BUILDING PERFORMANCE SIMULATION OF MYBOX ENERGY LAB IN NORWAY: INVESTIGATING THE HUMAN DIMENSION IN ENERGY USE ANALYSIS

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ABSTRACT

The MyBox energy lab at the University of Stavanger presents an innovative integration of living and research spaces housed within six repurposed shipping containers, where energy consumption data has been logged hourly over the past five years. Employing Building Performance Simulation (BPS), this study investigates the human dimension of energy use within the facility. Focusing on modelling human-related energy use, the research explores the customisation of occupant, equipment, and lighting schedules using BPS, revealing substantial day-to-day variability in energy consumption attributed to human factors such as presence, heating preferences, and cooking habits. While validation against actual data demonstrates a reasonable correlation on yearly and monthly scales, the study highlights the limitations of BPS in capturing finer temporal resolutions, emphasising the need for enhanced methodologies in simulating human behaviour within energy models.

1 INTRODUCTION

Since the pre-industrial era, the global average temperature has increased by 1.2°C (Lindsey & Dahlman, 2021). There is an overwhelming scientific consensus that this is caused by humanity's emission of greenhouse gases (IEA, 2021; IPCC, 2021). The problem has been well understood and high on the political agenda for more than 30 years (IEA, 2021; United Nations 1992). Greenhouse gas emission comes from numerous sources; however, around 73% of the global emissions are attributed to Energy in the form of electricity, heat and transport (World Resources institute, 2020). Breaking down the energy use by sector, the operations of buildings account for 30% of global final energy consumption and 26% of global energy-related emissions, according to IEA (IEA, 2023). The numbers are even higher in Europe; in 2021, 42% of the energy consumed in the EU was used in buildings (European Comission, 2023).

Because of this, it is crucial to focus on the energy use and emissions from buildings to reduce overall greenhouse gas emissions (IEA, 2021). Buildings today are continuously becoming more energy efficient. However, 85% of EU buildings were built before 2000, and among those, 75% have poor energy performance. Significant improvements will, therefore, have to be made to achieve a fully decarbonised building stock by 2050 in line with the targets of the European Union (European Comission, 2023).

Historically, the focus on energy efficiency in buildings has been targeted at minimising the energy use of a building through the emphasis on building materials and technical systems (Ionescu et al., 2015). However, several studies (D'Oca et al., 2018; O'Brien et al., 2020; Yoshino et al., 2017) argues that the research in "building energy efficiency" has down-prioritised the focus on energy use related to occupant behaviour (OB) to the advantage of technical solutions in buildings. This down prioritisation is problematic because the human dimensions play a significant role in energy savings in buildings. Also, this factor is poorly understood, so stakeholders often ignore or simplify human dimensions (D'Oca et al., 2018). A poor understanding of OB in buildings likely results in inadequate tools to address the energy efficiency potential of better addressing human dimensions of energy usage.

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Various tools can aid engineers and researchers in predicting the performance of both planned and existing buildings (Nguyen et al., 2014). Still, the industry standard of computer tools is a class called BPS, which utilise computer-based models founded on physical principles to quantify relevant aspects of building performance for design, construction, and operation purposes (Wilde, 2018). By utilising BPS, one can predict a range of factors for a building; however, energy consumption will be the focus of this paper.

However, in BPS research, the term "Performance Gap" is a commonly known factor influencing modelling. The performance gap of buildings is frequently defined as the difference between the performance value predicted in the design stage and that measured in the post-occupancy stage (Shi et al., 2019). The "Energy Performance gap" is a more specified term describing the discrepancy between predicted and measured energy use of a building (van Dronkelaar et al., 2016). According to research by (Menezes et al., 2012), the measured energy use of a building can be as much as 2.5 times greater than the simulated or predicted energy use. The causes of the performance gap are linked to causes rooted in the design, construction and operational stages of a building (de Wilde, 2014). Some researchers, like (D'Oca et al., 2018), attribute a significant portion of the energy performance gap to OB, while others, like Field (Mahdavi et al., 2021), argue that occupants as significant or exclusive contributors to the energy performance gap are not sufficiently substantiated by evidence.

