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CALIBRATION OF NUMERICAL SIMULATIONS MODELING OF NONRESIDENTIAL BUILDING IN HOT HUMID CLIMATE REGION

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ABSTRACT

In Egypt, energy use in buildings has grown in the last 20 years mainly due to the increases in population, number of households, number of offices, as well as increase in service demand, such as more air conditioners and computers. The aim of this study is to create a thermal model for Egyptian office building to represent actual building energy consumption trying the best fit for user behaviors and actual weather data.

The simulation model was created using IES VE 2014 and calibrated against measured data for an Egyptian office. The calibration process, intermediate and final results are presented and illustrated for a range of output parameters including internal temperatures, CO_2, lighting, equipment, and cooling energy use for different weather periods.

This calibrated model can then be used together with uncertainty analysis to evaluate future building upgrade scenarios in order to help improve the energy performance for Egyptian office buildings.

INTRODUCTION

Egypt is the largest non-OPEC oil producer in Africa and the second-largest dry natural gas producer on the continent. The government continues to fund energy subsidies, which cost the government $26 billion in 2012. Where became necessary to reduce the power consumption in buildings.

One of the best tools to inform measures to reduce the electric power consumption in building is numerical simulations. Numerical simulations are becoming more and more a key step in designing integrated building energy systems.

Complete building energy models provide a means of understanding building operation as well as optimizing performance. Energy Simulation tools have been used since the early 1960’s to analyse the thermal behaviour and energy consumption in buildings. Initially, they were primarily used in the design stage to optimize the design of the building envelope and HVAC systems. More recently, building energy simulation (BES) models have been employed in the post-construction stage of the building life cycle for a number of purposes. But results provided by software would not be worthwhile if the base case was not correctly calibrated. The virtual model of the building under analysis must represent realistic thermal and energy behaviour of that building.*" Since the calibration problem is itself over-parameterized and under-determined, it is impossible to find an exact, unique solutio*n" Daniel Coakley 2011. To achieve this objective, real data must be collected measured performance data must compared with those values predicted by the software. In this task, the user finds out many input parameters that can be adjusted to obtain the reference results. Even when the total energy consumption is calibrated, the major question remains is the end-use well represented by the model.

As the simulation tool is used for retrofit analyses, it is very important that the software accurately predict the energy used by the building. The annual and the monthly energy consumption may be quite well estimated but the end-use composition (lights, air-conditioning, plug loads, etc.) can be far away from reality. In this case, any retrofit analysis will provide incorrect results. Therefore, it is important to properly establish the model through a robust calibration process.

It must also be recognised that the building use pattern is inherently variable and stochastic in nature over both short timescales (hour by hour) and over the lifetime of the building, similarly weather is variable. These variations and uncertainties in user behaviour, operating parameters and weather must be considered in modelling the current and future performance of buildings.

LITERATURE REVIEW

There have been significant efforts at model calibration and incorporation of uncertainties in building simulation models, there has also been some previous work on the Egyptian context. These previous works are reviewed here.

Macdonald et al. in 1999 have integrated two methods for uncertainty analysis in the ESP-r program first is differential sensitivity and second Monte Carlo analysis. However, the authors recognize that the sensitivity analysis results can be complicated for an inexperienced user.

F. Simon and R. Lamberts in 2005 have presents the methodology for calibration of building simulation models divided into six stages. The first steps of a methodology for calibration of building simulation models through the definition of the parameters that most affect the main electric end-uses of a building. The next steps are directed to calibrate the envelope variables.

Paul Raftery et al. in 2009 mentioned that Three standards govern the bounds within which a simulation model can be considered calibrated; these are ASHRAE Guideline 14 2002, the International Performance Measurement and Verification Protocol (IPMVP) and the Federal Energy Management Program (FEMP) Monitoring and Verification Guide. The author proposes a novel methodology for calibrating building energy simulation (BES) models through the use of an evidence-based approach and detailed simulation modelling.

Daniel Coakley et al. in 2011 outline a methodology for the calibration of detailed building energy simulation (BES) models using an analytical optimization approach. The approach combines evidence-based model development with statistical Monte-Carlo based optimization techniques and due to the many degrees of freedom that may produce good calibration overall even though the individual parameters may be incorrectly identified. Therefore, this step involves ranking the solutions based on statistical goodness-of-fit (GOF) criteria, Farhang Tahmasebi and Ardeshir Mahdavi in 2013 focus on a specific problem faced by a monitoring-based optimization-assisted simulation calibration: In many realistic circumstances, it is not possible to install monitoring systems with full building coverage. To address this issue, they explore the potential of simulation model calibration based on monitored data obtained from a selected sub-set of building zones.

