Article

Office building tenants' electricity use model for building performance simulations

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Abstract: Large office buildings are responsible for a substantial portion of energy consumption in urban districts. However, thorough assessments regarding the Nordic countries are still lacking. In this paper we analyse the largest dataset to date for a Nordic office building, by considering a case study located in Stockholm, Sweden, that is occupied by nearly a thousand employees.
Distinguishing the lighting and occupants' appliances energy use from heating and cooling, we can estimate the impact of occupancy without any schedule data. A standard frequentist analysis is compared with Bayesian inference, and the according regression formulas are listed in tables that are easy to implement into building performance simulations (BPS). Monthly as well as seasonal correlations are addressed, showing the critical importance of occupancy.
A simple method, grounded on the power drain measurements aimed at generating boundary conditions for the BPS, is also introduced; it shows how, for this type of data and number of occupants, no more complexities are needed in order to obtain reliable predictions. For an average year, we overestimate the measured cumulative consumption by only 4.7%. The model can be easily generalised to a variety of datasets.

Keywords: Building simulation; Office buildings; Energy performance; Energy modelling; HVAC; Analytical modelling; Statistical analysis

1. Introduction

It is well known that the energy use of buildings depends remarkably on occupant behaviour, which e.g. includes indoor climate parameter preferences, how different systems are operated as well as when and by how many people the buildings are used. The reviews [1], [2] show a systematic performance gap between predicted and actual energy consumption of buildings; in some cases, this can reach even 300% difference. The authors conclude that this might occur by a loose implementation of the occupants' behaviour in building energy performance simulations (BPS), where climate data and physical characteristics of the building are addressed into detail whilst occupancy schedules are fixed according to generic standards.

Upon recognition of this problem, in the past decade a number of research efforts have considered how the modelling of occupant behaviour lifestyles impacts the building energy use, either for direct implementation into BPS [3] [4] [5] [6] [7] or with a more general formulation [8] [9] [10].

A common modelling approach relies on logistic regression, which is used in statistics to analyse and model binary dependent variables; an example is given by the status open/closed of a window, which can depend e.g. to a temperature increase or to carbon dioxide concentration [11]. Another interesting procedure by Zhao et al. [3] divides the users' role into "active" versus "passive", treating the occupants as "disturbances" in the HVAC control; the occupant individual behaviour is then implemented in BPS software. Klein et al. [5] use a distributed comfort evaluation based on Markov Decision Problems (MDP) to simulate the energy impact of the active occupant behaviour. Lee and Malkawi [6] introduce an open architecture agent-based modelling (ABM) to predict occupant behaviour with many diverse input data such as window and blind use but also behavioural, control, and normative beliefs.

Bonte et al. [7] addressed the building performance induced by using blinds, lighting system, windows, fan, thermostat and clothing adjustments via TRNSYS simulations. Menezes et al. [12] developed two models for estimating small power consumption in office buildings, alongside typical power demand profiles.

Behavioral models found an application as well in the work of Tetlow et al. [13], who addressed the contribution of various behavioural constructs to small power consumption in offices. They found that habit is only a behavioural construct that correlates with small power consumption.

Stochastic modelling is very popular, due to its flexibility and ability to fit non trivial profile patterns [8] [14] [15] [16]. The benchmark study by Page et al. [8] considers occupant presence as an inhomogeneous Markov chain, while Mahdavi et al. [10] emulate the stochastic nature of load fluctuations by means of Weibull distributions, using overall presence patterns as input. Gilani and O'Brien investigate in [17] the impact of manual and automatic lighting control systems on the lighting energy use in private offices with a probabilistic approach. They also show in [18] that non-probabilistic models reasonably represent occupants' impact at larger scales. In other words, beyond 100 offices simpler models can substitute stochastic models.

Zonal occupancy is addressed via Markov chain theory by Chen et al. [19], while Wang et al. [20] create a movement-based stochastic occupancy model by means of a homogeneous Markov chain (HMC) to simulate the occupants' behaviour as a function of time.

Richardson [9] addresses occupancy by formulating a two-state non-homogeneous Markov Chain Monte Carlo (MCMC) technique, distinguishing between two states: active and inactive users. This formulation is extended by Aerts et al. [21] through hierarchical clustering to a probabilistic model including three states: (1) at home and awake, (2) sleeping or (3) absent.

Applications of occupant behavioural models to building performance simulations (BPS) are addressed by Buso et al. [22], by implementing as input for window opening models in IDA ICE a refinement [23] of the Page method [8]. Finally, stochastic modelling of office buildings is not very common, however Zhou et al. obtain in [24] only a 2.5% maximum error of simulation results versus measurements.

The above literature review is summarised in **Table 1**. The entries in bold concern studies which we believe are more suitable to immediate implementation into BPS.

In this paper we consider energy consumption modelling of a large office building in Sweden. Nordic buildings constitute an interesting case, since the literature addressing their consumption is at the moment rather scarce. Furthermore, climate and cultural differences (regarding e.g. occupancy and lighting schedules as well as and holiday seasons) in principle constitute a case study with peculiar characteristics. Even the indoor temperature setpoints differ from the European values [25], holding respectively as 21.5 °C for heating and 23 °C for cooling for the building considered in this paper.

Our input data are very large in number (5 years of operation with 5 minutes time step), covering from district heating to HVAC system and tenants' electricity consumption. The latter, to which we focus our attention, is afflicted by some sort of an unusual problem: the tenants' appliances power plug load *and* lighting are aggregated together. Furthermore, no occupancy rate could be measured. These two features make our investigation fairly unconventional, considering the current literature.

Another research question we wish to answer here is how much we can simplify the analysis and reduce the time spent in resources and effort, so that the adopted approach is as simple as possible while still retaining data modelling and predictive accuracy. In this paper we tackle the issue on the side of data analysis, by generalizing measurement patterns and simplifying a method first introduced in [26]. Our main concern is constructing a simple predictive method that would easily and promptly be implemented into building performance simulations.

The paper is structured as follows: in Section 2 we address the dataset structure and methods of analysis, while Section 3 reports our results, featuring daily and monthly energy consumption as well as the predictive model for implementation into BPS. Section 4 is devoted to a discussion of the results and Section 5 to our conclusions.

Table 1. Literature data source and methods

First author	Data source	Method used	BPS?
Calí [11]	Window opening events	Logistic regression	No
Zhao [3]	Data mining, consumption	Nominal classification Numeric regression	Yes
D'Oca [4]	Data mining, occupancy	Cluster analysis	Yes
Klein [5]	Occupant behaviour	Markov chain decisions	Yes
Lee [6]	Occupant behaviour	Agent-based modelling	Yes
Bonte [7]	Occupant behaviour	TRNSYS simulations	Yes
Menezes [12]	Consumption data	Random sampling Bottom-up approach	No
Page [8]	Consumption data	Inhomogeneous Markov chain Inverse function method	No
Mahdavi [10]	Annual plug loads	Aggregate estimations Stochastic-Weibull distributions	No
Gilani [17]	Lighting energy use (offices)	Cumulative distributions Discrete-time Markov chains	Yes
Aerts [21]	Daily diary (users)	Hierarchical clustering	No
Richardson [9]	Occupation data	2-state non-homogeneous Markov Chain Monte Carlo (MCMC)	No
Buso [22]	Electricity Consumption HVAC parameters User behaviour	Lighting model Markov chains-generated window opening models	Yes

2. Methods

The data examined in this paper pertain to a portion of a large office building in Stockholm, Sweden shown in **Figure 1**. The building block consists of office spaces with only a marginal share of technical rooms; the data has been gathered only from the office spaces. These lie on 8 floors, with a total heated area of 19642 m^2. The building was constructed in 2014 and has been awarded Triple LEED Platinum certificate; according to the building owner, the number of occupants is in the order of 1000 persons.

