Innovative KPIs for Web-based Building Energy Performance Monitoring in the Tertiary Sector

Author:  
Etienne GRANGER

Supervisor:  
Ivo MARTINAC

Company:  
SMART BUILDING ENERGIES - VINCI ENERGIES

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2 Abstract

Today, energy monitoring webplatforms are increasingly numerous in the tertiary sector, especially due to recent French regulations which aim at reducing the power consumption of office buildings. In order for these webplatforms to make a difference, they need to deliver clear-cut messages to the users, through relevant key performance indicators (KPIs) adjusted to their will and supposed to "translate" information provided by massive data collected. However, most webplatforms like the WavePlatform by Smart Building Energies lack such customized KPIs and if they have any, they only pay attention to energy consumption aspects, without even going into detail. In addition, with the growing development of IoT objects, there are less and less buildings’ data that can’t be measured or collected. Consequently, this study dwells on the potential KPIs that could be displayed for office buildings on a common energy monitoring webplatform, i.e. the WavePlatform. KPIs about occupancy, comfort, power, plug loads and charging stations are first described. Then, the study examines the potential of energy signatures in terms of KPIs and energy consumption’s prediction. Finally, a connection is made between thermal comfort (related to occupancy) and energy use : how much energy is used to reach a certain level of thermal comfort ? This analysis is innovative because it sets on equal footing comfort (tightly linked to occupants’ productivity, hence value creation) and energy use (synonym of waste of money). As a whole, the first steps were to make the most of the WavePlatform, using all its functionalities. Then, Excel was used as an optional tool if the WavePlatform couldn’t help. All created KPIs have required both usages, underlining the possible limits of energy monitoring webplatforms. However, there is no doubt that these data collectors represent powerful tools with many improvements to come. Eventually, this study confirms the fact that it could be possible to help decision makers take well considered action through relevant KPIs adjusted to their office building and their needs. Massive data are exploitable and full of meanings, only if they are rearrange in a way they can be impactful and clearly understandable by users.
3 Introduction

3.1 Background

In France, buildings represent 45% of the total final energy consumption (tertiary and residential sectors), far before the transport sector which represents around 33%. In 2015, the tertiary sector only accounted for 15% of the total final energy consumption according to ADEME [1]. Today in 2023, proportions remain very similar. In the wake of the spreading digitization of the building’s sector, the French government has then implemented two decrees which are today the main guidelines for companies in the service sector when it comes to energy consumption’s management:
- The Tertiary Decree
- The BACS Decree

3.1.1 The tertiary decree

Rolled out in October 2019, the Tertiary Decree [2] is part of a regulation that compels owners and tenants of tertiary buildings (of an area over or equal to 1000 $m^2$) to reduce their energy consumption by:
- 40% by 2030.
- 50% by 2040.
- 60% by 2050.

In order to justify the savings, companies have to set a year of reference (between 2010 and 2019) which should be the basis with which each coming year would be compared in terms of energy consumption.

Eventually, this decree highly encourages companies to collect their buildings’ data through building energy management systems directly capable of capturing the energy consumption reduction with precision.

3.1.2 The BACS decree

The BACS decree [3] (Building Automation and Control Systems) dates back to July 2021 and stems from the tertiary decree. It clarifies the means of reaching the goals set by the Tertiary Decree: install a building automation and control system. More precisely, the buildings’ owners (tertiary non residential) have to get a building management system (of at least a C rank according to the ISO 52120 standard [22]) by:
- 08/04/2024 for new builds with a heating/cooling system of more than 70kW.
- 01/01/2025 for existing buildings with a heating/cooling system of more than 290kW.
- 01/01/2027 for existing buildings with a heating/cooling system of more than 70kW.

The overall objectives are the following:
- Follow, capture and analyse energy consumption data.
3.1 Background

- Adjust the systems’ energy consumption if needed.
- Estimate the building’s energy efficiency compared with a year of reference.
- Spot consumption drifts and alert.
- Centralize the management of the building’s technical systems to better operate them.

With these two decrees comes the roll-out of the French OPERAT platform [4] which compels companies to give public information (and thus unveil) on their energy consumption (from various sources: gas, electricity, heating, etc.) every year.

3.1.3 Today’s challenges

As a whole, the French government has intensified its energy policy through the implementation of concrete measures over the past few years, which gives all the more credit to companies like Smart Building Energies whose main mission is to roll out its own building energy management system, namely the WavePlatform. At first, the major goal was to get rid of all the useless switches and come up with a solution that could enable occupants to easily control their work environment in terms of temperature, lighting, ventilation... Today, with the increase of environmental concerns due to climate change, the company also needs to focus on the building’s energy consumption, because this is what future clients will be interested in. How to save energy to meet the goals set by the tertiary decree and the BACS decree? Considering the high electricity and gas prices, how to reduce energy consumption in winter when heating systems consume a lot? Which systems consume the most?

The main challenge is to find the good balance between energy consumption and occupants’ comfort, which is quite tricky in today’s society. Indeed, people tend more and more to strictly monitor their energy consumption and reduce the operational time of their building’s systems, no matter what degree of comfort they could lose due to such behaviours.

However, by taking an energy point of view only, disregarding occupants’ well-being, companies are likely to jeopardise the productivity of their employees, thus imperilling the global company’s prosperity (REHVA Guidebook No. 6, 2006 [5]).

Another challenge comes from the need for more flexibility when it comes to energy consumption. As we move towards sustainable and renewable energy sources, the traditional, centralized model of power distribution is giving way to a more dynamic and decentralized grid. On one hand, intermittent energy sources like wind or solar sources are more and more connected to the grid, making it challenging to maintain a consistent and reliable energy supply. On the other hand, storage solutions like solar batteries or boreholes add some complexity to grid operations.

Coordinating and optimizing these various elements to ensure a seamless and
resilient energy supply not only requires advanced technologies on the production’s side but also a robust building management system on the consumption’s side. Such a BMS should be able to gather energy data and provide occupants with relevant graphs and indicators that could help them know when to use energy-intensive systems, so that power peaks can be under control and as few as possible.

### 3.1.4 Emerging needs for new KPIs

Nowadays, engineers need to be picky when it comes to key performance indicators. Not all the old KPIs are interesting anymore and with the digital tools currently available, there is much more to come up with than old-fashioned squared meter ratios. Furthermore, most KPIs focus on energy efficiency and indoor environmental quality but struggle to connect with the occupants’ comfort and behaviour or to shed light on power peaks that could endanger the grid’s robustness. Ioannidis et al. (2016) well understood how paramount building occupancy was when it came to building performance. As a whole, KPIs that could make the connection between energy consumption, occupancy and comfort are more than welcome.

Considering IEQ, it is difficult to completely evaluate it because of its several parameters. More and more researchers tend to come up with new indicators that could encompass most aspects. Mujan et al. (2021) with their indoor environmental quality index is a case in point. Indoor Environmental Quality plays such a crucial role in maintaining the health, comfort and well-being of occupants within a built environment that specific KPIs still need to be created to monitor and control IEQ as much as possible.

Furthermore, there is a major lack of KPIs about plug loads while it represents a great part of the energy consumption in the tertiary sector. Li et al. (2020) notably tried to develop system-level KPIs that could capture the miscellaneous electric loads.

Eventually, one of the challenge in the tertiary sector is to include every occupant when it comes to energy consumption and expenditures. If people are aware of the energy behaviour of their building through clear-cut KPIs, understandable by anyone, they may be much more willing to make efforts and be mindful of their building’s energy consumption. For instance, Li et al. (2021) came up with a list of occupant-centric KPIs but they are often hardly understandable for the average person.

On top of that, since machine learning and AI are gathering momentum, the need for predicting consumption is increasingly emerging. Energy models tend to be developed in order to forecast energy expenses over a year for example. Wang et al. (2019) notably tried to predict plug loads through a deep learning approach. The most renown forecast graph is probably the energy signature which strives to foresee heating consumption based on degree-days.
3.2 **Aim and scope of the study**

The study focuses on office buildings from the tertiary sector. The main goal is to grasp what KPIs can be elaborated, merely based on data gathered by a web application (namely the WavePlatform by SBE). The aim is to come up with new relevant KPIs, appropriate for office buildings and intended to help buildings’ occupants (energy managers and decision makers above all) better understand the energy features of their building.