Andreas Kamilaris et al. in 2014 make a literature review studied the miscellaneous electric loads in offices. They stated that In 2008, commercial buildings consumed about 20% of total U.S. primary energy (18.3 Quadrillion BTUs per year), a figure projected to grow by 36% at 2030 (from 2008). Miscellaneous electric loads (MELs) account for more than 20% of primary energy used in commercial buildings, and this percentage projected to increase by 40% in the next 20 years; this has made MELs one of the fastest growing load categories. This growth relates to the fact that PCs and other office devices are penetrating office buildings, creating a large installed base of computing equipment.

Shady Attia et al. in 2014 investigated the use of building performance simulation tools as a method of informing the design decision of NZEBs (Net Zero Energy Buildings) in the Egyptian context. This is the first simulation-based decision support tool for early stages of zero energy building design in Egypt. The tool can help achieve the energy performance goal while exploring different ranges of a thermal comfort in hot climates to achieve the performance objective.

Research gap, focus and aims of this paper

There is then a lack of prior work on the characterisation of, performance of, and calibration of models of, current and future non-residential buildings in Egypt.

Specifically, the information available for office buildings in Egypt is either incomplete or outdated. Almost no current published work describes the status of energy consumption in the office building sector or representative models including the pattern of use of air-conditioners, lighting, equipment and other appliances in office buildings. This information is critical in estimating the space cooling loads and their influence on the electric load profile. There is a need for validated data on the representative load patterns of air-conditioned offices. Applying this information will help in future studies in estimating the energy effect of the new Egyptian energy standard in order to reform the building energy sector, since the cost of saving energy much less expensive than producing energy by building a new power plant.

The aim of this paper is to begin to address this gap, to establish a set of data for a typical Egyptian office building and to use that dataset to carry out a robust calibration process and create a representative model as a base case for future research and design studies.

METHODOLOGY

In order to understand the natural of the Egyptian office building a case study model must be developed and calibrate using some monitored data. An HR (Human Recourses) building was selected to be modelled as a representative Egyptian office building. The model development was in four main steps, the first step was data gathering, the second step to create a base model, after that third step was to perform a parametric sensitivity analysis, and finally the fourth step was to apply the calibration method. The process followed the steps outlined in the work of Fernando et al. 2005 & Farhang et al. 2012.

Data Gathering

In order to create an accurate representation of the chosen building within the BES (Building Energy Simulation) software, it is necessary to first gather and record the building geometry data, environmental & weather data, HVAC system specifications and detailed load/occupancy schedules. Building geometry and building envelope data was collected from the construction consultant for the building.

In order to complete the energy audit more data about plug loads, occupancy, lighting and schedules should be known. It must also be recognised that the building use pattern is inherently variable and stochastic in nature over both short timescales (hour by hour) and over the lifetime of the building, similarly weather is variable. These variations in user behaviour, operating parameters and weather must be considered in modelling the current and future performance of a building.

In order to fill this gap of the data some variables should be monitored e.g. dry bulb temperature, Humidity sensor, kWh meter, CO2 Sensor and lighting Sensor.

After necessary information had been collected, an initial BES model will construct using building simulation tool. In general, the base model represents the building as it would have been built according to design standards and fitted with equipment/system with designed efficiencies. Thus, the base model embodies real data and where necessary, initial estimates of the properties of the real building that will be subsequently refined by calibration.

In general a base model of a large building will contain hundreds of parameters. The parameters which the user will have to input are categorized into three main groups – building properties, HVAC systems, and HVAC refrigeration plant. By categorizing the input design parameters, a clear picture of the energy-related factors can be established. Each of the three main groups can be further sub-divided into different sub-groups.

Parametric analysis

When performing building energy simulations, certain energy changes from the input variables are more significant than others. Such selected inputs should, therefore, be given particular attention during modelling. In addition, high-sensitivity elements are important from both technical and economic point of view and should be designed with utmost care if optimization of the system performance is to be achieved. For this purpose, parametric analysis is carried out involving sensitivity and uncertainty analyses of the base model.

