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Buildings energy consumption generation gap: A post-occupancy assessment in a case study of three higher education buildings

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The existing stock of institutional buildings constructed before current thermal regulations is known to be high energy-consuming. In several cases, they contribute to a large share in local authorities' expenses, especially for those dedicated to education and research. These high consumption levels are due in general to low thermal regulations requirements and to the diversity of occupants, occupancy profiles and used equipment. We hereby report on a comparative study of the energy consumption of three campus buildings covering more than 50,000 m^2 useful ground area and located in Paris region. Used data were collected during more than three years between 2014 and 2017 and at different time steps, from yearly down to a 10 min time step. Statistical analysis tools are used, to identify the main energy drivers and their relative weight in the overall energy consumption for instance. The impact of different thermal regulations is clearly assessed through a post-occupancy study. Together with equipment, occupancy is shown to be the main electric energy consumption driver. Introduced tools lay the ground for a non-intrusive method for large tertiary buildings' power demand curves decomposition and reconstruction.

1. Introduction

Since the international climate summit COP21 successfully held in Paris in 2015, extensive commitments have been made regarding energy efficiency and carbon emissions. At the European level, the Energy Efficiency Directive (EED) and the European Performance of Buildings Directive (EPBD) have revised in November 2016 their energy efficiency target in 2030–30% of reduction compared to 2007 reference instead of 27% [1]. The main way to reach this goal, according to these directives, is to improve energy efficiency in the building sector, which accounts for 40% of final energy consumption in EU countries. According to the directive, 75% of total EU buildings are to be renovated and the annual renovation rate is 0.4–1.2% under current pace. It should be accelerated by ongoing reforms which promote the cost-effective renovation of existing buildings. In addition, in order to support the development of new data-based energy services such as real-time monitoring and assessment of buildings energy efficiency, demand response and dynamic pricing, the European legislation decrees the generalization of energy consumption smart metering, for both electricity and natural gas. For electricity, an 80% coverage rate is targeted by 2020 [2].

At the French level, the evolution of the buildings energy efficiency regulations and market, is completely consistent with the European trend. Indeed, sustained efforts have been made in the building sector in France during the past decade. In January 2012, a government decree was issued making energy audit compulsory for collective residential dwellings with more than 50 apartments [3]. In November 2014, the same obligations were extended to commercial or industrial buildings for companies over 250 employees. The energy audit is now compulsory every four-years period [4]. In 2015, the Law on Energy Transition for Green Growth [5] has been adopted. This law targets a 50% decrease in national energy consumption by 2050 and consequent retro-fitting actions to the building sector: starting from public buildings energy consumption to commercial buildings, then collective and individual dwellings. Moreover, the implementation of smart energy meters such as Linky [6,7] for electricity and Gazpar [8,9] for gas is currently being held, with a target of 100% coverage by 2021 and 2022, respectively. These energy meters provide real-time dynamic consumption data with a sub-hourly time step which offer large opportunities for optimization.

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Nomenclature

AHU	Air handling unit
B1, B2, B3	Respectively building 1, 2 and 3
BEM	Building energy model
HDD	Heating degree day
HDH	Heating degree hour
IAQ	Indoor air quality
IEQ	Indoor environment quality
LC	Load curve
kWhpe/MWhpe	kWh/MWh of primary energy
OAT	Outdoor air temperature
RMSE	Root mean square error
TR	Thermal regulation

In spite of all positive policies mentioned above, efficient actions are still hardly implemented for all buildings. Several reasons may explain these difficulties: i) the complexity and diversity of buildings together with their uses and related impacts on the energy consumption, ii) different possible levels of energy audits to fulfil legal requirements, and iii) financial support for deep retrofitting with long-term return. Firstly, the occupancy and uses have a significant influence on the total energy consumption [10,11] in a building. This behavioural impact is usually not accounted for in a simple walk-around audit protocol, thus, not covered by the recommendations. Then, among the three levels of energy audit defined by ASHRAE standard (ANSI/ASHRAE/IESNA 100–2006) [12], walk-through visit, short-term measurement/survey and long-term monitoring/analyses, the collected information accuracy can be very different. Concerned building managers often feel confused facing this complexity and they end up choosing the simplest audit protocol. Finally, as the audit recommendations not only include non-retrofitting but also retrofitting measures [13], the long-term payback time makes decision-making hard and long. For instance, for a high-tech company with a 10% annual return on investment and a very short-term development plan (5–10 years), a deep renovation that requires 25 years payback time is hard to be made into reality.

In the present work, we report on a comparative analysis of the energy consumption of three higher education buildings located on the same campus in Paris region, France. The three buildings have similar uses, mainly education and research, but were built at three different periods, with a 10-year shift starting from 1987. Consequently, they were built under three different national energy regulations. The present study targets the assessment of the effect of these regulations on the buildings energy efficiency through a global analysis of yearly and monthly energy consumptions and the use of statistical tools to characterize the dynamics of the power demand.

The present paper is organized as follows: first, the main methods and results of a recent study we conducted on a building of the same campus are briefly reminded (Section 1). Second, the methods used as well as details concerning the three studied buildings are described (Section 3). Then, the obtained results are presented and discussed (Section 4). A particular attention is paid to the discussion of the implemented methods and their limits. Paths for further developments are also suggested.

2. Context and motivation

We recently conducted a detailed energy audit and a comprehensive comfort assessment on a university building located in Paris region, France. The campaign lasted for six months and the case study results have been reported in [14]. In this section, we remind the main results and limitations of this previous study which strongly motivate the present work.

The audit protocol that was used is different from conventional audit approaches, in that both building energy diagnostic and occupancy comfort survey were conducted in detail. On one hand, long-term measurements have been performed on the energy distribution system, gas boilers and ventilation system. A detailed Building Energy Model (BEM) based on TRNSYS was also developed. We used heating degree-day (HDD) method to evaluate the heat consumption and TRNSYS simulations to estimate potential energy savings of different retro-fitting measures. On the other hand, quantitative measurements and subjective questionnaires were used to evaluate the IAQ (indoor air quality) comfort level in terms of ambient and radiative temperature, humidity, and CO_2 level. Moreover, the ventilation effectiveness test by gas tracer and air tightness test by blower door were implemented.

Several results were obtained revealing the energy consuming character of the building and savings potential of retrofitting measures. Regarding energy consumption, the studied building, with its 30,580 m^2 useful ground surface built in 1987, consumed 480 kWh/(m^2·yr) of primary energy from May 2014 to April 2015. This value is roughly twice that of primary schools reported by the city of Paris [15]. It is probably related to special activities in research and lab training in higher education buildings. Indeed, electricity consumption share of the studied building was 132 kWh/(m^2·yr) during the considered period. Regarding comfort evaluation, both on-site measurements and collected questionnaires revealed thermal and air quality discomfort. In classrooms, overheating frequently appears which is shown by thermal comfort indices PMV (Predicted Mean Vote). In staff offices, the overheating is less frequent. One of the reasons is the occupants' behaviours, with frequent windows opening for instance (65% responses according to the survey during heating season in January). Thus, potential energy savings could be achieved through better air handling units (AHU) control and lower heating supply. Finally, in terms of ventilation and air quality, a peak CO_2 concentration of 2400 ppm (above the outdoor concentration which is around 400 ppm) was recorded in classrooms suggesting insufficient air flow in these areas with respect to the high occupancy during weekdays.