First, a set of relevant KPIs about occupancy, comfort, power use and plug loads is developed, based on available data. Then, consumption prediction is studied through the creation of energy signatures. Generally speaking, the following questions are tried to be answered:

- What are the new KPIs intended to evaluate more precisely and in a more customized way the energy performance of office buildings?
- With which KPIs can a web application like the WavePlatform provide occupants? How to make them understandable by each and everyone?
- Which simple models can predict energy consumption?

The key findings and main contribution of this paper are discussed at the end.

3.3 **Acronyms**

- ADEME : Agence De l’Environnement et de la Maîtrise de l’Energie
- BACS : Building Automation and Control Systems
- BEMS : Building Energy Management System
- BMS : Building Management System
- CLO : CLOthing insulation value
- CV : Coefficient of Variation
- HVAC : Heating Ventilation and Air Conditioning
- IEQ : Indoor Environmental Quality
- KPI : Key Performance Indicators
- MET : METabolic equivalent
- Occ-hours : occupant-hours
- OPERAT : Observatoire de la Performance Energétique de la Rénovation et des Actions du Tertiaire
- PDH : Predicted Dissatisfied Hours
- PLC : Programmable Logic Controller
- PMV : Predicted Mean Vote
- PPD : Predicted Percentage Dissatisfied
- PPDH : Percentage Predicted Dissatisfied Hours
- REHVA : Representatives of European Heating and Ventilating Associations
- RMSE : Root Mean Square Error
- SBE : Smart Building Energies
- SE : Standard Error
4 Methods

On one hand, a state-of-the-art review was carried out. The idea was to understand what were the current KPIs and the different methods currently implemented in the tertiary sector to monitor and evaluate the buildings’ energy performance.

On the other hand, WavePlatform by Smart Building Energies was highly helpful to grasp what kind of buildings’ data could be available in offices. Based on these reachable data, it came obvious to come up with new KPIs directly observable through the energy dashboards provided by the web application. Excel was used as an optional tool when the WavePlatform was short of functionalities.

5 Results

In all that section, the data and dashboards are taken from the WavePlatform designed by Smart Building Energies, and rearrange via Excel if necessary.

5.1 Occupancy

One of the main limits of today’s KPIs is the lack of precise data about occupancy, especially the number of occupants within a space at every moment of the day. Indeed, energy consumption highly depends on occupancy, the more occupants there are, the higher energy consumption is. Consequently, in order to draw fair comparisons, occupancy has to be taken into account as precisely as possible.

Experts from Equa [11] have come up with a new metric they use in their IDA ICE software: the occupant-hours. In fact, a room occupied by two people during one hour is counted as two occ-hours. Similarly, seven people occupying a room for one hour will be counted as seven occ-hours. To know precisely the occupancy during a day, occupant-hours need to be added to have a global occupancy indicator per day, grasping every hour’s degree of occupancy.

Thus, in this section, the challenge is to calculate occupant-hours from the mere data extracted from motion sensors and display them over time through the dashboards provided by the WavePlatform.

The first step is to retrieve and understand the data provided by the motion sensors (displayed figure[below]).
5.1 Occupancy

Figure 1: Motion sensors data - WavePlatform

It is basically a suite of binary numbers 0/1 which indicates whether there is any motion detected within the monitored space. 1 indicates motion, 0 none. The refresh interval is 10 seconds, which means that every 10 second the Wave connector linking the PLC to the WavePlatform is questioning the motion sensors to know if there were any change of motion status. On a hourly base (mean of these data per hour), and by multiplying these values by 100, we get the percentage of time (over an hour) when the sensor detects some motion.

Then, the WavePlatform is able to calculate and directly display the hourly means of all these sensors’ data over time. This gives us a fairly good estimation of the hourly occupancy within a whole space along the day. For the SBE’s offices and the corresponding motion sensors, the data have been gathered and displayed on figure 2.

Figure 2: Hourly means of motion sensors data : percentage of presence in SBE’s offices - WavePlatform

The occupancy data are all the more reliable that they are directly linked to the energy consumption corresponding to lights and electric plugs, as exemplified by figure 3. This totally makes sense : the more occupants there are, the more computers are on, the more electric plugs are used and the more lights are switched on due to motion’s detection.
5.1 Occupancy

(a) Comparison of the evolutions of presence (yellow) and energy consumption (red) - WavePlatform

(b) Correlation between presence and energy consumption (lighting + electric plugs) and the corresponding trend line - Excel

**Figure 3:** Evolution’s similarities between presence and energy consumption in SBE’s offices

The linear model gives the following results (equation and coefficient of determination):

\[ y = 0.0088x + 0.2326 \text{ and } R^2 = 0.8562 \]

Given that \( R^2 > 0.85 \), there is indeed a correlation between the presence and the energy consumption, which gives credit to our occupancy estimation. What is also interesting is the intercept’s value, corresponding to the wasted energy consumption when no one is in the room (at SBE’s offices approximately 0.2 kWh/hour). This could be another KPI assessing the building’s energy management while unoccupied.

Eventually, to get to occupant-hours, the final trick is to identify the maximum number of people that could work at the same time in the room (13 in SBE’s case) and multiply it by the hourly means calculated by the platform. The results of this multiplication are displayed figure [4]: occupant-hours over time.
5.2 Comfort

When we compare the occ-hours’ data with the real number of people per hour within the space, the difference is very little (only one or two occupants at most). Anyways, it provides energy managers with an occupancy estimation which, if applied to every building, should make more relevant energy consumption comparisons between buildings with different levels of occupancy.

5.2 Comfort

Being able to evaluate the comfort level in an office building through relevant KPIs is necessary because the first objective of a BMS is to provide occupants with a minimum thermal comfort, not to jeopardise productivity. Often, energy is in the spotlight at the cost of comfort, that is to say the BMS doesn’t always deliver the occupants a high thermal comfort because of a certain fear of energy overconsumption. By developing KPIs on thermal comfort, office buildings are likely to find a good balance between energy use and thermal comfort. Indeed, with defined KPIs, the latter would be monitored and quantified, which would compel buildings’ operators to take care of thermal comfort just as much as energy consumption.

In order to achieve this goal, two indicators can be displayed on energy dashboards based on the WavePlatform’s available data, considering a few assumptions.

5.2.1 PPD - Predicted Percentage Dissatisfied

A common metric used for assessing thermal comfort is the Predicted Percentage Dissatisfied (PPD). It stems from the Predicted Mean Vote (PMV) model, which is widely used to predict occupants’ thermal sensation based on factors like air temperature and velocity, humidity, clothing insulation and metabolism. It represents the percentage of occupants within a built environment expected to find the thermal conditions dissatisfactory. Consequently, low PPD values indicate a better thermal comfort.

Engineers should use this indicator to optimize building systems and HVAC settings to enhance overall occupant comfort and energy efficiency, rather than
adjusting all settings only by taking into account energy efficiency.

The question is: how to display PPD over time while it seems to be dependent on so many factors? To do so, some assumptions need to be set:
- Air velocity is supposed to be 0.15 m/s. Indeed, an air velocity above 0.2 m/s produces noises that could disturb occupants.
- Humidity is set at 50%. According to captured data, humidity in office buildings doesn’t vary much and remains very close to 50%.
- Clothing insulation value (CLO) is equal to 1 in winter (trousers, deep socks and shoes, long sleeve t-shirt, sweater) and 0.5 in summer (light trousers, t-shirt), which corresponds to the common garments of occupants in office buildings.
- Metabolic equivalent of 1.2, corresponding to a sedentary activity peculiar to most work in office buildings.
- Temperature data are supposed to represent operative temperatures.

Therefore, it is possible to calculate PPD based on the correct PMV model:

$$ PPD = 100 - 95 \times \exp\left(-0.03353 \times (PMV)^4 - 0.2179 \times (PMV)^2\right) $$

Then, graphs showing the evolution of thermal comfort as a function of operative temperature can be displayed. Summer and winter models are represented in figure 5.

