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CALIBRATION OF A BUILDING ENERGY PERFORMANCE SIMULATION MODEL VIA MONITORING DATA

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ABSTRACT

Energy performance gap is considered as one of the most significant issues associated with the assessment of energy consumption in the built environment. In order to narrow this gap, simulation approach for energy performance assessment are requires comprehensive calibration procedures. Calibrated energy performance models facilitate a baseline representation of existing building performance patterns, thus, further accuracy in diagnosis, operation and energy conservation measures (ECMs) become possible through the use of calibrated models. The present study presents an iterative approach for calibrating a building energy model using full year monitoring data. The methodology focuses on disclosing the steps in calibrating the simulation model and the relative sensitivities of the assumed and monitored parameters used in calibration. The magnitude of the alteration in different levels of calibrated simulation models are evaluated with Mean Bias Error (MBE) and Root Mean Square Error (RMSE) and the model accuracy is controlled through benchmarks defined by ASHRAE Guideline 14, International Performance Measurement and Verification Protocol (IPMVP) and Federal Energy Management Program (FEMP).

INTRODUCTION

Given the fact that 40% of the world energy consumption originates from energy use in buildings for space conditioning, ventilation, hot water, lighting and appliances (DoE 2008), providing environmentally sensitive and efficient measures became a priority for researchers and professionals involved in the production of the built environment. Assessing building energy performance, decreasing fossil fuel resource consumption and endorsing the utilization of technologies that support integration of non-renewable energy sources became significant emphases (Fumo 2014; Ahmad and Culp 2006). Furthermore, regulatory approaches encouraged the decrease in energy consumption on building level through energy conservation measures (ECMs) for existing building envelopes such as insulation, better-performing glazing, solar shading, etc. and integration of renewable or clean energy technologies within the building services (Hens et al. 2010; Diakaki et al. 2010). In such a framework, evaluating the effects of ECMs became crucial in achieving decreased levels of energy consumption in buildings. Simulation software, machine learning, compliance systems (De Wilde 2014) gained importance due to their capability to replicate real world phenomena, and especially simulation tools were considered reliable when results were within error margins that were set via standards such as International Measurement and Verification Protocol (IPMVP 2001), ASHRAE Guideline 14 (2002) and the Federal Energy Management Program Monitoring and Verification Guide (FEMP 2008). Simulation modeling, the widely-anticipated energy performance assessment methodology, was distinguished with its capability to replicate the thermal behavior and energy performance of a building (Crawley et al. 2008). Validation and testing became of utmost importance to accurately assess the realistic energy performance of the buildings.

However, starting from the mid 1990s, strong indications of a “performance gap” were evident between the predicted and actual energy consumption, and the exhibited discrepancies, in some cases, were more than 100% (De Wilde 2014; Bordass et al. 2004; Menezes et al. 2012). Consequently, building energy performance gap turned out to be one of the widely-discussed issues associated with energy use in the built environment. Despite the national/international standards that recommend accurate assessment of building energy performance, the discrepancy between the design predictions and as-built energy performance of buildings was still significant due to an array of reasons related to factors affecting energy consumption (such as occupant behavior, simulation model simplifications, poor assumptions etc.). In addition to efforts that facilitate post-occupancy evaluation for buildings to bridge the performance gap, simulation modeling was as well designated as an assessment methodology that requires a certain degree of confidence. Hence, to holistically address whole-building energy performance assessment through the utilization of a simulation model, it became significant to implement a calibrated building energy simulation approach. Although intended to function as a design phase tool, building energy simulation (BES) models were developed into tools that allowed complex calculation of the energy performance of existing buildings mainly to evaluate the effects of ECMs (Royapoor and Roskilly 2015; Coakley et al. 2014). The forward approach in modeling and simulation briefly emphasizes the importance of acquiring (1) climate data for the case building, (2) building design, (3) geographical data (location, orientation, obstructions etc.), (3) construction data, (4) building installation characteristics, (5) building operations, occupancy and schedules (Harish and Kumar 2016), yet inadequacy in abovementioned data could result in a discrepancy between the simulation results and actual thermal behavior of the building. Ahmad and Culp (2006) established that uncalibrated simulation models produce discrepancies between the monitored and calculated consumption levels in the range of ±30% and suggested that the discrepancies even rise to a range of ±90% for end uses such as chilled water, hot water, and electricity consumption. Therefore, it is possible to assert that employment of uncalibrated simulation models is an important factor in the emergence of building performance gap and simulation models should be calibrated in order to decrease the effect of modeling errors, insufficient inputs, imprecise assumptions, and uncertainty related to design and operation on the simulation outcomes.

