Minimizing the performance gap of A-Rated Buildings while supporting high levels of user comfort

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Abstract

Energy efficiency in buildings is currently a fractured process, with a variety of stakeholders and compliance procedures focussing on separate parts such as design, construction, and building use without direct feedback loops that foster a holistic view of energy performance and Indoor Environmental Quality (IEQ). This leads to a performance gap between the energy consumption estimated by ratings against operations, lack of in-use data to verify compliance, and conflicting indoor environmental issues in A-rated buildings. This paper uses Dynamic Simulation Modelling (i.e. IES-VE) and new calibration methods integrating Machine Learning (ML) to identify insights into the conflict between energy efficiency and IEQ.

Introduction

To lower emissions and mitigate climate change, the EC issued the Energy Performance of Buildings Directive (EPBD), setting requirements for new buildings to be Nearly Zero Energy by 2020. EC member states have implemented the EPBD in national legislation and developed practical methodologies for the calculation of energy performance against reference models. Countries within the EU have created national methodologies of energy and carbon performance against reference models labelled. The official Irish methodologies are the DEAP (Dwelling Energy Assessment Procedure) and the NEAP (Non-domestic Energy Assessment Procedure), which are adapted from the UK equivalents (i.e. SAP and NCM) which in turn are based on EN ISO 13790:2008.

Buildings that require a DEAP or NEAP assessment are generally non-complex buildings. For complex buildings, a full Dynamic Simulation Model (DSM) using software such as the IES-VE would be used. However, the majority of the building stock is either residential or small to medium commercial, non-complex buildings (Navigant Research, 2016) and as such are not required to have a full DSM. As the majority of the building stock falls into this category, these buildings must still stand up to post-occupancy scrutiny, otherwise carbon reduction commitments across the Built Environment will not be achieved, in reality.

The literature shows significant challenges in compliance methodologies, such as the potential for sub-optimal building performance during operation, over-predicting energy savings by an average of 77% (Baranyi, 2013), under-rewarding efficient design and over-looking inefficient design while downplaying the significance of insulation and airtightness and assuming high levels of internal gains (Zero Carbon Hub, 2014). As a result, these better designed buildings do not have the expected correlating effect on the reduction of energy consumption.

This issue can be addressed from the top-down by increasing the accuracy of the design performance evaluation, however a bottom-up approach to understand the building in-use and the behaviour of the occupants is also important as is Measurement and Verification (M&V).

Further to this, the design of A-rated buildings is focused on the reduction of energy consumption, with highly specific standards that require significant care in design, construction and operation to ensure that user comfort is not compromised. Nonetheless, the increase in energy efficiency and air tightness has brought a rise of significant IEQ issues that have led not just to compromised user comfort, but also health hazards, such as mould formation due to high humidity levels. As such, the IEQ of the building must be considered when analysing the performance of the building energy efficiency in the same way that user behaviour must also be taken into consideration. However, these A-rated buildings are seldom monitored to gain a better understanding of the IEQ at an operational level (Shiel and West, 2016; Perez-Lombard et al., 2008).

In recent years, the cost of carrying out post-occupancy evaluation on these domestic or small to medium commercial buildings has been prohibitive. However, the emergence of the Internet of Things (IoT) and low cost wireless sensors is now shifting the landscape of post-occupancy evaluation and energy monitoring of existing buildings. The authors of this paper are currently undertaking a study of 100 domestic dwellings and 19 small to medium sized commercial buildings (schools, healthcare and office), monitoring energy use and IEQ through a low cost Lora-Wan IoT network. This data will be assessed along with the creation of Digital Twin calibrated models, to provide insights on how the DEAP and NEAP methodologies could be improved (top-down), to provide operational guidance for the building owners through

Augmented Intelligence (AuI) dashboards (bottom-up) and recommendations as to how the methodology could be improved so that energy efficiency does not compromise IEQ.

This paper focuses on the domestic dwellings and carries out an in-depth analysis into four of the dwellings in the study. Many of the expected issues with respect to the impact of the A-Rated building on IEQ are observed, however new issues regarding increased CO2 levels are also observed, which raises many serious questions to the importance of post-occupancy evaluation and M&V of the A-Rated dwelling. Other IEQ issues are also seen to have a negative knock on impact to energy efficiency, going against the design intent of the A-Rated home, as will be explained in the subsequent sections.

Methodology

Buildings in the Study

The domestic dwellings used for the study have come from a Co-Housing Alliance, which is a housing co-operative with Approved Housing Body status. The developer is a ‘not for profit’ company whose vision is to see fully integrated, cooperative homes at affordable prices in sustainable communities throughout Ireland. By collaborating with a Co-Housing Alliance, engagement with end users was relatively easy and 90% of the residents agreed to be part of the study and allowed the authors to install the necessary equipment and iteratively investigate the causes of the performance gap at their domestic properties.