A main conclusion of the detailed building energy efficiency and comfort study is the understanding of the complexity of such a process. First, the audit protocol requires not only a large number of skills in instrumentation, comfort survey, BEM but also significant manpower and equipment. Such a detailed audit campaign can be hardly generalised and applied to all buildings. Secondly, the complexity of a building energy system, coupled to a large diversity of activities and occupancy profiles, makes standard audit retrofitting recommendations less credible. Even with the help of BEM, large uncertainties remain, regarding phenomena such as the coupling of envelope air tightness and window opening for instance. The former is a pure physical phenomenon and the latter is highly related to human behaviours. Finally, the audit of an occupied building should not interfere with its normal operation. A trade-off should be made in this sense between the accuracy of data collection and the intrusive character of the study.

In spite of the difficulties of such auditing processes, educational buildings i.e. school buildings and university campuses are particularly concerned by the issues of energy efficiency and IEQ. They require a particular attention because of their specific character compared to other buildings. In fact, educational buildings have specific occupants, activities and occupancy patterns. They can take the lead as energy efficiency demonstrators, not only for their energy consumption weight, but also for their educational role. In France, and in the city of Paris in particular, schools account for 38% of the municipal facilities energy consumption [15]. Con-

Table 1
Comparison between earlier audit campaign [14] and current study.

	Previous study	Current study
Context	One university building (B1)	Three university buildings nearby on the same campus (B1/B2/B3)
Method	Detailed audit approach with on-site intervention • Bills analyses, meteorological data • Instrumentation (heating & ventilation) • Comfort (measurement & questionnaires) • TRNSYS BEM (Building Energy Modelling)	Data analyses approach (without intervention) • Aggregated electric power demand (10 min time-step) • Climate data • Hourly occupancy data collection & analysis • Statistical analysis
Results	Retrofitting recommendations • Heating substation control • Individual ventilation control by zones (classroom vs. office) • Individual heating control	Behavioral and building system identification • Energy saving potential in non-occupied periods • Building energy behavior analysis • Electricity demand by occupants and by degree-day • Demand diversity factor of the three buildings system

sequently, a large program for better energy efficiency in these facilities has been launched in 2008 targeting a decrease of their consumption by 30%. The program includes more than 600 school buildings built between 1880 and 2012 [15]. Similar assessments have been made in other countries and educational buildings have been driving increasing attention in recent years [16–19]. More generally, extensive reviews on energy efficiency assessment in non-residential buildings in general, and educational buildings in particular, can be found in [20,21].

For this reason, we target the generalization of the previously conducted study [14] on other campus buildings of different generations, hence ruled by different thermal regulations (TR), to assess the dependency of the obtained conclusions on the buildings construction years and usages. Due to the complexity of the previous study protocol and the encountered difficulties, we attempt a new and less intrusive approach combining historical data and statistical processing techniques which do not require any additional instrumentation. The success of this approach may path the way to the generalization of the methods used to implement fast and non-intrusive audits at a larger scale.

3. Methods

In the present study, we consider 3 buildings located on the same university campus. We previously conducted an extensive instrumentation of one of the three buildings to accurately characterize the IEQ, the building electric and heat consumption and the built thermal properties [14]. The collected data were used to calibrate a BEM that then helped to estimate the energy savings to be expected from different retrofitting actions. An extensive comfort assessment campaign was also held. This previous study highlighted the difficulty and the high cost of accurate data collection, in terms of equipment, time and man power.

Consequently, a different strategy is adopted in the present work: we avoid any *ad hoc* instrumentation. To do this, we mainly rely on data extraction from existing easily-accessible material and sources, to provide an efficient and low-cost energy efficiency characterization method. Used data include weather conditions, occupancy profiles, annual and monthly total energy consumption through bills, and detailed energy consumption at 10 min time-step provided by built-in smart meters. The development of methods to analyse the latter is of paramount importance in the context of large dissemination of smart energy meters described above. For this purpose, different tools are implemented [22–24]. Analysis criteria are suggested and used for the different case studies comparison.

3.1. Case study and methods

While in our recent work [14] we focused on a 30,580 m^2 building, the present one covers a total useful surface of more than 50,000 m^2. The different buildings of the case study as well as the used methods are presented in the following paragraphs. First, the main differences between the previously used methods [14] and the currently implemented one are summarized in Table 1. Then, the considered campus buildings are presented. Finally, the implemented method to carry on the present work is described in detail.

3.2. Buildings properties

The three buildings selected for the study are located on a French campus in Paris area. They will be respectively referred to as B1, B2 and B3 in the following. The numbering is assigned according to a decreasing useful surface area. Different technical information regarding the studied buildings such as the year of construction, architectural parameters, energy systems as well as the occupancy are given in Table 2. The choice of the studied sample among all the campus buildings is mainly motivated by their construction year difference with regard to the consecutive French thermal regulations (TR) of 1988, 2000 and 2005. More specifically, B1 was constructed in 1987, before the TR 1988, B2 between TR 1988 and TR 2000 while B3 was delivered under TR 2005.

This main difference enables the identification of the effect of the consecutive TRs on the energy consumption of tertiary buildings in general, and higher education buildings in particular.

It is worth mentioning that, in addition to its large surface area and its early construction year, B1 exhibits a main difference with B2 and B3. It provides additional specific equipment which can significantly affect the overall energy consumption. Such equipment mainly includes a gym of significant surface area with large mechanical air renewal rate, a canteen, several computer labs and server rooms with cooling needs, and a 600 m^2 R&D cleanroom facility with very large air renewal rate and humidity control needs. The additional induced energy consumption should be taken into account in the analysis.

3.3. Energy load and consumption

Annual and monthly energy consumption data, for both electricity and gas (for B1 and B2, gas is used for heating. For B3, only electricity is used), were retrieved from the energy bills for three consecutive years from 2014 to 2016. For B3, which is a positive energy building that produces an equivalent amount of its annual energy consumption, its photovoltaic solar electricity production is also provided. Such data are used to calculate usual preliminary ratios such as the consumption per surface area unit or the consumption per heating degree days (HDD). It enables a global characterization of the buildings and the identification of the largest opportunities of energy savings.

More detailed electricity consumption with a time-step of 10 min were collected for B1 and B2 during 6 months, from January to June 2017 (additional data are available for B1 starting from December 2014). Those data are used to perform various statistical analyses and enable the identification of common electricity

Table 2
Characteristics of the three studied buildings.