Calibrating building energy models based on monitoring data for existing buildings and from feedback data from various field studies for new designs could facilitate performance predictions with high accuracy (Raftery et al. 2011; Zhao and Magoulès 2012). In this framework, this study focuses on disclosing six distinct steps in calibrating the simulation model of an existing building through employment of monitored indoor temperatures, calculated/assumed infiltration rates, monitored occupant presence within the simulation model with an iterative approach. The outcomes are expected to provide sensitivities of the assumed and monitored parameters in calibrating building energy simulation models. The magnitude of the alteration in presented calibration steps are evaluated through Mean Bias Error (MBE) and Root Mean Square Error (RMSE) values and the model accuracy is inspected with respect to the benchmarks defined in ASHRAE Guideline 14 (2002), IPMVP (2001) and FEMP (2008). The present study, therefore, both underscores the significance of comprehensive calibration procedures in building energy performance simulation and interprets the research outcomes in terms of their impact on building performance gap.

METHODOLOGY

Building Information and the Monitoring Process

The case building, located in the main campus of Eskisehir Osmangazi University, Eskisehir, Turkey, predominantly accommodates office functions (Figure 1). Further information on the building is presented in Table 1. Situated on a flat and open lot, the spaces are oriented towards a central corridor aligned to the north/south. The building has a reinforced concrete structure with filled in brick walls and no insulation despite the cold/snowy climate in winters. Measured thermal characteristics of opaque building envelope components are presented in Table 2. Transparent envelope parts of the building consist of aluminum and PVC frames without thermal break and double-pane clear glass with U-values of 3.0 W/m^{2}K and 3.2 W/m^{2}K, respectively (TS2164, 2000). The building is conditioned only with an old non-condensing boiler using natural gas as the primary energy source. Indoor temperatures for office and classrooms were designed as 23 ºC and 20 ºC for circulation spaces during the heating season. Approximate discrepancies of ±1 to 3˚C in indoor temperatures were observed during the monitoring of the building. The building is used for administrative and teaching purposes between 8AM and 5PM on workdays.

Figure 1 (a) Typical floor plan of the case building (b) South façade of the case building

Table 1 Building information

Building Information	
Floor Area (m^2)	3402
Floor Height (m)	3.50 to 4.50
Volume (m^3)	13261
Façade Surface Area (m^2)	2678
Roof Area (m^2)	561
Glazing Area (m^2)	666
Glazing Ratio (%)	25
Compactness (A_{tot}/V_{tot})	0.23

Table 2 Building Elements and U-values

Building Elements	U-Value (W/m^2K)
Reinforced Concrete Walls	2,633
Basement Retaining Walls	0.352
Exterior Walls	1,852
Concrete Floor on Ground	0,866
Flat Roof	2,740
Sloped Roof	3,068
Roof Slab	3,480
Interior Walls	1,726
Interior Floors	2,566

Indoor temperature and humidity, gas and electricity consumption and weather data were measured in the building during 2016. Electricity consumption was monitored with a power analyzer data logger on 10 min intervals. Hourly gas consumption for 2016 was retrieved from the remote monitoring system of the gas provider company. Outdoor temperature, outdoor humidity, global horizontal solar radiation, wind speed, and wind direction were monitored with 10 min interval with a weather station. Cloudiness (0-1) data was retrieved from the macro-climatic weather station in Eskisehir, Turkey. Heating installation efficiency and U-value measurements for the opaque building envelope were completed during the monitoring process (Table 3).