The energy consumption data were collected from January 2014 to March 2019, with 5 minutes time step; they comprised external temperature measured in different locations, cold and hot water consumption, district heating, facility and tenant electricity load, free cooling pumps, room temperatures, ventilation devices and controllers, air pumping for humidity control, indoor air quality control and air heating. Due to the high collinearity between most of these predictors (which is addressed in pre-processing, Section 3.1), in this paper we shall address only the tenants' consumption measurements, which were obtained via a common meter for the appliances' plug load and space lighting. The appliances included were those typical of an office work environment, namely personal computers, printers as well as fridges, microwaves and coffee machines in the kitchens.

Figure 1. Entrance of the office building, https://www.skanska.se/en-us/our-offer/our-projects/57328/Entre-Lindhagen

2.1. Data pre-processing

The data analysis was performed with the software R [27], through various packages. Considering the full set of variables, the existence of near-zero variance and the correlations between the 7 predictors were computed with the "caret" [28] and the basic R "stats" packages. The correlation matrix was drawn with "corrplot" [29].

Pre-processing relied on "sn" [30] for building and analysing the probability distributions of measurements. For smoothening the data, we adopted instead "smooth" [31] and used the "sma()" function, namely a simple moving average that we computed by averaging five values at a time. We also rescaled the time variable and normalized it between 0 (=0:00) and 1 (=24:00), with 12 o'clock equal to 0.5, to reduce the sensitivity to the rounding of digits.

For the daily energy consumption, the distribution analysis was performed with the package "fitdistrplus" [32], which makes it possible to estimate and fit precisely the most suitable distribution with the aid of the Cullen and Frey graph, as well as the QQ and PP plots.

2.2. Statistical analysis of energy consumption

For modelling energy consumption towards a predictive model, we compared different approaches, namely common least squares regression and a Bayesian approach [16] [10] [24] [33]. The latter used a Monte Carlo-Markov Chain (MCMC) method to obtain posterior predictions. In other words, we generated a random binary sequence (Monte Carlo), which was then ordered by means of a constant transition matrix where the i-th event depended only on the (i-1)-th event (homogeneous Markov Chain).

First, we chose a regression model called GLMer, which adds random effects (by means of a matrix Z that encodes deviations in the predictors across specified groups) to the fixed effects addressed by Generalized Linear Models (GLMs). In a frequentist analysis, the Z matrix coefficient b is regarded as a random error term. The R package "rstanarm" [34] was used by assuming a normal distribution for the smooth data, consistently with our findings (see Section 3.2). For this specific regression analysis, we used stan_glmer with adapt_delta=0.99, since the default value 0.95 leads to 34 divergent transitions. adapt_delta is the target average proposal acceptance probability during fitting, and the chosen value makes the sampling more robust compared to the default value 0.95, since a larger adapt_delta corresponds to a smaller step size used by the numerical integrator. The simulation used 30000 iterations for increased accuracy.

The MCMC predictions were then compared with another very popular regression method, the cross-validation (CV) approach [35]. Generally speaking, k-fold CV consists of randomly splitting the data into two sets: one that is used to train the model (e.g. 75% of data) and the test set, the remaining data (25%) that are used to test the model. The process is repeated k-times and the model can be trained with a variety of methods; here we used the R package "caret" with the Metropolis algorithm that uses MCMC as well. We thus split the data into Train (75%, 56 observations) and Test (25%, 17 observations) subsets, and then used a k-fold CV with k=10 and a "cubist" fit model.

2.3. *Seasonal and monthly correlations*

For addressing seasonality and weather correlations, the outdoor temperature was recorded every 5 minutes by a sensor installed on the outer facade of the building (precision ±0.1 C), while sunshine duration data were retrieved from the database [36]. In the following, every "monthly" data (temperature, consumption etc.) refer to hourly-averaged measurements covering the entire 5 years period, from 2014 to 2018.

Correlation coefficients and matrices for energy consumption versus climatic conditions were obtained via the R packages "sn" and "GGally" [37]. We computed the Pearson coefficient and performed a Kendall test as well. Since the latter is more sensitive than the Pearson test, we deemed it more suitable for drawing the monthly correlation matrix.

3. Results

In this section we shall report the data analysis into detail, using a descriptive step-by-step approach guiding the reader through the development of a simple method for generating energy consumption profiles for application in BPS.

3.1. *Data pre-processing*

First of all, we checked that the full set of 7 predictors showed no problematic elements with near-zero variance. Using hourly averages of data consumption over the entire measurement period 2014-2018, we obtained the correlation matrix in **Figure 2**.

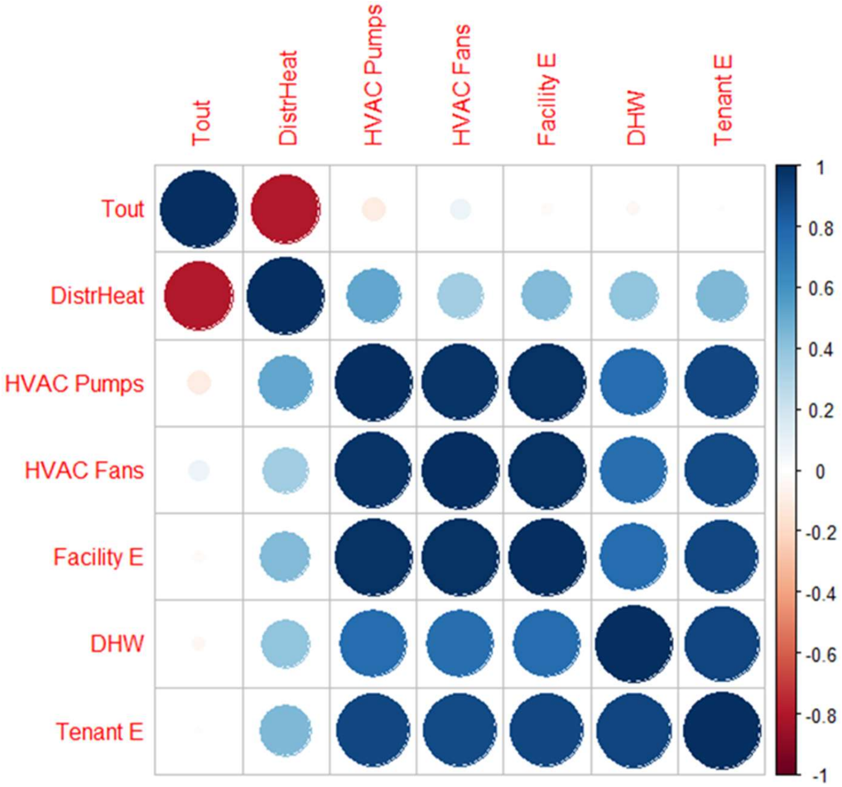


Figure 2. Correlation matrix for the set of predictors, monthly averages from 2014 to 2018

The mean outdoor temperature has units of [C], all the others have [kW] units. +1 means high (perfect) correlation, -1 perfect negative correlation, with 0 meaning no correlation. Specifically, one can notice that HVAC system and facility electricity are highly correlated (at order ~ 0.98), as expected; correlations with tenants' consumption (0.90) and DHW (0.76) are high as well. Tenants' consumption and DHW are highly correlated too, with value 0.91.

