Windows and ceiling fan occupant behaviour model coupling methodology with building energy models, a tropical case study

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ABSTRACT

In this work, we propose a method to couple the behaviour models developed with Python in a previous paper with the dynamic thermal simulation software EnergyPlus, an advanced code used in research and design. The proposed coupling method is applied to the thermal model of an office building situated in the humid tropical climate of Reunion Island after calibrating and validating it with measured temperature and relative humidity data.
Then, this resulting coupled model is compared with a typical design office energy model where behaviours are based on typical, deterministic scenarios. The comparison focuses on the power level of the ceiling fans employed, the level of opening use and the calculation time. The results obtained by coupling with the new behavioural models are better than in the conventional deterministic scenarios, providing a more faithful reproduction of user actions in the design phase.

KEYWORDS

Tropical climate, mixed-mode buildings, users behaviours modelling, operable windows, the power level of ceiling fans

1 INTRODUCTION

Buildings in humid tropical climates are witnessing a significant upsurge in their energy demands, primarily attributed to the use of cooling systems known for their substantial energy consumption. In low-energy buildings in such climates, occupants can employ both passive solutions, such as natural ventilation through windows, and low energy-consuming alternatives (in this study, we focus solely on using ceiling fans) to achieve thermal comfort, particularly during the hottest months. However, compared to other climatic zones, there needs to be more specific knowledge regarding occupant comfort and behaviour in this context. This leads to difficulties in the design phase for engineers who need to estimate the future operation of a building.

In a previous research paper (Payet, 2022), two deterministic methods based on machine learning supervised classification techniques (decision tree and random forest) and a probabilistic graphical model (bayesian network) were investigated to model occupant behaviour regarding windows and ceiling fans. In both cases, the random forest method obtained the highest performances. These techniques, explained in detail in (Payet, 2022), use historical measured data as explanatory variables for the variable to model (for example, in our case, the power level of ceiling fans). The whole methodology elaborated is described in detail in this previous paper.

In this work, we present a novel approach to integrate the developed behaviour models with dynamic thermal simulation software, coupling Python and EnergyPlus, an advanced code used in research and design. The proposed coupling method is applied to the thermal model of a case study after calibrating and validating it with measured temperature and relative humidity data.

The first part of this paper provides an overview of existing methods for coupling behaviour models with dynamic thermal simulation software. Subsequently, the proposed coupling methodology is detailed, from the case study's presentation to the coupling method's integration, before discussing the results obtained in the last part.

2 STATE OF THE ART

Existing tools offer solutions of varying complexity to incorporate user behaviour into simulations (Sun, 2017; Darakdjian, 2017)

Direct modelling involves inputting user data into software modules but cannot create detailed occupancy profiles and conditioned behaviours.

Code customisation enables users to add personalised scripts to the source code, facilitating the incorporation of user behaviour into simulations (Sun, 2017). For EnergyPlus, the EnergyPlus Runtime Language of the Energy Management System is used (BigLadder, 2020). Another approach involves customising the core code of the software itself, offering significant flexibility but requiring proficiency in the underlying programming language.

Co-simulation offers a collaborative approach, combining the strengths of different simulation tools through information exchange at each time step. This method allows users to harness multiple tools' capabilities without extensive programming knowledge. Co-simulation can be achieved using functions like "External Interface" in EnergyPlus or by using communication intermediaries such as the Building Controls Virtual Test Bed (BCVTB) (Nihar, 2019; Kwak, 2016; Jia, 2020; Langevin, 2014)

A recent intermediary solution available since version 9.3 of EnergyPlus is the PythonPlugin interaction method. This new approach is positioned between code customisation and co-simulation. It allows engineers to write code within the EMS using Python, a widely used language known for its extensive functionalities and various libraries. This integration offers a significant advantage over the EnergyPlus Runtime Language, which has more limited capabilities.

To our knowledge, this last method chosen for this work has not yet been implemented in the existing literature to simulate occupant behaviour. Table 1 compares the different methods for integrating occupant behaviour into the dynamic thermal simulation.

Table 1: Comparison of existing user behaviour integration methods in dynamic thermal simulation

Method	Ease of implementation	Flexibility
Direct modelling	++++	+
Code customisation	++	++
Customisation of Core code	+	+++
Co-simulation	++	++++
Python plugin	+++	++++

3 METHODOLOGY

3.1 Case study and associated building model

The case study "Ilet du Centre" is a 310 m² design office, part of a residential building, exposed to the humid tropical climate of Reunion Island, a French island in the Indian Ocean. The office has two floors divided into several open-plan areas, with several offices organised side by side. There is a meeting room, a server room and two individual offices.