The properties are newly constructed, A-rated dwellings, containing high levels of insulation and highly rated energy systems/household appliances. The ventilation system chosen in the dwellings is a Demand Controlled Ventilation system (DCV) as opposed to a Mechanical Heat Recovery Ventilation (MHRV) system. All dwellings also incorporate Solar PV for electricity production. Table 1 highlights the different archetypes and energy systems of the first 46 residential dwellings that have been examined.

Table 1: Total Number of Domestic Dwellings in the Study

Archetype	No. of Properties	Floor Area (m^2)	Heating System
3 Bed Mid Terrace House	31	101.9	Gas Boiler
3 Bed End Terrace House	5	101.9	Gas Boiler
4 Bed End Terrace House	3	135	Gas Boiler
4 Bed End Terrace House	2	135	Heat Pump
4 Bed Detached House	1	135	Heat Pump

Data Collection and Sensors

Several types of sensors were considered for the project including the initial design of a custom-built sensor and initial site surveys were carried out to determine the level of connectivity required. The project team could not rely on occupant Wi-Fi to enable the collection of operational data and the connectivity solution had to have a data granularity at a low cost. Eventually the Long Range wide area network (LoraWan) was chosen as it delivered all that is required for the project and remained inside the equipment budget.

The LoraWan network also contributes to the introduction of Internet of Things (IoT) technology into Ireland and is a good long-term solution for future research activities and projects. The sensors chosen for the study came from Elysys and record internal temperature, Relative Humidity (RH), carbon dioxide (CO2), illuminance and motion (Figure 1). The sensors also produce readings for the voltage used from the battery of the sensor, allowing the project team to track the continual successful operation of the sensor and identify site faults which may be a result of the gateway operation as opposed to individual sensor faults.

Figure 1: Elsys Sensors and Illustration of Size

During the installation, sensors were placed in the same position in different houses to allow consistent data streams and to enable accurate data correlations. Sensor placement locations were representative of areas to be controlled, therefore avoiding unrepresentative heat sources, stationary air pockets, draughts or doorways. A weather station was also placed onsite to record external temperature, wind speeds and natural light readings.

Low cost electricity monitors were also placed on a number of homes corresponding to each of the represented archetypes to monitor electricity use at a five-minute interval. Other data from electricity and gas utility bills was also collected from each home.

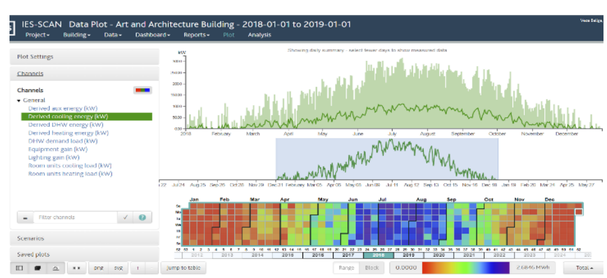

Figure 2: Illustration of the IES iSCAN Platform

All data, from the Elsys sensors, the electricity monitors and the utility bills were then incorporated into a single data management platform, called IES-iSCAN (Figure 2). iSCAN centralises any time-series data from different building and energy management systems, utility portals, IoT sensors and historic files etc. in a single cloud-based platform. Machine Learning and Artificial Intelligence (AI) are used to review data and fill gaps. Bespoke dashboards can also be created to enable specific actions to be taken by end users, for example to improve energy efficiency or IEQ. iSCAN also connects with IES-VE to enable model calibration, which leads to the creation of real-time building Digital Twins, as explained in the following sub-section.

Calibration Methodology and Digital Twin Creation

The calibration methodology leverages world-leading Dynamic Simulation Modelling software from IES, the IES-VE and the data management platform, iSCAN as previously mentioned. The IES-VE is based on first principles building physics data and hundreds of person-years has been invested by IES to ensure the Building Physics Intelligence within the software is as accurate as possible. This technology has existed for many years, and has been used to design over a million medium to large buildings across the world; however new disruptive solutions for the built environment are now enabling IES' technology to be applied to the existing built environment, improving the energy efficiency of existing buildings and planning strategies for future decarbonisation. These technologies include Artificial Intelligence (AI) and Machine Learning, the Internet of Things (IoT) and cloud technology to mention a few. These technologies work in co-operation with the IES building physics model and IES iSCAN, creating a hybrid physics-based/data driven approach for maximum accuracy and impact.