![Figure 5: Winter and summer PPDs as a function of operative temperature - Excel](image)

As exemplified by figure 24b and 24d, curb equations can be extracted from the sets of points. In the summer case, the following relation is obtained (T corresponding to the operative temperature):

$$ y = 1.5988x^2 - 75.88x + 1009 $$

$$ R^2 = 0.9956 $$
5.2 Comfort

\[ PPD_{\text{summer}} = 1.5936T^2 - 79.863T + 1009 \]

As for the winter case:

\[ PPD_{\text{winter}} = 0.9873T^2 - 43.322T + 481.01 \]

With these equations, it gets easier to display a comfort level through PPDs on the WavePlatform and it is interesting to have a look at the PPDs’ evolutions throughout the year (figure 6 below).

As expected, summer and winter PPDs stick to the operative temperature’s evolution. Moreover, summer PPDs are very high in winter because the CLO value is equal to 0.5, corresponding to summer clothes: occupants would be likely to feel cold, hence the considerable discomfort. Likewise, winter PPDs are very high in summer because the CLO value is equal to 1, corresponding to winter clothes: occupants would be likely to feel hot, hence the discomfort especially during heatwaves.

Consequently, it is suggested that winter PPDs should be taken into account only when maximum outdoor temperatures go down below 22°C (approximately
17°C as a mean outdoor temperature). Summer PPDs should be considered otherwise.

This KPI is more meaningful than mere indoor temperatures when it comes to thermal comfort but it is not sufficient to estimate the thermal comfort of a building because it doesn’t take into account the building’s occupancy. Indeed, the notion of thermal comfort is relevant only if related to the presence of occupants. Hence the creation of another KPI : the Predicted Dissatisfied Hours or PDH.

5.2.2 PDH - Predicted Dissatisfied Hours

The PDH represent the total hours of people dissatisfied in the zone (integral of number of occupants times PPD). More clearly, one hour with two occupants and 25% PPD is counted as 0.5 hours. This definition has been set by the Equa Team, in charge of the IDA ICE software. While IDA ICE is able to run energy simulations and give the corresponding PDH value over a year, the goal here is to be able to give the real PDH values only based on motion sensors data and temperature sensors data. The WavePlatform can directly display the following graph over a month figure 7 extracted from SBE’s data.

![Figure 7: PPD (v=0.15m/s) and occupant-hours displayed over a month in SBE’s offices - WavePlatform](image)

Given that the WavePlatform is not advanced enough when it comes to energy dashboards, Excel is used for the calculative tasks and for the display of PDH values. From December 2022 to November 2023, monthly PDH are calculated so that a yearly PDH can be obtained (equal to 1816). The corresponding graph is created figure 8.
Figure 8: Monthly PDH and occupant-hours represented from December 2022 to November 2023 - Excel

As exemplified by figure 8 above, occupant-hours vary along the year and have an influence on monthly PDH, given that the more occupant-hours, the more PDH obviously.

Therefore, to go even further, PDH divided by occupant-hours is calculated in order to have a better measure of overall indoor comfort quality for the whole building and to compare more accurately days, months and years. This new indicator is called Percentage Predicted Dissatisfied Hours (PPDH). The corresponding monthly values are displayed figure 9b. The curve’s shape is slightly different from the PDH’s curve only (figure 9a).

(a) Monthly PDH from December 2022 to November 2023

(b) Percentage of total occupant-hours with thermal dissatisfaction (PDH/occupant-hours)

Figure 9: Comparison between PDH and PPDH - Excel
Eventually, the PPDH over a day, a month or a year depending on the relevant precision, is more than welcome to evaluate any office building’s thermal comfort. However, WavePlatform isn’t prepared yet to display such a KPI but it gives food for thought for future web developments. Thermal comfort is a pivotal aspect of any indoor environment and it has to be taken into account, no matter how much energy needs to be saved.

5.3 Power - Smart grids

Be it energy consumption per occupant or energy consumption per area, energy consumption’s KPIs are widespread when it comes to building’s energy performance. However, these KPIs do not grasp the energy load at each and every moment of a day. In a society where the energy loads are more and more intense (due to an increase in overall electricity use in any region of the world) and the global electricity grid is more and more strained, the need for relevant KPIs linked to power loads has significantly increased. The question then is: how do office buildings really use electric power?

In this section, three KPIs are developed, the first one (P1) being the minimum power load, the second one (P2) being the difference between the mean power load under vacancy and P1, and the third one (P3) being a coefficient of variation linked to the standard deviation of electric power values over a week.

P1 represents the minimum electric load per area that is continuously used in office buildings. All electric systems are considered, from the lighting to the heating system by way of the electric plugs. This minimum value can be easily observed on heatmaps under vacancy, during the weekend or at night when the office building is empty. From one building to another, P1 can differ a lot, and bringing back the minimum electric power to the area can help compare more accurately the P1 values between different buildings.

As an example, the Santerne Fluides’ global heatmap (including all electric powers) is displayed figure 10 below.

Figure 10: Santerne Fluides’ heatmap over the past week (from 07/01/24 to 14/01/24) - WavePlatform
As a brief reminder, a heatmap represents the hourly means of electric power over a week. The orange and red zones correspond to the highest loads while green zones correspond to the lowest loads. It comes as no surprise that the nights and the weekend have fairly low loads compared to the rest of the week, due to vacancy. In the case of Santerne Fluides for the past week, the minimum electric power value (hourly mean) is 3.0 kW (cf. the top right of figure 10 in the red circle).

Brought back to the area (1550 $m^2$), it gives:

$$P_1 = \frac{3.00}{1550} = 0.00194 \text{ kW/m}^2 = 1.94 \text{ W/m}^2$$

Eventually, the higher $P_1$ is, the higher the minimum power load continuously used by the building is. In other words, $P_1$ is a good indicator of the energy systems’ minimum consumption. This KPI could be updated every week and its evolution over multiple weeks displayed (as in figure 11), in order to monitor its evolution over a year and detect potential energy drifts.

A second KPI $P_2$ is developed to complement $P_1$ : the difference between the mean power load under vacancy and $P_1$ (the value is not brought back to the area and is expressed in kW). Office buildings are supposed to be unoccupied and the heating system off from 8 p.m. to 6 a.m. (on weekdays) and during the weekends until 6 a.m. on Mondays. Based on this schedule, a weekly mean can be calculated from the power loads’ hourly means under vacancy extracted from the global heatmap over the past week.

Therefore, $P_2$ rather represents the energy management’s quality of office buildings under vacancy. The higher $P_2$ is, the higher the energy consumption when the building is unoccupied is, and the worse the energy management is.

After a quick Excel computing, the mean value is obtained (10.8 kW) and the coefficient $P_2$ as well:

$$P_2 = 10.8 - 3.00 = 7.8 \text{ kW}$$
In the same way as P1, P2’s evolution over multiple weeks is displayed in figure 12. Such a graph could also be used to detect potential anomalies. For example here, during the weeks of 26/11, 03/12 and 07/01, Santerne Fluides seems to have wasted a lot of energy under vacancy, probably due to an overworked heating system on weekends and at night.

![Figure 12: P2’s evolution for Santerne Fluides (from 01/10/23 to 14/01/24) - Excel](image)

Lastly, a third KPI P3 (without unit) is calculated, in order to evaluate the power load distribution over a week (mainly under occupancy). It is merely the coefficient of variation of electric power values over a week, that is to say the standard deviation divided by the mean of all the hourly mean values provided by a heatmap over a week.

In the case of Santerne Fluides:

\[
P3 = \frac{23.83}{27.54} = 0.87
\]

P3 represents a relevant comparative indicator of the loads’ variability over a week. With such an indicator, it may be possible, at a glance, to grasp if the power loads’ curve has rather significant load peaks (P3 high) or if the power loads are well distributed over a week (P3 fairly low). Moreover, like P1 and P2, P3 can be monitored over time, week after week: when it decreases, load peaks would be lower and/or more spread out whereas when it increases, load peaks would get higher. Generally speaking, P3 gives an overview of the load curve’s shape.

As a whole, be it for P1, P2 or P3, it is necessary to have an overview of the potential values taken by these three KPIs in order to be able to assess if a P value is high or low. Therefore, a recap chart (figure 13) sums up for different office buildings their respective P1, P2 and P3 values over the past week (from 08/01/2024 to 14/01/2024), including Santerne Fluides.
Based on this table, we can say that P2 values over 4 kW are worth questioning and the corresponding heatmaps should be analysed thoroughly. As for the other P2 values, they need to be interpreted at the same time as the P1 values which give information about the minimum power loads under vacancy. In other words, if P2 < 4 kW but P1 > 10 W/m² (VE Reims being a case in point with P1 = 11.4 W/m²), energy managers should look deeper into the heatmaps as well. Generally speaking, P1 values (without bringing back to the area) over 5 kW should incite managers to have a deeper look into their heatmap and their functioning systems under vacancy in order to explain such a minimum value.