Characteristics		Building 1	Building 2	Building 3
Teaching and research activity		Science and Technology, R&D	Art and Humanities	Science and Technology, R&D
Built	Year of construction	1987	1999	2013
	Thermal regulation	RT 1982	RT 1988	RT 2005
	Net floor area (m^2)	30,580	10,343	5178
	Outer surface (m^2)	35,728	9989	7546
	Floors	Ground Floor + 4	Ground Floor + 5	Ground Floor + 5
	Heated volume (m^3)	144,173	51,274	26,195
Energy system	Electricity	900 kW subscribed from grid	250 kW subscribed from grid	PV panels + grid subscription
	Heating	Gas furnace (2 × 1100 kW)	Gas furnace (2 × 540 kW)	Geothermal Heat Pump system
	Cooling/refreshment	Refrigeration units (lecture hall only)		Refrigeration units + geothermal energy system
	Ventilation	Central ventilation with heat recovery		
Occupancy	Maximum number of occupants simultaneously	1268	625	Variable, up to 300

consumption profiles as well as their dependency to the occupancy profiles. They can also enable deeper understanding of the electric energy demand through a load disaggregation for example [25–27]. In our case, those data contain averaged electric energy load over a 10 min time-step. They are directly and freely provided by the French national grid operator to clients with a subscribed power larger than 36 kVA. Some third party companies also offer remote energy consumption data retrieval and analysis tools. The analysis of such data for large tertiary buildings is challenging due to the large time-step and high aggregation rate. Nevertheless, it offers several opportunities since the data acquisition is straightforward and nonintrusive. Since no additional instrumentation is required, the data collection is nearly zero-cost. More opportunities will arise in the near future with the large roll-out and dissemination of smart electricity meters with similar time steps [2] in France.

3.4. Occupancy

As it has been extensively shown, occupancy is a critical information related to both energy consumption and IEQ (indoor environment quality) [28,29]. Consequently, it is necessary to collect occupancy data for the three studied buildings, to appropriately analyse and compare energy consumptions.

Several methods have been reported to measure and model occupancy profiles in institutional buildings [30]. In this study, occupancy information, similarly to other used data, is retrieved from existing data sources without resorting to additional instrumentation. Therefore, for B1 and B2 which were selected for a detailed analysis of energy consumption dynamics, courses planning and intended attendance of occupants are used. The schedule of courses is prepared for the whole year or semester by the institutions staff. For each time slot, each group of students, with a pre-defined number of persons, is assigned to a classroom. The total number of students is obtained by summing up the number of students of the different groups appearing in the schedule for each time slot. In addition to the students' population, faculties together with researchers and school staff are taken into account. Faculty and staff are assumed to be present during working hours. Their number is predefined.

Also, as used data are not real-time measured occupancy, an absence rate between 0 and 1 is manually applied for each course based on if they have mandatory attendance or not. Thus, examinations and classroom courses including lectures, tutorial classes and projects have an absence rate of 0 (meaning 100% attendance) since all students are expected to be present. However, lectures conducted in auditoriums, with high theoretical but non-compulsory attendance, are given an absence rate of 0.2, based on an observation of the attendance rates of the different lectures. Sick-leaves and other absence cases related to personal matters are not accounted for due to the unavailability of such information for privacy reasons.

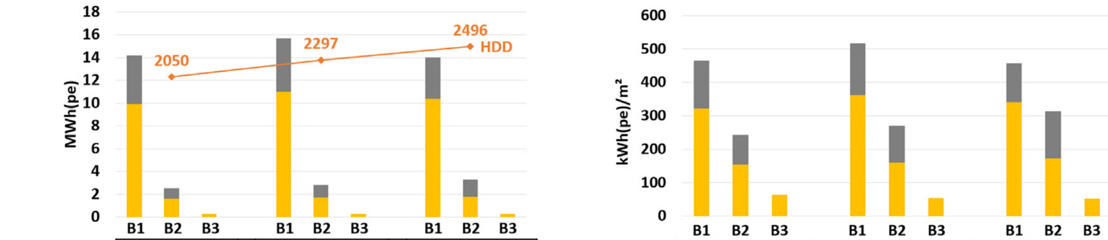
The occupancy profile is obtained by summing up the total number of occupants at a specific time slot of the day. The time-step of occupancy data is of 30 min for B1 and 60 min for B2. When courses are not planned and outside working hours – *inter alia* for nights and Sundays – the school is considered empty (occupancy is set to 0). Holidays are processed depending on the building and the time of the year: a distinction is made between spring/fall breaks, and winter/summer breaks since the whole building is closed for the latter.

3.5. Data analysis

Acquired data series, mainly of electricity consumption, occupancy and weather conditions, were processed to extract different indicators and key features of the studied buildings' energy consumption profiles. Data processing is mainly performed using the statistical computing software R [31]. In our case, data analysis is quite challenging due to the large sampling time-step (10 min) and large aggregation level (numerous identical and different appliances: more than 1000 personal computers, dozens of AHU and pumps, lighting equipment for more than 350 offices and teaching rooms, company canteen equipment, etc.). Indeed, commonly used methods are generally applied to either higher data sampling rates which enables appliance signature identification [32] or smaller samples and buildings. For the latter, there are fewer combinatorial possibilities, which simplifies the problem complexity [25,33]. Consequently, cross correlations between different variables, as well as univariate and multivariate regression analysis, are first performed to identify the main energy consumption drivers of the different buildings [34]. Then, we use autocorrelations with different time lags to identify typical daily and weekly electric consumption profiles. Finally, seasonal-trend decompositions using Loess (STL) are applied to perform preliminary decompositions of the overall consumption profiles [23]. An STL decomposition provides three components which are sub-time series: a trend component that reflects the long-term progression of the series, a seasonal component reflecting identical seasonal variations over the time series with a fixed period, and an irregular component, or "noise", covering random irregular events [24]. We assume a simple additive model of the form:

$$LC(t) = T(t) + S(t) + R(t)$$

where LC, T, S and R figure the total load curve (LC), the trend, the seasonal component and the residuals, respectively. Such tool can be considered as a starting point to load decomposition and disaggregation, even though it does not provide accurate information on the specific appliances that contribute to the LC at each time step.



(a)	2014			2015			2016		
Natural Gas	4.3	0.9	-	4.7	1.1	-	3.6	1.5	-
Electricity	9.9	1.6	0.28	11.0	1.7	0.28	10.4	1.8	0.27
Total primary energy	14.2	2.5	0.28	15.7	2.8	0.28	14.0	3.3	0.27

(b)	2014			2015			2016		
Natural Gas	142.3	88.9	-	154.1	110.9	-	116.7	141.1	-
Electricity	322.7	153.6	63.3	362.7	159.9	54.2	340.1	173.0	52.4
Total primary energy	465.0	242.5	63.3	516.9	270.7	54.2	456.8	314.1	52.4

(a) (b)

Fig. 1. Primary energy consumption (electricity and gas) of the three buildings in 2016, gross (a) and per surface area unit (b). For B3, heat is provided by a ground heat pump. Electricity consumption includes both heat and non-specific electricity consumption.