The sensitivity analysis used here involved changing the input values for each variable under analysis. The influence of each parameter is calculated from equation one below, that represents the “influence coefficient”.

$$\mathrm{IC} = \frac{\Delta \mathrm{OP} \div \mathrm{OP_{BC}}}{\Delta \mathrm{IP} \div \mathrm{IP_{BC}}} \qquad (1)$$

Where ΔOP and ΔIP are changes in output and input, respectively; and $\mathrm{OP_{BC}}$ and $\mathrm{IP_{BC}}$ are the output and the input base case values. This sensitivity coefficient is dimensionless and represents the percentage of changing in the output due to a percentage of perturbation in the input.

The influence coefficient is essentially a ratio of the percentage change (with respect to the base case value) in computed output (i.e., total annual building electricity use) to the percentage change in input design parameter. The magnitude of the influence coefficient indicates how sensitive the computed output would be in response to changes made to the input design parameter. Furthermore, the individual IC could help building designers get some idea about the potential energy savings of prospective energy conservation measures (ECMs). In order to ascertain the relative sensitivity of the parameters, mean and standard deviation of the ICs can be determined. It is envisaged that the mean ICs could give a general indication of the likely sensitivity of energy use to changes in the design parameters for the building.

Calibration

Building energy simulation programs may require hundreds of model inputs, many of which have high levels of uncertainty because they rely on software default assumptions and imperfect field data collection procedures. Therefore, accurate model predictions are not guaranteed, even if the underlying physical algorithms are accurate, because uncertainty in model inputs propagates uncertainty in the model output. That is; perfect agreement between model predictions and measured output data cannot be expected if the input parameter values have significant uncertainties or errors. The building model is said to be “calibrated” once a specified level of agreement is achieved between model-predicted and measured data.

For the purpose of building performance analysis, the error can be defined as the difference between a predicted value and a measured value.

Two model evaluation statistics were used to quantify the error in the cost function. The first statistic, CV(RMSD), aggregates time step errors over the runtime into a single dimensionless number:

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{i=1}^{n}(m_i - s_i)^2}{n}} \qquad (2)$$

$$\mathrm{CV(RMSD)} = \frac{\mathrm{RMSD}}{\bar{m}} . 100 \qquad (3)$$

The other model evaluation statistic used in the cost function is the "coefficient of determination" denoted by R^2. The coefficient of determination describes the proportion of the variance in measured data explained by the model. The coefficient of determination ranges from 0 to 1. An R^2 of 1.0 indicates that the regression line perfectly fits the data. Therefore, R^2 value is to be maximized in the optimization process. R^2 has been calculated via Equation 4.

$$R^2 = \left(\frac{n \sum m_i s_i - \sum m_i \sum s_i}{\sqrt{\left(n \sum m_i^2 - (\sum m_i)^2\right)\left(n \sum s_i^2 - (\sum s_i)^2\right)}} \right)^2 \qquad (4)$$

In Equations 1 to 3, m_i is the measured variable at each time step, s_i is simulated variable at each time step, n is the total number of time steps, and m is the mean of the measured values. The defined cost function f takes into account the CV(RMSD) and R^2 in an equally weighted manner in Equation 5.

$$f_i = 0.5 \,.\, CV(RMSD)_i + 0.5 \,.\, (1 - R_i^2) \,.\, \frac{CV(RMSD)_{ini}}{(1 - R_{ini}^2)} \qquad (5)$$

In Equation 4, $CV(RMSD)_i$ is the coefficient of variation of the RMSD at each optimization iteration, R_i is the coefficient of determination at each optimization iteration, $CV(RMSD)_{ini}$ is the coefficient of variation of the RMSD of the initial model, and R_{ini} is the coefficient of determination of the initial model.

CASE STUDY – DATA GATHERING

Weather

The climate in Egypt is moderate; it is mostly hot or warm during the day, and cool at night. In the coastal regions, daytime average temperatures range between a minimum 14 °C in winter and maximum 34 °C in summer. In deserts, the temperatures vary considerably, especially in summer; when they may range from 7 °C at night, to 52 °C during the day. While the winter temperatures in deserts do not fluctuate so wildly, they can be as low as 0 °C at night, and as high as 18 °C during the day. Egypt receives less than 80 mm of precipitation annually in most areas, although in the coastal areas it reaches 200 mm. It hardly ever rains during the summer.