As for P3, extracted values range from 0.31 (Cegelec Bourgogne) to 1.48 (Cegelec Perpignan). Most values are between 0.5 and 0.8, and rarely over 1. The extreme values are represented figure 14 below. Without surprise, both shapes are much different and P3 does well indicate that.

### Table 1: P1, P2 and P3’s table comparison for different buildings (from 08/01/24 to 14/01/24) - Excel

<table>
<thead>
<tr>
<th>Building</th>
<th>Area (m²)</th>
<th>P1 (W/m²)</th>
<th>P2 (kW)</th>
<th>P3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cegelec Bourgogne</td>
<td>423</td>
<td>11.3</td>
<td>2.9</td>
<td>0.31</td>
</tr>
<tr>
<td>Actemium Nancy</td>
<td>849</td>
<td>4.9</td>
<td>17.7</td>
<td>0.47</td>
</tr>
<tr>
<td>Actemium L’Armada</td>
<td>2500</td>
<td>7.7</td>
<td>22.7</td>
<td>0.55</td>
</tr>
<tr>
<td>Cegelec Le Puy Tertiaire</td>
<td>405</td>
<td>3.6</td>
<td>2.2</td>
<td>0.57</td>
</tr>
<tr>
<td>VE Reims</td>
<td>1061</td>
<td>11.4</td>
<td>2.8</td>
<td>0.59</td>
</tr>
<tr>
<td>Eurovia Denain</td>
<td>800</td>
<td>1.6</td>
<td>1.8</td>
<td>0.63</td>
</tr>
<tr>
<td>Chatenet Floriac</td>
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<td>4.7</td>
<td>0.63</td>
</tr>
<tr>
<td>Uxello Sud Ouest</td>
<td>700</td>
<td>2.1</td>
<td>4.8</td>
<td>0.72</td>
</tr>
<tr>
<td>Cegelec Lorraine</td>
<td>650</td>
<td>5.9</td>
<td>4.5</td>
<td>0.73</td>
</tr>
<tr>
<td>GTIE Rennes</td>
<td>950</td>
<td>0.7</td>
<td>6.7</td>
<td>0.75</td>
</tr>
<tr>
<td>Carré Constructeur</td>
<td>1748</td>
<td>2.0</td>
<td>2.0</td>
<td>0.76</td>
</tr>
<tr>
<td>Cegelec Toulouse</td>
<td>822</td>
<td>0.0</td>
<td>7.2</td>
<td>0.81</td>
</tr>
<tr>
<td>Santerne Flades</td>
<td>1550</td>
<td>1.9</td>
<td>7.8</td>
<td>0.87</td>
</tr>
<tr>
<td>Cegelec Perpignan</td>
<td>802</td>
<td>0.0</td>
<td>3.0</td>
<td>1.48</td>
</tr>
</tbody>
</table>

**Figure 13:** P1, P2 and P3’s table comparison for different buildings (from 08/01/24 to 14/01/24) - Excel

**Figure 14:** Load curves from 08/01/2024 to 14/01/2024 - WavePlatform
To go even further, what could be interesting would be to compare the evolution of buildings’ electric loads with the real electric loads on the grid. Such a comparison would make P3 much more relevant because it would help energy managers decide which buildings should definitely spread their power loads out over days and weeks.

5.4 Plug loads

Plug loads are often disregarded compared with HVAC systems or lighting. And yet, they can represent up to 50% of the total energy consumption of office buildings (according to the study ConsoIT carried out by ADN’Ouest and ADEME between 2012 and 2015 [12]). On average, plug loads would account for 25% of the total electricity bill in the tertiary sector. In this study, consultants have estimated that one fourth of the plug loads’ energy consumption could be avoided.

Based on this, it may be interesting to create KPIs that could help quantify the handling of plug loads in office buildings. Consequently, the goal here is to link occupancy with plug loads’ energy consumption in order to come up with relevant indicators (needless to say that plug loads consumption depends on occupancy).

A first model is created, based on the difference in plug loads consumption between the week, nights excluded and the weekend (added to the nights during the week). The different steps are the following:

- Daily plug loads’ energy consumption during a few weeks and weekends are extracted separately.
- For each building, a daily mean is calculated for the week and the weekend.
- Hourly means are induced by dividing by 24.
- Two KPIs are calculated: the plug loads’ energy consumption per occupant per week when the building is unoccupied (A in figure 16) and the ratio between energy consumption under vacancy and occupancy (B in figure 16).

The number of occupants within a specific office building is approximate, based on the average number provided by the respective companies.

Let’s take the case of Citeos (in Wave’s building) as an example, the plug loads data being the most exploitable. The evolution of their energy consumption is displayed figure 15.
As we can see, there is a sharp difference in daily energy consumption between the weeks and the weekends. Therefore, the mean values calculated for both periods are respectively 8.07 kWh and 4.30 kWh. Then, a hourly mean under vacancy can be calculated: 4.30 kWh divided by 24 equal to 0.18 kWh.

Finally, during a whole week (week + weekend), the respective energy consumption in occupancy and vacancy are calculated, based on a supposed average working day of 8:00-18:00.

\[
E_{\text{occupancy}} = (8.07 - 0.18 \times 14) \times 5 \quad \text{and} \quad E_{\text{vacancy}} = 2 \times 4.30 + 0.18 \times 14 \times 5
\]

Results for several office buildings are summed up figure 16 below. In addition, the modelled annual plug load consumption per area and per occupant is displayed.

In this table, office buildings are sorted out about the indicator A, which represents the plug loads’ energy consumption per occupant per week when the building is vacant. This KPI is particularly relevant because it compares office buildings on the basis of plugs’ consumption under vacancy, so the occupancy rate can’t influence it. It is divided by the average number of occupants within the building because there is no doubt that the more occupants, the more electric devices and the more plug loads there are. The indicator B brings another piece
of information and is then complementary. Indeed, this ratio between the energy consumption in vacancy and occupancy (%) indicates the share of an unoccupied weekly plug loads’ consumption compared to an occupied weekly plug loads’ consumption. The higher this KPI is, the lower the difference between occupancy and vacancy is and the worst the plug loads control is. For instance, Le Quartz and Demouselle PDC consume more under vacancy than under occupancy because their B value is higher than 100%.

5.5 Charging stations for electric vehicles

Electric vehicles have been gathering momentum for the past few years and the trend doesn’t seem to slow down. At the same time, the number of charging stations has significantly increased, particularly in companies, where most office buildings now have their own charging points in car parks. With these developments, it gets interesting to pay attention to charging stations’ power peaks at the same time as the global building’s power loads. The need for a flexible electricity grid is more and more pressing and if companies are not careful of the way they use energy, the risks of a grid saturation in the future may be high.

As an example, from 04/12/2023 to 18/12/2023, SBE’s building load is displayed right behind the 5 charging stations’ load curves (cf. figure 17a). It gives us a first overview on when the charging stations are used over two weeks. It comes as no surprise that all power loads happen on weekdays under occupancy. A second graph (figure 17b) is displayed below, showing the total load curve, with the whole building and all the charging stations’ power loads summed up.

Figure 17: Load curves from 04/12/2023 to 18/12/2023 - WavePlatform
As we can see, charging stations are often used at the same time (particularly on 08/12 when terminals 1, 3 and 5 are used), while people could strive to distribute the charging periods over the week (half of the week is systematically charge free).

A first relevant indicator can be the maximum value of the second curve. Here, on the selected period, the maximum is slightly superior to 30kW. For it to be more meaningful, it has to be compared to the approximate ideal power load that could be reached: \( P_{\text{max,building}} + P_{\text{max,charge}} \)

Therefore, a second charging point’s KPI is introduced:

\[
K = \frac{P_{\text{max,building}} + P_{\text{max,charge}}}{P_{\text{max,total}}}
\]

This KPI can also be expressed as a percentage by multiplying by 100. \( P_{\text{max,building}} \) represents the maximum power load of the building only, \( P_{\text{max,charge}} \) is the maximum power load among all the charging stations and \( P_{\text{max,total}} \) is the maximum power load of all the power loads summed up (first indicator above).