Table 3 Monitored building energy performance parameters

Monitored Building Energy Performance Parameters	Measurement Interval
Indoor Temperature (°C)	10 min.
Indoor Relative Humidity (%)	10 min.
Occupant Presence (%)	1 min.
U-value (W/m^2K)	Multiple
Gas consumption (m^3/h)	1 h.
Electricity consumption (kWh)	10 min.
Outdoor temperature (°C)	10 min.
Outdoor relative humidity (%)	
Global horizontal solar radiation (W/m^2)	
Wind speed (m/s)	
Wind direction (◦)	
Cloudiness (0–1)	3 h.
Boiler Performance (CO_2)	Once

Modeling and Calibration

The calibration approach employed in the present study intends to adjust simulation parameters iteratively, until certain degrees of accuracy between the monitored and the simulated hourly indoor temperatures and the monitored and simulated monthly heating consumption patterns were achieved. The model accuracy is controlled through benchmarks provided by the IPMVP (2001), ASHRAE Guideline 14 (2002) and FEMP (2008). EDSL Tas was used for energy performance modeling of the case building. A multi-zone simulation model was developed with respect to the spatial divisions of the building, since the calibration of the model would be conducted with hourly comparisons of monitored and simulated data for 37 zones. Figure 2 presents the steps in the iterative process in calibrating the energy simulation model. R01, the initial model, was created with basic information that was collected through building audit including as built information, measured envelope characteristics through thermocouple U-value measurements, monitored full year micro-climatic data, calendar and schedules for occupancy, heating season design temperatures and heating installation properties.

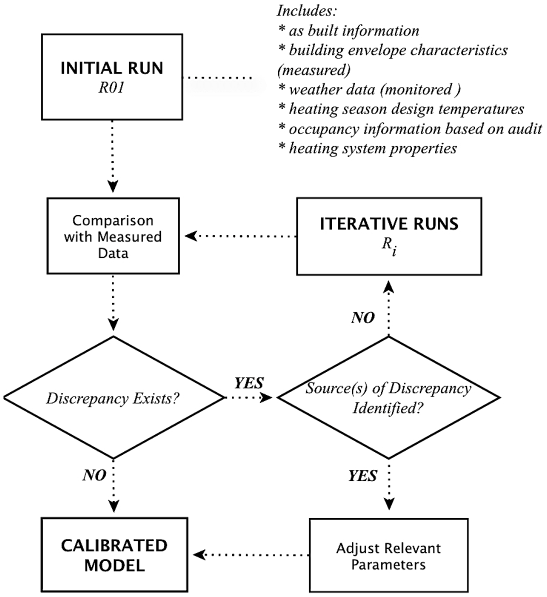

Figure 2 The iterative calibration process (Partly adopted from Raftery, Keane and Costa 2009)

Once the simulation outcomes were retrieved, hourly indoor temperature results of the R01 simulation model were compared to the hourly monitoring data, in addition to the comparison of monthly simulated and monitored heating consumption data. The initial model was not expected to yield an acceptable accuracy; however, the results were extremely discrepant from the actual monitored indoor temperature and monthly heating consumption data. Therefore, the calibration process was initiated to match the simulation outcomes with the monitored data as accurately as possible. As presented in Figure 2, the process in running iterative simulation models, followed the procedure of obtaining run results, comparing these results with monitored data, identifying the discrepancy and the possible source of discrepancy, adjusting relevant parameters, and running the next iterative model. This process was repeated until the model calibration was completed on the 15th run.

Figure 3 presents the integrations/adjustments in the abovementioned process of iterative runs. In the present study, simulation outcomes of the 6 of 15 runs are compared to monitored hourly indoor temperatures and monthly heating energy consumption data and the results of these comparisons are presented in detail to disclose the effect of the integration of monitored indoor temperatures, occupant presence, and adjustment of calculated/assumed infiltration rates within the energy performance simulation of an existing building.

