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On the influence of occupants on the energy flexibility of buildings: a sensitivity study at district scale

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Abstract

Energy flexibility of buildings is one solution that could help a better integration and an uptake of renewable energy sources. Energy flexibility consists in shifting some energy usages of buildings (e.g. heating, domestic hot water, wet appliances) according to the needs of the energy production systems. In order to better integrate the needs and constraints of occupants, indirect control strategies are foreseen to activate this potential. In this approach, the flexible loads are not directly controlled by the Transmission System Operator (TSO), but the control rely on signals sent and interpreted at the building level. Occupants will therefore interact with this signal, decreasing the level of confidence in the flexibility potential. The district scale increases the reliability by taking advantage of the coincidence of usages and the diversity of occupants.

The objective of this article is to evaluate the sensitivity of the response of flexible buildings to occupants' interactions. This indicator used to characterise flexibility is the decreased load during a 3-hour flexibility event at the end of January. Bottom-up simulations of buildings and occupants are performed for a new district composed of 337 dwellings located in France. The sensitivity analysis is conducted according to the Morris methodology, accounting for the diversity of occupants in terms of presence, behaviour, comfort and flexibility preferences. Finally, the influence of aggregation on the reliability of the potential is evaluated.

Introduction

Energy flexibility can be defined as the "ability of a building to manage its demand and generation according to local climate conditions, user needs and grid requirements" (Jensen et al., 2017). Some energy usages can be reduced or postponed, such as space heating, domestic hot water or wet appliances (dishwasher, washing machine). Energy flexibility can facilitate the integration of intermittent energy sources in national grids. Scenarios integrating flexibility for 25% up to 100% of these usages are proposed in prospective studies at national scale in France (RTE, 2017) (Ademe, 2018). Moreover, an independent aggregator entered the French market in 2020 with a program involving 10 000 houses equipped with electric radiator.

The main difficulty of using the energy flexibility of residential buildings lies in the small amount of power at stake (a few hundred Watts) and their controllability. Indeed, the availability of these flexible loads highly depends on the preferences and activities of occupants. At the building level, it is thus difficult to predict the availability of flexibility. At the district level, the diversity of usages allows a more reliable response.

Different researchers investigated the uncertainty of simulating building energy use at district scale. The different sources of uncertainty can be classified in the following categories: aleatory, epistemic, or due to the model or heterogeneity (Fennell et al., 2019). Tian et al. (2018) highlighted the uncertainty/heterogeneity in input parameters for building stock analyses. In a recent study from De Jaeger et al. (2019), the influence of envelope losses on district energy demand was demonstrated. The average set-point temperature of the night zone was the main occupant-related parameter influencing the district energy demand. Other parameters related to occupants had little influence, probably due to the high level of heat losses of the buildings. Moreover, a reduction from 65% down to 10% of the mean district energy demand was observed when evaluating a single building versus 50 buildings. Only few articles deal with the uncertainty from occupants when investing energy flexibility at district scale. Wang et al. (2018) estimated the energy flexibility potential of building clusters during unoccupied periods. They found that the uncertainty of energy flexibility was less than 10%, when about 700 households were aggregated. Hu and Xiao (2020) quantified the uncertainty from occupants on energy flexibility using the Monte Carlo sampling technique. The presence of occupants was modelled using a Markov-chain Monte Carlo occupancy model and different default set-points were chosen. The weekly uncertainty of energy flexibility exponentially decreased from 19% for 8 households down to 0.7% for 5120 households, but only 9 parameters were varied.

The objective of this article is thus to evaluate the influence of occupants on the flexibility potential and assess the aggregation effect. This potential is characterised by the mean load decrease during a 3-hour flexibility event on the 26th of January. Flexibility on both space heating (individual heat pumps) and wet appliances is considered. The parameters tested are related to the presence of occupants, their behaviour and their tolerances toward flexibility. The buildings and occupants are modelled based on a bottom-up approach, accounting for the district diversity. The case study is a new district located in the west coast of France and composed of 337 dwellings. The novelty of this work lies in the models used to account for the interaction between the flexible loads and the occupants. Occupants are no longer modelled as passive or perfect users, but their willingness to modify their behaviour is accounted for using agent-based models.