4. Results and discussion

4.1. Global overview of energy consumption

Following European standards EN 16247-1:2012 [35], EN 16247-2:2012 [36] and EN 15603:2008 [37], we collected historical energy consumptions for the three buildings. Based on the French national Primary Energy Factor(PEF), electricity consumptions are multiplied by 2.58 to obtain equivalent primary energy need.

4.1.1. Annual primary energy consumption

At annual scale, primary energy consumptions of the three buildings exhibit large differences due to their different sizes and occupancy profiles, as shown in Fig. 1a. The building B1, with a 30,580 m^2 useful surface and a maximal number of 1268 occupants, has an overall energy consumption of 14.0–16.8 MWhpe between 2014 and 2016. These values are around six times larger than those of B2 (2.5–3.2 MWhpe during the same period), followed by a much lower consumption for the positive energy building B3 (in average, only 0.3 MWhpe per year). It is worth noting that in terms of useful surface, B1 holds three times larger space than B2 (30,580 m^2 against 10,343 m^2) and six times more than B3 (5178 m^2). Accounting for the doubled occupancy of B1 compared with B2, we can approximately consider that the unit primary energy consumption per m^2 and per occupant is equivalent between the two larger buildings.

Both B1 and B2's heating needs are provided by natural gas furnaces. In average, the annual heating demand in B1 is 3.6-4.7 MWh during three heating seasons 2014–2016, with a peak consumption for the heating season of 2015. Compared with B1, B2 used 0.9–1.5 MWh per year but its largest consumption value occurred in 2016. Since the two buildings' heating systems are operated under the same weather conditions, the discrepancy can be explained by system management strategies changes. Collected information from energy systems managers revealed a change in B1 energy management policy between 2015 and 2016. More precisely, the energy facility management service is contracted in 2015 by a performance engagement, i.e., progressive heating savings are guaranteed for 3 years. Since the new contract started in 2015, considered as the reference year, the energy system management becomes savings-oriented starting from 2016. On the other hand, B2 energy management remains unchanged, with the same dependency to weather conditions.

Finally, by dividing the energy consumption data by the buildings' useful surfaces, we obtain unitary consumptions which are shown in Fig. 1b. B1 is still the largest overall primary energy consumer. Its annual consumption is around 457–517 kWhpe/(m^2·yr), 117–154 kWhpe/(m^2·yr) for heating and 322–363 kWhpe/(m^2·yr) for specific and non-specific electricity uses. Moreover, electricity consumption has less yearly fluctuations than that of gas demand which is more sensitive to yearly HDD variations. From gas demand trends for B1 and B2 from 2014 to 2016, we observe the continued increase for B2 and a reduced demand for B1 in 2016. Energy management is thus the cause of a reduced gas bill in the case of B1. Finally, compared with B1 and B2, B3 has very low energy consumption: its overall energy demand is 55–64 kWhpe/(m^2·yr). This value is very close to the 50 kWhpe/(m^2·yr) required by most recent TR in France, i.e., the TR 2012 [38]. It should be noted that TR cover specific consumptions only (heating, Domestic Hot Water, Ventilation, Refrigeration and Lighting) while the presented data of B3 cover its overall consumption, of both occupants and the building energy system.

4.1.2. Monthly

Down to a monthly time step, the primary energy consumed in heating and electricity of B1 and B2 are shown in Fig. 2. Regarding B3, equipped with PV panels which electricity production is entirely injected into the grid, its monthly solar electricity production is also plotted (Fig. 2c, green colour). Moreover, B3 is heated by a ground source heat pump system. Consequently, winter heating supply is accounted for in the electric demand.

For B1 and B2, a correlation between electricity and gas demand during heating seasons is observed. For example, in January and December, both buildings have yearly electricity and gas consumption peaks. This can be explained by two factors: i) non-specific electricity consumption (related to energy systems such as air handling units, fans, pumps, etc.) and ii) possible usage of additional individual electric heaters. The latter is often observed in office rooms during peak cold days. As shown in a previous indoor air quality study [14], according to in situ measurements and to occupants answers to questionnaires, the particular usage of the higher education building, i.e. a mixed usage of classrooms and office rooms, makes old building systems non-adapted to provide individual comfort: classrooms are overheated due to high occupants' heat contribution, and office rooms are under-heated for staff members. The lack of individual control possibilities on heating equipment in old buildings is a major cause of discomfort or non-efficient energy consumption.

Comparing B1 and B2 for summer periods, it appears that the two institutions have different closing periods. For B1, July and August are two very low occupancy months and the electricity consumption is thus the lowest in the year. While in the case of B2, June and July are two lowest consumption months. This might provide an opportunity for an interconnected grid scheme between the two

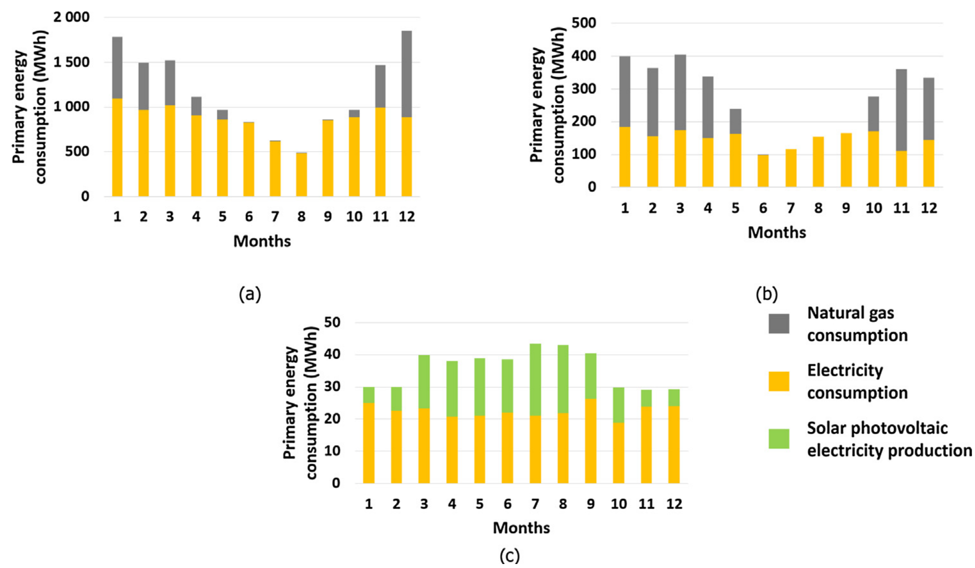


Fig. 2. Monthly primary energy balance of the three buildings in 2016–B1 (a), B2 (b), B3 (c).

buildings, instead of two individual electricity contracts. Interconnected grid with only one electricity contract may help to lower the electricity bills by diversity factor optimization. This opportunity can be assessed through shorter time-step (10 min) electricity demand curves analysis presented in the following sections.