The Digital Twin begins with the initial energy model, i.e. the IES-VE model, which is a DSM and far superior to the EPBD DEAP or NEAP models, which are static models used for compliance. This model is then updated through site surveys and integration of real data. The site surveys are used to collect current information on the geometry of the building, its zoning and use and identify schedules and equipment, occupancy patterns and profiles and how the occupants use the building from a behavioural aspect. Weather data is taken from the nearest weather station or on-site weather stations where available.

The merging of real data and virtual data in the physics based model creates an accurate hybrid Digital Twin. The improved accuracy can be proven through a Monitoring and Verification (M&V) statistical assessment. If the accuracy is statistically proven then the Digital Twin is classified as being calibrated. The result is a hybrid-calibrated model that is the most accurate model of the building in-use.

To calibrate a building model, Bou-Saada and Haberl proposed the adoption of standardised statistical indices, which better represent the performance of a model; these are (i) Mean Bias Error (MBE), (ii) Root Mean Square Error (RMSE) and (iii) the Coefficient of Variation of Root Mean Square Error (CV_{RMSE}). Currently the International Performance Measurement and Verification Protocol (IPMVP) adopts these indices and applies a standard for the CV_{RMSE} and MBE depending on whether the models are calibrated to monthly or hourly measured data. This is widely adopted as the standard approach to calibration of Building Energy Performance Simulation (BEPS). However this method does not address the issue of model uncertainty and as such, the performance gap between actual and predicted energy use still remains, even for calibrated models to the IPMVP standard.

The methodology used for this paper, adopts the IPMVP standard, however it is adapted for buildings that have incomplete datasets, by incorporating Machine Learning algorithms into the approach. This is based on the assumption that energy consumption can be predicted using variables such as day-of-week, time-of-day, holiday calendar and weather variables etc.

As such, a regression Machine Learning algorithm called Extreme Gradient Boost (XGBoost) is integrated with the IES-VE physics based model to extrapolate energy consumption data for the rest of the year and train a first 'Model A'. This was not something already available in the IES software and is a new development from the authors of the paper. Variables included in the regression model are: time of the day, day of the week (0 to 6), holidays (where normal day=0, holiday=1), day of the week (0 to 6), weather variables (dry bulb temperature and other solar radiation measures) and daylight summer time (no Daylight =0, daylight =1).

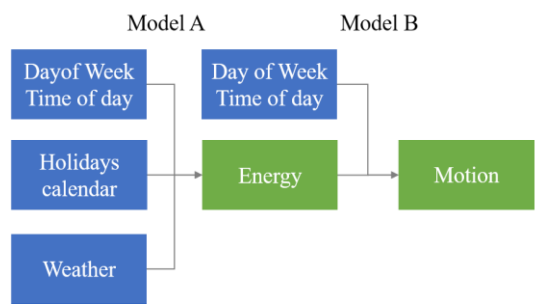

Figure 3: Model A and B Inputs

Following this, using the motion data also collected from the sensors in the dwellings, a second 'Model B' can be trained using day-of-week, time-of-day and predicted energy variables from model A, as presented in Figure 3. In all cases, models have a coefficient of determination > 0.80 on the validation dataset suggesting that explanatory variables are significant.

Energy prediction is then used as calibration target for the model. Model inputs such as occupancy, small power and lighting gains are derived from motion prediction. Finally, parameters such as maximum occupancy gain, maximum lighting gain and small power gains alongside air changes per hour are optimized to match the calibration target. This process is carried out until the calibration metrics (NMBE, CV_{RMSE}) reach acceptable calibration thresholds.

Results

A Digital Twin of each of the building archetypes outlined in Table 1 has been created; for the 4-bed end terraced house, the archetype with the gas boiler has been chosen as the 4-bed detached with heat pump is taken as the other archetype for the 4-bed dwellings. As such the 4 archetypes include the following and in these selected buildings, the number of occupants is indicated.

- 4 bed detached dwelling, heat pump, 5 occupants,
- 3 bed mid-terrace dwelling, gas boiler, 5 occupants,
- 3 bed end-terrace dwelling, gas boiler, 4 occupants,
- 4 bed end-terrace dwelling, gas boiler, 2 occupants.

Calibrating the Models

The Digital Twin models for the residential dwellings were created from architectural drawings. This created a base-line Building Physics model in the IES-VE, as illustrated for the 4-bed detached dwelling in Figure 4, to provide an example.

Figure 4: IES-VE Model for 4-Bed End Terrace Dwelling

The electricity consumption of each dwelling has been monitored using a clamp on meter, placed on the external electricity meter that measures electricity data at 5-minute intervals and records the data as a .csv file. This was collected for a period of 6 months (June to November plus part of December, as shown in Figure 5). Each of the home owners has also provided their gas and electricity utility bills but not all for a complete 12 month period.