Here, \( K \) is equal to \( \frac{10.3 + 11.2}{31.2} \times 100 = 68.9\% \), meaning that the maximum power load over the two selected weeks was 30% bigger than what it could have been with a smart distribution of charging slots. This KPI could be renewed every two weeks or every week depending on the company’s energy management.

Ideally, charging stations should be used under the building’s vacancy when power loads are minimal but in practice, occupants can’t charge their vehicle up at night or during the weekend because they need to go home. Consequently, they have to charge their car battery up from 8 a.m. to 7 p.m. on average. In order to avoid using all charging stations at the same time and increasing the grid pressure, a solution would be to create time slots (of 2 hours for example) from 8 a.m. to 7 p.m. and that everyday, all the time slots should be selected at first (meaning that two cars could be charged up at the same time only if all the daily slots are already used). In the case of someone needing to leave earlier, there could be a derogation mode allowing to charge on whatever slot. Such a system could definitely ease the electricity grid. It hasn’t been implemented on the WavePlatform yet.

5.6 Energy signatures

Energy signatures are very interesting features of any building’s behaviour. They are mainly used for the prediction of energy consumption, especially for the consumption of heating systems, which are by far the most energy-consuming. In this section, two types of energy signatures are dealt with: the heating signature (widespread) and the lighting signature (newly introduced in this section).

Today, the WavePlatform is not able to display any kind of energy signature because the x axis in the dashboards interface can only correspond to the time evolution. To be able to make predictions based on outdoor temperatures, occupancy or actual daylight, the x axis needs to be more flexible. Indeed, in energy signatures, the x axis is supposed to represent a periodic variable which has a significant influence on the energy consumption represented on the y axis. Though, all the data extracted by the WavePlatform should be sufficient to display such
kinds of graph in the near future. These graphs could then be used to create new relevant KPIs.

### 5.6.1 Heating energy signature

For energy signatures related to the heating energy consumption, the periodic variable is the outdoor temperature. In practice, outdoor temperatures are not represented on the x axis. Instead are introduced the degree-days. Cooling and heating degree-days exist but in this section only winter, hence the heating period is considered. A heating degree-day is merely the difference between the mean outdoor temperature over a day and an indoor temperature of reference (usually between 15 and 18), without taking into account extra heat supplies from occupants and equipment. Then, monthly degree-days are just the addition of all the degree-days from the corresponding months.

Some heating energy signatures are displayed on figure 18 below.

![Figure 18: Different heating energy signatures from buildings on the WavePlatform - Excel](image)

As a whole, heating energy signatures are interesting tools because they set up consumption models that can be used to compare different buildings, for example through the consumption per area predicted by the model for a specific degree-day. Likewise, the intercept and the slope can be relevant KPIs, as long as the energy consumption is brought back to the area. A comparison based on these KPIs between SBE (242 m²) and Cegelec Lorraine (650 m²) is carried out below (figure 19).
(a) Heating energy signature of SBE’s offices with KPIs (energy consumption per area)

(b) Heating energy signature of Cegelec Lorraine’s offices with KPIs (energy consumption per area)

(c) Comparison of both models on the same chart

**Figure 19:** Heating signature’s comparison between SBE and Cegelec Lorraine - Excel

On figure 19, three different KPIs can be identified:
- The slope: \(a\)
- The intercept: \(b\)
- The energy consumption per area for the specific degree-days of 60 (for weekly signatures only): \(E_{60}\)

In the case of Cegelec Lorraine and SBE, the following values are obtained (table 1):

<table>
<thead>
<tr>
<th>Facility</th>
<th>(a) (kWh/m(^2)/degree-days)</th>
<th>(b) (kWh/m(^2))</th>
<th>(E_{60}) (kWh/m(^2))</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBE</td>
<td>0.0139</td>
<td>0.091</td>
<td>0.925</td>
</tr>
<tr>
<td>Cegelec Lorraine</td>
<td>0.0058</td>
<td>0.0375</td>
<td>0.386</td>
</tr>
</tbody>
</table>

**Table 1:** Comparison of SBE and Cegelec Lorraine KPIs

Considering that \(a_{SBE} > a_{Cegelec\ Lorraine}\), the SBE offices are more sensitive to variations of temperature. It could be linked to a worse thermal insulation through walls and windows. As for the intercept \(b\), if different from zero, it can correspond either to a residual consumption due to hot water usages, or to a wrong temperature of reference when degree-days were calculated. Sometimes, it can also be linked to a bad heating control because it means that the heating system
is activated while the needs for heating do not exist. Here, no fast conclusion is
drawn because there are some uncertainties due to modeling.

Lastly, the E60 values indicate that SBE’s heating system consumes the most
during an average week when it is neither too cold nor too hot in winter.

Energy heating signatures can also be used to predict energy consumption
based on the calculated model and the forecast degree-days. They can also help
compare the energy consumption calculated by the model with the real energy
consumption, so as to assess the potential energy and financial savings that a
specific heating control could provide.

5.6.2 Lighting energy signature

In this subsection is introduced a new type of energy signature, the lighting
energy signature. It stems from the observation that the lighting energy consump-
tion may significantly depend on the number of sunny daylight hours, thereby
depending at the same time on the weather (variable from one region to another)
and the number of daylight hours (mainly linked to the building’s latitude).

In order to exemplify this potential trend, the number of sunny daylight hours
is extracted for each day (from autumn 2022 to late summer 2023) from the online
page Meteociel [13] but it could probably be provided by the Microsoft services as
well (directly accessible by the WavePlatform). For Wave’s building, the closest
weather station is the one located in Lille-Lesquin. In order to limit the influence of
the building’s occupancy, only weekdays from 8:00 to 18:00 are considered (for the
lighting energy consumption as well as for the number of sunny daylight hours).
SBE, Cegelec Lorraine and Eurovia’s monthly results are displayed figure 20 after
an Excel processing.
5.6 Energy signatures

The three energy signatures prove with their $R^2 > 0.7$ that lighting energy consumption depends indeed on the number of sunny daylight hours during occupied days. This dependence can be really useful for the prediction of lighting energy consumption. From one year to another, it might then be possible, based on the coming month’s forecast of the number of sunny daylight hours, to predict the monthly lighting energy consumption of a building, merely based on such an energy signature.

Furthermore, by bringing the monthly energy consumption back to the respective areas, it can be possible to compare different buildings through their lighting energy signature. Indeed, the intercepts can be compared, for example, as an indicator of the inherent performance of lights. Likewise, the slopes can be relevant indicators grading the lighting design of buildings. The steeper the slope is, the better the design is because it would mean that the sunny daylight hours have a greater impact on the lighting energy consumption, thus implying that windows better let daylight permeate the indoor environment (no need for lights anymore). Lastly, like for the heating energy signature, a comparison can be made through the consumption per area predicted by the model for a specific number of sunny daylight hours : $E_{100}$.

A comparison between SBE and Cegelec Lorraine is carried out below (figure 21).
What is interesting to notice is that both curves seem to have a very similar shape. The main difference lies in the intercept which is much higher in the case of Cegelec Lorraine. This can be interpreted as a better lighting performance of SBE’s offices, be it the lighting control or the lights themselves. The E100 values confirm this difference in lighting performance.

Eventually, with this brief KPIs’ comparison between Cegelec Lorraine and SBE in terms of lighting and heating, it can be assumed that the first one has a better heating system while the second one prevails with its lighting system.

6 Analysis

All the KPIs aforementioned obviously present limits and uncertainties which have to be taken into account. They all have to be considered cautiously and with a discerning eye. These KPI are mainly tools that can help capture the buildings’ behaviour and take wise energy management decisions.

6.1 Occupancy’s data

First, let’s have a look at the occupancy KPI. Although the link between the percentage of presence and the energy consumption is quite blatant through figure 3, it can’t give us the precise number of occupants within a room through the so-called occupant-hours. On one hand, this percentage represents a mean presence rate in a room but it doesn’t grasp the movement of occupants, whether they are
moving within the room or going in or going out. Unfortunately, information provided by the motion sensors is only partial. On another hand, in order to get the occupant-hours values, the multiplier is chosen approximately. It is indeed recommended to take the maximum number of people that could work at the same time in the room but when we compare the calculated occupant-hours with the real number of occupants per hour on site, there is often a difference. Usually, the calculated occupant-hours are higher than the real numbers when there are very few people in the room (cf. figure 22 at noon, this trend is observed during other days as well).