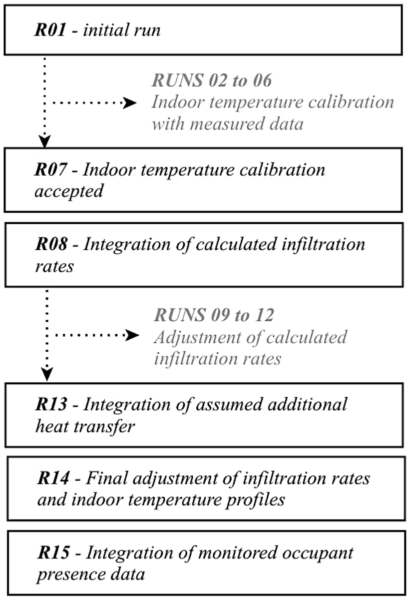

Figure 3 Iterative runs and calibration attempts

The comparison between monitored and simulated data was carried out with two analyses. The first approach is a linear correlation (*R*) analysis based on hour-to-hour correspondence of simulated and monitored indoor temperatures for a full year, for each of the 37 zones monitored in 2016. Second approach is an error analysis that intends to check the deviation of simulated hourly temperatures and monthly consumption patterns from the monitored data with root mean square error (RMSE) and the mean bias error (MBE). Equations (1) and (2) present the formulas employed for RMSE and MBE, where, n is the number of observations, $T_{m,av.}$ is the average of the monitored data for n observations, T_s is the simulated data for n observations, and T_m is the monitored data for n observations.

$$RMSE(\%) = \left(\frac{100}{T_{m,av.}}\right) \times \left[\frac{1}{n} \times \sum (T_s - T_m)^2\right]^{0.5} \tag{1}$$

$$MBE(\%) = \left(\frac{100}{T_{m,av.}}\right) \times \frac{\sum (T_s - T_m)}{n} \tag{2}$$

The results obtained with the linear correlation (R) analysis and the RMSE and MBE analyses were used to evaluate the accuracy of the iterative simulation runs with respect to the benchmark values provided by the IPMVP (2001), ASHRAE Guideline 14 (2002) and FEMP (2008). In Results and Discussion section, the iterative model characteristics, the nature of integrated/assumed parameters and the magnitude of the alterations in the outcomes due to the calibration attempts are discussed in detail.

RESULTS AND DISCUSSION

R01, created as the initial model with information collected through building audit and partly during the monitoring process, was setup with heating season design temperatures with the intention to demonstrate the effect of monitored indoor temperatures on the simulation outcomes. Simulation outcomes for R01 were correlated with the hourly monitoring data (37 spaces x 8760 hours=324120 hours) and the comparison of monthly simulated and monitored heating consumption data was carried out using RMSE and MBE analyses. The indoor temperature errors between the monitored and the simulated hourly data ($T_m - T_s$) were found to be normally distributed as presented in Figure 5. However, heating energy consumption comparison yielded a discrepancy of -58.55% (MBE) (Table 5), which is highly unacceptable when compared to the hourly calibration benchmarks provided by ASHRAE Guideline 14, IPMVP and FEMP (Table 4).

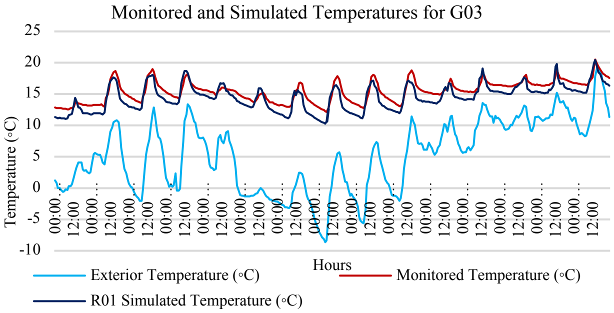

Figure 4 Monitored and simulated temperatures for the unoccupied and unconditioned space G03 (February 1st to 16th)

Simulation model R01 was checked for modeling errors and building envelope characteristics via indoor temperature comparison of unoccupied and unconditioned spaces, since such data could easily reveal the errors in thermo-physical characteristics of the building envelope in simulation. Figure 4 demonstrates the exterior, monitored, and simulated temperature fluctuations for ground floor entrance space G03, which is an unoccupied and unconditioned space. This evaluation indicated that building envelope characteristics were modeled with a certain level of accuracy since the average errors for eight unoccupied and unconditioned spaces between the monitored and the simulated hourly data ($T_m - T_s$) were found to be between 0.85 and 1.13°C. Such discrepancy did not necessarily have to be the result of errors in the thermo-physical characteristics of the building envelope integrated in simulation. Evaluation of the building envelope characteristics would be more substantial consequent to the calibration of other parameters that might be causing the model discrepancies. Identified sources of discrepancies for R01 were interpreted as follows: (1) absence of realistic indoor temperature profiles for the heating season, (2) omitted infiltration rates and (3) assumed occupant presence instead of the actual presence of occupants. In this respect, first monitored indoor temperature data was used to calibrate the model. Indoor temperature profiles were integrated in the simulation model in seven runs and required changes to schedules, set point temperatures, calendar days and the heating system operation schedule.