In order to calibrate the model using actual weather file the weather file EPW. file Downloaded from The energy plus was modified by the actual measured dry bulb temperature from a weather station in another location in Alexandria for 2014. The Figure 1shows the Dry bulb temperature through 2014 in Alexandria, Egypt. Figure 1 shows the variation of the dry bulb temperature for Alexandria, Egypt throughout 2014. Augest was the highest month and the maximum temperature was 34 °C.

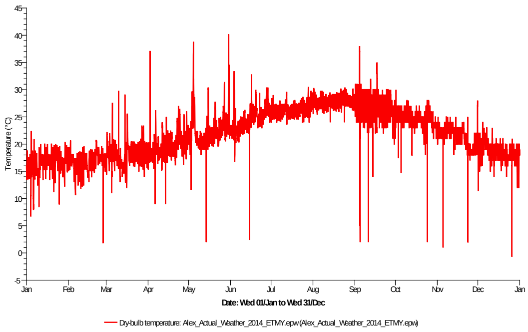

Figure 1 (Dry Bulb Temperature in 2014)

Building Description

The HR building was built in the mid-nineties of the twentieth century. This HR building serves a one of the biggest universities in Alexandria, Egypt Figure 2. It consists of three typical floors contains 25 offices of different areas, the outline of one of this floors are shown in Figure 3. Figure 4 & Figure 5 shows the building picture in simulation and reality. All the building specifications are shown in Table 1.

Occupancy and measured load profiles

The 'typical' schedules for the occupancy, equipment and lighting use for winter and summer seasons were estimated based on monitored data and are shown in (**Figure** 6,7&8). The graphs for occupancy profile shows more than one category large offices with one occupancy, small offices with one or two occupancy will the large offices with three and more occupancy with density 5 m^2/person. These graphs show the modulation with reference to the maximum values of equipment 150 W/ computer + printer, 4 w/m^2 for miscellanies equipment and 10 W/m^2 for lighting load.

Occupancy, indoor environmental conditions and power use varied substantially from office to office, typical values were selected and used in the calibration process however the ranges are important and will be useful as inputs to uncertainty analysis in future studies.

Figure 2 (Building Location Map)

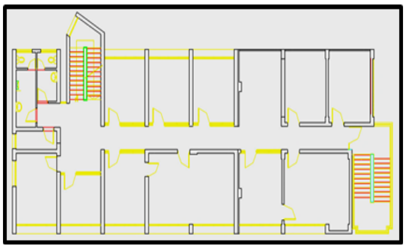

Figure 3 (Typical Floor Plan of the Model)

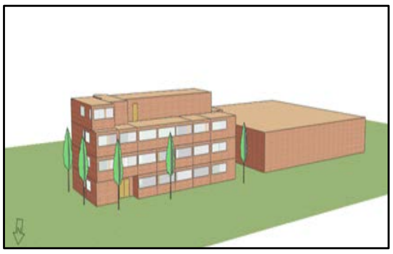

Figure 4 (Simulation Picture for the Building)

Figure 5 (Real Picture for the Building)

Table 1 (Building Description of the Simulation Model)

Building Configurations			
Total Floor Area		1090	m2
Floor to Floor Height		2.8	m2
Number of Floors		3	
Window to Wall ratio		16.5	%
Construction			
Category		U-value ($W/m^2 \cdot K$)	Thickness (mm)
Roof		0.3914	340
Internal Ceiling/Floor		2.1415	250
Door		2.1944	40
External Window		5.3223	6
Internal Window		3.6643	6
Internal Partition		2.1815	90
External Wall		2.0194	200
Air Conditioning			
Split Unit 1.5HP		Cooling Capacity	Power
EER(KW/KW)	3.27	4.1 kW	1235 W
		14000 BTU/hr	
Split Unit 2.5HP		Cooling Capacity	Power
EER(KW/KW)	2.96	5.2 kW	2880 W
		18000 BTU/hr	
Split Unit 4HP		Cooling Capacity	Power
EER(KW/KW)	2.68	8.79 kW	3275 W
		30000 BTU/hr	

CASE STUDY – CALIBRATION

Calibrating a computer simulation of a real building for a specific year/period requires the use of actual weather data in the analysis. Actual weather data should collected from a source such as weather station data. The physical location of the weather station should be the closest available to the project site. Hourly dry bulb temperature from a weather station in the same country but not in the same region was used to update a real-year weather data file based on local data instead of using a typical meteorological year weather data EPW file obtained from Energy Plus.