Nevertheless, human behaviour does not necessarily adhere to standard physical principles, and predicting OB using BPS could lead to inaccurate models and, therefore, imprecise energy calculations for a building. The mismatch between a building model is also reflected in the research comparing building energy standards and actual energy use of buildings. The American Society of Heat, Refrigerating and Air-Conditioning Engineers (ASHRAE) publish standard energy consumption profiles for different buildings. However, this is quite a simplified view, and studies show that the actual energy demand profile varies significantly from this standard (typically 20-30% both ways) (Annaqeeb et al., 2020), which OB could explain to a large degree.

Utilising the MyBox energy lab at the University of Stavanger—a complex of six insulated shipping containers serving living and research purposes—we've collected hourly energy consumption data over five years. These data serves as the basis for our study, which employs the BPS tool IDA ICE[1] to create a virtual model of the MyBox lab and compare simulated energy use with historical data.

Our study focuses on the human aspect of energy use, given the sector's significant global energy consumption and the impact of OB on usage patterns. Modelling this dimension presents challenges due to its variability. We explore the feasibility of incorporating human-related energy use into BPS tools, allowing for customised schedules for occupants, equipment, and lighting. This paper comprises four sections: an introduction to building energy use and the role of BPS, a description of the MyBox energy lab, a detailed model description using IDA ICE, and a discussion comparing simulation results with measured data. Ultimately, the MyBox living lab aims to provide open access to energy datasets, facilitating a deeper understanding of the human dimension in building energy usage.

2 SYSTEM DESCRIPTION

The MyBox energy lab is a living energy laboratory at the University of Stavanger in Norway. It comprises six retrofitted 40-foot shipping containers insulated with vacuum insulation panels and made into five student apartments. The two shipping containers on the top floor are connected by a door, making the apartment twice as large as the four others. The MyBox building was constructed at the University of Stavanger in 2014 as a student-driven pilot project to solve the campus housing problem (MacDougall, 2014).

[1] IDA ICE is a dynamic simulation software used for detailed analysis of building energy performance, indoor climate, and HVAC systems.

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In 2019, upgrades to the MyBox building were made to facilitate energy research in a living lab. Eight photovoltaic (PV) panels were installed on the roof and four on the east and west-facing walls. In addition, a vertical axis wind turbine (VAWT) was installed to investigate the potential for wind energy production in urban settings. Energy consumption has been logged continuously for the whole building hourly since 2018. The energy production from PV and the VAWT has also been logged since installation; however, intermittently due to partly faulty logging equipment. The six shipping containers in the lab are stacked two side by side and three in height (Figure 1). Each apartment has a combined kitchen and living room, a bathroom, and a bedroom/office. Students at the University of Stavanger can apply to live in the apartments for free in return for sharing their energy data, being part of energy interventions, and doing student projects linked to the lab. The following sections describe the construction and systems of the MyBox living energy lab.

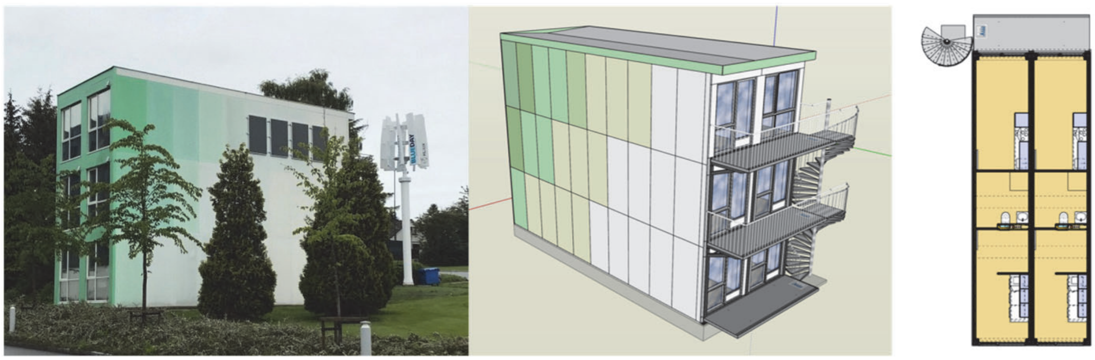

Figure 1: A) A photo of the exterior of the MyBox lab. Towards the right of the building, there are four east-facing PV panels. On the right side is a 3kW VAWT (Photo by H. Syse). B) A building information model (BIM) model used to create the BPS model. C): Overview of the interior of the apartments. BIM model and figure by (Sørstrønen, 2013).