Table 4 Calibration benchmark values

Calibration Benchmarks		**Calibration Type**	
		Hourly	**Monthly**
ASHRAE 14 (2002)	MBE	± 10%	± 5%
	RMSE	30%	15%
IPMVP (2001)	MBE	-	± 20%
	RMSE	10-20%	-
FEMP (2008)	MBE	± 10%	± 5%
	RMSE	30%	15%

R07 is presented as the next disclosed iterative run, since it could represent a level of mid-calibration with respect to the accuracy achieved for simulated indoor temperatures. Integrating monitored indoor temperature data in the simulation model resulted in improved correlation and error values in comparison to the outcomes of the initial run R01, with 7.32% RMSE, 0.16% MBE, 1.62°C absolute average error (E_{av}) and 0.91correlation coefficient (R) (Figure 5, Table 5). In addition, integrating monitored indoor temperature data in the simulation model resulted in a 38% improvement in annual heating energy consumption in comparison to the initial run. However, R07 could not predict the monthly heating energy consumption with an accuracy that would meet the calibration benchmarks, rather the prediction was inaccurate with a MBE of -42.66%. In order to accept a simulation model as calibrated, both indoor temperatures and consumption patterns should be within the acceptable calibration values presented in Table 4. Hence, the calibration process was continued with the integration of infiltration rates in the next simulation run, R08. Since blowerdoor tests could not be completed during the monitoring period, the infiltration rates were calculated based on the effective leakage area and volume of each zone, and to the ATTMA standard TSL2 (2010) benchmark for normal levels of building air permeability 0.7 $m^3/h.m^2$ @50Pa.

Table 5 Case building calibration results

RUNS	**Indoor Temperature Calibration**				**Heating Energy Consumption Calibration**	
	RMSE (%)	*MBE (%)*	E_{av} (°C)	*R*	*RMSE (%)*	*MBE (%)*
R01	10.60	0.74	2.35	0.86	72.41	-58.55
R07	7.32	0.16	1.62	0.91	54.27	-42.66
R08	8.18	1.39	1.81	0.85	27.94	-17.96
R13	8.41	2.16	1.86	0.85	23.76	-13.77
R14	7.78	0.95	1.72	0.85	18.96	-5.05
R15	7.87	1.06	1.64	0.88	18.49	-4.70

Calculated infiltration rates for the zones ranged between 0.3 and 1.8ach. Since the building was completed in 1992 and underwent no major renovation, infiltration rates were accepted and integrated in the simulation R08. Integrating the calculated infiltration rates within the simulation model resulted in decreased correlation and increased error values in comparison to the outcomes of the previous two runs, R01 and R07, with a RMSE of 8.18%, a MBE of 1.39%, an average absolute error (E_{av}) of 1.81°C and a correlation coefficient (R) of 0.85 (Table 5). The frequency of errors for R08 indicated an improvement towards obtaining a peak value for 0°C and the errors between the monitored and the simulated hourly data ($T_m - T_s$) ranging between -2°C and +2°C were found to be 82% of the total hours (Figure 5) for the 37 monitored spaces for a year (324120 hours). Moreover, integrating the calculated infiltration rates resulted in an improvement in the MBE of heating energy consumption prediction of the model, the result was significantly different, the underestimation of the model decreased to -17.96% when compared to the previous two runs R01 and R07, that yielded values of -58.55% and -42.66%, respectively (Table 5, Figure 6).