Data from the installed sensors, the electricity monitors and the utility bills was then integrated into iSCAN and weather data was taken from the on-site weather station. Each of the home-owners filled out a short ten-question survey with respect to how they use their home. Example questions include what time do they turn on their heating systems, what time of the day to they use their appliances, what type of plug-load equipment do they have in their home etc.

Using the regression algorithm that takes inputs from the time-series data, the utility data and the IES-VE physics model, the missing data for the remainder of the year was then predicted, as shown also in Figure 5. This was then incorporated into the Digital Twin model and the model was calibrated as per the approach described by the Methodology, to create a hybrid Digital Twin. For the monthly calibration approach, the NMBE was 0.5% and the CV_{RMSE} was 5.7%; for hourly calibration approach, the NMBE was 1.93% and the CV_{RMSE} was 29.63%. These values are well within the recommended thresholds from ASHRAE.

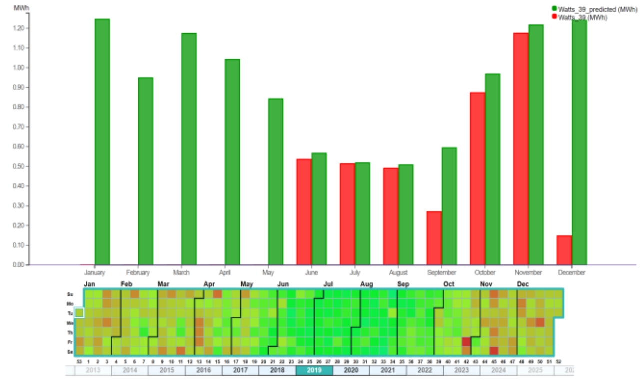

Figure 5 – Data Generation using Machine Learning integrated within IES-iSCAN and incorporating data from Physics Based IES-VE model for Building 4.

This physics based, real-time data, hybrid Digital Twin, calibrated model, was then used to generate structured data to reflect the energy usage divided into heating, lighting and all other energy-consuming loads in the dwelling. This was then used as a comparison against the BER and also to identify optimal IEQ conditions and understand where the dwellings were not performing with respect to both energy consumption and IEQ.

Energy Analysis

Figure 6 outlines the results for the energy End Use Intensity (EUI) for each dwelling. The EUI is the actual energy output from the building in use as calculated from the hybrid Digital Twin model, which is calibrated to real data as described previously.

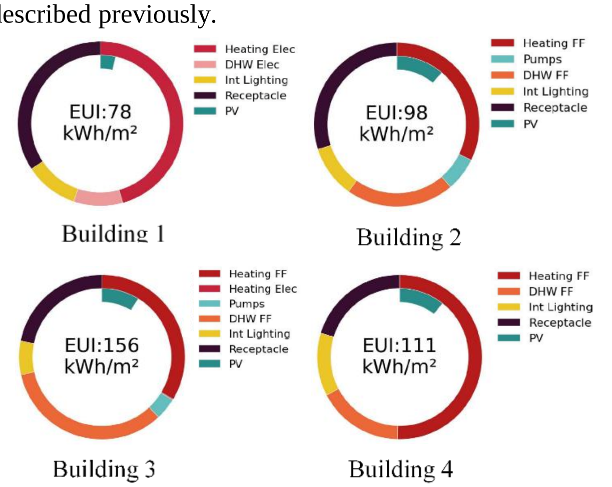

Figure 6: EUI Values based on Digital Twin Model

It is seen that the EUI varies significantly from 78kWh/m2/yr (Building 1) to 156kWh/m2/yr (Building 3). Figure 6 also shows the split of each of the loads in the dwelling between heating and pumps (electricity or fossil fuel), domestic hot water (DHW), internal lighting, receptacles (i.e. appliances and small plug loads) and solar PV output.

Table 2: Values for the DEAP Assessment

	DEAP Assessment					
	Floor Area	Energy Value	CO2 Emissions	Renewable Contribution (PV)	Renewable Contribution (HP)	BER Result
	[m2]	[kWh/m2/yr]	[kg/m2/yr]	[kWh/m2/yr]	[kWh/m2/yr]	
Building 1	133	45.10	8.87	3	17	A2
Building 2	100	48.66	8.82	13	0	A2
Building 3	100	48.41	8.71	15	0	A2
Building 4	133	49.61	8.96	14	0	A2

Table 4: The Performance Gap

	Performance Gap (including appliances)		Performance Gap (excluding appliances)	
	[kWh/m2/yr]	%	[kWh/m2/yr]	%
Building 1	33	42%	5	11%
Building 2	50	50%	16	25%
Building 3	108	69%	70	59%
Building 4	61	55%	36	42%