Once all necessary information is collected, the data gathered was then used in IES-VE software to create the initial model In general, the initial model represents the building as it would have been built according to design standards and fitted with equipment/system with designed efficiencies. Thus, the initial model embodies real data and where necessary, initial estimates of the properties of the real building, which is subsequently refined by calibration.

As the initial model of a large building will contain hundreds of parameters. The uncertain parameters, which input are categorized into two main groups – building properties and HVAC system as shown inTable 1. (Joseph et al. 1997 & Joseph et al 2008)

Parametric analyses were then conducted for key energy variables for the representative office, across typical ranges of values as described in Table 2. The most effective variables based on influence coefficient which had mean deviation greater than 0.05 are, in order of decreasing influence: Infiltration rate , Equipment, Lighting, SEER, cooling set point temperature, and window shading coefficient.

Table 2 (Uncertain Input Parameters and There Ranges)

Variables		Units	Initial Case Value	Min Value	Max Value
Building Properties	*Absorbance of Roof*	----------	0.6	0	1
	U-value of Roof	$W/m^2.K$	1.6083	0.391	2.125
	Absorbance of Wall	----------	0.7	0	1
	U-value of Wall	$W/m^2.K$	2	0.513	4.208
	U-value of Internal Wall	$W/m^2.K$	2.18	0.445	3.139
	Shading Coefficient of Window	----------	0.6	0.2	0.95
	Transmittance of Windows	----------	0.78	0	0.93
	Equipment Load (Computers)	*W*	150	50	300
	Equipment Load (Computers) D.F	----------	0.7	0.1	1
	Equipment Load (Miscel.)	W/m^2	4	1	10
	Equipment Load (Miscel.) D.F	----------	0.7	0.1	1
	Lighting Load	W/m^2	10	5	30
	Lighting Load (D.F)	----------	0.6	0.1	1
	Infiltration Rate	$L/S.m^2$	1.1	0.5	10
HVAC System	*SEER*	*kW / kW*	7	2	8.5
	Cooling Set point temperature	°C	21	16	26

By applying the calibration method for the Initial model as shown in Table 3, the first step in the calibration of the intial model was to establish the infiltration rates which gave best agreement with measured CO2 levels, resulting in a best fit (R2 = 0.67, RSMD = 18.6%) value of 0.8 l/s.m2 which was then applied in model 1 and subsequent models. Since the HVAC and equipment were not able to be separately monitored, the winter period (no AC) was used to calibrate the equipment load, and the summer period (AC) for AC related parameters. The next step then was to establish the best fit equipment load which gave best agreement with measured power consumption in kWh during December (no AC), resulting in a best fit (R2 = 0.95, RSMD = 26.9%) value of 150 w for each computer and 4.5 W/m2 in model 2.

After that the Cooling Set Point Temperature was calibrated to the measured inside resultant temperature through August, resulting in a best fit (R^2 = 0.82, RSMD = 4.5%) of value 21 °C to get model 3. Then the HVAC SEER was calibrated using the measured power consumption in kWh during June (AC) resulting in a best fit (R^2 = 0.93, RSMD = 37.7%) for SEER of value 8 in model 4. External Window Shading Coefficient calibrated using resultant temperature resulted in a best fit (R^2 = 0.81, RSMD = 5.3%) value of 0.8 (model 5). Finally lighting load was calibrated resulting in a best fit (R^2 = 0.75, RSMD = 37.7%) to get to the final model.

RESULTS AND DISCUSSION

Following the calibration process, the following results were obtained: The two graphs Figure 9 & Figure 10 compare the Equipment and Air conditions power consumption between the simulation model and measured data, While Figure 11 Compare the lighting power consumption between the simulation model and measured data.

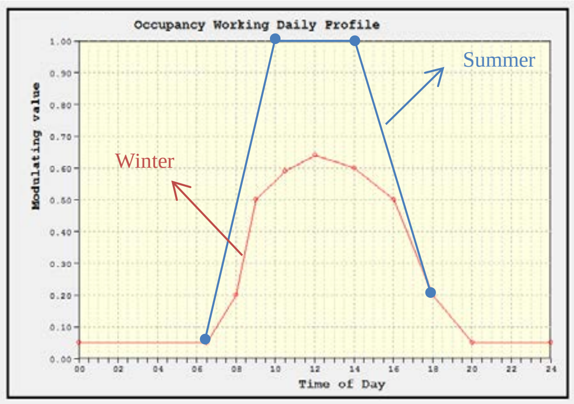

Figure 6 (winter & Summer Occupancy Working Daily Profile)