Finally, the green building B3 holds the most balanced monthly electricity demand between 18 and 27 MWhpe all the year round. This is partially due to a better insulation of the building's envelope which results in low heating needs. Moreover, heating is supplied by a reversible heat pump which ensures the IEQ while keeping a low electricity consumption. The relative weight in total energy consumption of occupancy-related usages is thus more important for B3. Regarding its PV production, it can be noticed that most monthly consumption is larger than the production for July when PV production is at its highest value. Switching from grid injection to self-consumption can be considered.

4.2. Buildings occupancy

For both B1 and B2, occupancy was extracted from courses schedule provided with half-hour time steps. For B1, the schedule reports the students group, course and classroom number for each slot and for each working day. The resulting occupancy varies from one day to another. On the contrary, a weekly schedule is provided for B2 for the whole semester. The resulting occupancy profile remains constant from one week to another. Consequently, the occupancy profile of B1 exhibits larger amplitude variations all the year round, up to 1268 occupants, compared to that of B2, with a maximum of 625 occupant and low variation around this maximum. In both schedules, several time slots are dedicated to self-managed projects with no binding attendance. Such slots induce an uncertainty on the calculated occupancy. It is also the case for staff occupancy calculation: staff members are assumed present during working days. Finally, a main difference is observed between B1 and B2 during school breaks: B1 is open with reduced occupancy, mainly researchers and staff, while B2 is completely closed with zero occupancy.

4.3. Energy consumption dynamics

In this section, the energy consumption dynamics is described and compared for the two largest buildings: B1 and B2. The main goal is to compare the sensitivity of the consumption to different energy drivers for two similar buildings of two consecutive generations (B1 was built before 1988 French thermal regulation while B2 was built under this regulation). In addition, these two buildings have the largest energy consumptions among the considered sample of three buildings. Hence, they offer the largest opportunities for energy efficiency improvements.

In the following sections, we mainly focus on electric energy consumption. Data have been collected for 6 months with a 10 min time-step. We show in Fig. 3 the LC of the two buildings during one week of January 2017 as well as their occupancy profiles and OAT. Occupancy data were determined according to the previously described method and weather data obtained from the nearest airport weather station, Le Bourget [39].

We observe clear dependencies between the electric power load and the occupancy on one hand, and the power load and the OAT on the other hand. The former is expected to be larger since the heat consumption is more OAT-sensitive and both buildings are heated with gas furnaces. Such expectation is also suggested by the profiles during the weekend where the LC is flatter, as well as the occupancy, in spite of large variation of OAT. The LC of B2 is not completely flat during this specific weekend. This may be due to residual occupancy by students and a special event. These correlations are confirmed and quantified by the statistical analysis presented in the following paragraphs.

4.3.1. Statistical analysis and energy drivers' identification

Correlation coefficients are calculated for both B1 and B2, between hourly power demand and both occupancy and OAT. The linear correlation coefficient, ranging from −1 to 1, estimates the strength of the linear relationship between two sets of variables. Weak and strong linear relationships are characterized by absolute values of the correlation coefficients smaller than 0.3 and larger than 0.7, respectively.

4.3.1.1. Linear univariate models. We plot in Fig. 4 the distribution of the hourly electric power demand versus the number of occupants and the OAT during four months, between January 1st and April 27th, 2017. The plotted dataset can be divided into four different sub-sets with respect to possible combinations of the considered parameters (occupancy and OAT): heated & occupied, not heated and occupied, heated and not occupied, not heated and not occupied.

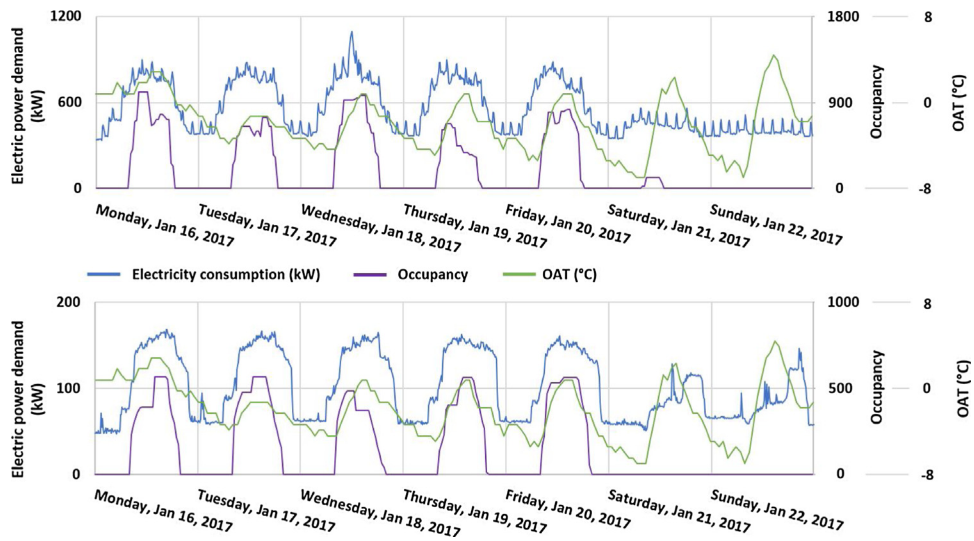


Fig. 3. Electric load, occupancy and OAT for B1 (up) and B2 (down), for a typical week from Jan. 16th to Jan. 22nd, 2017.