To be as reliable as possible, the multiplier for calculated occupant-hours should be adjusted depending on the difference with the real ones. In addition, it comes as no surprise that each office building should adjust this multiplier to their occupancy’s capacity.

Lastly, it is worth mentioning that office buildings are often mixed buildings, with open spaces and single rooms at the same time, which doesn’t help count with precision the number of occupants.

To give food for thought, another way of extracting occupancy’s data could be to link the CO$_2$ level to the real number of occupants within an indoor environment, for a specific ventilation schedule. Then, based on the actual CO$_2$ level, the number of occupants could be induced from the relation previously found.

6.2 Comfort’s estimation

As for the comfort’s section, let’s go back to the assumptions in order to better understand their influence on the PPD results:

- **Humidity**: relative humidity is generally kept between 40% and 60% in office buildings all over the year (cf. figure 23). The thermal discomfort appears only when the relative humidity exceeds 30% or 70%.
Figure 23: Evolution of relative humidity (%) in SBE’s offices all over the year 2023 - WavePlatform

In SBE’s offices, variations of relative humidity have very little influence on perceived thermal comfort, as long as it remains between 40% and 60% all over the year. In the majority of office buildings, assuming that relative humidity doesn’t vary much and remains close to 50% is not ludicrous.

- **Metabolic equivalent**: the MET value describes the actual activity of occupants within their indoor environment. In office buildings, there is no doubt that people spend most of their time sitting behind their desk in front of their computer. Consequently, the MET value can be nothing but 1.2, according to the table about the metabolic rates of different activities (cf. appendices figure 29). The other activities are indeed: reclining, seated (relaxed), standing (light activity), standing (medium activity) and walking on level ground (at different speeds).

- **Operative temperature**: the temperature provided by sensors is in reality the air temperature and not the operative temperature. The latter is the mean between the air temperature and the surfaces’ temperature. It is more realistic in terms of real perceived temperature by occupants. Indeed, someone next to a window would feel much colder than any other occupant in the center of the room. The cold radiation would definitely affect the thermal comfort of this occupant. And yet, the air temperature could be highly reasonable.

In this study, it was impossible to get the operative temperature due to a lack of measuring tools. Given that temperature is necessary to proceed to PPDs’ calculation, the air temperature provided by the WavePlatform is used here. It gives all the same a fairly good estimation of the perceived indoor temperature (and occupants trust it).

- **Clothing insulation value**: the CLO value can be estimated in different ways. In summer and winter, only one combination of garments is chosen respectively, which brings uncertainty as long as every occupant usually dresses up differently. Furthermore, as emphasized by [19], the chairs’ thermal insulation should be taken into account as well. Consequently, it is quite difficult to generalize garments to all the occupants within a specified building, all the more that people don’t feel the same thermal comfort when working in a given indoor environment. Some could be freezing and wearing several layers while others could be merely wearing short-sleeved shirts without getting cold at all. To be the most precise, occupants should have their own PPD graph based on the garments they are used to wear. Personally, looking at figure 30 and [19], my winter CLO value would be 0.96.
6.2 Comfort’s estimation

(standard office chair 0.10, underpants 0.10, thick long socks 0.10, shoes thick soled 0.04, t-shirt 0.09, normal trousers 0.25 and sweater 0.28) and my summer CLO value 0.53 (standard office chair 0.10, underpants 0.10, socks 0.02, shoes thin soled 0.02, t-shirt 0.09 and light-weight trousers 0.20). As a whole, 0.5 in summer and 1 in winter are chosen because they represent reliable CLO values’ averages over a year and displaying only one PPD graph per indoor environment is more than welcome.

- Air velocity: air velocity is the most unknown parameter in this study and its influence is not negligible. Indeed, from 0.05 m/s to 0.15 m/s, the PMV values vary (cf. ISO 7730 [19]) and consequently the PPD values as well. In order to estimate the differences, the figure 24 below shows the PPDs’ evolution in winter (from 05/11/2023 to 05/02/2024) and summer (from 01/07/2023 to 01/10/2023) for v<0.10m/s and v=0.15m/s in SBE’s offices.

![Figure 24: Comparison of winter and summer PPDs for v<0.10m/s and v=0.15m/s in SBE’s offices, indoor temperature in red - WavePlatform](image)

At first glance, winter and summer shapes for v<0.10m/s and v=0.15m/s are very similar. To be more precise, in winter, PPD values for v=0.15m/s are slightly higher than those for v<0.10m/s while in summer, it is the opposite. Over a year, the differences in PPD are not bigger than 5%.

This first estimation drives us to take a look at PPDH values for v<0.10m/s in order to compare it with PPDH values for v=0.15m/s. Indeed, PPDH includes occupancy’s information and is then much more relevant. This comparison is carried out on Excel over the complete year 2023 and is displayed figure 25 below.
Over a year, the shape of the PPDH’s evolution doesn’t seem to be affected by air velocity. However, monthly speaking, PPDH values differ slightly, the maximum difference occurring in December and January (1.3% difference). Considering that such a graph should be mainly used to detect periods with unexpectedly high PPDH values compared to the rest of the year, be it $v=0.15\text{ m/s}$ or $v<0.10\text{ m/s}$, such periods can be detected, as exemplified by figure 25. Indeed, from June to September included, there is no doubt that PPDH values are higher than usual. Practically speaking, it could assist energy policymakers in taking relevant decisions when it comes to the BEMS. For example, here in the case of SBE, PPDH values were very high in summer because of very high temperatures without any air conditioning. Policymakers could then reflect on the potential installation of an air conditioning unit.

Eventually, to make sure that PPD values are reliable, it could be relevant to ask occupants about their real feelings and compare them to predicted values. The PPD values would be all the more valuable and could definitely be taken into account to guide energy politics.

### 6.3 Energy use related to thermal comfort

Nowadays, energy use and thermal comfort are rarely connected. Worse still, thermal comfort is often disregarded because money doesn’t seem to be at stake at first sight. And yet, a poor thermal comfort can highly jeopardise the employees’ productivity, thus affecting the financial health of companies. What if both were connected? What if energy managers could tell how much energy is used to reach a certain level of thermal comfort? Let’s examine the case of SBE.

Given that there are many sub-meters in SBE’s offices, it is possible to extract distinctly the energy usages which affect indoor thermal comfort: HVAC systems, that is to say heating and ventilation systems, but no air conditioning because

**Figure 25:** Percentage of total occ-hours with thermal dissatisfaction for $v=0.15\text{ m/s}$ and $v<0.10\text{ m/s}$ in SBE’s offices - Excel
there is none in SBE’s offices. Consequently, first of all, monthly heating and ventilation energy consumption are collected over the year 2023 and adjusted to outdoor temperatures, namely degree-days. In SBE’s offices, these energy systems are affected by outdoor temperatures only in winter, so from May to October included, heaters being turned off, monthly energy consumption is not adjusted because it corresponds to ventilation consumption only. Data are displayed on a graph.

Then, monthly PPDH over the same months are added to the same chart with a second axis adjusted to PPDH values. The result can be found figure 26 below.

![Figure 26: Monthly thermal comfort (PPDH) and energy consumption over the year 2023 in SBE’s offices - Excel](image)

This chart leads us to different interpretations and comments:
- The summer period was more uncomfortable than the winter period (i.e. the heating period), probably due to the lack of an air conditioning system.
- In December, the energy consumption was unexpectedly high compared to the thermal comfort provided. Indeed, November and December had the same level of thermal comfort but in December, the offices consumed almost 300 extra kWh adjusted. Indeed, in December it was very cold and the heating system wasn’t working properly so it may have over-consumed.
- March was a very good month considering the ratio PPDH over energy consumption. Compared to April, energy consumption was very low (almost 400 kWh adjusted less) for about the same thermal comfort’s level. The ventilation system may have over-consumed.
- Between May and October (heating system off), the ventilation system seems to have over-consumed in May, June and August because this over-consumption didn’t lead to a better thermal comfort. It would not be surprising that some free-cooling was implemented in vain.
Eventually, such a graph can definitely help energy managers and decision-makers analyse their building’s energy behaviour in light of occupants’ thermal comfort on a macro level, month by month. It puts back in the center occupants’ well-being and productivity while keeping an eye on energy consumption. Both compared over a year, it paves the way for relevant changes in terms of energy policy and energy systems. Nevertheless, in order to mitigate risks related to hasty decisions, this kind of graph should only be a first indicator or signal, giving ideas of potential changes. After analysing it, decision makers should confirm their interpretations with the real occupants’ feelings to make sure that collected data are valuable and reliable. If so, their energy decisions and actions would be all the more successful.