Table 3: Values for the Digital Twin Model

	Digital Twin Model										
	PV Production	Space Heating		Domestic Hot Water		Lighting		Appliances		EUI	CO2 Emissions
	[kwh/m2/yr]	[kWh/m2/y]	[kgCO2/m2/yr]	[kwh/m2/y]	[kgCO2/m2/yr]	[kWh/m2/y]	[kgCO2/m2/yr]	[kWh/m2/y]	[kgCO2/m2/yr]	[kWh/m2/yr]	[kgCO2/m2/yr]
Building 1	3	37.1	19.3	7.8	4	8.5	4.4	27.9	14.5	78	42
Building 2	13	43.1	10.9	23.5	4.6	11.4	5.9	33.3	17.2	98	39
Building 3	16	65.73	15.3	57.7	11.4	11.4	5.9	37.6	19.5	156	52
Building 4	13	62.9	13.6	21	4.5	15.5	8	25.3	13.2	111	39

Table 2 shows the results from the DEAP assessment. This shows that the expected Energy Value for each home is between 45.10kWh/m2/yr and 49.61kWh/m2/yr. However the DEAP assessment does not consider appliances or small plug-loads in its analysis as it is a static assessment of the building envelope only so it also does not take into account behaviour or other unknown factors. In contrast the Digital Twin model, as it has been calibrated to the real data and conditions of the building in use, is a much closer representation to the reality of the building in operation.

The DEAP assessment also shows only a slight variance between the four house types with respect to the energy value, however it is clear from Figure 6, representing the hybrid Digital Twin model that each house has a significantly different actual EUI, which could be attributed to behaviour and/or the unaccounted for appliances and small plug loads.

Table 3 now outlines the disaggregated load breakdown from the hybrid Digital Twin model. It can be seen here that the space heating for Building 3 and Building 4 is significantly higher than Building 1 and Building 2, which raises questions with respect to the operation of the end of terrace dwellings, as Building 3 and 4 actually have less occupants than Building 1 and 2.

It can also be shown that the DHW value for Building 3 is significantly higher than the other dwellings, even though Building 3 has four occupants when Building 1 and 2 have five occupants each. Building 4, which only has two occupants, actually has significantly higher DHW use than Building 1 that has five occupants, which questions any correlation between DHW use and number of occupants that are typically assumed when using static methods.

Lighting values do not vary significantly apart from Building 4 which is double the value of Building 1. As both of these dwellings have 4 bedrooms and increased floor space, it would be expected that they should have similar values, in addition, Building 4 has two occupants whereas Building 1 has five occupants, which suggests that Building 4 is leaving lights on unnecessarily.

The load value for appliances for all 4 homes is comparable, which suggests all have good to adequate appliance use.

As the DEAP assessment does not take into account appliances or small plug loads, it is important to also look at the final EUI values with this load value removed from the calculation. When this value is removed, the EUI for the four dwellings are 50kWh/m2/yr, 65kWh/m2/yr, 119kWh/m2/yr and 86kWh/m2/yr, respectively.

As shown in Table 4, which highlights the performance gap when appliances and small plug loads have been removed, Building 1 correlates quite closely to the DEAP assessment, within 11% variance. As Building 1 has a heat pump, which is typically automated in dwellings, this would suggest that automating controls, results in a better correlation between design intent and operation. It should be noted that the heat pump would also have a better Co-efficiency of Performance (CoP) than the gas boilers, which could also contribute to a better correlation between the Digital Twin model and the DEAP assessment.

Building 2 is within 25% of the DEAP assessment energy value. This dwelling has a higher DHW value compared to Building 1, which would account for the difference, i.e. if Building 2 had the same DHW value of Building 1, the variance would only be 1%.

Building 3 has a 60% variance from the DEAP assessment, which is considerable, however this dwelling has both considerably high DHW usage and space heating usage.

Building 4 has a 42% variance from the DEAP assessment, which is also considerable and this variance can also be attributed to the space heating aspect of the dwelling.

As such, further investigation into the dwellings and their IEQ values has been carried out to identify if there are other reasons why the end-terrace dwellings have considerably higher space heating requirement than the two mid-terrace dwellings. This is reported in the following sub-section along with an analysis of IEQ in general for the A-Rated Dwellings.

Indoor Environmental Quality (IEQ) Analysis

All 46 dwellings have been monitored with respect to temperature, relative humidity, CO2, illuminance and motion. Five sensors have been placed in each dwelling, one in the kitchen, one in the living room, one in the master bedroom, one in the en-suite and one in the second bedroom. Each dwelling has the same sensors, placed in the same rooms and the same places for comparable analysis of the results.