Such high collinearity simplifies the analysis remarkably, since one can reduce the set of predictors and safely investigate only the tenants' energy consumption.

Noticeably, on the other hand, strong negative or null correlations do exist. Clearly the outdoor temperature has -0.8 (thus, highly negative) correlation with district heating, however with HVAC, DHW and tenants' consumption this is very weak, ~0.02. We will address the influence of outdoor temperature and sunshine hours on tenants' plug loads into detail in Section 3.3.1.

3.2. Daily energy consumption

Let us begin by analyzing the measured energy consumption per square meter for a single day, which will provide a benchmark with good time resolution as the data were collected every 5 minutes. Measurements for Wednesday (middle-week working day) of a central February week (large occupancy) from 2014 to 2019 are plotted in

Figure 3. Specifically, in this section we shall analyze Wednesday Feb 18th 2015, as it does not deviate too much from the general trend, yet it constitutes a non-trivial example due to some outliers (at about 14:52).

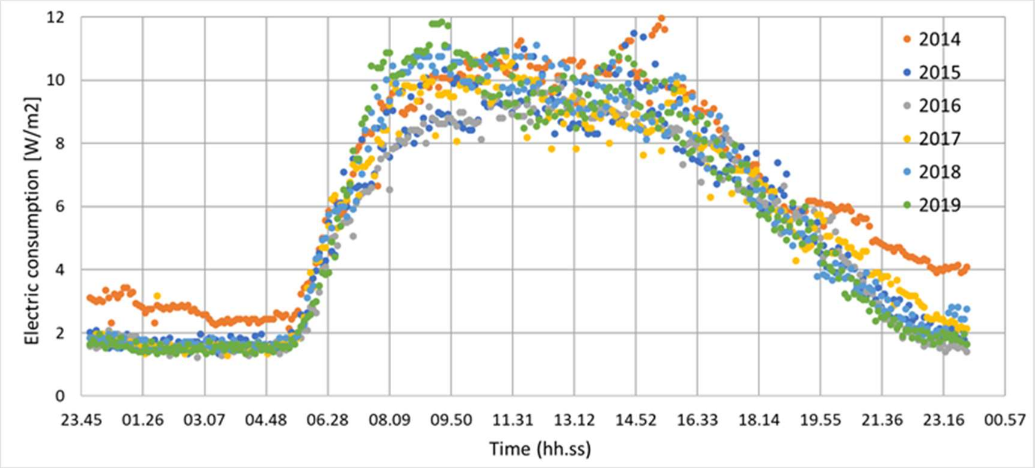
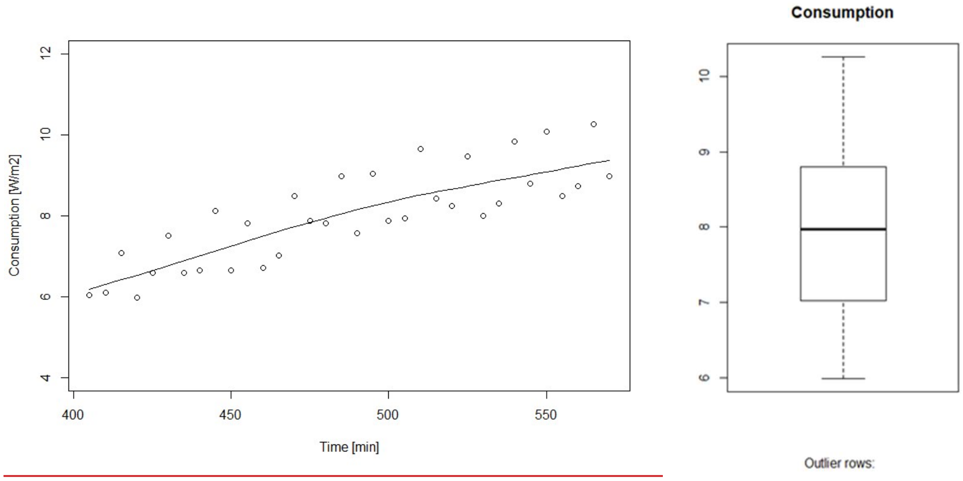


Figure 3. Daily consumption, February Wednesdays from 2014 to 2019

The raw data showed a large dispersion during daytime. The maximum value was found at ~3 pm, holding as 11.49 W/m2. Since we were interested in the occupied hours, the time interval was narrowed between ~7 AM and 10 PM. Following [24], we divided the working day into three subperiods, namely 1. Going-to-work, 2. Daytime, 3. Off-work. The scatter and box plots for Going-to-work (6:45-9:30) hold as in **Figure 4**.

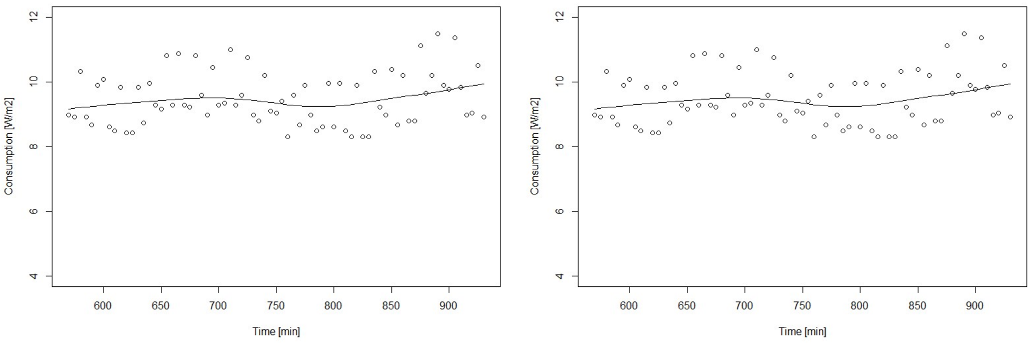


(**a**) (**b**)

Figure 4. Going-to-work period (6:45-9:30): (**a**) Scatter plot; (**b**) Box plot.

We recall that an outlier is any datapoint that lies outside 1.5 times the inter quartile range (IQR), which is the distance between the 25th percentile and 75th percentile values for that variable. In other words, there are no outliers here. Moreover, the correlation was 0.83, which is satisfactory (see e.g. [36]), indicating that the trend is approximately linear.

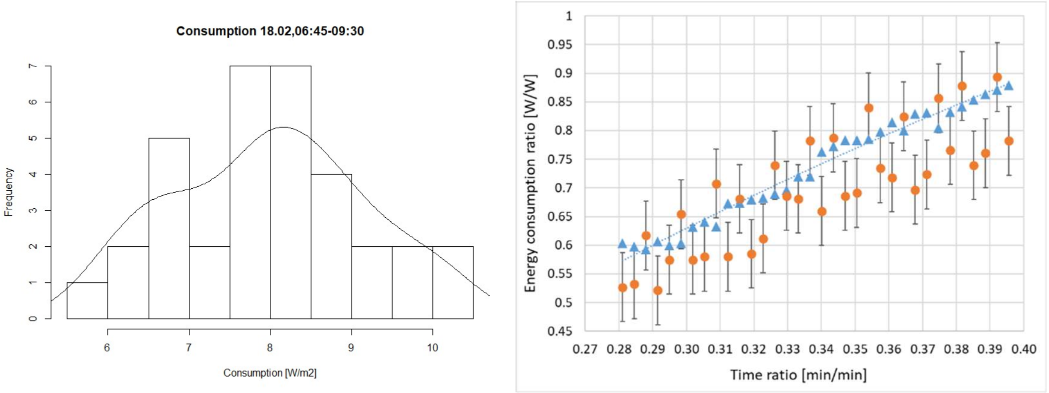
For Daytime (09:30-15:30) we obtained instead a very scattered plot, with a low correlation holding as 0.13. The measurement error was computed as 0.61 W/m2, therefore it is clear from **Figure 5** that many outliers were present.



