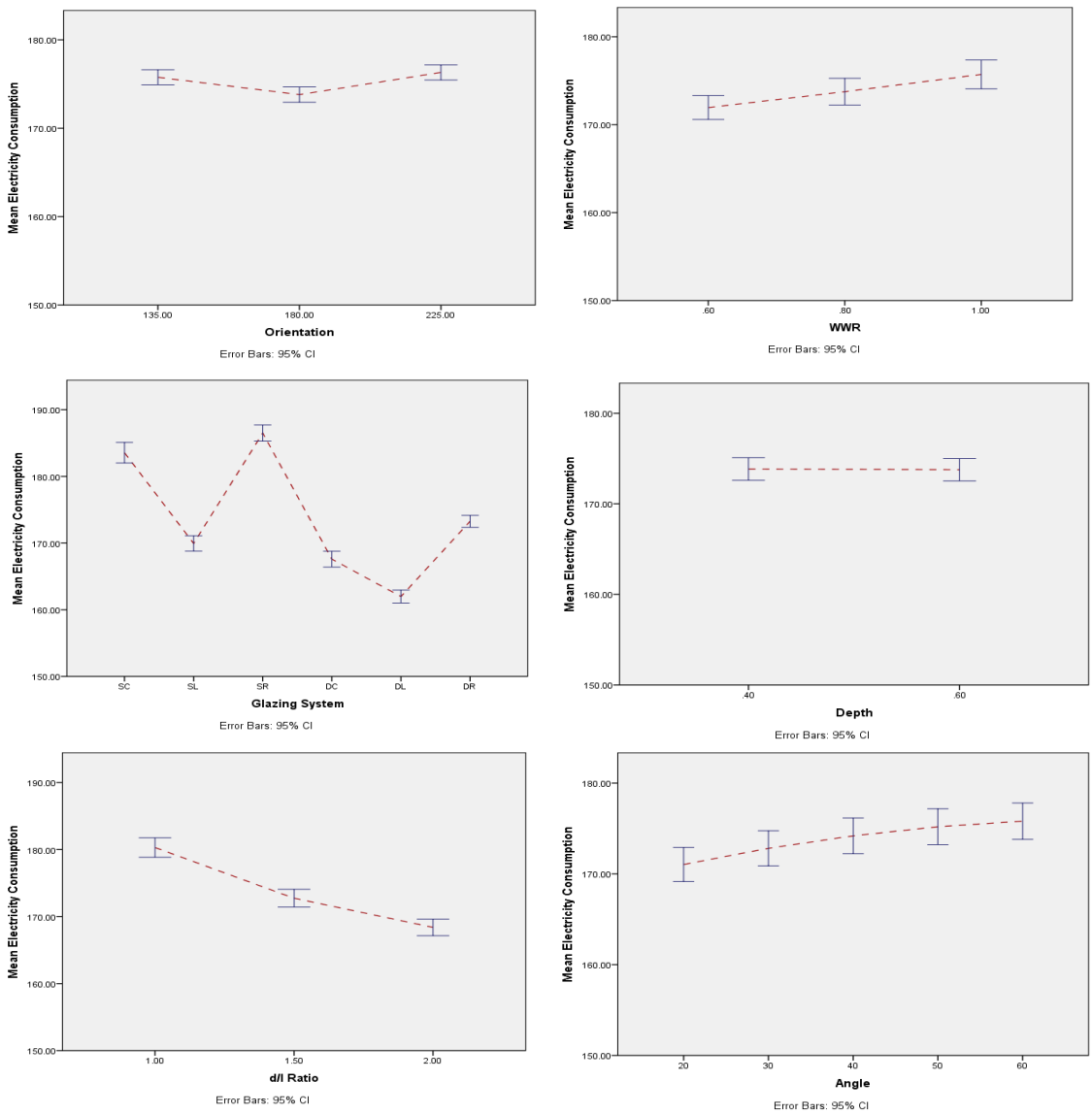

Figure 10: OAAT graphs of the mean values of energy consumption

DISCUSSION OF FINDINGS AND CONCLUSION

Three different building orientations have been investigated in this study: South, South-east and South-west. Combinations at South orientation are less energy intensive compared to those at south-east and south-west. In the sensitivity analysis, orientation was found the least influential variable. For WWR, variations of 60%, 80% and 100% were tested. The trend of the mean electricity consumption shows that the bigger the WWR is, the more energy intensive the combinations are, reflecting a quite significant variation in the range of mean values. The SA substantiates the fact that WWR is significant in its effect on energy consumption but as a second most impactful parameter. Surely this correlates to the amount of the solar gain and the influence of that on increasing the cooling loads thereby increasing the electricity consumption. The depth has the minimal effect, as the OAAT figure shows that the change of the depth from 400mm to 600mm has a negligible influence on energy consumption. Some previous studies suggest otherwise. For example, Kang et al. (2012) assert that the depth is more effective. Such contradiction could be because that study mainly focused on the electricity generation by PV panels and did not include any

other aspects such as cooling loads or daylighting, which can significantly contribute to electricity consumption. The d/l varied from 1, to 1.5 and 2. It was found that the mean value of electricity consumption negatively correlates to the d/l ratio, as shown in OAAT figure, with d/l scoring the second most influential variable on electricity consumption. This is because increasing the distance between the PVSDs will allow for more sun beam to penetrate into building and results in higher solar gains, hence introducing more cooling loads. When examining the angle of inclination for its range of variations (20, 30, 40, 50 and 60), OAAT figure of the mean values of electricity consumption shows a nearly steady increase in the electricity consumption with an increase in the angle of inclination. Although increasing the angle of inclination of the PVSDs reduces the solar gain, it negatively affects the dimming of the internal artificial lights, which in turn, results in additional internal heat gain that contributes to cooling loads, hence an increase in the electricity consumption. In all cases, it was found that 20° seems to be the optimum angle of inclination, but that is only true when the electricity consumption figure was considered on its own. The SA shows that the angle of inclination is the third most influential parameter on electricity consumption. In OAAT analysis of