Methods

Case study

The district *Atlantech* located in La Rochelle (west part of France) has been selected to evaluate the influence of occupants on the energy flexibility potential (*Figure 1*). This residential district is composed of 337 dwellings in 97 buildings. The geometry of the district has been simplified to a level of detail LOD 1 to ensure a fast computation time. The weather data measured in La Rochelle in 2017 is used for simulation; this year is classified as typical for future weather conditions (slightly warmer winter conditions with 1926 heating degree days and heat waves in the summer). Couples with or without children are living in these dwellings, characterised by a mean floor area of 65 m². *Figure 2* provides an overview of the main district characteristics.

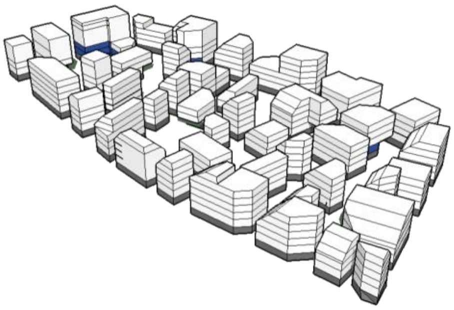

Figure 1: View of the district model.

In order to comply with the performance criteria set for the district, the buildings should be designed according to the future building regulation (environmental labelling E+C-, level *Energy 3/Carbon 2*). The energy consumption of the buildings is thus decreased by around 20% compared to the current building regulation and local energy production is mandatory.

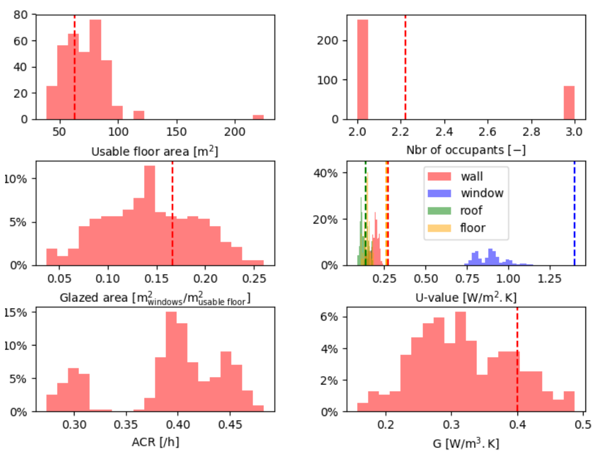

Figure 2: Main properties of the 337 dwellings (vertical lines represent the current building regulation).

The thermal resistance and airtightness of the building envelope are thus increased compared to standard levels and the fresh air intake is humidity-controlled. *Figure 2* shows the main properties of the building components and highlights the generated diversity. Several air-to-water heat pumps provide space heating to the dwellings, which are equipped with low-temperature radiators. The nominal coefficient of performance (COP) of the heat pumps is 3 (7°C/35°C) and works at variable speed. The sizing of the heat pumps is performed with an oversizing coefficient of 20% and the supply water temperature of radiators is set to 45°C. The regulation is performed at the dwelling level and both the heat pump and dwelling thermostats are PI controllers tuned according to the Ziegler-Nichols methodology.

District energy model

The modelling tool used to evaluate flexibility at district scale is Dimosim (DIstrict MOdeller and SIMulator, Riederer et al., 2015), which is a modular Python-based simulation environment. Particular attention has been drawn to model the diversity of buildings, occupants and equipment within the district. The diversity will thus lead to variability in the flexibility potential, which is important to capture.

Each dwelling is modelled by one thermal zone. The composition of walls, floors, roofs, windows is defined for each dwelling based on random draws from distributions assuming a variation of ±15% around the default value (*Figure 2*). Opaque walls are discretised in 4 layers, namely the external finish, the thermal mass, the insulation and the internal finish. Conduction through walls is then solved using the finite difference method, with a time-step of 10 minutes. Shading between buildings is evaluated according to the geometry and updated for different time of the year.