The 28 users can regulate temperature by generating crossed air flows, thanks to many manually adjustable and full-height louvre-type openings. They can also activate ceiling fans to reduce the temperature felt on the hottest days when air temperatures are high, and there is not enough natural airflow. There is no mechanical air conditioning system except for the server and meeting rooms.

Using specific power sub-meters, ceiling fans and electrical outlets were recorded between 2020 and 2022. In addition, air temperature and relative humidity, as well as the opening of windows using magnetic contacts, were monitored. The outdoor temperature, humidity, wind and solar radiation were recorded using a weather station.

From these actual measured data, we could calibrate a thermal model of the case study and then validate it to overcome modelling errors unrelated to occupant behaviour.

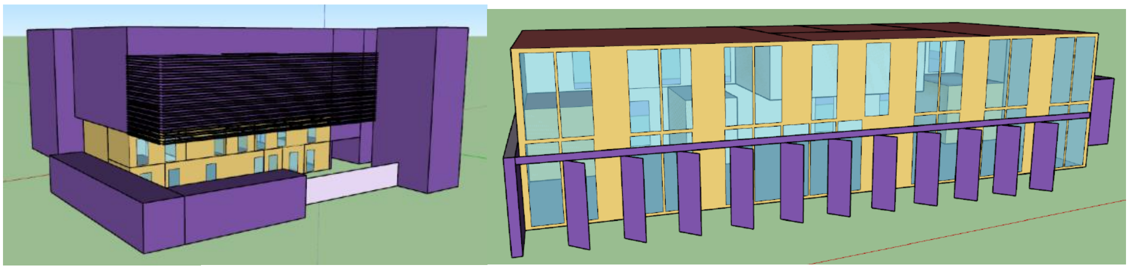

Figure 1: BEM model, view of the North façade (left) and South façade (right) displayed without shading

The calibration was performed manually using an iterative procedure in which various parameters are adjusted until the simulation results align with the measured data (Royapoor, 2015). Validation occurs when this iterative process is finished, and normalised metrics are used to determine the level of real-world representation achieved by the model.

Acceptable values for these metrics are provided by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers Guideline 14 on Measurement and Energy

Demand (ASHRAE), the Federal Energy Management Program (Of EnergyEfficiency & Renewables Energy), and the International Performance Measurement and Verification Protocol recommended in France by ADEME and the Ministry of Sustainable Development. Hourly and monthly thresholds must be verified.

However, these normalised threshold values were developed to validate building models based on measured energy data and do not enable objective comparisons when they relate to temperatures in °C or K. The existing literature offers limited guidance on validating building models using hourly temperature and humidity measurements (Baba, 2022), as in our case study, where indoor conditions were measured over a year using recording sensors.
To address this gap, we supplemented the existing normalised metrics, expressed as percentages, with the calculation of Mean Bias Error (MBE) and Mean Absolute Deviation (MAD), expressed in degrees Celsius (as described by Baba (2022)).

Following the method of O'Donavan et al. (O'Donavan, 2019) and to adjust the building parameters and avoid uncertainties related to user presence and their behaviours on controls, the model was calibrated during an unoccupied week (S1). Various adjustments on solar shading and thermal inertia were made during this week.

Internal load data (including the power demand of electrical outlets, ceiling fans, and window opening schedules) measured over 2020 were then integrated into the latest calibrated version. From this point, hourly validation metrics were then calculated based on indoor temperature and humidity data over different occupied weeks: a summer week (S2), a winter week (S3) and a mid-season week (S4). Metrics were also calculated for each month of the year 2020.

The hourly validation values obtained from indoor temperature data are:
0.05 % ≤ NMBEh ≤ 5.3 %
- 3.6% ≤ CV(RMSE)h ≤ 6.6
- 1.8 ◦C ≤ MADh ≤ 2.8 ◦C
- 0.01 ◦C ≤ MBEh ≤ 1.2 ◦C

As the values obtained were below the normalised thresholds, the model was considered validated based on indoor temperature data.

Once the building model was validated, the entries related to the use of ceiling fans and windows were modified in two ways: a case integrating the behaviour models developed using the PythonPlugin method and a case typically found in design office-type simulation (noted BE), where assumptions are made from expert knowledge.