the electricity consumption, the most obvious observation is the wide range of variation of the energy use due to variation of different glazing systems. It also shows that Single-clear (SC) and Single-reflective (SR) are the most energy intensive glazing systems; SC for being the system with the least improved thermal properties and SR for being the system with its unique optical properties. Low-e glazing – both single (SL) and double (DL) – seem to be better choices for energy-efficient purposes than double-clear (DC). Double-low e (DL) shows the most improved combination. The SA of electricity consumption proves that varying the glazing system accounts for 80% of influence on electricity consumption.

It was also shown, with the help of sensitivity analysis, that the effect of alteration of each input variable on energy consumption can be quantified to allow for more accurate decisions to be made for optimum design solutions. Results from the sensitivity analysis show that parameters at sub-system level have a higher influence on the outcome than those at the system level. These results help understand where design efforts should be heading if a successful application of IFS is intended.

The findings of this study conformed to some of the previous research findings. The previous research in this filed seems to be restricted to study of individual components of IFS, 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 envelop, such as shading devices, especially when they are integrated with PVSDs. The absence of a holistic, comprehensive study and systemic analysis is one of the major contributions of this study for which this paper laid the foundations by devising an instrument as a witness case to measure and monitor the impact of change in different input variables on selected output variables; in this case energy consumption of the building.

On the other hand, some findings of this study contradicted previous research findings (e.g. the effect of the depth of PVSDs on energy consumption). This is not unexpected because previous research has had limited scope and has only focused on part of a problem in an actual setting with a deterministic approach to freeze or factor out other influential parameters. By contrast, the research, is unprecedented in its comprehensiveness and its unique methodological approach which is customisable, adaptable and usable in other

contextual conditions and has the capability to take full account of parametric combination of all different input variables on a selected output parameter.

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

ACKNOWLEDGEMENT

This research has been sponsored by Iraqi Ministry of Higher Education and Scientific Research.

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