2.1 Building Construction Description

The load-bearing structure of the MyBox lab is six steel shipping containers. The long sides of the shipping containers are not modified, but the short sides are cut out on both sides to make room for windows and doors. The corners of the containers have been reinforced to make up for the missing steel walls on the short side (Sørstrønen, 2013). The primary insulation of the walls is vacuum insulation panels (VIP), a material that provides low U-values without adding a lot of thickness to the wall. The windows and doors are double-glazed. Table 1 delivers an overview of the dimensions of each container unit. Table 2 shows the build-up of the walls, with thickness of each element and corresponding u-values, taken from (Sørstrønen, 2013) and (Shen et al., 2019):

Table 1: Dimension of each of the six living modules of the MyBox living lab (Sørstrønen, 2013)

Specifications	Outside	Inside
Area	29,74 m^2	26,18 m^2
Length	12,19 m	11,64 m
With	2,44	2,25 m
Height	2,90	2,50 m

Table 2: Overview of the wall materials, their thickness, and corresponding U-values.

Material	Thickness (mm)	R-Value (W/m^2K)
Gypsum	12	0,22
Light insulation	50	0,04
Steel shipping container	27	42,00
Air gap	30	0,16
VIP	30	0,01
Tricoya (composite wood)	12	0,14
Total	**131**	**0,13**

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2.2 Overview of MyBox Energy Lab's Integrated Energy Systems

The MyBox energy lab comprises several systems that contribute to the building's overall energy system. The heating system is direct electric heating in the form of two standalone electric smart IoT-enabled heaters in the bedroom/office and kitchen/living room area. The occupant can set the room temperature by adjusting the smart heaters. The IoT-enabled heaters allow for remote management and optimisation of the heating. The occupants can program the heaters to lower the night temperature or remotely control the heating through a phone app. The ventilation system is a constant air volume fan with a reheater. The apartments are in Norway, where heatwaves are infrequent, so there is no dedicated cooling system, as is common in northern European countries (Ruuhela et al., 2021).

Each apartment also has a 28-litre electric hot water tank used for showers and tap water. The flats have natural lighting from the windows on the north and south sides of the building. In addition, there are LEDs on each room's ceiling. Each apartment has several fixed electric appliances: a dishwasher, washing machine, oven, cooking hob, fridge, and TV. In addition, the occupants living there can have other appliances drawing power, like a computer, phone, etc. All these electrical components contribute to the load profile throughout the day for these apartments. Some loads, like the ventilation system, run continuously without being influenced by the occupants. Other components, such as heating, are influenced by the occupant changing the indoor temperature.

For power generation, the lab is connected to the regional electricity grid and supplemented by renewable energy sources, namely 16 270W PV and a VAWT with a capacity of 3200W. The photovoltaic panels are strategically installed—four mounted vertically on east and west-facing walls, and eight positioned at a 10° inclination to the south on the flat roof. In 2021, the lab's total energy consumption was documented at 34,816 kWh, with the PV array contributing 2,408 kWh, accounting for 6.9% of the total consumption. The wind turbine's yield was notably lower at 11 kWh, representing a mere 0.5% of total yearly consumption, an inefficiency attributed to suboptimal siting characterised by low and variable wind conditions.

Though the energy generation aspect of the MyBox Energy Lab provides a crucial context for the building's operational dynamics, the primary focus of this paper is on the demand side of the energy equation. Table 3 describes the components constituting the lab's energy system, serving as a basis for analysing consumption patterns and modelling the building. The table lists the components for each of the apartments inside the building.

Table 3: Overview of the MyBox apartment´s components that form the basis for the lab's energy consumption and production. The peak power for each component is obtained from the relevant datasheet.

System component	Description	Peak power
Heating	2 x smart electric heater	2x 1500W
Ventilation	Constant air volume fan with re-heater	Fan: 172W Re-heater: 500W
Hot water	Electric hot water tank, 28 litre capacity	1950W
Lighting	10 x 5W LED spots in ceiling, 3W bed lamp, 8W office lamp	61 W total
Dishwasher	Dishwasher from IKEA	2200W
Washing machine	Washing machine from Electrolux	2200W
Oven	Electric oven from IKEA	2600W
Cooking hob	Induction hob from Matsui	3500W
Fridge	147l fridge from IKEA	132W
TV	32-inch TV from IKEA	70W
Miscellaneous chargers and devices	Computer, phone charger, etc.	N/A
Power production	Grid connection 16 PV modules (270Wp each) 3200Wp VAWT	PV 4320Wp VAWT 3200Wp