6.4 Plug loads’ model

The plug loads’ model is interesting for a first estimation of plug loads’ use. However, to be more precise and to make the comparison between different buildings more relevant, it should be linked to occupancy. Indeed, the more occupants there are on weekdays, the higher the plug loads’ consumption is, so the lower the indicator B would be. Consequently, buildings with a high occupancy rate would be likely to have a “better” B value.

With the WavePlatform, given that there is no access to precise hourly consumption, plug loads’ consumption under occupancy and at night on weekdays can’t be distinguished, so this study is not carried out here.

As for the indicator A, occupancy’s data don’t affect it because it only takes into account plug loads consumption under vacancy. In order for this indicator to be more accurate, the ideal way of calculating it would be to get precise hourly consumption values so as to extract the plug loads consumption at night. Unfortunately, such precise data are not available so the right alternative would be to calculate the yearly mean of plug loads’ consumption over a “weekend day”. From this value, a hourly mean could be induced and used for an estimation of plug loads’ consumption at night on weekdays.

In the case of Citeos, this mean value over a year is 3.95 kWh, which is 8% lower than 4.30 kWh, estimated over 7 weeks. $E_{\text{vacancy}}$ is then equal to 19.42 kWh compared to 21.2 kWh over the same period. Eventually, A is equal to 1.62 kWh/occupant on one hand, and on the other hand, it is equal to 1.76 kWh/occupant. These two values are slightly different but they give the same kind of information: Citeos is in line with the average weekly consumption under vacancy according to figure [16].

6.5 Energy signatures’ uncertainties

Energy signatures represent energy models that can help determine energy savings and make energy consumption’s predictions. In order for them to be reliable, they need to have a reasonable level of uncertainty. Errors may arise due
to meter inaccuracy, modeling procedures and adjustment procedures. Consequently, true values are not known, only estimates with some level of uncertainty. In the following paragraphs, these three kinds of uncertainties are discussed and exemplified, based on [14], through examples of heating energy signatures.

First, when it comes to meter inaccuracy, it is worth pointing out that no meter is 100% accurate, even though some are very precise and tend to be 100% accurate. The accuracy is often published by the meter manufacturer. Specifically, SBE’s offices are equipped with Carlo Gavazzi meters which are less than 1% inaccurate, so this uncertainty can be neglected thereafter.

As for uncertainties related to modeling procedures, they can be linked to insufficient or unrepresentative data, or an inappropriate functional form for example. Let’s have a look at two different energy signatures (figure 27 below) to understand how uncertainties can be dealt with.

![Figure 27: Heating energy signatures of LCR and Wave - Excel](image)

(a) Heating energy signature of Wave’s building (per month)  
(b) Heating energy signature of LCR’s building (per week)

When evaluating the accuracy of a regression model, the first step is to analyse the coefficient of determination $R^2$, which tells to what extent the variations of the dependent variable and its mean value are explained by the regression model. The $R^2$ check should only be used as an initial check. In other words, models should not be accepted or rejected merely on the basis of the $R^2$ value. Generally speaking, if $R^2 > 0.75$, the model should not be rejected and a further uncertainties’ analysis should be carried out. If $R^2 < 0.75$, another model should be tested or more points should be added to the energy signature.

In the two examples above, coefficients of determination are both higher than 0.75 so further analyses can be undertaken (0.86 for Wave and 0.81 for LCR). However, at first sight without even calculating anything in terms of uncertainties, there is no doubt that Wave’s energy signature is less reliable than LCR’s energy signature, considering the number of points and their overall distribution around the respective linear models.
Wave’s linear model is expressed as follows:

\[ y = 34.792x - 2379.3 \]
\[ a = 34.792 \text{ kWh/m}^2/\text{degree-day} \text{ and } b = -2379.3 \text{ kWh/m}^2 \]

LCR’s linear model is the following:

\[ y = 51.226x - 351.41 \]
\[ a = 51.226 \text{ kWh/m}^2/\text{degree-day} \text{ and } b = -351.41 \text{ kWh/m}^2 \]

The goal now is to estimate the uncertainties on coefficients \( a \) and \( b \) respectively. With the LINEST function in Excel, the table below can be automatically calculated.

<table>
<thead>
<tr>
<th></th>
<th>( R^2 )</th>
<th>SE (a/b)</th>
<th>RMSE</th>
<th>CV(RMSE)</th>
<th>t-statistic (a/b)</th>
<th>DF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave</td>
<td>0.80</td>
<td>6.4/1997.3</td>
<td>2216.6</td>
<td>28.6</td>
<td>5.45/1.19</td>
<td>7</td>
</tr>
<tr>
<td>LCR</td>
<td>0.86</td>
<td>3.4/231.6</td>
<td>740.2</td>
<td>27.6</td>
<td>15.22/1.52</td>
<td>37</td>
</tr>
</tbody>
</table>

**Table 2:** Uncertainties’ estimation of Wave and LCR’s energy signatures

Then, based on the table, the t-statistic for each coefficient can be compared with the critical value corresponding to a certain confidence level and degree of freedom. For both energy signatures, a confidence level of 90% at least should be looked for.

For Wave, the comparative value is 1.89. Likewise, for LCR, it is 1.69. Both values are higher than the t-statistic \( b \), itself being lower than 2, be it for Wave or for LCR. It means that the \( b \) values can’t be fully trusted because they are precise at \( \pm 100\% \). However, for the coefficients \( a \), given that 5.45 > 1.89 and 15.22 > 1.69, the degree-day is a highly significant independent variable. In addition, the ranges at the 90% confidence level for the coefficients \( a \) are respectively:

- **Wave:** 22.7 to 46.9, equivalent to a relative precision of \( \pm 35\% \).
- **LCR:** 45.5 to 57, equivalent to a relative precision of \( \pm 11\% \).

In other words, for Wave’s offices, we are 90% confident that each additional degree-day increases the daily energy consumption between 22.7 and 46.9 kWh. Likewise, for LCR’s offices, we are 90% confident that each additional degree-day increases the daily energy consumption between 45.5 and 57 kWh. As expected, Wave’s energy signature is less reliable than LCR’s energy signature, considering the respective relative precision.

To go even further, let’s discuss about uncertainties linked to adjustment procedures, which can be carried out for prediction (based on predicted degree-days) or for some comparison between a given model and real data (cf. figure). In both cases, the procedure is the following:

- An energy signature’s model is created for a specific period called "baseline period" (last year, last month or more specific periods).
- If used for prediction, this model is applied to predicted degree-days.
- If used for comparison, the same model is applied to degree-days from a period of monitoring called "reporting period" (the past few weeks for example).

In both cases, the energy consumption values calculated by the model present uncertainties that need to be estimated. For example, to predict the electric consumption under average heating conditions (let’s say 350 degree-days per month and 60 degree-days per week), these mean values are respectively inserted into the regression models:

\[
\begin{align*}
\text{Wave predicted consumption} &= 34.792 \times 350 - 2379.3 = 9797.9 \text{ kWh} \\
\text{LCR predicted consumption} &= 51.226 \times 60 - 351.41 = 2722.2 \text{ kWh}
\end{align*}
\]

Given that the standard errors of the estimate (RMSE) are respectively 2216.6 (Wave) and 740.2 (LCR), the ranges of possible prediction are (based on table 31 and a confidence level of 90%):

- **Wave**: 5608.5 to 13987.3 kWh, equivalent to a relative precision of ±43%.
- **LCR**: 1471.3 to 3973.1 kWh, equivalent to a relative precision of ±46%.

Considering the very high relative precision for both predictions, the respective models should definitely be revised in order to increase certainty and reduce risks of making mistakes. Nevertheless, if no other data are available, energy signatures are worth being displayed all the same, along with uncertainties, because they would provide energy managers with an interesting overview of the evolution of energy consumption in relation to outdoor temperatures.

