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Minimising the Deviation between Predicted and Actual Building Performance via Use of Neural Networks and BIM

Ahmed WA Hammad

Faculty of Built Environment, UNSW Sydney, Sydney 2052, Australia; a.hammad@unsw.edu.au; Tel.: +61-2-9385-6723

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Abstract: Building energy performance tools are widely used to simulate the expected energy consumption of a given building during the operation phase of its life cycle. Deviations between predicted and actual energy consumptions have however been reported as a major limiting factor to the tools adopted in the literature. A significant reason highlighted as greatly influencing the difference in energy performance is related to the occupant behaviour of the building. To enhance the effectiveness of building energy performance tools, this study proposes a method which integrates Building Information Modelling (BIM) with artificial neural network model for limiting the deviation between predicted and actual energy consumption rates. Through training a deep neural network for predicting occupant behaviour that reflects the actual performance of the building under examination, accurate BIM representations are produced which are validated via energy simulations. The proposed method is applied to a realistic case study, which highlights significant improvements when contrasted with a static simulation that does not account for changes in occupant behaviour.

Keywords: building performance; energy predictions; artificial neural networks; BIM

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1. Introduction

An increasing number of governments around the world have set a target for reducing carbon emissions and enhancing the energy efficiency of buildings. For example, Australia specified that it plans to reduce 50%–52% of its emissions per capita by 2030 [1], with emissions from buildings expected to be significantly reduced due to advanced integration of technology [2]. In the UK and Germany, the government targets emission reductions of up to 80% by the year 2050 [3,4].

Around 40% of the total emissions worldwide come from buildings [5]. Currently, embodied energy in buildings constitutes anywhere between 30%–60% of the total share of the lifecycle of typical buildings [6–8]. Such significant environmental concerns have led to the adoption of certain measures to enhance the sustainability of the built environment. Common strategies adopted in the building sector include the use of low-carbon materials [9], recycling [10] and optimising the planning operations of construction [11]. For governments to achieve set targets, there is a need to place emphasis on the delivery of energy efficient buildings, through adoption of current advances in energy efficiency measures proposed for buildings [12].

Buildings are complex in nature. This complexity arises due to the integration of various systems, including structural, exterior envelopes, heating, cooling and ventilation systems, along with electrical, communication and plumbing systems, that all need to operate in conjunction with one another [13]. Heat loss in a building predominantly occurs due to energy leakage from the building's envelope [14]. For the purpose of the discussion presented in this paper, the focus will be on the assessment of the performance of the energy systems in buildings. A challenging issue in building performance is the deviation between predicted building system performance, and realistic energy consumption that occurs during the operation phase of the building [15]. To close this gap and ensure a reliable system is delivered for building performance, it is necessary that the design envisaged at the initial stage of building construction is truly represented in the final outcome once the building is operating [16]. To do so requires an understanding of the management of data that can be collected during the operation of the building, which can then be analysed to determine how well the building system designs reflect the actual performance capacity of the systems installed [17]. Performance evaluation for operating buildings is often associated with the type of measurements taken (i.e., what sensors are used to collect the data?), the implications of the data (i.e., what are the impacts of the data on decisions made?), and the feedback mechanism adopted (i.e., how is the data utilised to continually monitor the performance of the building to ensure that it complies with the generated designs?) [18].

Deviations between predicted and actual building performance leads to inefficiencies in terms of cost and energy consumption: van Dronkelaar et al., (2016) reported a 15%–80% discrepancy in total energy between design and building performance [19], while Knight et al., (2008) indicated a 22% difference between actual and predicted performance in university buildings [20]. A case study by The Carbon Trust, (2012) indicated that an extra £10/m2 in annual operating energy costs resulted due to the performance gap between predicted and actual performance of the building [21]. The evolving nature of the world paved the way for the introduction of various capacity-extending technology, including automated sensors [22], artificial intelligence (AI) [23], and digital models, including building information modelling (BIM) [24]. The integration of all the latter is the topic of various discussions on the practical and research arenas [25]. As a result, this work presents the first steps into an integrated implementation via a systematic platform for building performance management, which makes use of sensors, AI and BIM.

As indicated in [26], significant deviations between predicted and actual building performance is mostly attributed to the dynamic nature of the behaviour of building occupants, leading to a 40% difference between actual and predicted performance. The challenge thus lies in simulating real-world behaviour of occupants and reflecting their actions on the building system being monitored [27]. One way of handling this, as suggested by Samarasinghe, (2016), is to observe real-world data, rather than attempt to model each individual relationship in theory [28]. This paper proposes a technical method for integrating several key tools to enhance the monitoring of the performance of buildings. The focus is on enhancing the prediction of occupant behaviour to reflect the actual energy use of the building. BIM and AI are integrated within the proposed framework to predict the energy consumption of the building, with the results then contrasted with data collected from sensors and system logs present in the building. The work presented in this paper is organised as follows: first, a literature review on relevant elements of the proposed method, including existing building performance deviation assessment techniques, use of AI in building performance and adoption of BIM for building performance measure, is examined. Next, the framework developed is explained. A case example for a realistic project in Australia is then presented. Finally, results obtained from the implementation of the proposed framework are discussed.