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2.3 Energy data and logging equipment

The MyBox lab has a smart meter that has logged the energy consumption for the whole building consisting of 6 container units since 2018. This dataset provides the benchmarking data for the BPS model. The day with the lowest consumption (18.08.2023) sees a consumption of 31 kWh, and the day with the highest (27.01.2021) has a total consumption of 241 kWh. The main driver for electricity consumption is the outdoor temperature, with the coldest days having the highest consumption and the warmest days having the lowest. The average daily energy consumption across the dataset is 91 kWh per day. Table 4 provides an overview of the energy consumption data collected:

Table 4: Electricity consumption data logged for the MyBox lab

Description	Hourly energy data MyBox energy lab
Time start	01.08.2018
Time end	Continuous monitoring
Resolution	1 hour
Unit	kWh

In addition to the smart meter data capturing the whole building, a new logging system was installed in the two ground-floor apartments in September 2023. This system logs the power load for each circuit with a 10-second resolution. This means that data will separately be available for fridges, lights, ventilation and power outlets, hot water boilers, washing machines, cooking hob, dishwashers, power outlets for heating, indoor temperature, outdoor temperature, wind speed and electricity price. The system is still being tested and calibrated; however, in future work, the data from this system will be used to get better insight into the OB impact on energy consumption.

3 MODEL DESCRIPTION

3.1 Choice of BPS tool

The software used to create a BPS model of the MyBox was IDA Indoor Climate and Energy (ICE), which EQUA Simulation AB developed. The software was chosen after reviewing available BPS software, which has the potential to simulate OB. In a review paper by (Hong et al., 2018), programs that can represent and implement OB are critically reviewed. In the paper by (Hong et al., 2018), IDA ICE is highlighted as a tool that provides flexibility for users via the input of predefined and customised occupant schedules. Previous research investigating the simulation of OB in buildings and its relation to energy use has employed IDA ICE (Buso et al., 2015; D'Oca et al., 2014; Tuniki et al., 2020).

3.2 The physics of BPS

The software performs calculations using the input data through its simulation engine. The key processes include:

Heat Transfer Calculations: The foundation of BPS software is calculating heat transfer through the building envelope (walls, roof, floors, windows) using thermodynamic principles. It considers conduction, convection, and radiation mechanisms between the building and the external environment and within the building's elements.

System Simulations: HVAC and other systems are simulated to determine how they respond to internal and external heat loads. This involves simulating the operation of heating, air handling units, and other equipment based on heat transfer calculations while considering the set control logic to meet the thermal demands.

Energy Balances: The software calculates the energy balance for each zone in the building, considering the heat gains and losses and the energy used by the HVAC systems to maintain the desired indoor conditions.

Thermal Comfort and Indoor Air Quality: The models also assess parameters like CO_2 concentration, humidity, and temperature to ensure that indoor environmental quality is within acceptable comfort ranges.

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3.3 Steps taken to build a BPS model of the MyBox lab

This section outlines the steps taken to build a BPS model in IDA ICE of the MyBox lab. The first step is to create the geometry of the building, the second step involves putting all relevant data, the third step is to simulate, and the final step is to analyse and verify the results obtained from the simulation.

Geometry

The first step of the modelling involved importing the SketchUp-3D model of the MyBox lab into IDA ICE. Afterwards, the six modelling zones that make up the living quarters of the living lab were created. The 3D model was imported to consider the shading objects, which consisted of balconies and stairs outside the building.

Each apartment has been modelled as a single thermal zone with the same geometry for all apartments. The windows and doors have been added to correspond to the correct placement within the building. It was decided to model each apartment as a single zone, even though each apartment/shipping container has three rooms. It is assumed that the doors between the different rooms are usually kept open, so for practical purposes, each unit functions as a single zone, simplifying the modelling.

Input data

The input parameters for the modelling were derived from the building's BIM model, measurements, and literature sources, specifically (Andersen et al., 2020; Sørstrønen, 2013). Where available, product datasheets provided specific values; otherwise, the most applicable Norwegian Standards (NS) were applied. Table 5 lists the input parameters and corresponding values or descriptions.