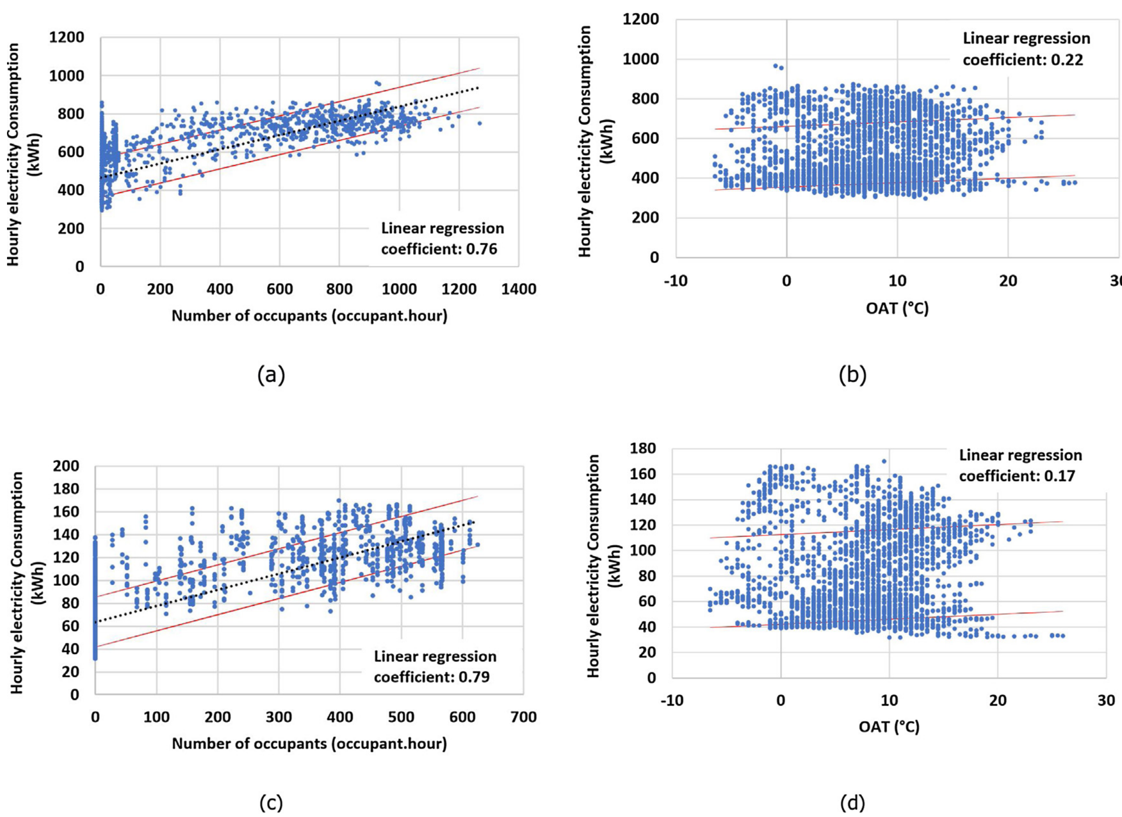
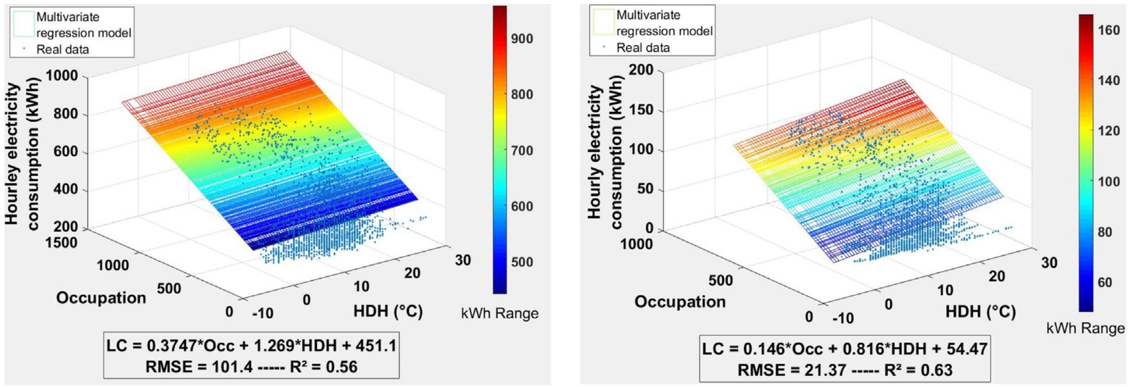


Fig. 4. power demand vs. occupancy (left) and OAT (right) for B1 (top) and B2 (down). The red lines delimit dispersion bands with a width of $\pm 1 \times RMSE$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

As expected, the electric power demand-occupancy correlation (0.76 and 0.79 for B1 and B2, respectively) is larger than power demand-OAT one (0.22 and 0.17 for B1 and B2, respectively). Surprisingly, no significant difference in demand-occupancy correlation nor in demand-OAT one is observed between B1 and B2, in spite of their 10 year difference.

We also highlight in Fig. 4 the dispersion of the measured data by the continuous red lines plotted at $\pm RMSE$ around the linear regression curve. The RMSE of B1 is 102 kWh and 153 kWh for demand-occupation and demand-temperature data, respectively. For B2, the RMSE values are 22 kWh and 35 kWh, respectively. The framed bands contain 70% and 62% of the measured data for B1, and 69% and 64% for B2. These values go up to 90% for demand-occupancy and demand-temperature for both B1 and B2 for a $\pm 1.5 \times RMSE$ wide dispersion band. It is worth noting that contrarily to monthly [40] or even daily consumption-HDD correlation [14], hourly correlation is more dispersed with respect to the linear relation between energy consumption and HDH (Heating Degree Hours). This is particularly due to the fact that the hourly occupation related consumption dominates the weather related one. In



(a) (b)

Fig. 5. Multi-variate regression of the electric energy consumption for B1 and B2 between 01/01/2017 to 04/27/2017.

addition, occupancy independent appliances consumption can be significant, especially in large buildings with diverse research activities. This dispersion, and the resulting power consumption, can be hardly reduced without a power management system that controls equipment turn-off behaviour according to a predefined schedule [41].

4.3.1.2. Linear multi-variate models. We simultaneously consider in Fig. 5 the two explanatory variables, occupation and OAT. OAT is here taken into account through HDH, defined as the difference between indoor reference air temperature, 18 °C in this case, and OAT. We obtain a model of the form:

$$LC = a \times Occ + b \times HDH + c$$

where a and b, are weight factors of one occupant (Occ) and one HDH, while c is the LC baseline.

For both buildings, occupant weight factor a is lower than weather weight factor b. This does not reflect the actual weight of occupancy compared to OAT in the electric consumption since Occ and HDH do not have neither the same unit, neither the same variation magnitude. Indeed, for B1 for example, the occupancy ranges between 0 and 1268 while HDH ranges between −7 °C and 20 °C approximatively. Consequently, for maximal occupancy and HDH, occupancy and OAT contributions to electric demand are respectively 475 kWh and 25 kWh, *i.e.* 49% and 3%. The baseline consumption accounts for the remaining 48%. Similar trends can be observed for B2 with 54% and 10% for occupancy and HDH, respectively, while the baseline consumption accounts for more than one third of the maximal power demand. However, the weight of an occupant of B1 is more than twice that of B2. This can be explained by the additional equipment of B1 (canteen, gym, server rooms and specific research equipment). On the other hand, the heating needs per HDH for B1 are 50% larger than for B2. This is expected because of the 10 year construction time difference. In addition, the constant term of the multi-linear regressions is very close to what can be extracted manually from the hourly consumption profiles. Indeed, a calculation of the average consumption during night hours leads to a baseline consumption of 410 kWh and 54 kWh for B1 and B2, respectively. The values provided by the multi-variate regression are 451 kWh and 54 kWh for B1 and B2, respectively. Finally, it is worth noting that the relationships obtained in Fig. 5 are not perfectly linear. This is probably due to a lack of explanatory variables. Other variables such as the scheduling of heavy equipment like air handling units, cooling units, and canteen equipment should be considered in future studies. The operating status of small but numerous appliances such as computers can also be considered. Such information can be easily obtained through a monitoring of the computers network activity. This information is relevant for educational buildings heavily equipped with office automation systems. For instance, B1 is equipped with more than 1500 desktop computers. In addition to other explanatory variables, autoregressive models, as suggested by the large autocorrelation values for short lags shown in Fig. 6 and the following paragraph, can improve the load curves description.