An assessment of building performance involves collecting data on the energy performance and emissions of building systems, by monitoring water consumption, gas consumption and electricity consumption [29]. When using real data from sensors to match with simulated data in buildings, the presence of multiple sources makes it difficult to match data from these sources. In a bid to handle this challenge, Wang et al., have proposed the merging of data from sensors and external databases through a building identifier [30]. When it comes to building performance, a great deal of research has been conducted in the realm of building performance management and the use of technology for enhancing the management of constructed facilities. In this section, the literature review is divided into three main areas, namely facility management and energy efficiency in building performance, use of AI in building performance and BIM for the management of building performance.

1.1. Management of Building Performance

Effective building management through performance monitoring is essential for ensuring minimal environmental impact of the buildings [31]. Extensive research has been conducted on zero carbon and energy buildings, green buildings and passive houses, where the building performance is a critical object for ensuring that the required energy and carbon targets are met [32].

State of the art tools for building performance management reported in the literature rely on the integration of complex engineering system with computer simulations [33]. The approaches mostly monitor the thermal and energy behaviour of the building.

Attia et al. highlighted that there is a need to address computational issues and the lack of standard system approaches on the use of building performance optimisation tools in zero energy building design [34]. An assessment tool for building performance was proposed in [35] which relies on a multi-criteria decision-making approach. In [36], multi-objective optimisation was combined with building energy simulation models in order to optimise building specification so that its annual performance in terms of energy consumption is minimised. In [37], the stochastic behaviour of occupants and its impact on the building performance was captured via an occupancy simulator.

An uncertainty analysis was carried out on an office building in [38], as part of examining the impact of different physical uncertainties in building performance, considering thermal comfort and energy requirement. In [39] an online building performance tool for fault detection and diagnostics in buildings was developed. Dynamic thermal simulation was adopted for assessing building envelope refurbishment in [40]. Optimisation approaches were also proposed in the literature for the determining the trade-off between energy consumption and occupant comfort. In [41], design of windows for low energy consumption and high visual comfort was established via an optimisation approach. In [42] retrofits for buildings which are optimal in energy consumption, occupant comfort and heritage conservation was proposed.

1.2. AI in Buildings

The use of AI in design and construction of buildings has been discussed previously in the literature. A study by [43] investigated the use of AI for safety planning during construction. Yousefi et al. proposed an AI-based framework for predicting causes of delay in construction [44]. Azari et al. utilised AI for guiding the choice of materials that minimise the environmental impact of building envelopes [45].

In terms of applications of AI for building assessment and performance monitoring, [46] used neural networks to predict annual thermal and electrical energy use of buildings. Similarly, [47] adopted deep neural networks for space exploration in building designs that minimise the amount of energy required to operate the buildings. Deep learning techniques were also applied to predict building energy consumption in [48]. Genetic algorithm was used for predicting the energy performance of residential buildings in [49]. Cooling loads for buildings were predicted using deep learning method in [50]. Support vector machine was deployed by [51] for predicting next day electricity consumption in buildings. In [52], data-driven models were contrasted for predicting retrofit energy savings, in building retrofit projects. In [53], machine learning was adopted to predict energy consumption based on insulation thickness and envelop materials of a building.

1.3. BIM in Building Performance

BIM is a process for delivering construction projects on a digital platform [54]. Its use has been highlighted in the building and construction literature, through its applications for design, cost estimation and sustainability analysis [55]. In terms of building performance, several studies are present in the literature which elaborate on its main use. A comprehensive review was presented in [56] on the applications of BIM in facility operation. The use of building performance analysis software tools for assessing their suitability as BIM-based sustainability analysis methods was examined in [57].

A study of the barriers preventing the integration of BIM with building performance management tools was conducted in [58], where the authors found that building performance needs to be standardised to enable effective utilisation of automated tools for capturing building performance. In [59], BIM was adopted for instantaneous energy and exergy calculations in the early design stage of the project. In a similar context, [60] examined the use of BIM and BPS tools to facilitate energy-efficient buildings. A standardised approach for integrating information from BIM and BPS tools, via Industry Foundation Classes (IFC) schema was proposed in [61]. In [62], acoustic performance monitoring via use of semantic rule checking was implemented for a building model. A BIM-based performance optimisation framework was developed in [63]. The use of open standards to enhance interoperability for performance-based design was proposed in [64]. An IFC-based framework for use of BIM to perform energy performance management analysis was developed in [65]. Building performance modelling for sustainable design using BIM was discussed in [66].

1.4. Motivation of the Study

A considerable discrepancy between predicted and actual consumption of energy in buildings was found in a number of studies. In some cases, the difference was as large as the actual consumption being three times higher than that of the predicted consumption [67]. Differences were attributed to the choice of material during the construction stage, technical variations caused by workmanship and the disregard of occupant behaviour in energy simulation models [68]. In particular, [69] concluded that the impact of the behaviour of building occupants on the performance of the building in terms of energy consumption can be drastic. As a result, the work presented herein primarily focuses on occupant behaviour prediction, where an intelligent framework that enhances the behavioural prediction of occupants, based on integrating BIM with deep neural networks for the calculation of energy consumption of a building, is proposed.