Table 5: Overview of input parameters used for modelling each identical zone of the building.

Parameter	Value/description
Apartment area	26,18 m^2
Ceiling height	2,50 m
Occupants	1 per apartment
CO_2 emission per person	IDA ICE default equation
Lights	61 W
Equipment	260 W (NS 3031:2014)
Occupancy schedule (Monday-Friday)	Figure 2
Occupancy schedule (Saturday-Sunday)	Figure 2
Solar shading	Manually operated internal blinds
Ventilation operation time	24 hours
Ventilation airflow rate	2 L/s m
Heat exchanger efficiency	80%
Window area	8,5 m^2
U-Value external wall	0,125 W/m^2 K
U-Value windows and glass door	0,8 W/m^2 K

The next modelling step involves setting the correct building materials and corresponding u-values in the computer model. Energy loads were added according to Table 3 and Table 5. When available, the data sheet for the specific equipment was used, and when not available, the best-fitting generic equipment from the IDA ICE database was used. The heating set point was 20°C, and the ventilation was set to 2 L/s m^2 with a heat exchanger on the exhaust air. The apartment has no cooling unit, but window opening is set as a possible response to reduce high indoor temperatures in the software. Hot water usage was set to 45 l/occupant per day following average data from a study by (Fuentes et al., 2018). The ASHRAE 2021 "typical" weather file for Stavanger was used for weather data, and the wind profile was set to "default urban". Lastly, the occupancy schedules for the apartments were set to be able to consider the OB influence on energy in the modelling. The schedules were set based on talks with the students living in the apartments and aimed to represent a "typical" student day. Figure 3 shows the occupancy, equipment and lighting schedules that were used.

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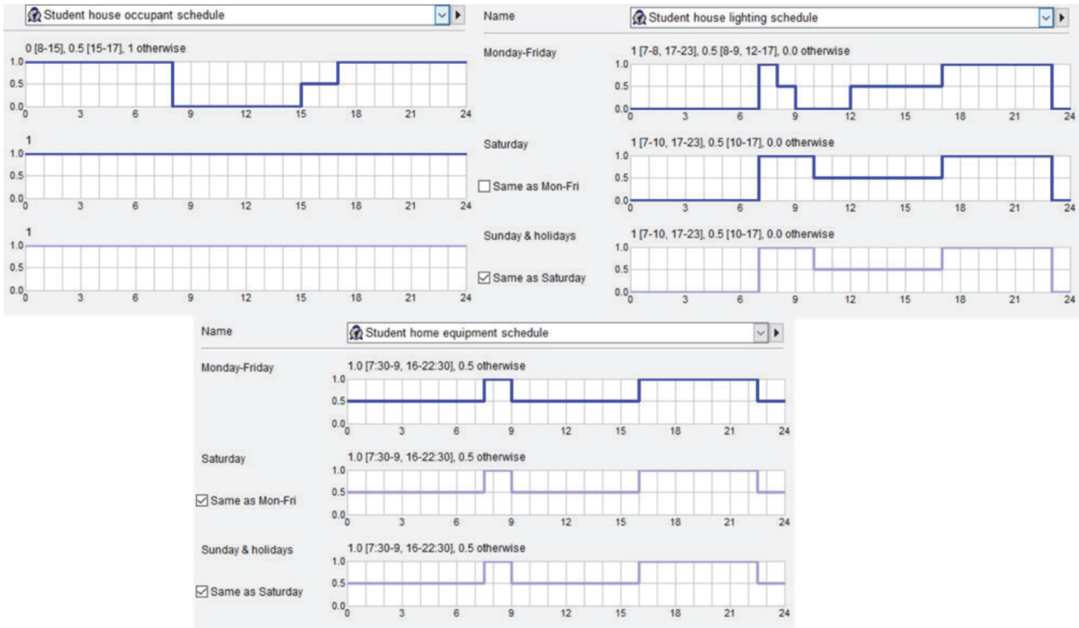

Figure 2: The occupancy, equipment and lighting schedules used in the model to consider the OB influence on energy consumption.