(**a**) (**b**)

Figure 5. Scatter plots: (**a**) Daytime period 09:30-15:30; (**b**) Off-work period 15:30-22:00.

For the Off-work period (15:30-22:00), the box plot did not show any outliers, however the correlation was 0.13. To understand the data distribution and compare our measurements with those of similar cases such as [24], we thus performed further tests on the daily dataset.



(**a**) (**b**)

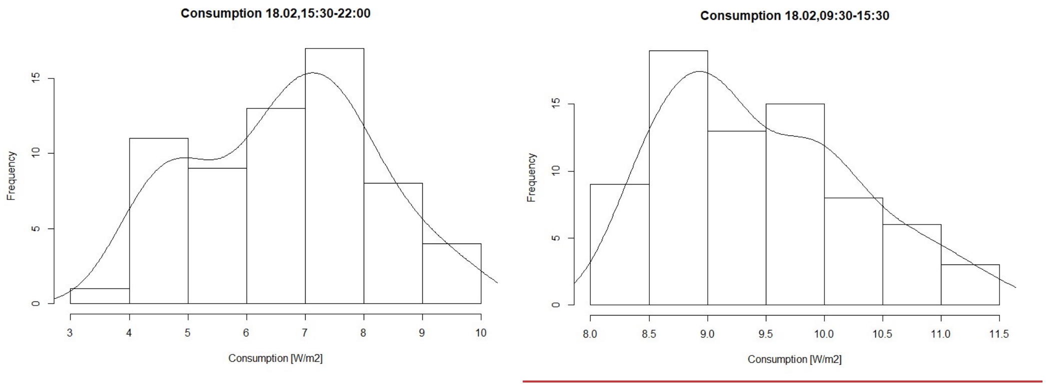
Figure 6. Going-to-work, 06:45-09:30: (**a**) Histogram for measurements; (**b**) smooth (triangles) vs bare data (dots).

The Going-to-work data (06:45-09:30) in **Figure 6** correspond to a distribution with median 7.97 and mean 7.996. The estimated standard deviation (sd) is 1.176, with skewness and kurtosis holding as 0.052 and 2.27, respectively. The low skewness confirms a standard (symmetric) normal distribution, while the kurtosis approaching the value of 3 means that there are no outliers, or that the tails are well-behaved. This confirms the box plot in **Figure 4**.

For the Daytime data (09:30-15:30), we find a median of 9.29 and a mean of 9.47. The estimated sd is 0.816, with skewness 0.569 and kurtosis 2.51. The kurtosis is still close to 3, thus we confirm the absence of outliers for this case too. The positive skewness is however ten times larger than for the symmetric normal distribution, namely this dataset corresponds to a right-skewed distribution.

Finally, the Off-work period gives a median of 6.72, a mean of 6.65, sd=1.538 and a negative skewness -0.008, with kurtosis 2.247186. The distribution is indeed very slightly left-skewed, again with no outliers.

The three normal distributions in **Figure 6** and **Figure 7** are therefore symmetric and right- and left-skewed, respectively, see e.g. [36]. These differ from Zhou et al. [24], who instead found Poisson for the Going-to-work and Off-work periods, and Normal for Daytime. This might be due to the tenants' appliances and lighting energy usage being aggregated together since no other qualitative differences seem to distinguish the two cases.



(**a**) (**b**)

Figure 7. Histograms for: (**a**) Daytime period; (**b**) Off-work period.

3.2.1. Least squares interpolations

Aiming to generate fitting curves for predicting the measured daily energy data, we preprocessed the measurements as illustrated in Section 2.1. A comparison of smooth and original datasets is given in **Figure 6**.

The Daytime dataset (9:30-15:30) was then cut into subperiods because it is the most difficult period to interpolate. Fitting the smooth data with minimal squares returned the formula for the five subperiods as E [W/m2] = $a+bt+ct^2+dt^3+et^4$, t ϵ [0,1], with coefficients listed in **Table 2**.

Table 2. Interpolation formulas coefficients for Wed, February 18th 2015: E [W/m2]=$a+bt+ct^2+dt^3+et^4$, t ϵ [0,1]

Period	a	b	c	d	e	R^2
6:45-09:30	6.0403	18.882	-11.234	0	0	0.9778
09:30-11:10	- 13.512	176.74	113.74	- 3497.2	6664	0.9136
11:10-12:10	- 135.64	1266.7	-3665.6	3526	0	0.96
12:10-13:50	170.44	-1014.5	2125.3	-1483.9	0	0.9013
13:55-14:50	- 2854.7	15573	-28220	17044	0	0.9666
14:55-15:30	0.53×10^6	-3.526×10^6	8.793×10^6	-9.742×10^6	4.046×10^6	0.97
15:30-22:00	11.264	2.5483	-9.5371	0	0	0.9748

3.2.2. Statistical inference of energy consumption

As illustrated by the R^2 values in **Table 2**, a common least square regression could fit the smooth data for a winter day with good accuracy. Comparison between predicted and measured cumulative value [MWh] results in only a 4.7%~5% difference indeed. This was possible because of the well-known property that any curve can be approximated by *n* parabolas, if *n* is sufficiently large.

As much as this is common practice, we wondered whether it was instead possible to obtain a fit for the daily dataset as a *whole* curve. We therefore adopted a Bayesian approach and attempted to model the dataset with this alternative prescription.

Comparison of measured data with predictions from both MCMC and Cross-Validation methods is given in **Figure 8**. A 10-fold cross validation managed to reproduce the observations rather well, while the overall profile looks more regular; remarkably, MCMC with GLMer could instead match even the outliers with no overfitting. MCMC had an MSE=1.13x10^{-5}, corresponding to a RMSE of 0.0033; cross validation instead reported an MSE of 1.66x10^{-4} and an RMSE of 0.0129. We obtained R^2=0.903 for the train set and R^2 =0.926 for the test set, with a very small overfitting -0.0227. CV underestimates the energy consumption by only 0.12%, while MCMC overestimates it by 0.01%.