2. Technical Framework

Figure 1 displays the overall framework developed for monitoring the building performance so that deviations in predicted and actual measures are minimised. The first phase of the proposed framework involves setting up the sensors/log systems used to track and monitor the actual building performance. This enables the collection of building data in real-time. An as-built digital representation of the building is then developed, which incorporates all systems that are required to run the building, including the heating, ventilation and air conditioning (HVAC) system, water system and lighting. The BIM file is built with certain occupant behaviour profiles defined to assess the impact on the overall energy consumption. Examples of parameters that define occupant behaviour profiles for a HVAC system include type of system that is operating, whether the system is turned on or off, the temperature set for the system, and any open/close windows in the room examined. Concurrently, the machine learning AI algorithm is formulated to yield optimum user occupant behaviour profiles which minimise the deviations from the actual building performance. The AI component is composed of a series of artificial neural networks (ANNs) that are trained to predict energy profiles. Such energy profiles are generated to yield the least deviations between real performance and predicted performance of the actual building systems utilised in the building. The deviation in performance is tracked and detected via use of process simulation that is run in BIM: optimum occupant behaviour profiles that are generated via the ANNs are input into the BIM file in order to run necessary energy simulations to validate the estimates of energy use of the building system. Once the results are validated, they are plotted on the performance graph; predicted performance is labelled as "baseline" in Figure 1, and this is then contrasted with the data collected from the sensors (i.e., the line labelled "Actual" in the graph in Figure 1). The BIM model thus acts as a reference module for assessing the energy consumption of the building based on occupant behaviour predictions made in the ANN.

The neural networks are developed to help generate consumption levels in the building that align with actual performance measures, based on a set of input that defines the characteristic of the occupant behaviour. At each time step assessed, once the output of the ANNs is passed on to BIM for carrying out the simulations, the generated energy profile is contrasted with the actual performance of the building. If the output of the neural network indicates a significant deviation from the actual data collected, the input that defines the occupant behaviour is varied to try to bridge the gap between actual performance and baseline (i.e., predicted) design. In Figure 1, this is indicated by a test of comparison that is conducted against a threshold value. It is stipulated in the framework developed that a change in the occupation behaviour due to the results obtained from the neural networks is instigated only when it helps in reducing the energy consumption of the building. This is defined in the threshold limit based on which the deviations are assessed. The next section describes in detail the composition of the neural networks developed. Via a set of algorithmic approaches developed to automatically extract data generated from the neural networks and parametrically embed them in the BIM module, the simulations are re-run in BIM to validate the outcome of the ANNs. As indicated in Figure 1 model training of the ANNs is based on a combination of its historic performance and the real-time updates obtained from the sensors/system logs within the building.

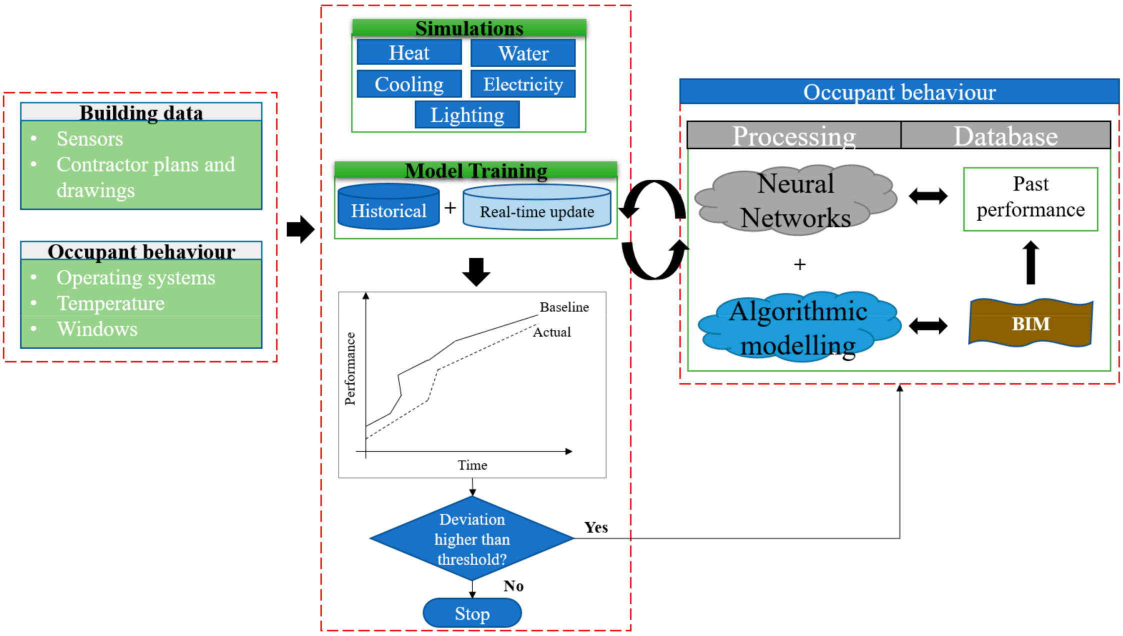

Figure 1. Framework developed for building performance modelling.