In Ireland it is expected that the average temperature range for the different rooms under analysis is as follows:

- Living Room: 20-22ºC in winter and 23-25ºC in summer
- Bedroom: 17-19ºC in winter and 23-25ºC in summer

Relative Humidity should on average be between 40% and 50%, but any values below 60% are usually deemed acceptable. Relative humidity above 80% for prolonged periods can result in mould growth on walls and on any unventilated surfaces, such as behind curtains, blinds, wardrobes, etc. Levels of humidity can also affect the occupant's feeling of well-being, for example, low levels of humidity can lead to drying of the eyes and nose and throat irritations, particularly for those who are susceptible to such conditions.

For Carbon Dioxide (CO2), a gas which can make us feel lethargic and drowsy if too high, below 1,000 parts per million (ppm) is quite normal, while up to 1,500 ppm can make us less alert, and above 1500 ppm can have an effect on energy and concentration levels.

The IES iSCAN software, allows for in-depth analysis of the metered data. Through the software, using python scripts, insights such as 'tell me the % of time that CO2 is greater than 1,500ppm' can be created and the results outputted in a .csv file. As such, Table 5 now outlines the detailed results for the 5 rooms for each of the 4 buildings considered in the analysis.

This table outlines the average and max temperature values as well as the % of time that the temperature is above 25^0C. It outlines the average and max RH level along with the % of time that the RH is greater than both 60% and 80%. It outlines the average and max CO2 levels as well as the % of time that CO2 is greater than 1,000 but less than 1,500 and the % of time that CO2 is greater than 1,500.

Results that are outside the thresholds with some impact to the occupants have been marked in yellow and results that are well outside the thresholds and could have significant impact on the occupants have been marked in red.

It can be observed in Table 5 that Building 1 has the most issues with respect to RH and CO2. The RH is >60% the majority of the time for all rooms apart from the Living Room and in the En-Suite, RH was greater than 80% for 50% of the time. Further to this, the CO2 max levels are significantly high with a peak of 5191ppm and the CO2 in the Master Bedroom and the Second Bedroom is greater than 1,500ppm for 27% and 67% of the time, respectively. This would suggest that the ventilation system in the dwelling is not working adequately or is being turned off. It is interesting however that this dwelling, from an energy

Table 5: IEQ Results from the Sensors

	Temperature			Relative Humidity				Carbon Dioxide			
Room	**Avg. Temp**	**Max Temp**	**% > 25oC**	**Avg. RH**	**Max RH**	**>60% RH**	**>80% RH**	**Avg. CO2**	**Max CO2**	**1,000-1,500**	**>1,500**
	oC	**oC**	**%**	**%**	**%**	**%**	**%**	**ppm**	**ppm**	**%**	**%**
	Building 1										
Living	21.75	26.6	6.44	54.4	82	50.8	0.01	771	3701	26	11.5
Kitchen	23.3	28.5	23.28	61.98	95	80.7	0.9	744	2501	13.2	1.74
Master Bedroom	21.35	25.4	0.48	65	81	76.9	0.03	1103	2699	21.6	26.8
En-Suite	20.1	25.6	0.1	79	100	83.7	52.34	-	-	-	-
2nd Bedroom	21.97	25.2	1.1	66.56	82	100	0.1	1672	5191	23.8	66.5
	Building 2										
Living	22.26	25.7	0.26	52.13	85	26.54	0.05	629	2136	3.7	0.59
Kitchen	23.14	30	8.22	49.91	85	13.51	0.05	594	1816	1.14	0.24
Master Bedroom	23.06	26.7	9.99	51.88	79	19.8	0	767	1750	38.4	1.21
En-Suite	23.29	27.5	11.31	51.41	90	19.71	0.23	-	-	-	-
2nd Bedroom	22.47	26.2	1.62	52.85	70	8.5	0	792	2677	29.55	3.6
	Building 3										
Living	21.89	26.5	1.41	59.87	89	53.73	0.04	797	3569	31.23	6.66
Kitchen	22.94	28.1	11	54.86	83	25.52	0.02	651	3332	4.72	1.14
Master Bedroom	22.04	26.1	2	61.64	73	63.31	0	1006	3259	18	18.59
En-Suite	21.84	26.2	1.05	63.5	95	73.74	1.94	-	-	-	-
2nd Bedroom	22.42	25.9	4.3	58.45	71	46.19	0	940	2990	20.54	17.16
	Building 4										
Living	21.65	29.3	12.29	50.4	71	7.75	0	620	2314	8.9	2
Kitchen	21.7	29.2	8.5	53.63	89	52.25	0.05	532	3750	2	1.1
Master Bedroom	21.33	26.5	0.62	53.23	71	23.36	0	659	1611	31	0.3
En-Suite	20	25	0	62.04	94	63.66	3.3	-	-	-	-
2nd Bedroom	20.65	25	0	56.65	74	50.78	0	614	1700	18.7	0.77

efficiency perspective was the best performing and had the closest correlation to the DEAP assessment.