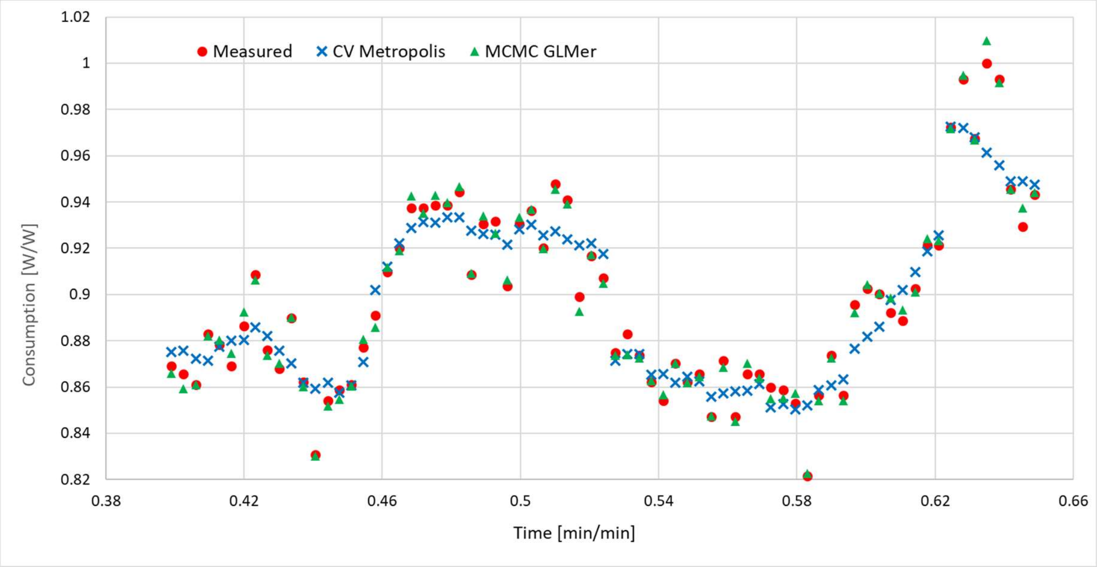
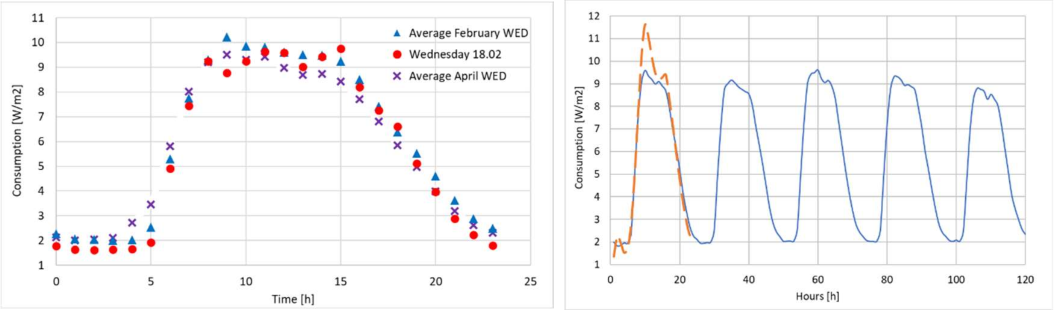


Figure 8. Data (dots) vs MCMC (triangles) and Cross-Validation (crosses) predictions.

3.2.3. The structural dataset for daily values

The distributions for January weekday and weekends look very similar, while for June the weekend shows a sharp difference in the peaks' ratio. From the comparison in **Figure 9**, clearly one cannot use the daily profile that was analysed and fitted in the previous sections, as the trend deviates qualitatively from that of other typical days.



(**a**) (**b**)

Figure 9. (**a**) Wednesday 18.02.15 vs average February and April Wednesdays; (**b**) structural curve (dashed) vs yearly average (solid) for each weekday, Mon to Fri.

On the average, the peak consumption occurred mostly at around 9:30 (**Figure 9**), rather than at 15:00 (as on Wed 18.02). As a representative day we accordingly chose Wednesday 24.01.2018 (middle of the week, out of holidays), aiming to reflect an average daily profile for weekdays without the outliers appearing for the February day in Section 3.2.1.

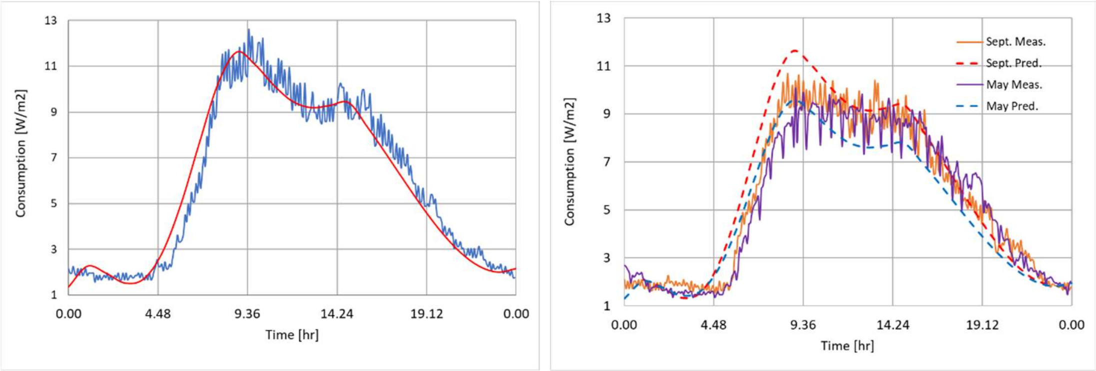
Interpolating the January measured values with a standard least squares method returns a 2.1% difference in total energy consumption between fit and measurements, which is satisfactory. However, for higher accuracy and for reasons that will be explained in Section 3.3.2, the coefficients listed in according to the generic formula E [W/m2]=a+bt+ct^2+dt^3+et^4, t ϵ [0,24) were obtained with a nonlinear analysis, by applying to the fit an "energy constraint" which minimizes the difference between observed and fitted values [26]. Moreover, we demanded that the fitted values at the joining points (at 9 AM and 3 PM for weekdays in **Table 3**) differ by less than 0.01 W/m2. The according constrained fit returns an observed/fitted difference of only 0.05% for the January consumption; it will be called "structural curve" henceforth.

Table 3. Interpolation coefficients for the structural dataset formula: E [W/m2]=a+bt+ct2+dt3+et4, t ϵ [0,24).

	Time [h]	a	b	c	d	e
Weekday	0 ≤ t ≤ 09	1.35599	1.95966	-1.31185	0.270996	-0.01504
	09 < t < 15	-234.6721	86.1842	-11.0208	0.60992	-0.012394
	15 ≤ t < 24	-40.72306	10.53113	-0.67086	0.0127718	0
Weekend	0 ≤ t ≤ 11	2.0512	-0.14973	0.017555	0.000736	0
	11 < t < 17	10.5839	-1.53503	0.11062	-0.00269	0
	17 ≤ t < 24	38.0761	-4.67618	0.20861	-0.00319	0

In **Figure 9.b**, the structural curve is compared to the energy profiles computed by averaging the data, hour by hour for each day, over all the working weeks from 2013 to 2018. While the prediction does overestimate the peak value, the overall trend is clearly matched by the structural curve; such overestimation is expected, since averaging over large ensembles always normalises peak values. Predictions for two random May and September weekdays are compared with data in **Figure 10**.

For the weekend instead we fitted energy data from an average profile, since the Saturday and Sunday curves had a large variety of trends thus a specific representative could not be identified. The Weekend fit reported in **Table 3** matches the daily consumption within a ~5% error.



(**a**) (**b**)

Figure 10. Interpolations vs data: (**a**) January 24th 2018; (**b**) May and September, weekdays.

3.3. Monthly energy consumption

In this section we first briefly analyse the energy consumption data on a monthly basis, then based on the January profile in **Table 3** we evaluate correlation formulas for all the 11 remaining months, which are to be used as boundary conditions of BPS. The differences between months are highlighted and searching for possible weather correlations shall help in determining the impact of occupancy on energy consumption. To our knowledge, such an analysis is still very scarce in energy consumption studies of large office buildings, with the only exception of [37].

Averaging the hourly power [kW] over each month and then dividing by the corresponding February consumption gives the ratios in **Table 4**: February is the month showing the largest consumption. Since a striking as well as expected difference exists between autumn/winter and summer months, one might wonder whether this is correlated to weather or to occupancy.