The number of occupants per dwelling is set according to the dwelling floor area and the French census data (INSEE, 2010). Occupants' activities are then simulated for each type (workers, unemployed, retired, student) based on Time Use Survey (TUS) (INSEE, 2010). The 27 900 logbooks (reported each 10 minutes for 24 hours) of the TUS allow the creation of diverse but coherent occupation schedules. These daily schedules are drawn randomly (based on a seed) in different clusters, which consist of occupants with similar patterns (Vellei et al, 2020).

According to the dwelling and occupants' characteristics, the different equipment is set using conditional probabilities based on INSEE data. The energy class and the size of each electrical appliance is then set according to national surveys. Each dwelling can have up to 12 different appliances, whose usage is linked to the occupants' schedules. For example, the usage of the washing machine is linked to the activity *laundry* of the occupants.

Model validations

The thermal model of the Dimosim tool has been compared to the results of the benchmark test BESTEST on free running cases and heating cases. The results are in accordance with other tools, both in terms of temperature and energy.

Given the large number of input parameters necessary to build up the district (around 15 000 for this district), controlling the coherence of these parameters with typical values is of main importance (*Figure 2*). The heat loss coefficient (*HLC*) of each dwelling is compared to ensure the overall performance of the district ($G = HLC/V$). Additionally, each energy usage is also verified. *Figure 3* (left) represents the average daily and yearly profiles of the electrical load from appliances for the considered district. The summer and Christmas breaks can be clearly observed. The average daily profile has been compared to the results from Vorger (2015). The variations are similar, but the average load level is lower as there is no single-family house in the district considered. The yearly electricity consumption of appliances (27 kWh/m²$_{\text{heated area}}$.year) corresponds to the mean value measured in French collective buildings (Ademe, 2019).

Internal heat gains from occupants and electrical equipment are in accordance with typical values used in France (*Figure 4*, up). It should be noticed that 85% of the electricity used by appliances is transformed into internal heat gains, similar to the results of Ademe (2019).

Finally, the coincidence factor has been evaluated to check the diversity of usage within the district (*Figure 3*, right). This factor is equal to the peak of a system divided by the sum of peak loads of its individual components. These values are compared to the relationship proposed by Velander (1947) for appliances energy use with electrical heating. This relationship is valid for a high number of households (>30). The diversity of usage seems coherent within the district, slightly lower than the values proposed by Velander. Similar observations were made by Sørensen et al. (2019), in which the peak power measured was around 20% lower than Velander's formula (for 1000 apartments).

The resulting heating need is equal to 30 kWh/m²$_{\text{heated area}}$.year in average and ranges from 8 up to 80 kWh/m²$_{\text{heated area}}$.year. Despite similar thermal properties, not all buildings can benefit from passive solar heat gains within the district. The electrical load of the different heat pumps is presented in *Figure 5* (up) for three cold days of the winter season (24$^{\text{th}}$ to 27$^{\text{th}}$ of January). Due to the high level of insulation of the buildings, the mean heating load is highly dependent on both internal loads and solar heat gains. The load is thus relatively low during daytime. The positive effect of aggregation on the predictability can also be observed when comparing the load profile of a specific building to the mean profile over the entire district. The load from the dishwasher (*dw*) and washing machine (*wm*) is also presented in *Figure 5* (down). The mean profile remains uncertain due to the low frequency of usage of these devices. A larger district would be necessary to gain reliability.

Comparison with measured data could not be performed as only half of the district is built so far.