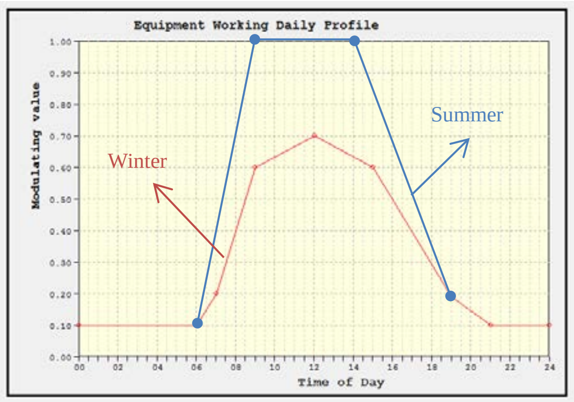

Figure 7 (winter & Summer Equipment Working Daily Profile)

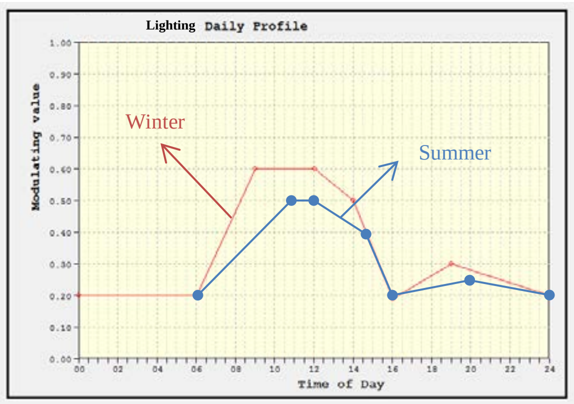

Figure 8 (winter & Summer Lighting Working Daily Profile)

Figure 12 & Figure 13 compare measured and simulated inside dry resultant temperature for a one of the offices while Figure 14 shows the comparison of the CO2 percent in the same office.

The defined cost function f takes into account the CV(RMSD) and R2 in an equally weighted by applying the cost function on the power consumption kWh resulting f = 42.4 for june while f = 26.0 for december , on the other hand by appling the function on the inside dry resultant temprature gave f = 4.77.

Figure 15 shows a comparison between model output and the monitored kWh for the Equipment & HVAC power consumption through June, September, October, November and December. Also comparison between model output and monitored kWh for the lighting power consumption through July and august.

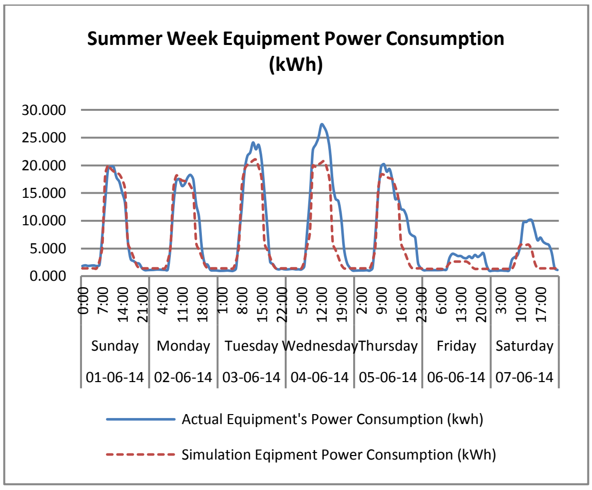

Figure 9 (Summer Week Equipment & A/C Power Consumption)

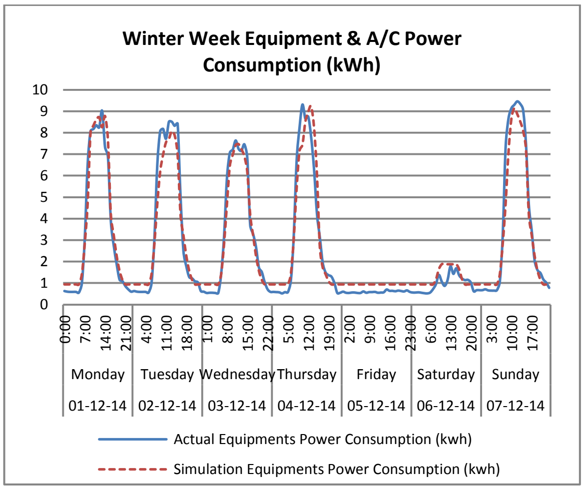

Figure 10 (Winter Week Equipment & A/C Power Consumption)