Examining Building 3, which was the worst performing Dwelling with respect to energy efficiency and the furthest correlation to the DEAP assessment, also shows some interesting observations. The temperature and RH levels are typically ok with the Master Bedroom and En-Suite exceeding 60% RH for 63% and 73% of the time, but otherwise RH levels are below the recommended max thresholds. There are some max CO2 levels which are considerably high, however these seem to be mainly peaks as the average time spent above 1,000ppm and less than 1,500ppm is only 30% of the time for the Living Room and there is only a small amount of time, i.e. <20%, where the ppm goes above 1,500 in the Master and Second Bedrooms. This would suggest that the ventilation system is primarily working within its manufacturing guidelines.

Similar results to Building 3, are observed in Building 2 and Building 4, also suggesting that the ventilation system is working adequately.

From engagement with the end users, the occupants of Building 3 and Building 4 (the two end-terrace dwellings) have complained the most about feeling cold. However, on examination of their temperature range values, the average temperature is inside the recommended thresholds. On examination of the energy results of these dwellings, their use of space heating is considerably higher than Building 1 and 2 (i.e. the mid-terrace dwellings), which would suggest that the end-terrace dwellings are not performing as well as expected. Through examination of the RH and CO2, their ventilation systems seem to be performing adequately and hence this would suggest that there could be issues with the external envelope itself, or perhaps issues with perceived comfort of the occupants as a result of the DCV system.

Discussion and Future Work

It is clear from the results that Building 1 preforms very well with respect to its energy efficiency and correlates well with the DEAP assessment, when the appliances and small plug-load values are taken away from the final EUI value. This Building has a Heat Pump and therefore the system use is likely to be automated and have a good CoP. However, Building 1 has high levels of RH and CO2, suggesting that their ventilation system is either not working, or they have turned it off for comfort reasons. While the thermal comfort of the homes is good based on the results of indoor temperature observed, the poor results for RH and CO2 clearly show there is a conflict between the A-Rated home and overall performance of the IEQ of the dwelling.

Given that Building 1 is a detached dwelling and the two end-terraced dwellings (i.e. Building 3 and Building 4) have reported issues with respect to perceived comfort, it is likely that Building 1 is experiencing the same comfort issues and has manually turned off their ventilation system to account for these issues. In contrast, the results would suggest that Building 3 and Building 4 have not adjusted their ventilation system and instead they have increased their space heating requirements, to improve the perceived comfort by adjusting their gas boiler set points and schedules manually. This has a resulting significant negative impact on their energy efficiency.

Based on these results, the initial analysis suggested that Building 1 was performing best with respect to energy efficiency as it had a heat pump in contrast to the other buildings that have a gas boiler. However based on this further analysis of IEQ, the results would now suggest that the other buildings are simply less efficient due to increasing the effort from the gas boiler to mitigate any poor perceived comfort issues and Building 1 actually needs to address its IEQ issues with respect to CO2 and RH.

The results also show the importance of adequate ventilation in A-Rated dwellings and the dangers that can arise with respect to high levels of CO2 and RH if the ventilation is not working properly or is turned off. Increased CO2 would impact the health of the occupants and high levels of RH would impact on health and result in mould growth on surfaces.

Finally the energy performance of Building 2, i.e. the only mid-terrace dwelling, is only 25% variance from the DEAP assessment and it can be noted that this variance is due to increased DHW usage, as such, it can be considered to be performing well with respect to its A-Rated design, from a space heating perspective. This dwelling also performs the best with respect to IEQ, with the lowest max CO2 peaks and CO2 is only over 1,500ppm at a maximum of 3.6% of the time. This would suggest that for the mid-terrace dwellings, there is no issue with perceived comfort as both the space heating energy values and the IEQ results are within the expected thresholds, and the A-rated dwelling design intent is close to its operation.

Further investigation into the end-terrace and detached dwellings will be carried out in the next phase of the research to determine if the issue is with the ventilation system or the external envelope or perhaps another unknown reason.

Future work will also include mechanisms to provide information back to home owners, in the form of simple dashboards, to educate and inform them on how their dwelling is operating, ensure the dwelling is performing as to the design intent (for both energy efficiency and IEQ) and enable the occupant to take an action when it is not performing as expected. This work will utilise the approach of Augmented Intelligence (AuI). AuI is an alternative prediction of how Artificial Intelligence (AI) will be used in the future. It focuses on AI's assistive role, emphasizing the fact that cognitive technology is designed to enhance human intelligence rather than replace it.