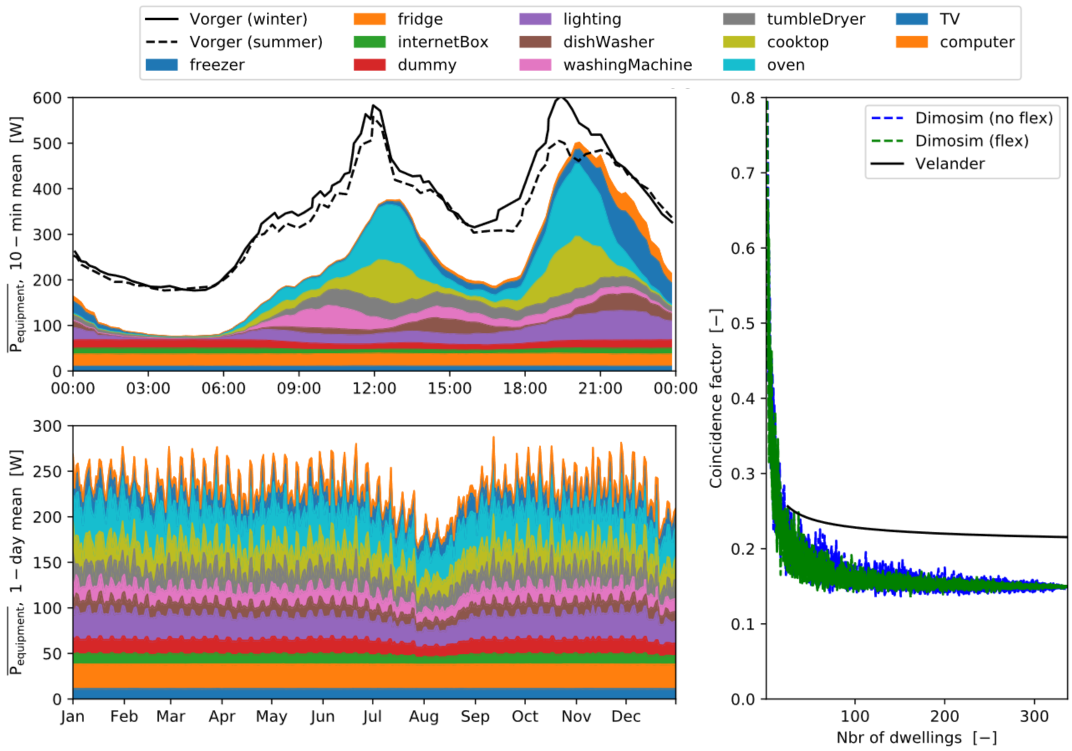

Figure 3: Average electrical load per household from appliances, heating excluded (left) and coincidence factor, heating included (right).

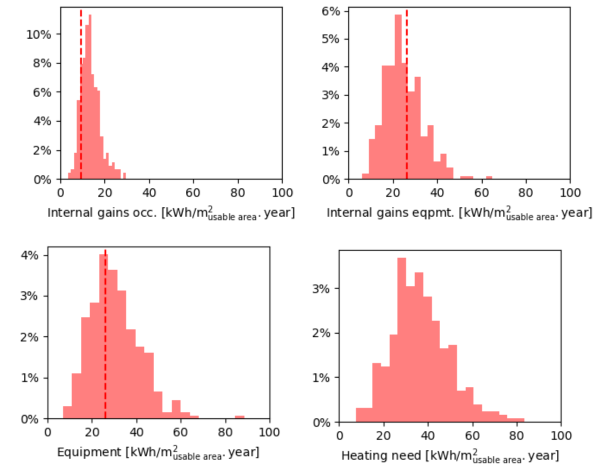

Figure 4: Yearly internal heat loads from occupants and equipment and yearly heating need.

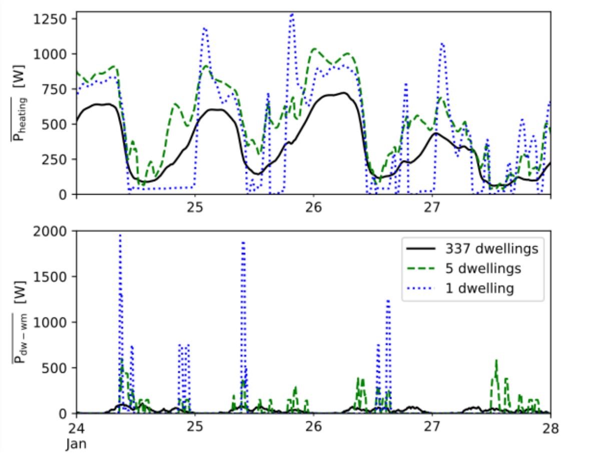

Figure 5: Mean electrical load of the heat pumps and dishwashers-washing machines for three winter days.

Flexibility: modelling and KPIs

The objective of activating flexibility on the considered district is to be able to decrease the electrical load from 6pm until 9pm. In fact, the stress on the electrical grid is usually at its maximum during this period in winter, when residential buildings use electricity both for space heating and cooking. The activation of flexibility is thus performed according to the need of a centralised electrical system and not according to a local energy production.