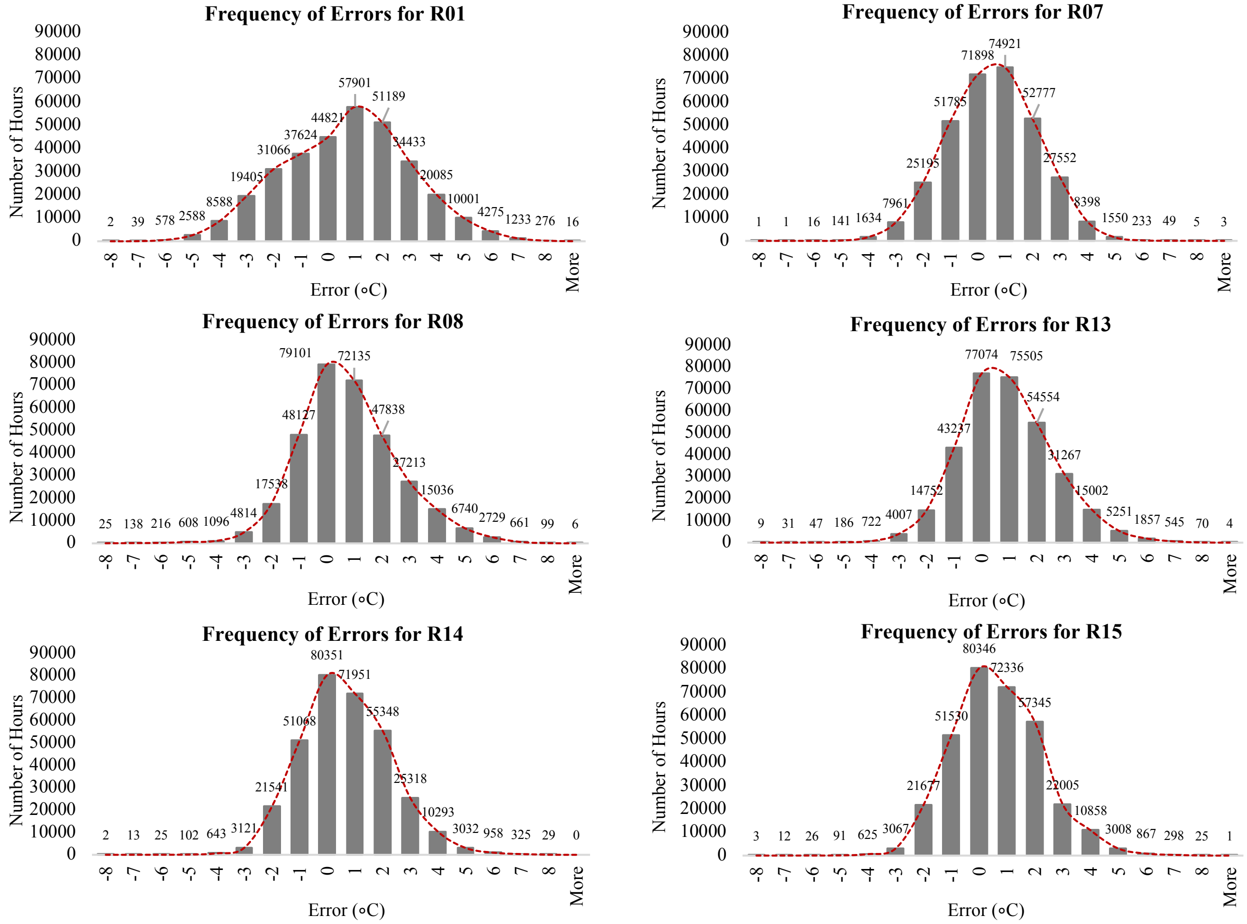

Figure 5 Frequency of errors (T_m -T_s) for iterative simulation runs

These outcomes indicated that the infiltration rate of a building could be highly influential on its energy consumption and is an important parameter that should be included in simulation to obtain a higher level of accuracy. However, outcomes of the simulation run R08 did not yet meet the calibration benchmarks defined in Table 4, since RMSE and MBE values for heating energy consumption calibration were not in acceptable margins. The following four runs focused on the fine tuning of infiltration rates (adjustments of ±0.1-0.2ach for monitored zones and other zones represented by the monitored zones) with the aim to reduce the increased frequency of errors between ±4°C and ±8°C (Figure 5) and an improvement of 1.12% MBE was achieved for heating energy consumption at run R12. The model was thenceforth analyzed for indoor temperature fluctuations for the unoccupied and unconditioned spaces once more (as in R01) and it was concluded that the U-values integrated in simulation could contain an inherent error from the thermocouple measurements. Additional heat transfer of 10% was defined for the building envelope elements in contact with the exterior environment. This run was R13 and yielded improved results for heating energy consumption with respect to the monitored data, with a RMSE of 23.76% and a MBE of -13.77% (Table 5, Figure 6). However, due to the changing envelope characteristics, the simulation model yielded decreased accuracy in indoor temperature data when compared to the previous two runs R07 and R08, with 8.41% RMSE, 2.16% MBE, 1.86°C average absolute error (E_{av}) (Table 5, Figure 5). This result indicated that the altered envelope parameters in the simulation model helped further in calibration for improved consumption patterns, however the thermal behavior of the indoor environment was negatively affected by such an intervention. Therefore, the consequent run, R14, was utilized for final adjustment of infiltration rates and indoor temperature profiles through an hourly comparison of monitored data for 37 zones. The adjustments made on indoor temperatures ranged between ±0.2 to 1.0°C and the adjustments made on infiltration rates were between ±0.2 to 0.3 each. The results of the run R14 provided acceptable error margins with respect to the benchmarks defined by the IPMVP (2001), ASHRAE Guideline 14 (2002) and FEMP (2008) standards (Table 4). As presented in Table 5, the indoor temperature comparison between the R14 data and the monitored data yielded a RMSE of 7.78%, a MBE of 0.95%, an E_{av} of 1.72°C, and a correlation coefficient (R) of 0.85 and the comparison of monthly energy consumption resulted in 18.96% RMSE and -5.05% MBE. The