3.2 Implementing random forest behavioural models in EnergyPlus with the Python Plugin method (case noted as "RF")

This first case concerns the coupling of the Random Forest-based behavioural model with our BEM model.
The primary objective of the implemented method (noted as "RF" for Random Forest (Payet, 2022)) is to dynamically adjust the opening of windows and the use of ceiling fans in a thermal zone at each time step of an EnergyPlus simulation. This adjustment is based on data from the previous time step (Tn), ensuring the simulation accurately reflects real-time conditions. The process involves transmitting simulation outputs, such as indoor temperature and relative humidity, to the Python-coded behaviour models (one for windows and one for ceiling fans).

These models then estimate new control levels, subsequently updated in EnergyPlus to simulate the next time step (Tn+1).

For implementing the method on the EnergyPlus side, the Python module must be specified in the description file of the building model. On the Python side, a specific library allows us to create the link between the two software.

One notable advantage of this method is its user-friendly interface. Designers can seamlessly integrate the method into EnergyPlus, launching the simulation tool without additional technical complexities. This approach simplifies the workflow for designers, allowing them to incorporate occupant behaviour dynamics into their simulations effectively.

3.3 Comparison with a typical design office model (noted as "BE")

The second case we conducted is based on a more conventional way of designer model behaviours in BEM models. This second case is a reference point to compare with the newly implemented method results of 3.2.
We conducted a simulation representing a typical design office scenario (noted as "BE"), where assumptions were formulated based on expert knowledge and no longer from the behavioural

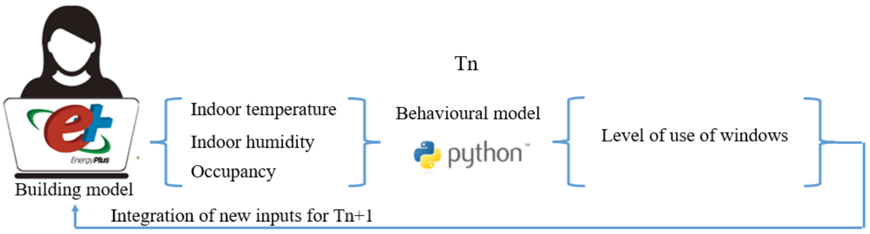

Figure 1: Simulation process with integration of the windows opening model

models developed in 3.2.
We have tried to make assumptions that reflect the standard practices employed by field professionals.
Concerning the ceiling fans, we assumed they were operated at full power during daytime hours in the summer period from January to the end of March, as well as during November and December. We estimated a reduced use of the ceiling fans during the transitional seasons (30% of use) and no use at all during the winter period from May to September. A power ratio of 5 W/m² was applied to calculate their impact.

Regarding the windows, we assumed the occupants would open them throughout the year during occupancy hours.

4 RESULTS AND DISCUSSION

The outputs of both the BE and RF simulations were analysed and compared with the actual data measured on "Ilet du Centre" in 2020.

In Figure 3, depicting the annual evolution of power demand for ceiling fans, it can be observed that the RF simulation more accurately replicates the triggering/extinction cycles of the ceiling fans compared to the BE simulation, which represents behaviours in the form of regular steps.

Nevertheless, discrepancies emerge as the simulated power levels during January and March are often below the maximum values observed in the measurements.

This can be attributed to the original nature of the behaviour models developed, which provide discrete classes rather than continuous values. To incorporate these models into the simulation, the results were transformed into single values by calculating the expected value using the median values of each class (as described in (Payet, 2022)). As a result, even if the highest class of ceiling fan use is estimated at a given time, the associated value will never reach the upper limit of that class.