Table 4. Correlation coefficients with January as the structural dataset according to the formula E[W/m2] = A* E_{Jan}+B

Month	A, B (Weekdays)	R^2	A, B (Weekend)	R^2	Ratio over February [kW/kW]
January	1, 1	1	1, 1	1	0.97
February	1.0504, - 0.0975	0.9996	0.8433, 0.3444	0.9902	1
March	1.0281, - 0.0538	0.9996	0.8514, 0.3546	0.9883	0.99
April	0.9258, 0.214	0.9898	0.8246, 0.3662	0.9545	0.93
May	0.8058, 0.2058	0.9992	0.7904, 0.2808	0.9859	0.82
June	0.7039, 0.1853	0.998	0.5065, 0.4663	0.9868	0.72
July	0.6486, 0.7221	0.9965	0.483, 1.0726	0.948	0.76
August	0.9048, 0.0714	0.9982	0.5998, 0.8055	0.9716	0.89

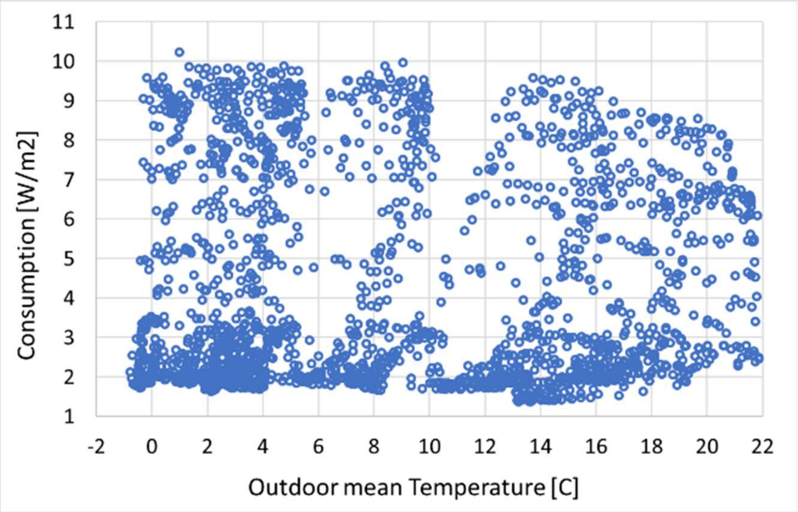
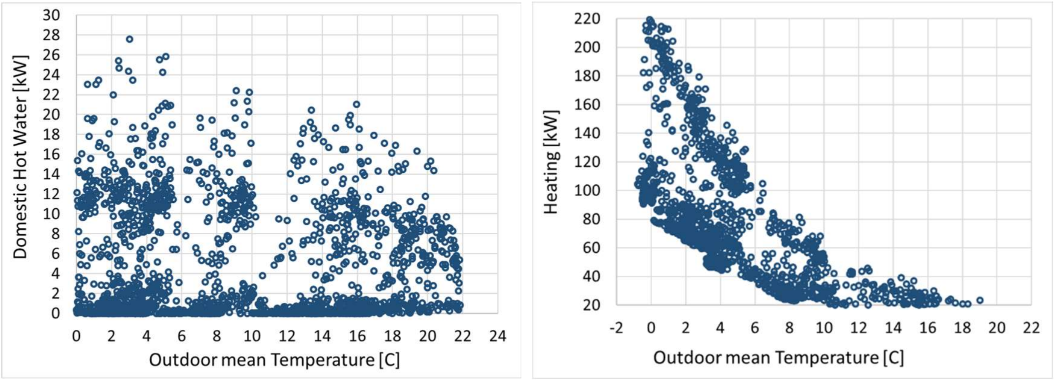
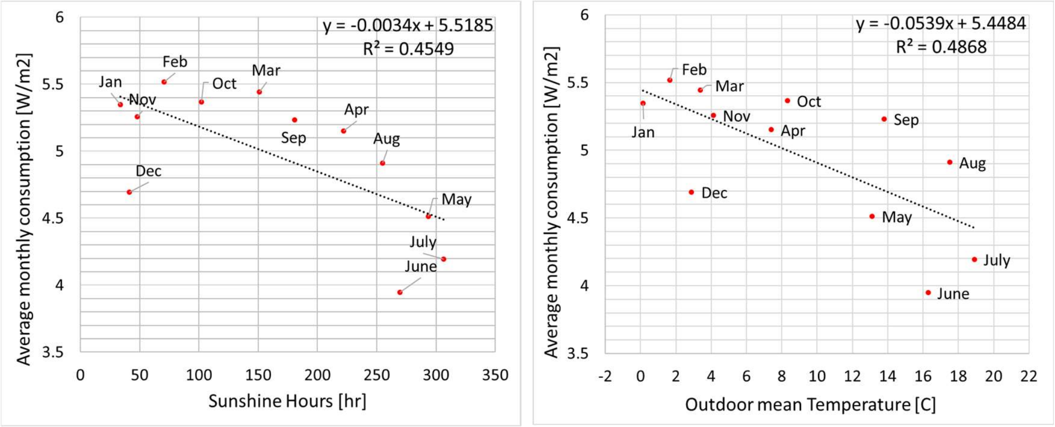


Figure 11. Daily consumption vs average outdoor temperature.



(**a**) (**b**)

Figure 12. Electric consumption in function of outdoor mean temperature, daily data: (**a**) DHW; (**b**) air heating.



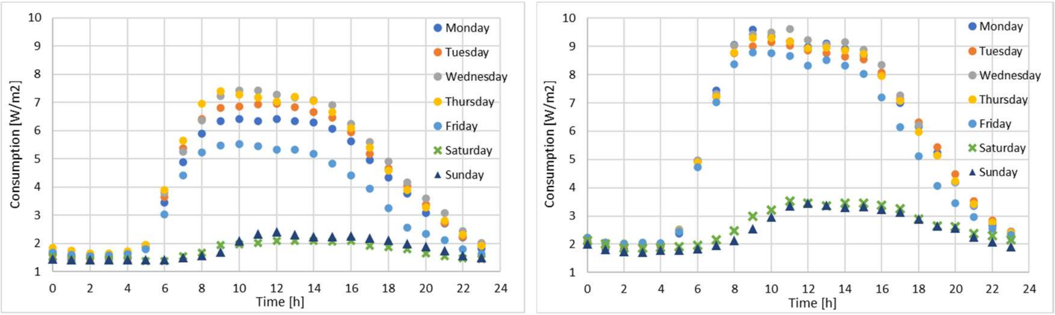
(**a**) (**b**)

Figure 13. Average monthly consumption vs measured (**a**) sunshine hours; (**b**) outdoor mean temperature.

3.3.1. Seasonal variations

It is easy to see that weather and consumption are weakly correlated, as it is shown in **Figure 11**, **Figure 12** and **Figure 13** for consumption vs measured irradiation hours and average outdoor temperature. The measurements are averaged over the entire period 2014-2018. This is confirmed by an additional Pearson test, which holds respectively as -0.67 and -0.70, as well as by the values in **Table 4**.

Domestic hot water (DHW) consumption is also independent of the external temperature, while only air heating shows a clear correlation as expected, as illustrated in **Figure 12**. More into detail, **Figure 14** considers two specific days in winter and in summer. As a reference for an average winter profile, we chose one week in January (the coldest month). Hourly averages for the consumption data are averaged for the same weekday at each week of the month.