4.3.2. Autocorrelations and daily/weekly profile identification

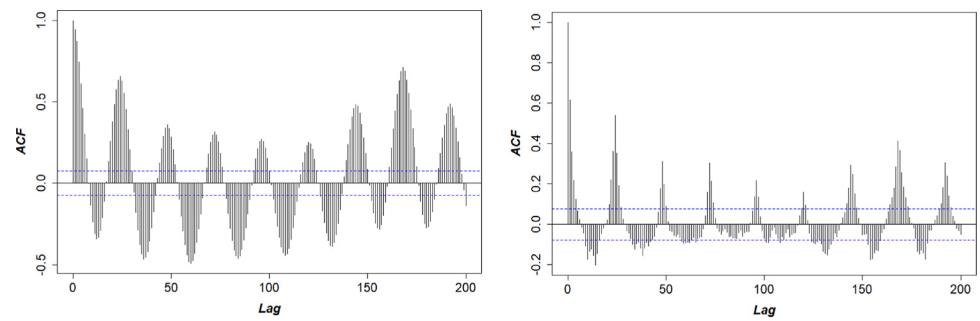
The goal of the present section is to identify the existence of typical daily load curve profiles for both buildings and extract their main features. For this aim, we calculate the auto-correlation functions for hourly consumption data series for B1 and B2 with a time lag ranging from 1 h to 8 days. The results are shown in Fig. 6.

We observe large auto-correlation values for short lags. For 1 h, it is almost equal to 1, which is quite expectable. We also observe a decreasing but still large auto-correlation coefficient for a one-day lag. This is explained by the similarity between weekdays' profiles and suggests the existence of a typical week day profile. The auto-correlation then decreases for larger lags before increasing again for a seven-day lag which suggests strong similarities of the LC profiles for the same weekday of consecutive weeks. In the following paragraphs, the main features of these profiles are described.

4.3.3. Load curves decomposition

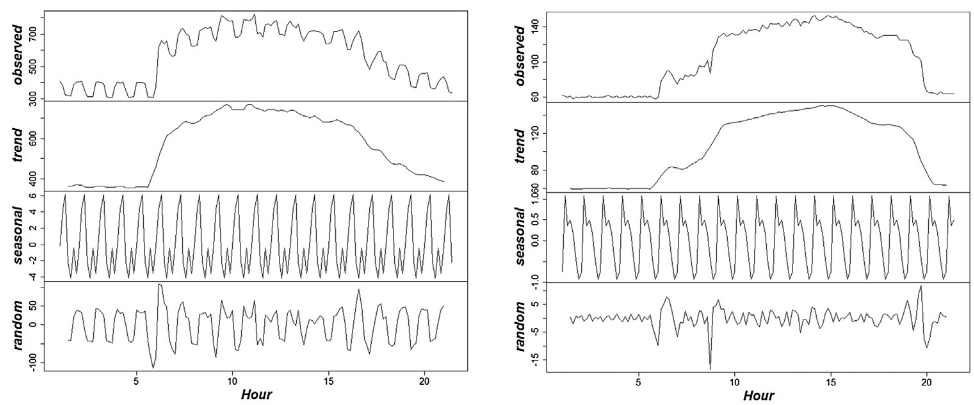
This section reports an attempt of the LC decomposition into three components: a trend (T), a seasonal (S) effect and a residual (R), as presented in Section 3.5. Fig. 7 shows a results sample of an STL decomposition of the daily electric energy consumption of B1 and B2, with a 10 min time-step, on March 9th, 2017. The curves from top to down are the plots of LC, T, S and R, respectively.

For both buildings, the trend captures main variations of the electric power demand. However, seasonal components do not seem to have a trivial physical meaning: on the raw load curve, no such regular events are observed. The corresponding power range accounts for 2.0% and 1.7% of the daily minimum power demand for B1 and B2, respectively. Therefore, the seasonal component can be considered as negligible. On the other hand, for B1, the remainder component provides interesting information. For instance, positive power peaks ranging from 25 kW to 106 kW with a similar shape and power increase than the ones on the raw time series can be identified. These are known from the previous study on B1 [14] to correspond to the triggering of cooling units. Their daily electricity consumption is assessed to 459 kWh, then 3.4% of the total daily electricity consumption. Finally, for B2 the remainder does not reveal any equipment triggering or specific energy behaviour of the building (1% of the daily electricity consumption).



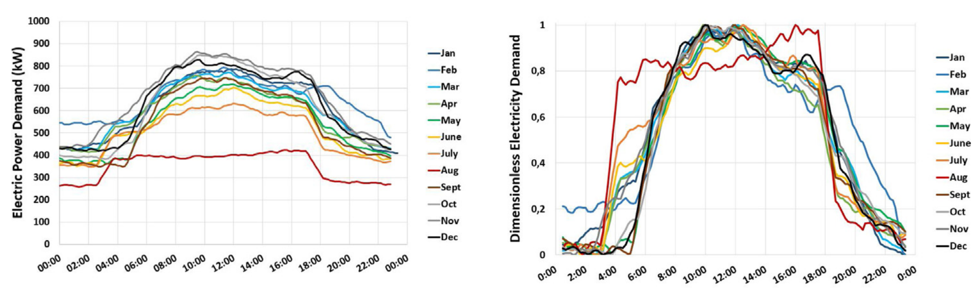
(a) (b)

Fig. 6. Daily electric energy consumption autocorrelations with a time lag ranging from one hour to 192 h (8 days) for B1 (a) and B2 (b). Used data were measured from 01/09/2017 to 02/05/2017.



(a) (b)

Fig. 7. Times series decomposition analysis of the electric energy consumption for B1 (a) & B2 (b), with a 10 min time-step, the day of March 9th, 2017.



(a) *(b)*

Fig. 8. Daily averaged trend curves for B1 (a) resulting from time series decomposition over one typical business week of each month in 2015 and the corresponding normalized electricity demand (b).

Using this LC decomposition, we can extract different trend curves for different periods of the year to observe the related change of electric power demand. For B1, a typical week is selected for each month of the year 2015. The resulting trend curves are averaged to get a single daily averaged trend curve for each selected week, then one curve per month (Fig. 8a). Normalized profiles are also obtained by subtracting the LC baseline to the total LC, and dividing by the daily power demand variation magnitude.

We observe on Fig. 8 similar trend profiles for the different months, but varying in terms of electric power range depending on the season. There are two exceptions: in August, when the building is unoccupied – but the AHU units' consumption still accounts for around 1.5 MWh per day, then 45 MWh monthly – and February where heating needs are maximal, affecting the energy equipment management (15 °C daily HDD in average for the considered week). Thus, the main differences between dimensionless profiles of other months can be related to energy equipment management. For instance, AHU triggering happens earlier in summer months, at 4:00 am instead of 6:00 am in winter.

The same method is then applied to both B1 and B2 for January-June 2017 for comparison. We observe the change of the LC trend in different months, because of both weather and occupation variations, for both B1 and B2 (Fig. 9a & c). Dimensionless profiles on Fig. 9b and d show that energy equipment management is also changing depending on the time of the year for B1. Contrarily, B2's normalized trends are almost month-independent, suggesting no season-driven energy equipment operation. Also, the occupancy profiles shift between the two buildings, previously observed on Fig. 4, is confirmed: the electricity demand for B2 is temporally shifted by two hours compared to that of B1.