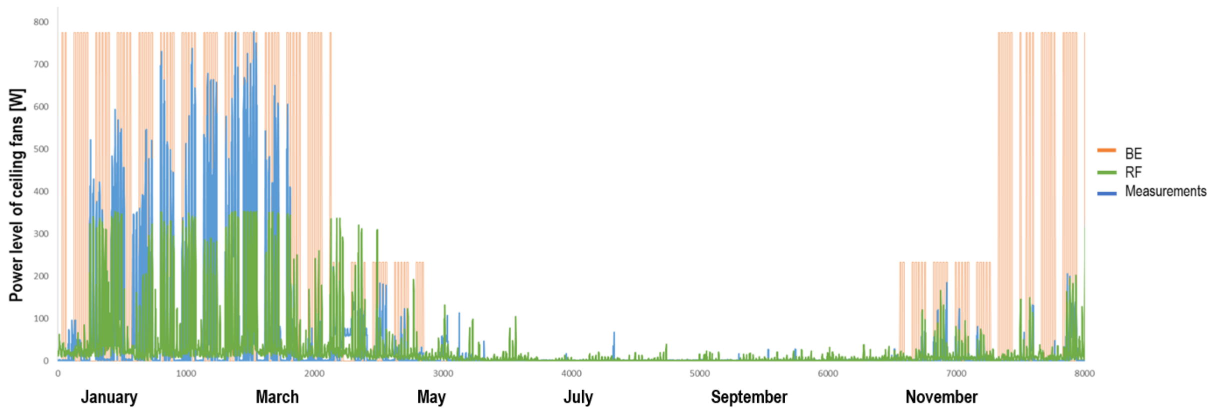

Figure 3: Comparison of the hourly average power level of the ceiling fans obtained by the BE method (in orange) and the coupling method (in green) with the actual measured data (in blue) for the year 2020

Various methods were tested to transform the original classes (such as calculating the expected value using the maximum and minimum values of the classes), but they yielded less accurate simulation results.

However, during the mid-season and summer periods in November and December, the simulated data from RF aligned much more closely with the measured data.

The use of the windows (Figure 4) simulated by RF follows the same trend as for the ceiling fans. It aligns more closely with the measured data compared to the results of the BE simulation.

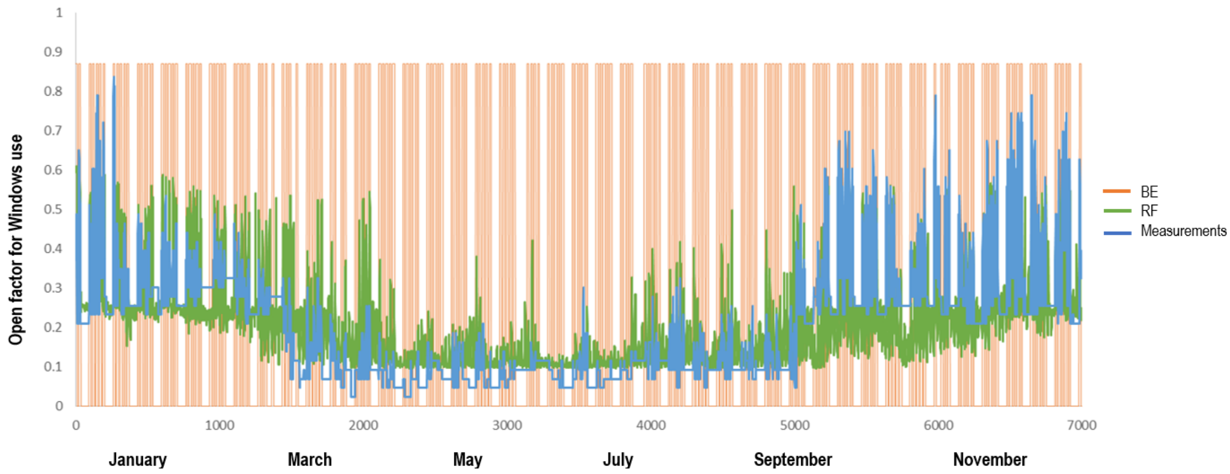

Figure 4: Comparison of the hourly open factor for the level of windows use obtained by the BE method (in orange) and the coupling method (in green) with the actual measured data (in blue) for the year 2020

The values of the various metrics calculated for each of the simulations are summarised in Table

Table 2: Comparison of the different simulations

		BE	RF
Calculation time		4 min 43s	2 h 21min
Indoor temperature	**MBE (°C)**	-0,59	0,19
	NMBE (%)	-2,4%	1,7%
	CV(RMSE) (%)	5,7%	5,2%
	MAD (°C)	4,89	4,53
	RMSE (°C)	1,43	0,80
Indoor humidity	**MBE (%)**	3,03	3,42
	NMBE (%)	5,5%	4,9%
	CV(RMSE) (%)	11,5%	8,6%
	MAD (%)	29,39	24,07
	RMSE(%)	7,95	5,95
Use of windows (opening factor)	**MBE (%)**	-0,12	-0,01
	NMBE (%)	-59,3%	-5,0%
	CV(RMSE) (%)	207,7%	45,8%
	MAD (%)	0,85	0,55
	RMSE(%)	0,43	0,10
Power level of ceiling fans	**MBE (W)**	-65,86	9,03
	NMBE (%)	-142,8%	19,6%
	CV(RMSE) (%)	480,2%	178,3%
	MAD (W)	774,80	661,54
	RMSE (W)	221,55	82,28

The obtained scores validate the observations made from the behaviour evolution curves, where the RF simulation outperforms the BE simulation. In the BE simulation, the average deviation (MBE) over the year is 66 W, while the RF simulation demonstrates a significantly lower deviation of only 9 W compared to the measured data.