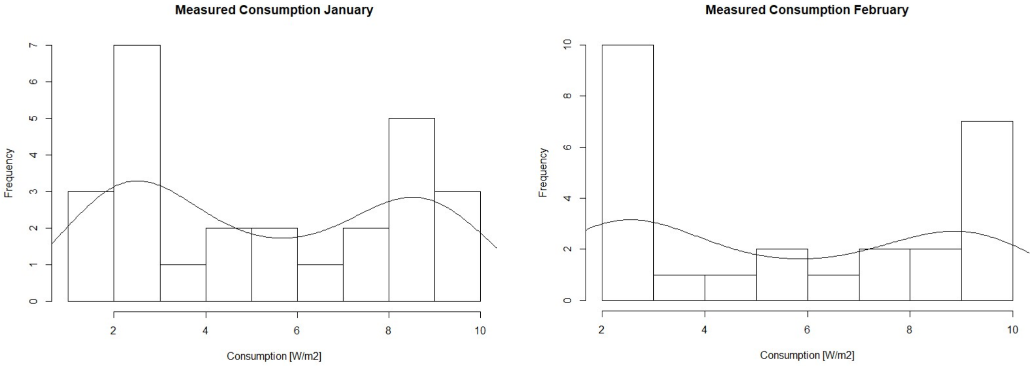
(a)

(b)

Figure 14. Tenants' electric consumption for representative weeks: (a) January; (b) June.

3.3.2. Monthly correlations

The density distributions of consumption data (hourly values averaged over 2014-2018) are very similar to each other, the only exception being February, see **Figure 15**.



(a)

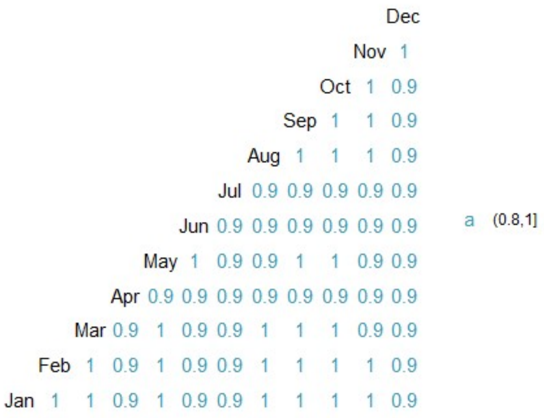
(b)

Figure 15. Histograms for tenants' monthly consumption during weekdays: (**a**) January; (**b**) February.

Interestingly, one finds a strong linear correlation between months, as shown below by the correlation matrix in **Figure 16**. The "1" entries are due to rounding of R-squared values that are very close, yet obviously not identical to unity. Correlation coefficients for each month against January, which constitutes our structural dataset, are provided in **Table 4** for both weekdays and weekend.

The numerical values are computed with the Kendall test, that is more sensitive than the Pearson test. The correlation is very strong, only April has a couple of outliers in **Figure 17**, where each month is plotted against January (the interpolation formula holds for May, as an example). We also wondered about the role of the Christmas holidays, which are distributed less evenly than summer vacations: **Figure 18** addresses the working week starting on Dec 21st and ending at Christmas, which is compared to a Summer week (last working week of June).

At this point, let us recall that we aim to obtain formulas for a prompt implementation in BPS software. One immediate option would be to simply produce interpolation formulas for each month as in **Table 3** and list them in 12 tables, with a loss in generality; here we prefer a more general and time-saving approach that is described in the next section.



	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Nov											1
Oct										1	0.9
Sep									1	1	0.9
Aug								1	1	1	0.9
Jul							0.9	0.9	0.9	0.9	0.9
Jun						0.9	0.9	0.9	0.9	0.9	0.9
May					1	0.9	0.9	1	1	0.9	0.9
Apr				0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Mar			0.9	1	0.9	0.9	1	1	1	0.9	0.9
Feb		1	0.9	1	0.9	0.9	1	1	1	1	0.9
Jan	1	1	0.9	1	0.9	0.9	1	1	1	1	0.9

a (0.8,1]

Figure 16. Correlation matrix displaying Kendall test values.

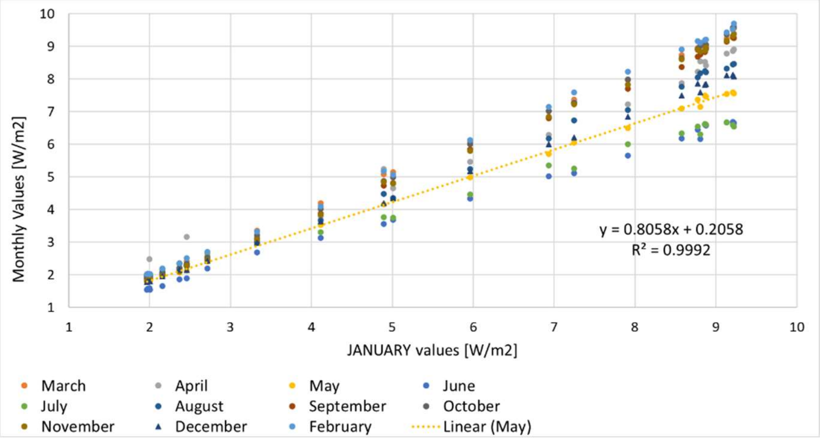


Figure 17. Linear correlation for the 12 months, weekdays.

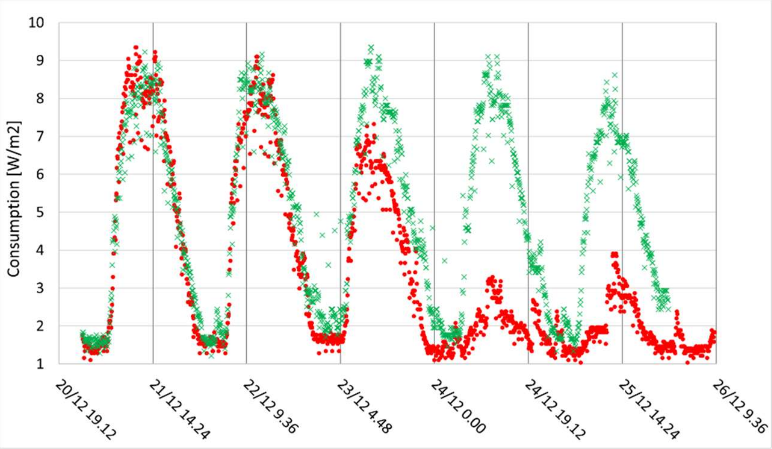


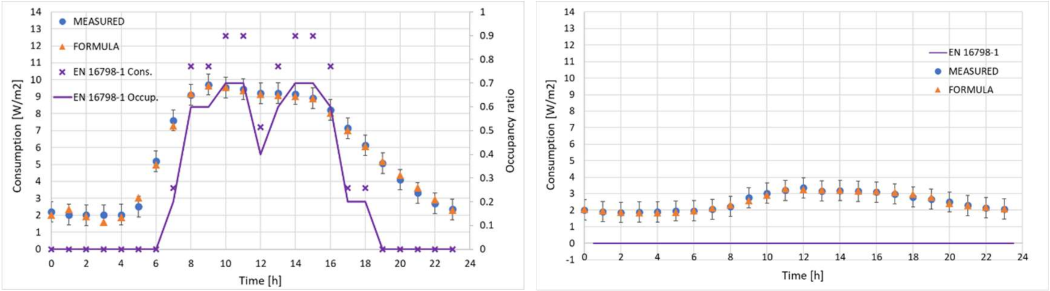
Figure 18. Measurements for Christmas 2015, Mon 21st to Fri 25th (dots) compared to a June working week (crosses).