There is a need to provide current practitioners with an easy-to-access framework that can be used in the early design phase of a building to assess the energy performance and determine the energy requirements. As a result, Insight360 was adopted in the proposed framework in this study, as its use has been labelled as efficient and effective in the literature to simulate the energy requirements of a building [70]. In addition, Insight360 utilises the EnergyPlus simulation engine to carry out the simulations [71]. Alternative tools exist in the research community, including eQUEST [72] and OpenStudio [73].

3. Artificial Neural Networks

In this study, ANNs are adopted as an effective computational framework for modelling the consumption rates of various systems adopted in the building. Their function is based on imitating the biological networks constituting animal brains [74]. Key aspects that underpin the structure of an ANN include the input layer, hidden layers incorporated, output layer, weights and the activation function utilised to map the input, going in the neurons, into a suitable range for the output. The initial step adopted in developing the ANN, is the normalisation of the data via a linear transformation, where the impact of the magnitude and range of variation in input data is minimised through normalisation. The second step involves dividing the data into a training and validation data set (70%–30% respectively), to enable the derivation of the optimum weights and biases of the ANN. The definition of the number of layers comprising the ANN constitutes the third step, where the architecture of the network is defined via choice of the number of neurons in each layer. The input variables need to equal the number of neurons in the input layer, whereas four neurons are modelled for the outer layer. The overall framework of ANNs developed in this research is shown in Figure 2. In particular, the ANN developed in Figure 2 corresponds to that used for predictions made relating to the HVAC system adopted. For the purpose of maintaining the brevity of the discussion, the focus of the developed ANN is only on monitoring the HVAC system, though the framework can easily be extended to encompass other systems too. In this case, a single ANN would need to be developed and trained for each of the building systems analysed.

In the case of Figure 2, there exist five neurons as input, three hidden layers each composed of 24 neurons, and a single layer comprised of four neurons as output. The input neurons correspond to factors that can help predict the impacts of the behaviour of occupants. Neighbouring buildings include the energy consumption data of near-by houses, as it was indicated in [75] that neighbouring houses tend to have similar energy consumptions. BIM simulations conducted for establishing the energy consumption of the modelled project are also adopted as an input. It is important to note that the type of building systems that consume energy are defined within the BIM file. Initially, baseline conditions are considered in the BIM model. Once the output is generated from the neural network, it is adopted to modify conditions of the simulation model in BIM, and this in turn becomes an input for the subsequent run of the neural network. This process is repeated up until the deviations between baseline and actual performance is deemed to be negligible. Historical energy bills of the associated building form an input to the neural network developed. In terms of historical bills, the main information that is related to its inclusion as an input in the neural network is the past energy consumption of the building. Past trends in energy consumption can be of high relevance when predicting the existing energy consumption, as indicated in [76]. The number of occupants and outside temperature conditions of the building examined have also been indicated as factors that help predict the behaviour of occupants in buildings and have therefore been included as input to the neural network.

The output produced by the neural network is a prediction of specific parameters that define the occupant behaviour. Such predictions are thus recommendations for the best settings to adopt on the implemented systems so that the smallest deviations between actual and predicted performance result. Examples modelled in the neural network developed in Figure 2 for estimating the behaviour of occupants relative to the HVAC system deployed in the building, include the period of time that windows are left open and indoor temperature settings [77].

In order to ensure that the ANN prediction error is minimised, two main error components are targeted, namely systematic errors and random errors. In systematic errors, the main factors influencing the degree of the error are related to the architecture of the ANN [78]. Modifying the number of neurons making up the neural network during the testing process is carried out to minimise the systematic error. Random errors on the other hand are related to the differences between parameters and their measured values [79]. Random errors therefore mostly reflect the difference between actual and predicted energy consumption rates, which are very complex to minimise in building performance assessment as discussed in [27,80]. For the ANNs developed in this study, the tanh function is adopted as the activation function given its fast convergence rate [81].

The prediction capacity of the ANNs is further enhanced, via use of a gradient-based decent approach [82]. Weights within the network are updated based on back propagation, which involves carrying the error from the output layer to the input layer so that total error in the ANN is minimised [74].