Simulation

A simulation is run according to the processes outlined in 3.2. In IDA ICE, running Energy, Power, Comfort and Daylight simulations in the software is possible. In this case, all the different simulations were run. The energy and power simulations are of primary interest in this study. However, the comfort and daylight simulations were run to evaluate the relevant comfort metrics, given the modelling set-up, and serve as an extra validation point by checking that the indoor temperature stayed within normal boundaries. The first simulation run revealed a lower simulated energy use than the measured data. Previous thermal scans of the outside of the building have shown a potential leakage in the vacuum insulation panels, leading to a lower overall u-value than the building design criteria. This was accounted for by adjusting the thermal bridge setting in IDA ICE. This setting lets the user adjust the thermal bridges of different building sections from "good", "typical", "poor", and "very poor". Adjusting the thermal bridges to match the actual building envelope obtained a close fit with the measured data.

Analysing and Verifying results

The last step in the modelling involves analysing and verifying the results. In this case, the modelled building has already been built, and the energy data has been logged for the previous five years to verify the energy simulation against the data. It is common to benchmark simulated and measured data on a monthly or hourly scale or both (Coakley et al., 2014; Maile et al., 2012). For this study, we decided that the benchmark was to get the monthly simulated energy consumption data as close as possible to the measured monthly energy data. We used the appropriate validations to match building energy simulation data with measured data, as outlined by (Coakley et al., 2014). The first rounds of results from the simulation revealed a poor fit between the measured and simulated energy consumption data. Monthly deviations between 20-40% between measured and simulated data were observed. Additional input parameters and changes to the model were then made, as described in the previous sections, to address the observed energy performance gap.

4 Results and Discussion

4.1 Comparing measured and simulated energy data

The benchmarking for the BPS model was to obtain an as close as possible correlation between the measured energy consumption data and the simulated energy data on a monthly basis. The results show

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a good match between the monthly measured and simulated energy data, as seen in Figure 3. For most of the months (January, March, April, May, June, July, August, September and December), the simulated data are within 10% of the measured data. For some months (February, October, and November), the match between simulated and measured data is slightly higher but still within 20%. Correlation analysis shows that the correlation coefficient between the measured and simulated data sets is approximately 0.975. This indicates a very high positive correlation on a month-to-month basis, suggesting that the simulated data closely follows the trends of the measured data.

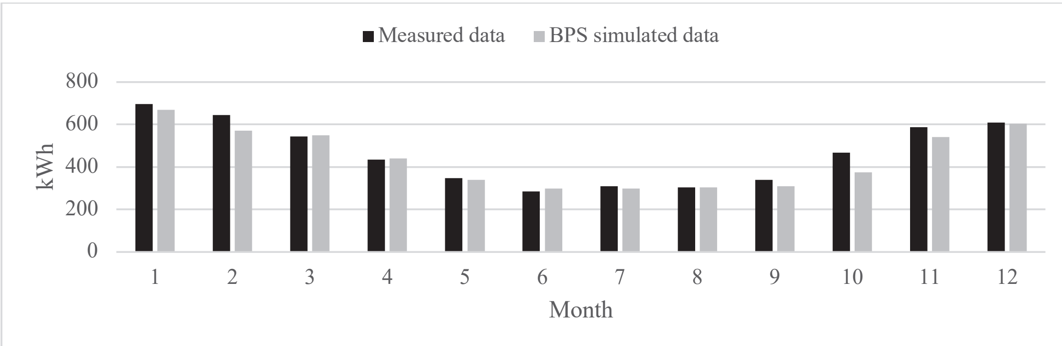

Figure 3: Monthly comparison of the simulated and measured energy consumption data

The next step after comparing the monthly data was to investigate further the BPS tool's ability to simulate the hourly energy values from day to day. Given our system input, we examined the BPS tool energy demand simulation on an hourly scale. An example of the typical correlation seen daily has been highlighted in Figure 4. After comparing the hourly values for each day over a year, the month of January was chosen to highlight in Figure 4. The reason January was selected is that it is the month with the highest overall energy consumption, and the month with the highest hourly peaks. This makes it easier to see the characteristics of the plots, and provides more variation between days. To improve readability three different days was chosen. In Figure 4, we can see that on day 1, there is a reasonable fit between the measured and simulated data; the same is true for day 15. However, on day 31, we see a substantial divergence between the measured and simulated data.

There are several reasons for the poor fit on the hourly scale. One issue is that the MyBox lab only has five occupants. BPS tools' occupant modelling is more tailored towards modelling buildings with a larger number of occupants. A larger number of occupants would naturally lead to occupant schedules averaging out and becoming more aligned with the profiles used. Our work highlights the challenge of accurately simulating energy consumption influenced by human behaviour in energy models for small buildings with few occupants.