In this study, flexibility is activated every day over the same time period, by an economic incentive (such as a time-of-use tariff). Two energy usages will be set flexible: space heating and wet appliances (dishwasher and washing machine, noted *dw-wm*).

The flexibility on heating is activated semi-automatically by the dwelling thermostat, according to the occupants' preferences (tolerated temperature decrease) and presence within the dwelling. In case the setback is not used, the dwelling set-point remains constant over the day. In case the setback is used, the set-point decrease down to 15°C during unoccupied hours and 18°C during the night (these periods are defined according to the daily routine of occupants' activities). When activated for flexibility, the dwelling set-point decreases automatically during the period 6pm-9pm in case the dwelling is occupied *(Figure 5)*. In case the dwelling is not occupied during this time period and the set-back is active, the set-point is not modified.

The ability of the RC model to reproduce the temperature variations from set-point changes was tested against a detailed building energy simulation tool (multizone EnergyPlus model). Similar results were obtained, with errors below 0.5°C or 10% of the energy during the flexibility events (Le Dréau, 2019).

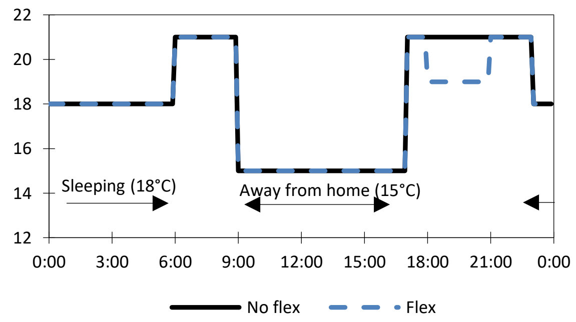

Figure 6: Example of temperature set-point in a dwelling (comfort set-point of 21°C and tolerance towards flexibility of -2°C).

The flexibility on wet appliances is activated manually by occupants using the built-in delay functionality. For each start of a dishwasher or washing machine during the time period 6pm-9pm (high price), the occupant decides whether shifting the start of the device. Modelling the flexibility potential relies on an agent which takes probabilistic decisions according to the hour of the day. The acceptability of occupants to shift some of the usages has been evaluated in the Belgian project Linear. The model has been validated against measured data in France, on households with single-rate or two-rate tariffs (Vellei et al, 2020). This flexibility potential is based on established routines and on occupants having a prior knowledge of the tariff structure. It should be highlighted that the considered time period (6pm-9pm) is not the most favourable one for gaining flexibility. Indeed, the little use of the dishwashers coincides with a high probability of shifting (40%), and the normal usage of the washing machines is concomitant with a little probability of shifting (15%).

KPIs. At the building scale, the flexibility from space heating and wet appliances cannot be accurately predicted and is not usable (*Figure 5*). Aggregated at district scale, the diversity of usages allows a better stability in the response to an external signal. An example of the aggregated flexibility potential over three winter days is presented in *Figure 7*. These results were obtained using the default values of *Table 1* and are expressed in relative terms ($\Delta P_i(t) = P_{flex\ i}(t) - P_{no\ flex\ i}(t)$). A decrease of the electrical consumption of the heat pumps and wet appliances can be observed during the period 6pm-9pm. The indicator used to characterise the flexibility potential is the mean load decrease per household (evaluated over the n_{HH} dwellings) between 6pm and 9pm (calculated with a time-step Δt of 10 minutes):

$$\overline{\Delta P_{flex\,i}} = \frac{1}{n_{HH}} \sum_{n_{HH}} \left(\frac{\Delta t}{60 \times 3} \sum_{t=18:00}^{t=21:00} \Delta P_i(t) \right) \quad [W] \qquad (1)$$

The sensitivity analysis will be conducted for the entire district (n_{HH} = 337) and for the 26th of January, which is considered as a typical winter day. $\overline{\Delta P_{flex\ heating}}$ and $\overline{\Delta P_{flex\ dw-wm}}$ are represented by the red lines in *Figure 7* for the considered case.