Future work in this research study will also report on all 100 dwellings in the study and the correlations between the dwelling types, which will be discussed with respect to the hypothesis resulting from this paper. Data on the non-domestic dwellings, i.e. 16no. schools, 3no. healthcare buildings and a number of small offices will also be analysed to determine if the impacts on IEQ of A-Rated dwellings is the same in non-domestic buildings.

Conclusion

This research paper has analysed four A-Rated dwellings in Ireland with respect to their energy efficiency and IEQ. The four dwellings chosen represent four building archetypes from an initial study of 46 buildings, which will be expanded to 100 dwellings in the coming months. A DEAP assessment, which is the Irish national methodology that conforms to the EU EPBD legislation was carried out on all four dwellings.

In conjunction, a hybrid Digital Twin of each of the four dwellings was created. The hybrid Digital Twin utilises the IES-VE Dynamic Simulation Modelling Software, which is a physics based modelling software, and the integration of real-data from external electricity meters and IEQ sensors placed in the dwelling using the IES iSCAN software. A new calibration approach, derived from the IPMVP, but incorporating Machine Learning to fill in missing data gaps and utilise the information coming from the IEQ sensors (e.g. motion) was applied to create the hybrid Digital Twin models. These models were then used to disaggregate the loads in the dwellings and understand the breakdown of space heating, DHW, lighting, appliances and small plug-loads in order to analyse the operation of the dwellings and perform a comparison against the DEAP assessment.

When the energy loads of the dwellings were analysed on their own, an assumption was made that the 4-bed detached dwelling was performing the best because it utilised a heat pump system instead of a gas boiler that is utilised in the other three dwellings. However, on further analysis of the IEQ, it was determined that this building was performing poorly with respect to CO2 and RH and therefore it is likely that the ventilation system is not performing as it should or is turned off. On further investigation and engagement with the home owners, the occupants of the end-terraced dwellings reported that they have issues with perceived comfort. Therefore the likely conclusion is that there is issues with the ventilation system that are impacting perceived comfort on both the detached and end-terrace dwellings.

The analysis also shows that the mid-terrace dwelling does not have any issues with perceived comfort or IEQ and correlates well with the DEAP assessment, apart from a slightly increased DHW consumption, which could be a attributed to behaviour. As such, the recommendations to the developer for their next phase of A-rated dwellings will be further investigation of the comfort levels of the end-terrace and detached dwellings and the potential to use Mechanical Heat Recovery Ventilation (MHRV) systems in these dwellings instead of the lower cost Demand Control Ventilation (DCV) systems. Further analysis will also be carried out as part of this on-going research.

Finally, a significant conclusion of this paper is the importance to analyse the whole picture of a buildings performance with respect to both energy use and IEQ in order to identify the impacts on energy efficiency. Through the emergence of low cost IoT sensors, and the hybrid Digital Twin approach that utilises building physics modelling, integration of time-series data and the application of Machine Learning, this analysis is now practically possible for any domestic or non-domestic building, including small to medium sized buildings which make up the majority of the building stock. Furthermore by creating a post-occupancy Digital Twin of the building, any performance or behaviour issues can be identified and rectified with the home owners and hence the performance gap can be minimised, without compromising IEQ. This also validates the need for M&V of all buildings, including dwellings, once they have been occupied to ensure they are operating as per their design intent.

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References

Ashrae (2002). *ASHRAE Guideline 14 -2002: Measurement of Energy and Demand Savings. American Society of Heating, Ventilating, and Air Conditioning*.

Baranyi, A. (2013). FutureFit: Monitored Data Analysis. VERCO (Client: Affinity Sutton).

Bou-Saada TE., Haberl, JS (1995). An improved procedure for developing calibrated hourly simulation models. *Proceedings from the 5th international IBPSA conference*. Montréal (Canada).

EVO; Efficiency Valuation Organization. (2018). Uncertainty Assessment for IPMVP. *Evo*, 1 (April).

Navigant Research (2016) Executive Summary: Energy Efficiency Retrofits for Small and Medium Commercial Buildings, Research Report.

Shiel, P. and West, R. (2016). Effects of building energy optimisation on the predictive accuracy of external temperature in forecasting models. *Journal of Building Engineering*, vol. 7, 281-291.

Pérez-Lombard, L., Ortiz, J., and Pout, C. (2008). A review on buildings energy consumption information, *Energy and Buildings*, vol. 40, 394-398.

Zero Carbon Hub (2014). Closing the Gap Between Design and As-Built Performance: End of Term Report.