5 CONCLUSION

We have introduced a novel approach to integrate user behaviour models into the EnergyPlus dynamic thermal simulation software using the recently developed PythonPlugin method. In this way, the use levels of louvres and ceiling fans are updated at each simulation time step of the simulation, based on data calculated at the previous time step in the BEM model.

To determine the performance of this method, we tested it on the Ilet du Centre building model, which had been calibrated and validated using temperature and humidity data for 2020. This step was necessary to eliminate modelling errors unrelated to user behaviour as far as possible. Once the building model was successfully validated, user behaviour was incorporated through two methods: a simulation based on assumptions derived from expert knowledge and a simulation incorporating random forest-based behavioural models.

A comparison between these two cases revealed that the method of coupling the building model with behavioural models allowed for more accurate replication of user actions compared to conventional practices employed by engineering and design firms.

Finally, it is worth noting that despite the evident advantages of the proposed coupling method during the design phase, it does result in relatively long simulation times (over 2 hours in our case study), which may pose challenges for some projects. To mitigate this issue, we replaced the random forest technique with decision trees in the developed behavioural models, achieving satisfactory simulation results while reducing computational time.

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7 REFERENCES

Darakdjian, Q. (2017). *Prédiction des performances énergétiques des bâtiments avec prise en compte du comportement des usagers*, 249.

Payet, M., David, M., Lauret, P., Amayri, M., Ploix, S., & Garde, F. (2022). *Modelling of occupant behaviour in non-residential mixed-mode buildings: The distinctive features of tropical climates.* Energy and Buildings, 259, 111895.

Payet, M. (2022). *Simulation du comportement des usagers dans les bâtiments tertiaires à faible consommation énergétique, en zone tropicale.* Thèse de doctorat, Université de la Réunion.

Sun, K., & Hong, T. (2017). *A framework for quantifying the impact of occupant behaviour on energy savings of energy conservation measures.* Energy and Buildings, 146, 383-396.

Nihar, K., Bhatia, A., & Garg, V. (2019). *Optimal Control of Operable Windows for Mixed Mode Building Simulation in EnergyPlus.* IOP Conference Series: Earth and Environmental Science, 238, 012052.

Kwak, Y., & Huh, J.-H. (2016). *Development of a method of real-time building energy simulation for efficient predictive control*. Energy Conversion and Management, 113, 220-229.

Jia, M., & Srinivasan, R. (2020). *Building Performance Evaluation Using Coupled Simulation of EnergyPlus™ and an Occupant Behavior Model.* Sustainability, 12, 4086.

Langevin, J., Wen, J., & Gurian, P. L. (2014). *Including occupants in building performance simulation: integration of an agent-based occupant behavior algorithm with EnergyPlus*. In Proceedings of the ASHRAE/IBPSA-USA Building Simulation Conference (pp. 10-12).

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

Ramos Ruiz, G., & Fernandez Bandera, C. (2017). *Validation of calibrated energy models: Common errors.* Energies, 10, 1587.

ASHRAE. (n.d.). Preview ASHRAE Standards and Guidelines. Retrieved from https://www.ashrae.org/technical-resources/standards-and-guidelines.

U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy. (n.d.). Federal Energy Management Program Publications. Retrieved from https://www.energy.gov/eere/femp/federal-energy-management-program-publications.

Baba, F. M., Ge, H., Zmeureanu, R., & Wang, L. L. (2022). *Calibration of building model based on indoor temperature for overheating assessment using genetic algorithm: Methodology, evaluation criteria, and case study.* Building and Environment, 207, 108518.

Efficiency Valuation Organization. (n.d.). *International Performance Measurement and Verification Protocol (IPMVP).* Retrieved from https://evo-world.org/en/products-services-mainmenu-en/protocols/ipmvp.

O'Donovan, A., O'Sullivan, P. D. & Murphy, M. D. (2019). *Predicting air temperatures in a naturally ventilated nearly zero energy building : Calibration, validation, analysis and approaches*. Applied Energy **250,** 991-1010.