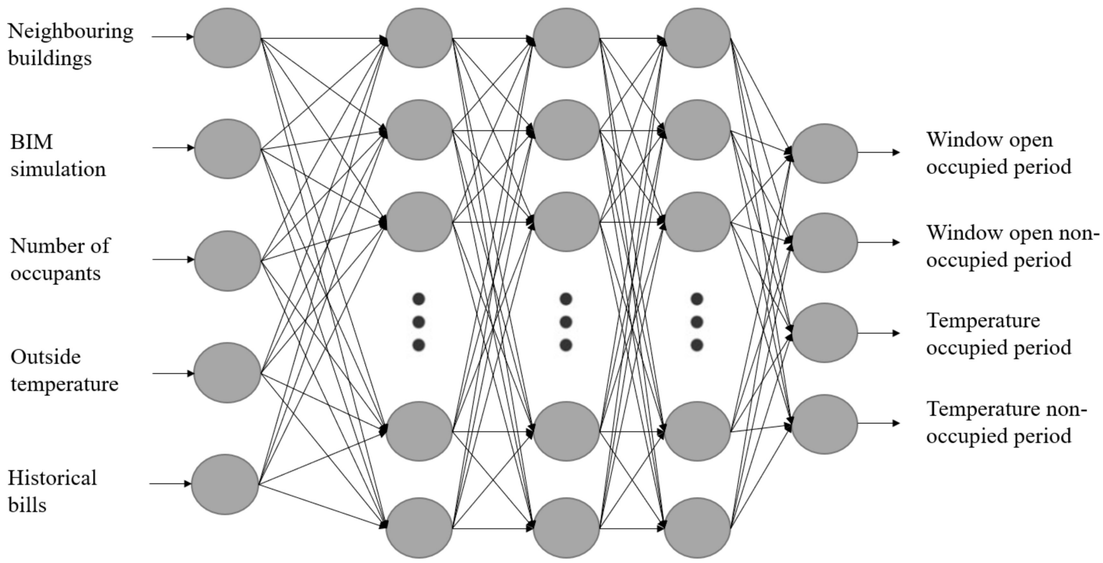

Figure 2. Neural network layers.

Random Forest

Random forest (RF) is a supervised learning approach, where multiple data trees are created and merged to get an enhanced prediction [83]. In this paper, RF is adopted due to its ability in revealing the most important input variables when predicting a given output variable. In particular, the wrapper aspect of the RF [84] (Hastie et al., 2009) is utilised to indicate which of the input factors are strongly associated with the predicted output (in this case the energy consumption loads).

4. Case Study

The application of the proposed framework is conducted on a family house building project, located in Sydney, Australia. The house is a two-storey building, with a total space of 280 m^2 and a ceiling height of 2.4 m, as displayed in Figure 3. As mentioned above, to maintain the brevity of the discussion, the framework is applied to predict occupant behaviour that leads to the least deviations in the performance of the cooling and heating system. Energy consumption in the house was monitored for a duration of 12 months. In Sydney, Australia, December-March is the heat season.

Occupant behaviour is typically represented by setting indoor temperature, and schedule of appliances, lighting and HVAC systems. As a result, during the energy consumption simulations for the cooling and heating systems, the temperature is fixed at a specific temperature for a certain duration during the day and night. The windows are assumed to be open for a certain percentage of the time in which rooms are occupied and non-occupied. Certain behavioural profiles are also modelled in the neural network trained, including the alteration of the operating period of the systems during occupied and non-occupied hours and varying the percentage of time that windows are left open/closed. Heating and cooling set point temperatures are defined as 21 and 27 °C respectively. Occupant behaviour is assumed as defined by the behavioural profile in Table 1. It is important to note that the information given in Table 1 is used to generate the baseline BIM simulations, which are in turn used as input in the neural network.

The sensors utilised in the case study are listed as follows:

i. H22 HOBO Energy Logger; used for assessing the performance of the HVAC system installed in the building; data is logged every five minutes
ii. Onset HOBO UX100 Temp/RH; used for monitoring the indoor environmental quality by determining comfortable temperatures indoors; data is logged every 15 min.

Table 1. Initial occupant behaviour assumed.

<table>
<tr><th></th><th>Factor</th><th>Action</th></tr>
<tr><td rowspan="4">Cooling</td><td>Window</td><td>Windows shut during unoccupied time; windows open 15% of occupied time</td></tr>
<tr><td>Operation Temperature</td><td>21</td></tr>
<tr><td>Number of occupants</td><td>3</td></tr>
<tr><td>System</td><td>Refrigerated cooler—Mitsubishi SEZ-KD bulkhead air conditioner</td></tr>
<tr><td rowspan="4">Heating</td><td>Window</td><td>Windows shut during unoccupied time; windows open 10% of occupied time</td></tr>
<tr><td>Operation Temperature</td><td>27</td></tr>
<tr><td>Number of occupants</td><td>3</td></tr>
<tr><td>System</td><td>Heat pump system—Stiebel Eltron WPL 25 AC/WPL 25 ACS</td></tr>
</table>

The physical properties of the building are displayed in Table 2. The BIM file for the building is generated in Revit, after which it is sent to Insight360 [85] (Autodesk, 2019) for performing the energy performance analysis and simulation, including thermo-physical properties of the building, and the resulting HVAC energy consumption analysis. It is important to note that the location of the building needs to be specified before conducting the energy simulation in Revit to ensure that the sun path and the respective building orientation is accounted for in the energy analysis. Once the results from Insight360 are generated, they are then passed on to the neural network of Figure 2 in order to predict the most appropriate occupant behaviour parameters that result in smallest deviation in energy consumption, as contrasted with actual monitoring data obtained for the HVAC system of the building.