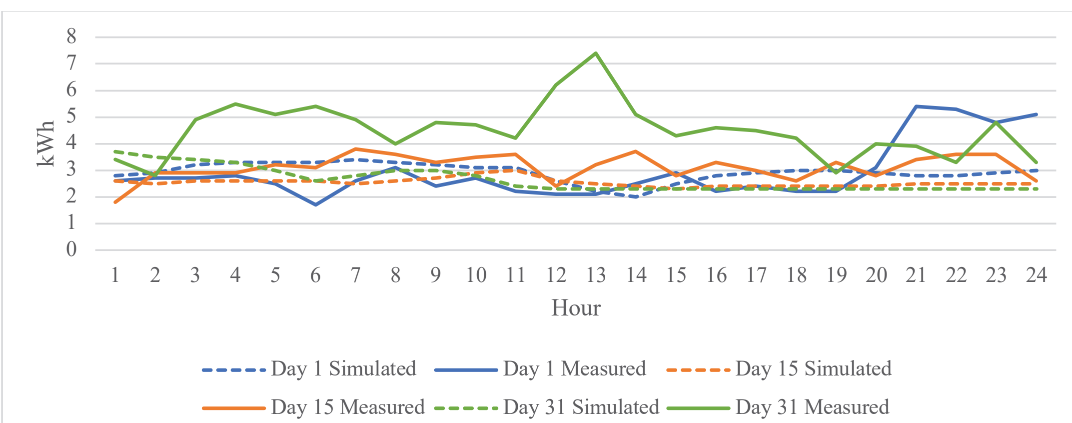

Figure 4: Hourly energy consumption profiles for the 1st, 15th and 31st day of January

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Analysis of measured data from MyBox shows substantial day-to-day variability in energy use. While climatic conditions explain some variations, a significant portion is attributed to human factors such as presence, heating preferences, hot water use, and cooking habits. Understanding these human influences is crucial for accurately dimensioning building systems like heating, cooling, ventilation, and local renewable energy generation. Another reason why accurately predicting daily consumption has become more important is due to the changing nature of energy production. Predicting demand at monthly and annual scales is normally sufficient when considering fuel-based heating systems. However, with higher shares of intermittent renewable energy, a better understanding of occupant behaviour, and how to capture it in building performance simulation, would provide additional insight into the utilisation of renewable energy sources, as well as improved evaluation of the demand-shifting potential to increase self-consumption.

Validation of our model against actual data from MyBox reveals interesting preliminary findings. While our current BPS model provides a reasonable correlation between modelled and actual energy use yearly and monthly, its reliability could improve at finer temporal resolutions like weeks, days, or hours. It remains to be seen if this is due to software limitations or model calibration issues.

4.2 Study limitations

The present study has certain limitations that must be acknowledged. Foremost among these is the aggregation of energy data from the MyBox laboratory, which encompasses the collective consumption of the entire building. This approach inherently introduces uncertainties in discerning the unique energy profiles of the five individual apartments within the building. Consequently, each apartment's differential consumption patterns, which may be attributed to varied OB or distinct physical attributes (like varying degrees of insulation), are not distinctly quantified.

Further limitations stem from ambiguities inherent in the input data. While efforts have been made to ensure the accuracy of the energy consumption records, the very nature of such data collection can be subject to inconsistencies and measurement errors.

Another methodological consideration is the treatment of temperature control within the modelling framework. In the real-world scenario, occupants can control the indoor temperature, potentially leading to a broad spectrum of thermal conditions. However, for simulation, the indoor temperature is assumed to be a constant 21°C. This assumption does not encapsulate the dynamic and self-regulatory behaviour of the occupants in managing their thermal environment, thereby introducing a deviation from the actual energy consumption that would result from varying temperature preferences.

Occupancy variance presents another challenge to the integrity of the simulation. There are intervals when one or more apartments may be unoccupied—due to occupants being on vacation or during the transition period between tenants. These fluctuations in occupancy are not directly accounted for in the model, which assumes a consistent occupancy pattern. Additionally, the daily occupancy schedules are extrapolated from what is deemed a 'typical' day. However, as evidenced in the comparative analysis of measured versus simulated data, the stochastic nature of human behaviour renders a perfect match elusive. The figure illustrating the disparities between measured and simulated data underpins the profound impact of human unpredictability on energy consumption. This variable remains challenging to capture accurately in any simulated environment.