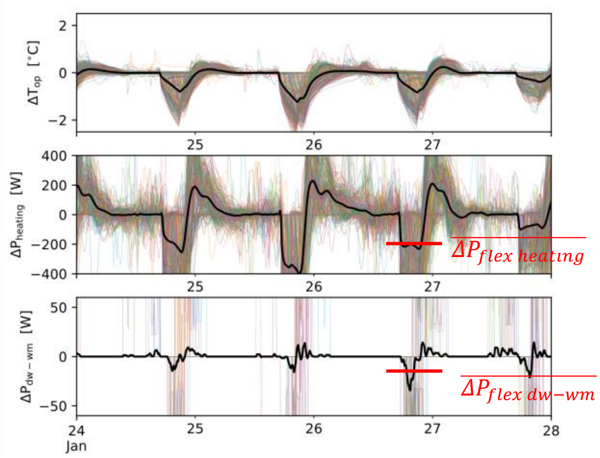

Figure 7: Variation of the operative temperature and electrical loads in the 337 dwellings (average temperature and loads represented by the black lines).

Methods for sensitivity analysis

The objective of the sensitivity study is to evaluate the influence of the occupants on the flexibility potential of a district, in order to identify the parameters that need to be accurately known or better characterised. As we are interested in a specific district, we assume no variation related to the physical characteristics of buildings (e.g. areas, orientation, level of insulation, properties of the production systems). It should however be highlighted that the results would be different for another insulation level (Le Dréau et al., 2019).

The descriptions and distributions of the evaluated parameters are given in *Table 1*. These parameters are related to the presence of occupants (*occNbr, occPctEmployed, scheduleSet*), their behaviour (*scheduleSet, heatingSP, heatingEco*) or their preferences towards flexibility (*flexdT, flexWmCycles, flexDwCycles*).

The sensitivity study is performed using the Morris methodology for 7 parameters with 10 different trajectories. This method has been selected for its robustness and rapidity of convergence (Goffart and Woloszyn, 2018). A total of 80×2 simulations, repeated for 10 different sets of occupants' schedules, were performed for the considered district.

Results and discussion

Flexibility on heating

The results of the sensitivity analysis are presented in *Figure 8* for space heating ($\overline{\Delta P_{flex\ heating}}$). μ* indicates the linear part of the total sensitivity score for each parameter while σ indicates the non-linear or interactive part. The uncertainty bars (in black on the figure) represent the influence of occupants' schedules on the considered parameters (5-95% confidence interval). The different occupants' schedules are represented in the model by a seed used to generate random numbers and pick the different sequences of activities.

From *Figure 8*, it can be observed that most of the evaluated parameters influence the flexiblity potential (mean effect between 5 and 15 W) and are correlated. This mean effect should be compared to the mean load decrease, equal to 178 W. This influence can be explained by the fact that the heating need in these low energy buildings is highly influenced by occupants, especially during the time period 6pm-9pm. Some occupants are not at work, some others are at home and their presence influences the heating need.

Table 1: Parameter variation considered for the sensitivity analysis.

	Parameter	Distribution	Default value
Presence of occupants	Mean number of occupants per dwelling (*occNbr*)	Uniform [1; 4]	2.22
	Percentage of workers (*occPctEmployed*)	Uniform [26%; 66%]	46%
	Set of occupants' schedules (*scheduleSet*)	Random seed [1; 9998]*	17
Heating	Default set-point (*heatingSP*)	Uniform [18°C; 22°C]	21°C
	Usage of set-back when away (15°C) & at night (18°C) (*heatingEco*)	Binary [Yes / No]	No
	Tolerated temperature decrease (*flexdT*)	Uniform [-2°C; -0.5°C]	-2°C
Dishwasher	Mean probability of shifting the cycle (*flexWmCycles*)	Uniform [20%; 70%]	40%
Washing machine	Mean probability of shifting the cycle (*flexDwCycles*)	Uniform [10%; 60%]	30%