last run in calibrating the simulation model of the existing building (R15) was intended to integrate the monitored occupant presence data to determine the discrepancy between the assumption of constant presence of office occupants and their actual presence patterns in an office space (Figure 7). Integrating solely the actual presence related occupancy gains within the simulation model resulted in outcomes that yielded a 0.35% improvement in RMSE and 0.47% improvement in MBE for the heating energy consumption. Further modeling of occupant behavior and controls in addition to actual presence could provide a more significant improvement in simulation outcomes.

In summary, it is possible to assert that; (a) parameters such as building audit data, actual weather data, heating installation efficiency, measured U-values, and design temperatures were effective on obtaining acceptable indoor thermal environment results from the simulation model R01, however, were insufficient in terms of accurately predicting the heating consumption of the building, (b) calibrating the simulation model with hourly monitored indoor temperatures (R07) resulted in 15.89% of improvement in MBE for heating energy consumption in comparison to the prediction of R01, (c) integrating calculated infiltration rates in the simulation run R08 for each zone resulted in an improvement in the MBE by 24.7% compared to R07, (d) modeling U-values with a 10% of error caused an underestimation of heating energy consumption by 4.19% in comparison to R08, (e) further adjustment of indoor temperatures and infiltration subsequent to the integration of additional heat transfer was conducted and 8.72% improvement was achieved in MBE for heating energy consumption calibration, and finally (f) actual occupant presence was integrated in the model and a 0.35% improvement in RMSE and 0.47% improvement in MBE for the heating energy consumption were achieved for the particular calibration attempt presented in the study.

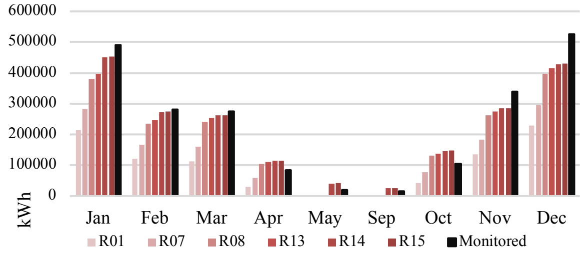

Figure 6 Simulated and monitored heating energy consumption

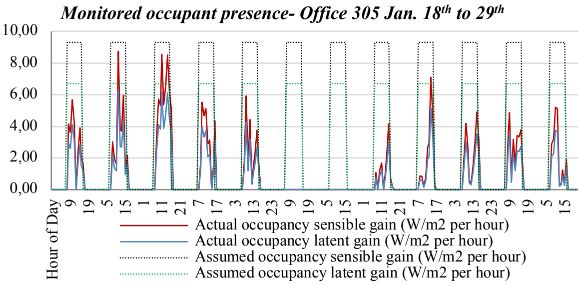

Figure 7. Occupant presence in sample office space

CONCLUSION

Simulation efforts that solely rely on predictions and assumptions could result in a significant discrepancy when compared to the actual energy performance of a building. Although calibration of simulation models via monitoring data is considered as a time-consuming and difficult process in building energy performance studies (Yoon, Lee and Claridge 2003), present research underscores the significance of such calibration approach in terms of controlling different parameters correspondingly and understanding their sensitivities on the overall consumption prediction of an accurate simulation model.