3.3.3. The monthly structural dataset and prediction formulas

Following Ref. [26] and using its terminology, we first identify January as our representative month with its *structural dataset*, then derive for each other month the according correlation formulas with January, written in the form E[W/m2]=A*E_{Jan} + B, from the according *measured* consumptions as in **Figure 17**. Now one needs only to input the interpolation coefficients for January (**Table 3**) and the correlations for each month (**Table 4**) into any simulation software, then proceed with e.g. annual simulations of energy consumption.

This is a very simple method, based on linear interpolations, which naturally returns only a small sensitivity on the coefficients, as well as a small error (see [26] for a more detailed discussion). January is chosen because, according to **Figure 16**, it is the month with the highest correlation with any other month.

Let us immediately test this approach by comparing June measurements (24 hourly averages over weekdays), with error 0.61 W/m2, with the values obtained by means of the correlation coefficients in **Table 4**. For generating the average January weekday profiles, namely the 24 hourly E_{Jan} values, we shall use either linear regression (**Table 3**) or MCMC (**Figure 8**).



(**a**) (**b**)

Figure 19. February measurements vs correlation formula as in Table 4: (**a**) weekdays; (**b**) weekend.

Figure 19 shows the result for June, when using the January structural coefficients in **Table 3**. The agreement is excellent, with every point within the experimental error and an average % residual of 3.7% for weekdays, 2.46% for weekends. Using instead Bayesian inference (MCMC here) to compute the structural dataset lowers the average % residuals to resp. 1.83% and 1.7%.

The plot in **Figure 19** also features purple crosses, i.e. the hourly consumption computed according to the occupancy profile (solid purple line) of the EU Standard EN 16798-1 [25]. The Standard estimates 12 W/m2 for lighting and 6 W/m2 for occupancy, neglecting the weekends completely and assuming null occupancy throughout. We thus conclude that in this case one cannot infer energy consumption directly from the EN 16798-1 occupancy profile.

This is confirmed by comparing the cumulative measured data for an average year with the profiles obtained with the structural dataset (**Table 3** and **Table 4**), that gives a 4.69% overestimation of the total consumption when using our formulas. On the other hand, simply assuming the occupancy profile from the standard EN 16798-1 returns an underestimation of the real consumption of the order ~27%.

Comparison with the yearly accumulated consumption for each year is given in **Table 5** (the year 2019 was not considered as the data were recorded only until March, 20th).

Table 5. Annual tenants' consumption for different years, measured vs predicted for an average year.

Year	Measured [kWh/m2]	Predicted [kWh/m2]	% Difference
2014	42.84	40.11	-6.60 %
2015	37.57	40.11	6.52 %
2016	35.72	40.11	11.58 %
2017	37.44	40.11	6.87 %
2018	37.80	40.11	5.92 %

4. Discussion

The daily energy consumption analysed in Section 3.2 showed some peculiar characteristics. Interestingly, the distributions for each period were different for the analogous cases of large office buildings in China [24] and in Austria [10]. While one cannot be sure whether this is due to geographical differences (lighting component) rather than to appliances usage, this combined evidence might suggest that generalizing consumption patterns of a building typology at an international level is not as immediate as it seems.

Besides, we have shown in Section 3.2.1 that fitting the data for a non-trivial profile with the good old minimum square method returned an error of only ~ 5%, in agreement with [18]. A more sophisticated Bayesian approach showed an even higher accuracy, with error well below 1%. In other words, it is quite feasible to model this type of energy data with high accuracy even with simple methods; models should be conveniently chosen according to the specific BPS.

Regarding the seasonal variations and weather correlations, the pre-processing showed that there exists a high collinearity between the electric consumption of facility and HVAC system. Furthermore, these are highly correlated also with the DHW and tenants' appliances power plug and lighting consumption. Only the district heating is (negatively) correlated with the outdoor temperature, as expected. These results are accordingly pointing at occupancy as the main cause of energy consumption fluctuations in the building.

More specifically, one can notice the low R-squared values for a linear fit in **Figure 13**, showing small correlation with the climate. December, June and July, i.e. the holiday months, are especially intriguing: June and July *incidentally* have smaller consumption *and* higher temperatures/irradiation, due to the fact that they are the holiday months. On the other hand, May recorded about the same irradiation yet a larger consumption. Comparing these two plots might therefore suggest a more prominent role of plug load (i.e. of occupancy) than of lighting.

January weekdays are almost indistinguishable from each other, with the only exception being Friday (**Figure 14**). The weekend is slightly more interesting, as Saturday's curve is different from Sunday's. It can be shown that Monday and Tuesday have a similar density distribution, as well as Wed, Thu and Fri; the daily consumption has anyway little variations within each of the two sets (weekdays & weekends). These considerations are consistently valid for all the twelve months, with little variance. Interestingly, these according distributions are all skew normal, in contrast with the profiles plotted in Wang [16] and Ding [33] for large Chinese buildings. We can speculate that this might be due to the plug loads and lighting being aggregated together.

Identifying the structural dataset and computing the structural curve followed the principles explained in [26]. The specific dataset reflected the general trend *qualitatively*: looking for common patterns in the full data is the most important step in the analysis. Choosing e.g. the February day analysed in Sections 3.2.1 and 3.2.2, with its outliers and peaks at ~3 PM, would have determined a different outcome at least in terms of daily consumption distribution, if not of annual energy simulation. Since instead the Weekend profiles where highly different for all the five years considered, we used a profile that was constructed by averaging the hourly values over the full dataset. We shall finally remark that here we showed only one way to obtain the structural curve, for illustrative purposes: any other method can be equally valid, since a whole class of very sophisticated statistical models already exists, as summarized in **Table 1**.

5. Conclusions

As building performance simulations constitute an increasingly common practice among engineers for assessing the energy analysis at different levels, it is needed to bridge the gap between observations and predictions with simple, yet reliable approaches for the implementation into BPS that are suitable to academics as well as to practitioners. In this paper we have argued whether this is possible, by examining the presently largest ensemble of energy consumption data of an office building in a Nordic country.

Considering the employees' appliances plug consumption and lighting for a calendar year, we found no evident weather correlation. Rather, holiday periods and their impact on occupancy proved to be more important: the highest consumption occurred in February and the lowest in June. All the months were highly correlated.

Daily consumption patterns showed on the average a clear peak at around 9:30 AM for weekdays, while weekends exhibited a larger variance. Comparing regression curves obtained with a standard frequentist analysis to Bayesian inference (MCMC), we obtained an extremely high accuracy with the latter; nevertheless, the least squares method returned only a 2% error, which is low enough for implementation into BPS.

These results lead to the definition of an analytical bottom-up model, for predicting any daily consumption given a benchmark daily profile with an error smaller or equal to 5%. The coefficients reported in **Table 3** and **Table 4** can be immediately implemented into building performance simulations addressing comparable datasets.

In this paper we analysed a substantially large amount of data obtained during five years of measurements. Further studies should address the role of tenants' plug load when it is aggregated separately from lighting consumption, how different occupancy models could impact the overall energy use, and how the prediction model benefits investigations through BPS by applying the structural dataset method to e.g. annual simulations with IDA ICE and other simulation programs.

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