* influence evaluated by Monte Carlo technique

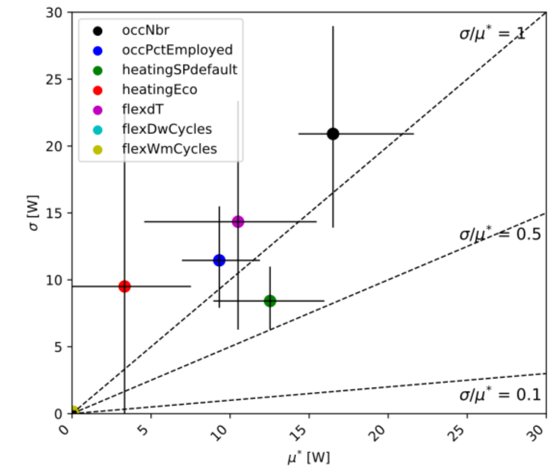

Figure 8: Results of parameter screening for heating flexibility ($\overline{\Delta P_{flex\ heating}}$, 337 dwellings) with Morris method.

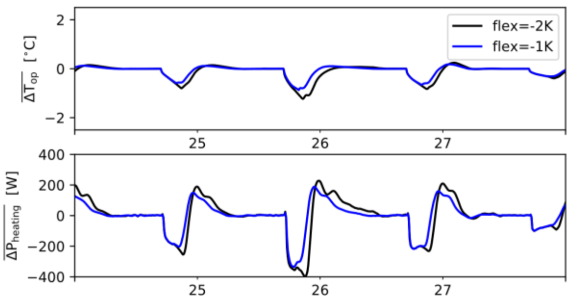

Figure 9: Influence of the tolerated temperature decrease on the mean load decrease (337 dwellings).

It can also be observed that the tolerance towards flexiblity influences only slightly the decreased power. The thermal inertia is indeed so high in these well insulated buildings that the temperature drops slowly, 1°C per 3 hours in average (*Figure 9*). The results would be different for a colder day or for older buildings.

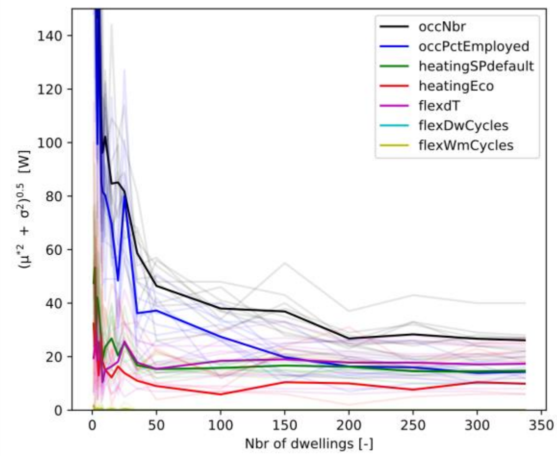

Figure 10: Mean effect of aggregation on the sensitivity of input parameters on heating flexibility ($\overline{\Delta P_{flex\ heating}}$).

From these simulation results, the positive effect of agggregation can also be observed (*Figure 10*). The global sensitivities strongly decrease when aggregating more than 50 dwellings, especially for the parameters related to the number of occupants and the percentage of workers.

In order to relate the influence of these parameters to the load shedding effect, it is important to observe the mean value of load decrease ($\overline{\Delta P_{flex\ heating}}$) for different aggregation sizes and for different occupants' schedule sets (*Figure 11*). The predictability of flexiblity increases much with the aggregation and a relatively reliable response can be obtained from 200 dwellings (178 W ± 15%). It can also be observed that the uncertainty on the response follows a Student's t-distrubution (displayed with a 95% confidence interval), caracteristic of a small sample size. Moreover, it has been observed a correlation between the mean load decrease and the mean internal loads (from occupants and equipement) during the considered time period.

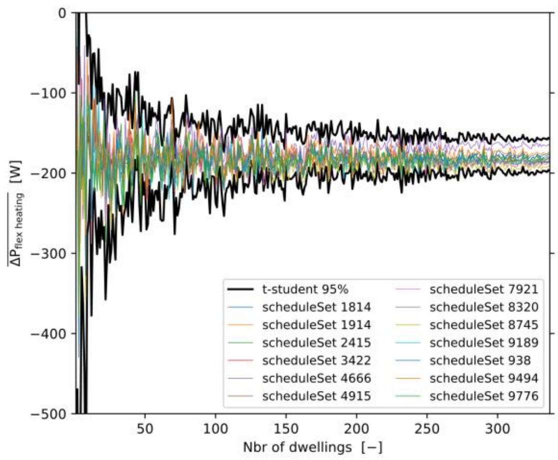

Figure 11: Effect of aggregation on the heating flexibility ($\overline{\Delta P_{flex\ heating}}$), default input parameters.