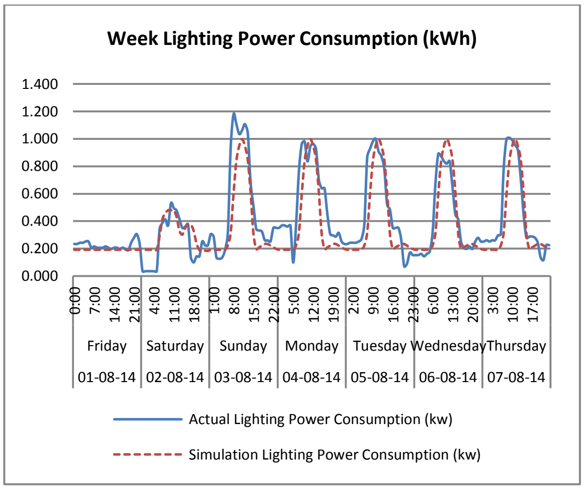

Figure 11 (Week Lighting Power Consumption)

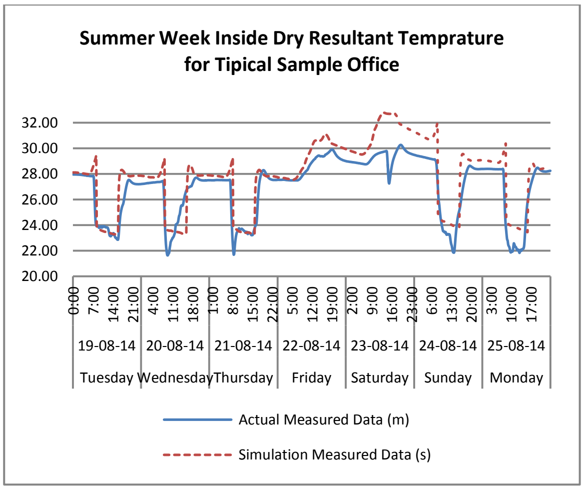

Figure 12 (Summer Week Inside Dry Resultant Temperature)

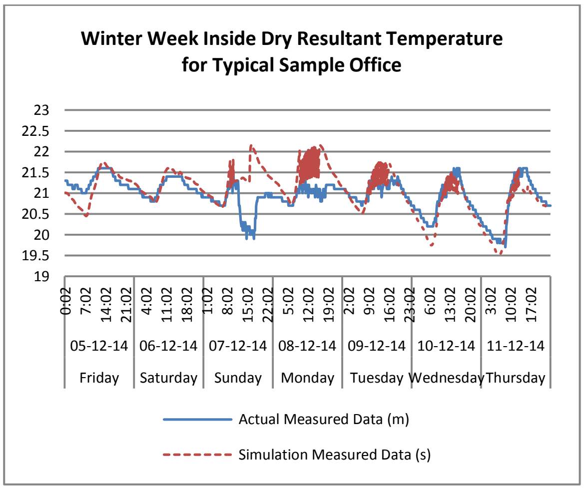

Figure 13 (Winter Week Inside Dry Resultant Temperature)

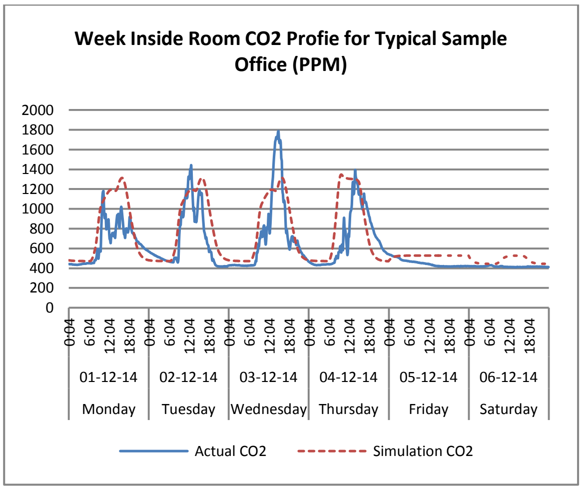

Figure 14 (Week Inside Room CO2 Profile)