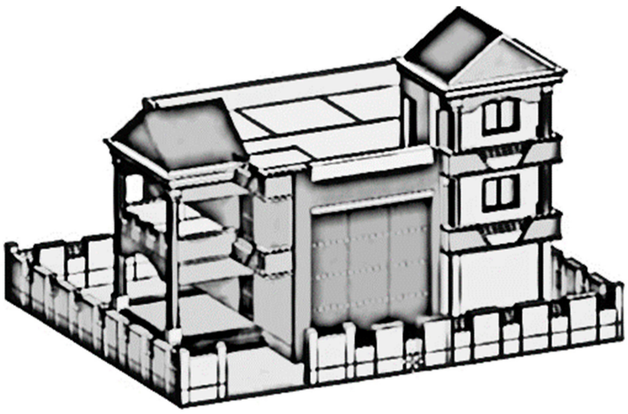

Figure 3. Case example model.

Table 2. Building materials for case study.

Component	U-Value (W/m^{2}K)
Internal Walls—partition wall, 10 mm plasterboard with 90 mm steel frames	0.54
External Walls—rendered brick	0.29
Concrete floor—150 mm	0.41
Gabbled tile roof	0.29

The time period of analysis is discretised into quarters. Throughout each time period, the occupant behaviour predictions made by the ANN, combined with the simulations conducted in BIM are used to generate the baseline (predicted) curve shown in Figure 1. The data from the sensors within the building are used to plot to the actual performance curve in Figure 1.

5. Results

5.1. Recommendations by ANN

Before presenting the results of the application of the framework proposed in Figure 1 to the case study of Figure 3, a summary is first presented here: the test data R^2 for the developed ANN, with 72 hidden neurons and 4 neuron output is given as 0.991. The training time of the network is given as 4.4 min.

The analysis of the heating and cooling energy requirements is conducted over a specified number of periods; after several computational experiments, it was revealed that the best period for assessment of the overall consumption power in the building is one that is assessed every quarter, in line with how the energy consumption billing system is set up in Australia [86]. Table 3 displays the recorded average energy consumption, as assessed by the ANN and the actual sensors, at each quarter. For each quarter, the corresponding occupant behaviour recommended by the ANN is displayed in Table 4.

As can be noticed from Table 3, during the 1st quarter of the year (JAN—MAR), the cooling system is operating at its highest capacity due to the hot weather, and the recommended occupant profile, displayed in Table 4, corresponds to: (i) windows open for 10% and 55% of the time when occupants are not present during day time and night time respectively; (ii) windows open for 0% and 5% of the time when occupants are present during day time and night time respectively; (iii) the cooling system to be set at 19 °C and 21.5 °C during the day and night times respectively; and (iv) the heating system is not utilised for 98% of the quarter.

During the 3rd quarter (JUL—SEP), the heating system is operating at its highest capacity (Table 3), while the cooling system is disengaged for 95% of the quarter. Aspects revealed in the optimum profile of Table 4 corresponding to the latter period for the heating system include: (i) windows are open for 25% and 3% of the time when occupants are not present during day time and night time respectively; (ii) windows open for 45% and 0% of the time when occupants are present during day time and night time respectively; (iii) the heating system is set at 25 °C and 28 °C during the day and night time respectively.

In Figure 4 the average percentage deviation across each analysed quarter of the year between: (i) the ANN results and the actual performance of the HVAC system; and (ii) the conventional building simulations and actual performance of the HVAC system is examined. In Figure 5 the overall average percentage deviation across the whole year is plotted for both the proposed ANN approach and the conventional static simulation. Conventional building performance simulations are conducted by assuming the static behaviour of occupants, based on the parameters reported in Table 1, without varying the occupants' behaviour across the year. As can be seen, in Figure 4, the ANNs always report a lower deviation from actual performance, contrasted with the static simulation approach which does not account for the changing behaviour of occupants. In Figure 5, the ANNs report an average 10.4% deviation from actual HVAC performance, compared to 33.5% for the conventional simulation approach.

Table 3. Recorded average energy consumption by HVAC system, as assessed by the ANN and the actual sensors, at each quarter.

		Recorded Average Consumption (kWh/m^2)			
		1st Quarter	**2nd Quarter**	**3rd Quarter**	**4th Quarter**
Heating system	Actual system	4	33	25	5
	Predicted via ANN	6	35	28	3
Cooling system	Actual system	41	12	15	29
	Predicted via ANN	44	9	7	33

Table 4. Optimum occupant behaviour recommended by neural network to minimise deviations in building HVAC performance.