Flexibility on wet appliances

The results of the sensitivity analysis are presented in *Figure 12* for wet appliances ($\overline{\Delta P_{flex\ dw-wm}}$). The flexibility potential from these appliances is much lower than space heating (15 W vs. 178 W) and also less constant (*Figure 7*). The parameters related to the occupants' activities (*occNbr, occPctEmployed, scheduleSet*) have an influence similar to the one related to flexibility (*flexWmCycles, flexDwCycles*). In fact, this potential depends on both the usage and the flexibility tolerance of occupants. The mean effects of these sensitivity coefficients are in the same range as the mean flexibility potential. This indicates that the controllability of wet appliances' flexibility is difficult to achieve for this size of district due to the high level of interaction with occupants.

The influence of increasing the flexibility of washing machine is shown on *Figure 13*. An increase of the load shedding effect can be observed, but the magnitude is small. In fact, this influence is small as there is little use of this equipment during the considered time period.

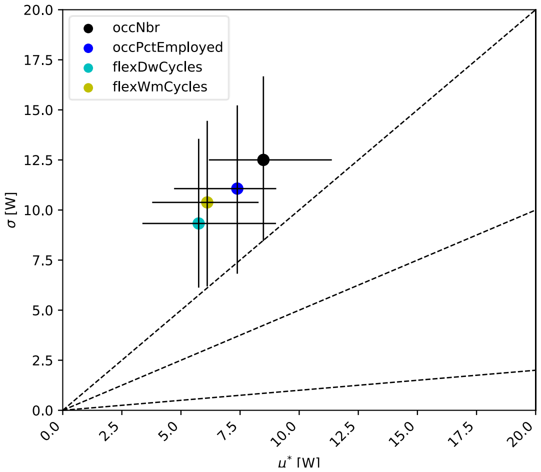

Figure 12: Results of parameter screening for wet-appliances flexibility ($\overline{\Delta P_{flex\ dw-wm}}$, 337 dwellings) with Morris method.

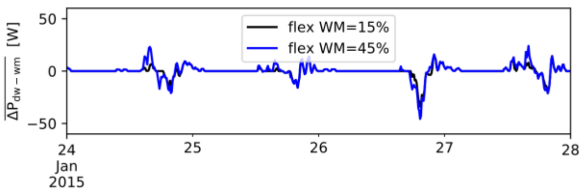

Figure 13: Influence of the flexibility tolerance on washing machine on the mean load decrease (337 dwellings).

Conclusion

The influence of occupant behaviour on the flexibility potential of a new district has been evaluated through simulations. A bottom-up approach is considered to model buildings and occupants. Occupants' activities are built upon the TUS data and form the basis of the energy usage of appliances. The flexibility on heating and wet appliances is based on agent-based models. Flexibility on heating is activated through smart-thermostats and occupants interact with the control system based on their presence. Flexibility on wet appliances is activated manually by occupants based on an external signal and their flexibility tolerance.

The mean load decrease between 6pm and 9pm is 178 W per household for the heat pumps and 15 W per household for the wet appliances for the day considered (26th of January). The sensitivity analysis showed the major influence of occupants when implementing an indirect control strategy for activating flexibility. At aggregated scale (337 dwellings), the effect of occupant behaviour can be estimated to ± 15% on the mean load decrease of the heating system. The influence of occupants is especially important in these highly insulated buildings, where internal and solar heat gains are of the same order of magnitude than the heating load. The wet appliances flexibility for the considered district is relatively difficult to control.

Moreover, the influence of the aggregation on the reliability of the response was observed. A stable response of the space heating flexibility can be obtained when aggregating 200 dwellings. For wet appliances flexibility, larger district should be considered. Aggregation is thus necessary to get a reliable source of flexibly that can be traded on energy markets.

Further work should be performed to evaluate the influence of occupants for different periods of the year and an uncertainty analysis should be performed considering occupants, building envelope, systems and climate uncertainty.

Acknowledgement

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