The case study used in this paper contains about 30 different offices in different locations, with variable numbers and density of occupants and equipment use, with varying density of furniture and documentation etc., each occupant has their own behaviour, desired comfort temperature, and schedules. It is impossible to capture all of these variations and uncertainties in the model and this explains why residual errors after model calibration remain. The monitoring included a range of offices and the range of behaviours about the typical selected was captured. This range in behaviours will be used to inform sensitivity analysis when using the calibrated model in future studies

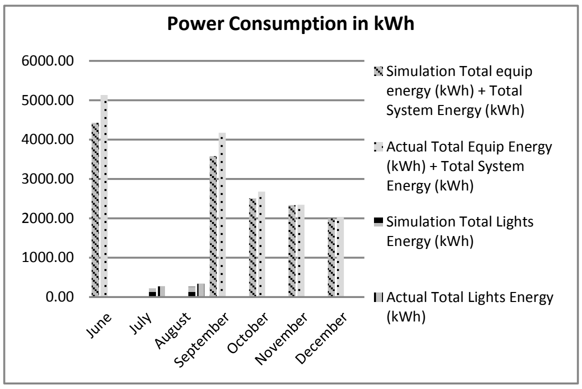

Figure 15 (Total Equipment and Lighting Power Consumption through the Monitoring Months)

Figure 16 showes the comparison between the HVAC, Equipment and Lighting power consumption for the simulation model according to the analysis for this graph equipment have the higher power consumption followed by the HVAC and finally the lighting power consumption.

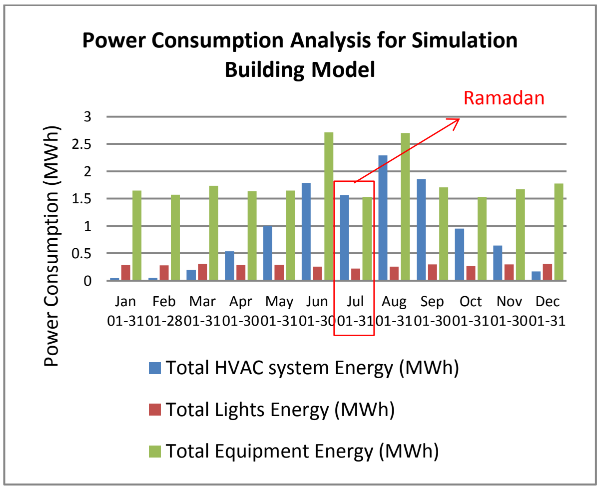

Figure 16 (Model Annual Power Consumption)

CONCLUSION

The paper demonstrated a recurrent optimization-based calibration of the dynamic simulation model of a typical Egyptian office building. Data obtained via monitoring was used to populate the initial simulation model and to maintain its fidelity through a systematic optimization-based calibration process. The resulting model was compared to hourly measured data and good agreement achieved. This suggests that the model may be used to represent actual building operation. A range of user behaviours was captured to be used together with the calibrated model in future sensitivity analysis.

Table 3 (Recurrent Calibration Process)

Variables	Units	Value	Base Case		Value	Model 1		Value	Model 2		Value	Model 3		Value	Model 4		Value	Model 5	
			R^2	CV (RMSD)		R^2	CV (RMSD)		R^2	CV (RMSD)		R^2	CV (RMSD)		R^2	CV (RMSD)		R^2	CV (RMSD)
Infiltration Rate	*$L / S . m^2$*	*1.1*	0.64	19.20%	*0.8*	0.67	18.60%	*0.8*	0.67	18.60%	*0.8*	0.67	18.6%	*0.8*	0.67	18.6%	*0.8*	0.67	18.6%
Equipment Load	*W/Computer + W/m2 miscel.*				*150 + 4*	0.95 4	26.90%	*150 + 4.5*	0.957	23.30%	*150 + 4.5*	0.957	23.3%	*150 + 4.5*	0.957	23.3%	*150 + 4.5*	0.957	23.3%
Cooling Set point temperatur e	*°C*							*21*	0.826	4.50%	*21*	0.826	4.50%	*21*	0.826	4.50%	*21*	0.826	4.50%
SEER	*kW / kW*										*7*	0.876	44.34	*8*	0.934	37.7%	*8*	0.934	37.7%
Shading Coefficient of Window	----------													*0.8*	0.816	5.35%	*0.8*	0.816	5.35%
Lighting Load	*W/m^2*																*9*	0.757	37.7%

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