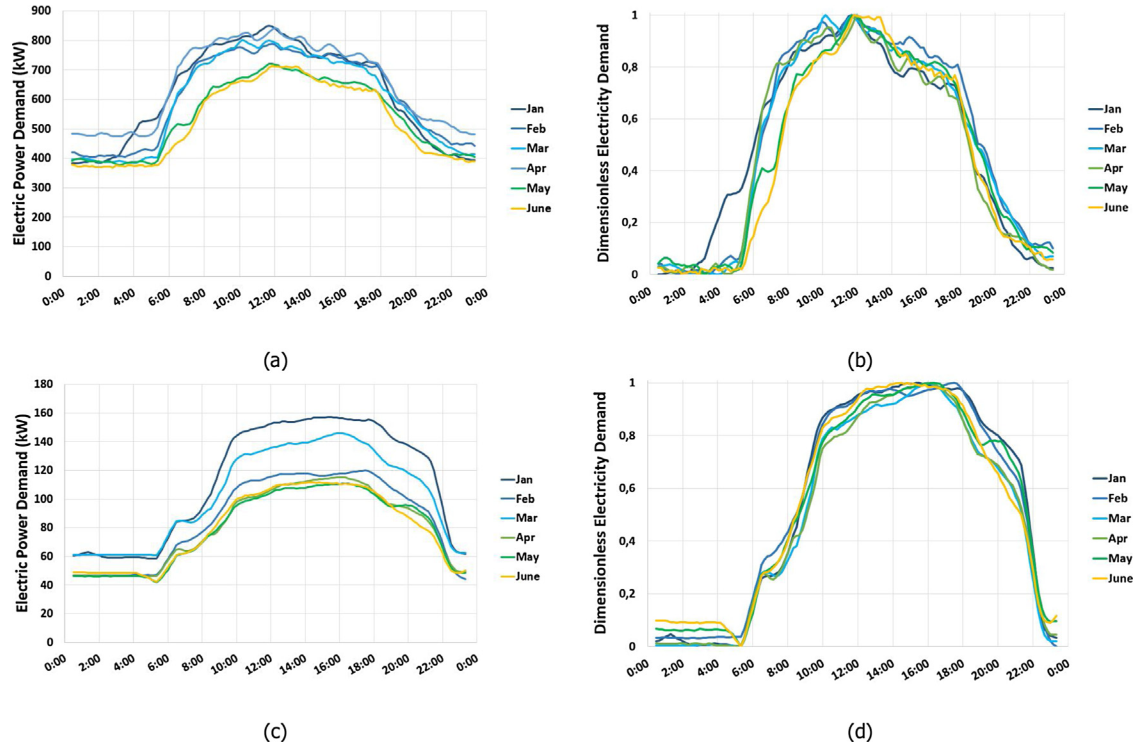


Fig. 9. Daily averaged trend curves for B1 (a) and B2 (c) and the corresponding normalized electricity demand (B1: b, B2: d).

4.4. Discussion and recommendations for future works

The present work tackles the question of energy consumption of campus buildings, through a comparative study of three campus buildings of different generations. The study is mainly based on the analysis of available data, without intrusive *ad hoc* instrumentation, such as electric load curves collected through communicating smart meters. The use of such data avoids expensive instrumentation and enables the development of methods to take the full benefit of data that will be, in a near future, widely provided by smart meters currently being rolled out.

A global analysis of the three buildings annual and monthly consumptions is helpful to highlight the impact of the building construction year and the underlying thermal regulations on the building energy performances.

The collected electric load curves time series are then analysed through a wide range of statistical tools such as univariate and multi-variate linear models, auto-correlations and STL decomposition for energy drivers, and typical load profiles identification. The understanding of the load curves dynamics would path the way to innovative energy services such as demand response and capacity management. The methods used, although being particularly useful in the comparison of different buildings, are still to be improved. One drawback is that they do not enable an accurate modelling of the dynamic load curves, with a 10 min' time-step. This is mainly due to two reasons: the lack of monitored explanatory variables and the large aggregation level of the data used. Indeed, only occupation and outdoor air temperature have been used as explanatory variables. Additional information about the equipment scheduling and actual operating profiles can be considered. Large autocorrelation coefficients with short time lags also suggest auto-regressive models to be possibly relevant. The large aggregation level is also highly challenging. Indeed, the used data exhibit a double aggregation: a spatial aggregation because of the big buildings size and their large appliances number, and a temporal aggregation because of the 10 min time step. This time step is due to the use of data collected by electric utility smart meters. Indeed, we are targeting generic methods applicable to similar data provided for a large number of buildings already equipped with such smart meters without any additional instrumentation. Some load disaggregation methods recently proved to be efficient for simple cases such as individual houses. Their successful application to more complex cases like large non-residential buildings, and educational buildings in particular, is not trivial without a finer monitoring of the different loads and/or a better load profiles knowledge database. To make these methods suitable for more complex cases, intermediate aggregation cases can be addressed first. For this purpose, small samples of the buildings considered in the present work are currently being finely instrumented to obtain load curves for less complex ensembles with smaller numbers of appliances and occupants. In addition, all appliances of the considered sub-samples are being individually monitored in order to have unitary load curves. Such terminal measurements would allow us to validate the load disaggregation results from a bottom-up point of view. They would also enable the identification of the aggregation thresholds beyond which the used disaggregation methods are not applicable anymore.

5. Conclusions

The present study reports on a comparative analysis of the energy consumptions of three campus buildings located in Paris area for three years and at different time scales, from a yearly down to a 10 min time-step. The main findings of the current work include:

i A post-occupancy proof of the impact of construction year and subsequent thermal regulations on the energy efficiency of university buildings;
ii An insight on the potential of non-intrusive data analysis and statistical data processing in the analysis of energy drivers, such as temperature and occupancy, of large buildings;

iii Electric energy consumption and production analysis has revealed imbalances in individual buildings profiles. A district-level energy management should be beneficial;
iv Finally, the limits of non-intrusive methods for large building energy behaviour analysis.

Indeed, the method hereby presented faces strong limitations: it is still unsatisfactory if a predictive modelling is targeted since it provides energy consumption values with errors larger than 10%. Improving this method requires the use of additional information on appliances, such as the machines operating schedules, and a more accurate occupancy counting, and the sub-metering of particular parts of the building. the latter is currently being done. Moreover, the STL method is shown to be straightforward with informative outputs. Nevertheless, some of its components can be hardly related to physically meaningful consumption shares without additional knowledge of the buildings' features. In spite of these limitations, the introduced methods pave the way towards simple energy analysis tools for large buildings. Such tools would enable the development of reduced low-knowledge models for load curves decomposition and reconstruction. These methods are useful to take the full benefit from the ongoing large-scale roll-out of smart-meters and decentralized energy generation solutions.

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