To give an example of what could be a more reliable energy signature, the graph below extracted from Eurovia’s data is displayed (figure 28).

![Figure 28: Eurovia’s energy signature (per week) from December 2022 to January 2023 - Excel](#)

Relevant features are the following:
- Model’s equation: \( y = 4.6387x + 25.807 \)
- \( R^2 = 0.8993 \)
- Degrees of freedom: 40
6.5 Energy signatures’ uncertainties

- RMSE : 47.1
- t-statistic (a/b) : (18.9/1.30)
- Range at the 90% confidence level of coefficient a : 4.2264 to 5.0510, equivalent to a relative precision of ±8.9%.
- Range at the 90% confidence level of the model’s prediction at 70 degree-days (predicted consumption = $4.6387 \times 70 + 25.807 = 350.52$ kWh) : 271.39 to 429.65 kWh, equivalent to a relative precision of ±22.5%.

As a whole, what needs to be retained is that $R^2 > 0.75$ is a necessary condition to keep a model but it is not sufficient. The more points (= the more degrees of freedom) are extracted, the more likely the energy signature is reliable. Moreover, the t-statistic of coefficient a is the most valuable. Indeed, the b value is often very approximate (with the WavePlatform’s data) because it can change drastically with a slight change in coefficient a. Anyway, by displaying the energy signature, the coefficient a is much relevant and interesting because it gives information about the building’s sensitivity to changes in outdoor temperature. The higher coefficient a is, the more sensitive the building is. For a to be reliable, its t-statistic has to be around 20 or its standard error has to be no more than 0.1 or a itself. If not, the precision in its value is about ±100%, which doesn’t increase confidence at all. As for the relative precision with real extracted data, it seems difficult to reach reasonable values (below 20%), Eurovia being an exception. In this case, whenever displaying prediction results, it is essential to indicate uncertainties and associated levels of precision. Even with a relative precision of 50%, results along with uncertainties are valuable and can be used with full knowledge of the facts.

Finally, it is worth noting that the procedures would be the same if models were polynomial instead of linear.
7 Discussion

7.1 Conclusion

Data from occupancy sensors, temperature sensors or various sub-meters represent valued information of which energy managers have to make the most to communicate energy trends with occupants/employees. The more occupants are informed, the more they can be prone to take part in the energy consumption reduction of their office building.

In order to be as clear-cut as possible, relevant KPIs need to be created and they have to be in line with the company’s objectives. Indeed, from one building to another, KPIs shouldn’t necessarily be the same. What would decision-makers prefer to display? Financial KPIs? CO₂ emission KPIs? Or energy KPIs? Furthermore, not every building has all kinds of sub-meters installed, and some don’t even have charging stations and/or solar panels. Thus, KPIs should be created accordingly.

Then, for each indicator, it is necessary to make adjustments because buildings behave differently and have specific features: size, area, number of occupants, occupancy level, energy systems and their management, thermal insulation, building management system, location, etc. For example, when it comes to occupancy, each building has a specific maximum number of occupants which influences the occ-hours indicator. As for the location, it obviously affects the degree-days and the sunny daylight hours, hence the energy signatures. Likewise, air velocity varies from one building to another and affects the PPD’s calculations.

In order for KPIs to be as relevant as possible, they need to be adjusted and monitored continuously, week after week, month after month, year after year. If not, they could either mislead energy managers or merely lose their full potential.

As a whole, given that KPIs are made of uncertainties, they have to be used very carefully and shouldn’t be taken at face value. Though, they represent powerful tools that could help decision-makers and energy managers better understand the way their building behaves over the yearly seasons. If those persons were to know how to use their KPIs, that is to say knowing what inputs and outputs they have, when to doubt about them, how to deal with their uncertainties and how to communicate and take action on their basis, they would definitely be able to make the most of energy monitoring webplatforms like the WavePlatform by Smart Building Energies. However, today, this monitoring tool still presents some limits in terms of data analysis and the display of energy dashboards. Most KPIs introduced in this report were calculated and/or displayed on Excel, hence restricting the possibilities of creating and having easy access to relevant indicators. This study could then influence the future web developments of the WavePlatform.
7.2 Future work

The following list details the different topics that could complement the ones approached in this report. They haven’t been dealt with here due to a lack of time and functionalities.

- How to smartly combine PV production with the charging stations’ consumption?
- How to determine more precisely occupancy levels (through CO$_2$ levels for example)?
- How to harness demand response, balancing the demand on power grids by shifting electricity demand to times when electricity is abundant? Which role can smart buildings and KPIs play into the impact’s management of variable renewables and growing electricity demand, in order to ensure stability and reliability of electricity grids?
- How to link power loads on the general electricity grid (provided by RTE in France) with the actual power loads of a building?
- Which financial KPIs and CO$_2$ emission KPIs could also be displayed?
- What about the creation of universal KPIs?

To give food for thought, in the foreseeable future, what if building’s certifications were based on KPIs such as the one linking energy use to thermal comfort (cf. section "Energy use related to thermal comfort")?

8 Appendices

8.1 PPD and PMV

<table>
<thead>
<tr>
<th>Activity</th>
<th>Metabolic Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(W/m$^2$)</td>
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<tr>
<td>Laying down</td>
<td>46</td>
</tr>
<tr>
<td>Sitting, relaxed</td>
<td>58</td>
</tr>
<tr>
<td>Standing, relaxed</td>
<td>70</td>
</tr>
<tr>
<td>Sitting activity (office work, school etc.)</td>
<td>70</td>
</tr>
<tr>
<td>Standing activity (shop, laboratory etc.)</td>
<td>93</td>
</tr>
<tr>
<td>Moving activity (house work, working at machines etc.)</td>
<td>116</td>
</tr>
<tr>
<td>Harder activity (hard work at machines, work shops etc.)</td>
<td>165</td>
</tr>
</tbody>
</table>

Figure 29: Metabolic rates of different activities - [20]
<table>
<thead>
<tr>
<th>Garment description</th>
<th>Ig (clo)</th>
<th>Garment description</th>
<th>Ig (clo)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underwear</td>
<td></td>
<td>Dresses and skirts</td>
<td></td>
</tr>
<tr>
<td>Bra</td>
<td>0.01</td>
<td>Skirt (thin)</td>
<td>0.14</td>
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<td>Panties</td>
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<td>Skirt (thick)</td>
<td>0.23</td>
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<tr>
<td>Men’s briefs</td>
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<tr>
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<td>Short-sleeve shirtdress (thin)</td>
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</tr>
<tr>
<td>Long underwear bottoms</td>
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<td>Long-sleeve shirtdress (thin)</td>
<td>0.33</td>
</tr>
<tr>
<td>Full slip</td>
<td>0.16</td>
<td>Long-sleeve shirtdress (thick)</td>
<td>0.47</td>
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<tr>
<td>Long underwear top</td>
<td>0.20</td>
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<td></td>
</tr>
<tr>
<td>Footwear</td>
<td></td>
<td>Sweaters</td>
<td></td>
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<tr>
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<td>0.25</td>
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<tr>
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<td></td>
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<td>Carl-length socks</td>
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<td>Double-breasted (thick)</td>
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<td></td>
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<td>Trousers and coveralls</td>
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</tr>
<tr>
<td>Short shorts</td>
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<td>Short-sleeve hospital gown</td>
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<td>Walking shorts</td>
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<td>Coveralls</td>
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<td>Long-sleeve long wrap robe (thick)</td>
<td>0.69</td>
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**Figure 30:** Thermal insulation for common garments - [21]
8.2  

### t-statistic

<table>
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<th>Confidence Level</th>
<th>Degrees of Freedom</th>
<th>Confidence Level</th>
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<td>90%</td>
<td>80%</td>
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<td>1</td>
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<td>6.31</td>
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<tr>
<td>2</td>
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<tr>
<td>3</td>
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<td>2.35</td>
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<td>15</td>
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<td>1.75</td>
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**Figure 31:** t-statistic table - IPMVP [14]

8.3  

### Adjustment procedure

**Figure 32:** Comparison between a baseline energy consumption adjusted and the reported energy consumption in Wave’s offices - Excel
References

[1] https://www.ademe.fr/les-defis-de-la-transition/energies/


Kungliga Tekniska Högskolan
Brinellvägen 8
114 28 Stockholm