In order to evaluate the effects of energy conservation measures (ECMs) on building energy performance, it is necessary to obtain a base case simulation model that represents the existing thermal behavior of the building as closely as possible. In this respect, the findings of the present study suggest that long term monitoring data (full year) could facilitate an accurately calibrated building energy simulation model through a manual iterative method. Such approach could as well be influential on reducing the energy performance gap and the discrepancy between simulated and monitored energy performances of buildings. In addition, present research could help to underscore the fact that energy performance modeling and calibration for existing buildings are detailed, yet convenient, since the baseline model could be developed through a meticulous audit and monitoring process. However, modeling and calibration efforts during design phase could be more challenging where especially monitoring data does not exist. The findings of the present study could as well be significant for design phase energy performance modeling and calibration, where input parameters such as occupant presence are considered as probabilistic data sets instead of assuming as deterministic inputs based on building schedules.

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REFERENCES

Ahmad, M., and Culp, C. H., 2006. Uncalibrated building energy simulation modeling results. HVAC&R Research, 12(4), 1141-1155.

ASHRAE Guideline 14, 2002. Measurement of Energy and Demand Savings, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., Atlanta.

ATTMA TSL2. 2010. The Air Tightness Testing & Measurement Association. Technical standard L2. Measuring air permeability of building envelopes (non-dwellings).

Bordass, B., Cohen, R. and Field, J. 2004. Energy Performance of non-domestic buildings: closing the credibility gap. In: Proceedings of IEECB'04 Building Performance Congress, Frankfurt, Germany.

Coakley, D., Raftery, P. and Keane, M. 2014. A review of methods to match building energy simulation models to measured data. Renewable and Sustainable Energy Reviews, 37, 123-141.

Crawley, D. B., Hand, J. W., Kummert, M. and Griffith, B. T., 2008. Contrasting the capabilities of building energy performance simulation programs. Building and Environment, 43(4), 661-673.

De Wilde, P., 2014. The gap between predicted and measured energy performance of buildings: A framework for investigation. Automation in Construction, 41, 40-49.

Diakaki, C., Grigoroudis, E., Kabelis, N., Kolokotsa, D., Kalaitzakis, K., and Stavrakakis, G. 2010. A multi-objective decision model for the improvement of energy efficiency in buildings. Energy, 35(12), 5483-5496.

DoE, U. S., 2008. Energy efficiency trends in residential and commercial buildings. US Department of Energy, Washington, DC.

EN ISO 13791, 2004. Thermal Performance of Buildings-Calculation of Internal Temperatures of a Room in Summer Without Mechanical Cooling-General Criteria and Validation Procedures.

FEMP, 2008. Measurement and Verification Guidelines: Measurement and Verification for Federal Energy Projects Version 3.0. DOE, US.

Fumo, N. 2014. A review on the basics of building energy estimation. Renewable and Sustainable Energy Reviews, 31, 53-60.

Harish, V., and Kumar, A. 2016. A review on modeling and simulation of building energy systems. Renewable and Sustainable Energy Reviews, 56, 1272-1292.

Hens, H., Parijs, W., and Deurinck, M. 2010. Energy consumption for heating and rebound effects. Energy and Buildings, 42(1), 105-110.

IPMVP, 2001. International Performance Measurement & Verification Protocol—Concepts and Options for Determining Energy and Water Savings, Volume I, Oak Ridge.

Menezes, A. C., Cripps, A., Bouchlaghem, D. and Buswell, R., 2012. Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap. Applied Energy, 97, 355-364.

Raftery, P., Keane, M. and Costa A. 2009. Calibration of a detailed simulation model to energy monitoring system data: A methodology and case study. Proceedings of Building Simulation 2009, Eleventh International IBPSA Conference Glasgow, Scotland July 27-30, 2009

Royapoor, M. and Roskilly, T. 2015. Building model calibration using energy and environmental data. Energy and Buildings, 94, 109-120.

TS2164, 2000. Turkish Standard on Principles for the Preparation of the Projects of Central Heating Systems.

Yoon, J., Lee, E.J. and Claridge, D.E. 2003. Calibration procedure for energy performance simulation of a commercial building. Journal of Solar Energy Engineering, 125, 251-257.