While these limitations delineate the scope of the study's accuracy, they also open avenues for future research. Subsequent investigations could focus on enhancing data granularity, incorporating adaptive thermal comfort models, and integrating occupancy sensors to understand better and predict energy usage patterns. The findings of this study must be interpreted within the context of these stated constraints.

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4.3 Future Work

The present study has laid a foundational understanding of energy consumption patterns within the MyBox energy lab. To enhance the granularity and precision of our energy consumption data, the following avenues are proposed for future research:

1. **Enhanced Data Granularity with In-depth Energy Logging**: We plan to implement an advanced energy logging system to acquire high-resolution data. This system will enable us to identify and attribute the energy consumption to specific systems within each apartment. By discerning which systems contribute to energy usage at particular times, we can create a more detailed consumption profile for at least two flats within the building complex.
2. **Refined Modeling and Benchmarking**: With the acquisition of more detailed consumption data, subsequent research efforts will focus on refining our existing energy consumption models. These improved models will be benchmarked against this enhanced dataset to validate their predictive accuracy and reliability.
3. **Innovative Approaches for OB in BPS**: Given human behaviour's dynamic and stochastic nature, alternative methods for accounting for OB within BPS must be explored. To this end, we will investigate the application of cutting-edge methodologies such as AI and machine learning algorithms. This approach offers promising prospects for capturing the complex and variable patterns of occupant interactions with energy systems.
4. **Mixed Methods Approach for Deeper Behavioural Insights**: Future research will adopt a mixed-methods approach to supplement quantitative data with qualitative insights. By conducting questionnaires and interviews with the building's occupants, we aim to understand the determinants of energy-related behaviours better. This comprehensive approach will add to the empirical data and enrich the interpretation of energy usage patterns, potentially revealing opportunities for behavioural interventions and energy efficiency improvements.

Through these initiatives, we anticipate significantly contributing to the body of knowledge in energy consumption analysis and sustainability in building design. Our commitment is to develop more robust models that depict actual consumption, facilitate the design of more efficient energy systems, and promote the adoption of energy-saving behaviours among occupants.

5 CONCLUSIONS

This study, conducted at the MyBox Energy Lab, University of Stavanger, has provided insight into integrating human factors within BPS. The research highlights the impact of OB on energy consumption, as evidenced by the variability in energy use attributed to human activities such as presence, heating preferences, and appliance usage. By comparing the BPS results with actual energy consumption data, the current study has revealed a strong yearly and monthly correlation, validating the BPS approach and identifying the limitations of BPS tools in capturing the stochastic nature of human behaviour at finer temporal resolutions, given the outlined limitations.

Our research emphasises the performance gap observed between predicted and actual energy usage. We recognise that this gap is due, in part, to the simplification of OB within simulation models, which typically need to account for the dynamic and adaptive nature of human interactions with building systems. While the research has successfully utilised IDA ICE software to model energy consumption and has adjusted for thermal bridging discrepancies, it also acknowledges that precise modelling of OB remains a significant challenge, especially for buildings with few occupants.

The MyBox Energy Lab's data, enriched with new logging systems, presents a pathway for future research to delve deeper into the nuances of OB and its implications on energy use. The enhanced granularity of data, further refinement of the model and the application of innovative methodologies, such as machine learning, promise to yield more accurate simulations of OB, thus bridging the performance gap further.

This research is a stepping stone towards a more occupant-centric approach to building performance analysis. Future research directions, armed with higher-resolution data and a mixed-methods approach,

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will aim to refine the predictive accuracy of BPS tools. Through such endeavours, we hope to contribute meaningfully to the field of energy consumption analysis and, ultimately, to the design of more energy-efficient buildings that are responsive to the human dimension.

NOMENCLATURE

ASHRAE	American Society of Heat, Refrigerating and Air-Conditioning Engineers
BPS	Building Performance Simulator
BIM	Building Information Model
VAWT	Vertical Axis Wind Turbine
PV	Photovoltaic
OB	Occupant Behaviour
kW	kilowatt
kWp	kilowatt-peak
KWh	kilowatt-hour
PV	Photovoltaic
VIP	Vacuum insulation panels

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