	Recorded Average Consumption			
System Recommendation	**1st Quarter (JAN—MAR)**	**2nd Quarter (APR—JUN)**	**3rd Quarter (JUL—SEP)**	**4th Quarter (OCT—DEC)**
		Window day no occupants: 35%	Window day no occupants: 25%	
		Window night no occupants: 10%	Window night no occupants: 3%	
		Window day with occupants: 65%	Window day with occupants: 45%	
Heating system Recommendations	Disengaged for 99% of the time	Window night with occupants: 10%	Window night with occupants: 0%	Disengaged for 90% of the time
		System temperature day: 25 (operating for 140 h)	System temperature day: 25 (operating for 310 h)	
		(operating for System temperature night: 28 140 h)	System temperature night: 28 (operating for 310 h)	
	Window day no occupants: 10%			Window day no occupants: 10%
	Window night no occupants: 55%			Window night no occupants: 55%
	Window day with occupants: 0%			Window day with occupants: 15%
Cooling system Recommendations	Window night with occupants: 5%	Disengaged for 90% of the time	Disengaged for 99% of the time	Window night with occupants: 15%
	System temperature day: 19 (operating for 360 h)			System temperature day: 19 (operating for 234 h)
	System temperature night: 21.5 (operating for 360 h)			System temperature night: 21.5 (operating for 360 h)

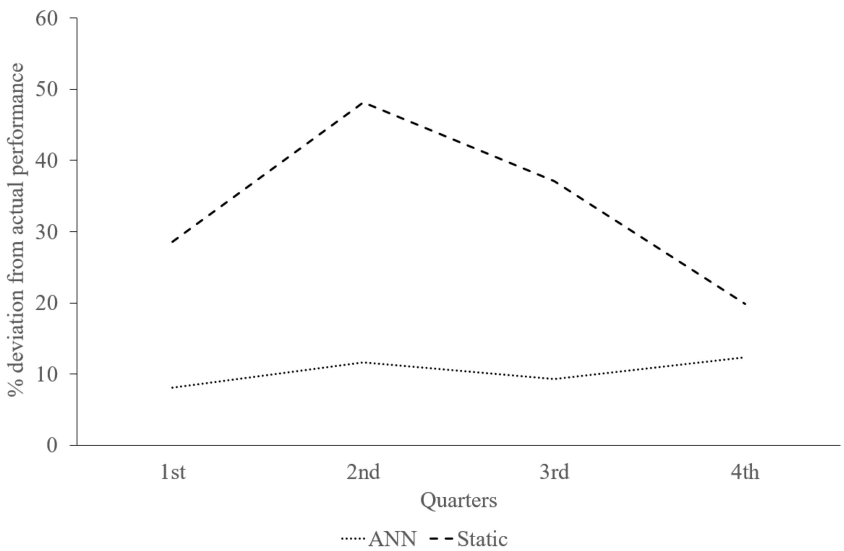

Figure 4. % deviation from actual performance of HVAC system, for ANN and static conventional simulation at each period.

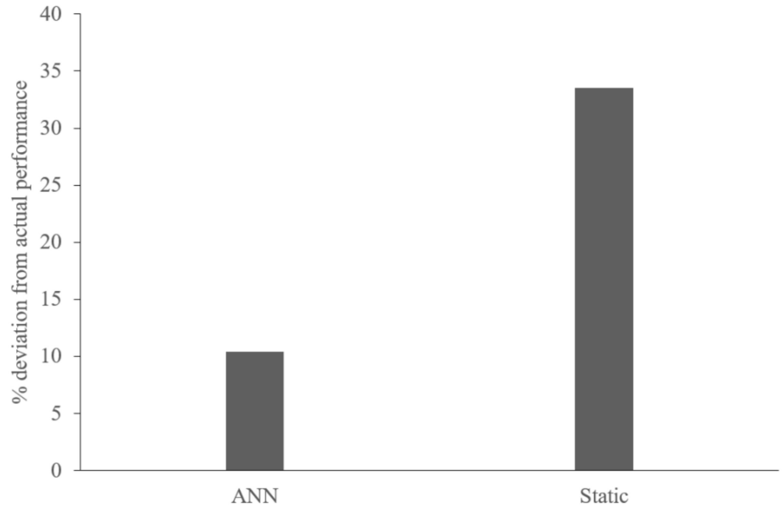

Figure 5. Average % deviation from actual performance of HVAC system, for ANN and static conventional simulation.

5.2. Sensitivity Analysis

A sensitivity analysis is conducted by modifying the number of inputs that are adopted in the developed ANNs. As can be seen in Table 5 the percentage error in predictions made are assessed to range from a maximum of 51% to a minimum of 10.4%. The analysis starts with only considering the outside temperature as input for both the heating and cooling systems' predictions. The input neurons are then increased successively to incorporate additional inputs shown in Table 5. Only input combinations with significant results are displayed. The percentage prediction error tends to successively decrease as additional input is incorporated for both the cooling and heating systems, though certain parameters have a larger influence on improving the prediction of the neural network (see for instance outdoor temperature). This result is an indication of the necessity of incorporating all the assessed factors that impact the occupant behaviour when predicting the resulting energy consumption. The maximum number of factors impacting the occupants' behaviour is modelled as five in the trained neural network, in line with what has been proposed in the literature (Clevenger and Haymaker, 2006, 2006; Toftum et al., 2009; Yan et al., 2015). Additional factors can be incorporated, and these could increase the prediction accuracy of the ANN, though it should be noted that increasing the number of input factors does not always correlate to an increase in accuracy, as was revealed in (Paterson et al., 2017).

Table 5. Sensitivity analysis in terms of neural network input features.

Input Modelled	Average Prediction Deviation from Actual Performance
Outdoor temperature	44%
Outdoor temperature and Historical Bills	38%
BIM Simulation	51%
Neighbouring houses	31%
BIM Simulation and Neighbouring houses	23%
BIM Simulation, Neighbouring houses and outdoor temperature	17%
Number of occupants	42%
Number of occupants and outdoor temperatures	20%
Number of occupants, outdoor temperatures and BIM simulation	15.6%
Number of occupants, outdoor temperatures, BIM Simulation, Neighbouring houses and Historical Bills	10.1%

5.3. Results of Random Forest Examination

A random forest analysis is conducted to assess the importance of each examined input variable shown in Table 1, on the output (i.e., energy consumption load prediction). The results of running the RF, where the training and testing process on the sample is repeated multiple times, to ensure the generalisation of the performance of the RF learner, is displayed in Table 6. The table suggests that the neighbouring buildings, BIM simulation and historical bills all have a significant influence on the predicted temperature that the cooling system should be set at during the occupied period. For the heating output, all the previous features mentioned for the cooling system are also imperative though this time, the outside temperature has a much bigger influence on the occupant profile predicted for the heating system. For the RF analysis conducted on both the cooling and heating system occupant output, the input features in the ANN, through their impacts on the time for which the windows are left open during the occupied period and non-occupied periods and the temperature set indoors.

Table 6. Impact of neural input features on the predicted occupant behaviour profile.

Input Feature	Impact on Cooling Occupant Profile	Impact on Heating Occupant Profile
Neighbouring buildings	61.12 ± 0.23	92.78 ± 0.78
BIM simulation	81.32 ± 1.21	95.09 ± 1.77
Number of occupants	31.12 ± 1.32	39 ± 1.11
Outside temperature	42.43 ± 0.43	51.28 ± 0.91
Historical bills	78.23 ± 1.37	86.23 ± 0.98

6. Conclusions

The automated framework proposed herein, which dynamically accounts for the influence of occupant behaviour in buildings on energy consumption, was examined through a realistic case example. For the developed ANNs, input features include the choice of the system made (through use of an as-built BIM model), neighbouring houses' energy consumption, historical bills of the corresponding building under examination along with the number of occupants present in the room. The output neurons correspond to factors that model certain aspects of the occupants' behaviour, including the temperature of the room occupied and period of time for which windows are open. These are all factors which have been noted down in the literature as being imperative in impacting the performance of HVAC systems in buildings.

The results of the example presented in the previous section leads to several insights. It was demonstrated that the heating and cooling energy consumption can be predicted with an average of 10.4% deviation from the actual performance measured in the buildings. This approach thus eliminates the need for running a separate simulation every time a change in occupant behaviour occurs, as the ANN model will automatically re-run to predict the impacts on the cooling and heating energy loads, in a matter of a couple of seconds. The results of the proposed building performance monitoring method enable decision makers to: (i) schedule upcoming maintenance work required for the building systems installed; and (ii) take steps to enhance the sustainability of their building by suggesting alternative energy saving measures, to try to minimise the energy loads. The impact of the five main variables used as input features on the output was also examined, with results indicating that outdoor temperatures, energy consumption of neighbouring houses, historical bills and results of successive BIM simulations all aid in predicting the occupant behaviour. Modelled profiles for occupant behaviour are based on the temperature that the system is set at during the buildings occupied and non-occupied periods, along with the time period for which windows are open. Such results are supported from an engineering perspective since air flow through windows is a major cause for increased cooling and heating loads imposed on the ventilation system in buildings [87].

The ANN approach was contrasted with conventional approaches that rely on performing a static simulation, with results highlighting that the prediction of energy performance is on average 72%

more accurate in ANNs. The system provides a comparative analysis of actual energy consumption vs. simulated consumption. A diagnostic process whereby random and systematic fluctuations in energy consumption are identified, based on examining individual factors relating to occupant behaviour that induces a change in consumption levels, has thus been attempted by the work proposed herein. By monitoring the performance gap, additional operational management measures can be taken to enhance the effectiveness of the building's consumption level. This would require calibrating energy models to match with real-time data collected for buildings. The calibration of existing models has been attempted in [88–90].

A number of limitations exist in the research presented herein. First, it is assumed that the original building design is deemed to be efficient. As a result, only the deviation between actual and simulated performance of the system was targeted, and the energy consumption of the system itself is not minimised. Second, the framework needs to be tested on several case examples that resemble various building shapes, sizes and building use classifications to ensure a robust method. These will be the subject of future research by the author.

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