Determinants of energy flexibility in residential hot water systems

Attila Balint^a, Hussain Kazmi^{a,b,*}

^a*Enervalis, Belgium*

^b*ESAT, KU Leuven, Belgium*

Abstract

With increasing proliferation levels of variable energy sources, flexible energy loads will become increasingly important to help stabilize the energy grid. Increasing electrification of heating systems means that the thermal inertia of buildings and hot water vessels can provide a ubiquitous, low cost alternative to electrical storage for providing this energy flexibility. However, it is unclear how this flexibility fluctuates with various factors such as occupant behaviour and ambient conditions in the real world. This paper quantifies the effect of different influencing factors on the energy flexibility of residential hot water systems using data from a large scale real world pilot. All the houses considered in this analysis feature identical air source heat pump hot water systems, along with 200 litre storage vessels. It is shown that ambient conditions, control algorithm and occupant behaviour, all influence the available energy flexibility of the hot water system, albeit in different ways. Available capacity for energy flexibility and the corresponding recovery periods can differ by as much as two to four times for identical storage, meaning that these differences should be taken into account during operational planning with flexible loads. Additionally, it is shown that the implemented control strategy provides a meaningful avenue to alter the available energy flexibility. The paper also highlights key differences in the way these factors influence the overall energy demand when compared to available flexibility.

Keywords: energy flexibility, residential buildings, occupant behaviour, hot water systems, heat pumps, control algorithm

1. Introduction and Literature review

With the shift to distributed generation and more variable renewable energy sources in the supply mix, much emphasis has been placed on demand side management (DSM) and energy flexibility to help improve efficiency and stabilize the electric grid [1], [2]. DSM is, in itself, a broad, umbrella term for any mechanism which influences consumer demand, either automatically or through human intervention, to better align it with some supply-side constraints [3]. It includes both demand reduction (reducing energy consumption while still

*Corresponding author

Email address: hussain.kazmi@enervalis.com (Hussain Kazmi)

guaranteeing user requirements are met) and demand response (shifting energy consumption forwards or backwards in time) [4], [5].

Buildings represent one of the most important loads for the energy grid today, accounting for between 20 and 40% of the end energy demand in many countries [6], and can be an important source of energy flexibility and DSM. The change in consumer demand in buildings is usually achieved through either changing the behaviour of thermal loads (e.g. space heating or cooling, domestic hot water production etc.) [7] or electric loads (e.g. batteries, electric vehicles or white goods etc.) [8]. The central tenet of leveraging this flexibility is to avoid inconveniencing the end user (the building occupant in this case), i.e. any shift in demand must take user comfort into consideration [9].

Hot water systems represent a useful source of flexibility in buildings which can be utilized for grid-supportive behaviour. The energy consumed for hot water production accounts for between 10% and 25% of end energy demand in many countries [10], [11] and will gain in relative importance because of improvements in building envelopes reducing the share of space conditioning [11], [12]. Operational control of hot water systems has been explored in existing literature extensively, both in the context of optimizing local objectives such as energy efficiency [13], [14] and global objectives such as grid supportive behaviour [15], [16], [17]. Some examples of grid supportive behaviour include peak shaving, valley filling and maximizing self-consumption of local renewable energy. A detailed review of these use cases can be found in [18].

Energy consumption in buildings is influenced by a number of variables, both internal and external [19], [20]. Internal driving forces encompass different aspects of occupant behaviour and are, in turn, influenced by biological, social and psychological factors, while external factors include ambient conditions etc. The effect of ambient conditions, such as seasonal variations, on building energy use has been long recognized and planned for. However, today, it is widely understood that occupant behaviour also plays an important role in determining the energy consumption in buildings, even when everything else is held constant [21], [22]. This effect is particularly pronounced in modern, nearly zero energy buildings where occupant behaviour usually leads to large differences in actual and theoretical performance of the building, and is referred to as the human-gap between design and operation [23], [24]. Similar effects have also been observed for hot water systems where the number of people living in a household and their individual preferences determine the hot water and therefore end energy consumption [13]. Likewise, the choice of control algorithms also substantially effects the end energy consumption of thermal loads [14], [25].

Unlike energy consumption, the determinants of energy flexibility offered by thermal systems in general and hot water systems in particular remain poorly understood. There has been some recent work in this direction recently. For instance, [26] have quantified the available energy flexibility of combined heat and power plants (CHP) systems with district storage while [27] have used a data-driven model to quantify available energy flexibility of heat pump hot water systems. However, these do not distinguish among the many variables influencing flexibility. More recently, [28] and [29] have shown the clear link between ambient conditions and energy flexibility of heat pump based systems and the building thermal mass respectively. This causal link notwithstanding, other factors (especially the internal ones

relating to occupant behaviour) have not been addressed in existing literature, to the best of our knowledge. Likewise, there is no empirical evidence of whether there is any difference in the way these internal and external factors impact energy flexibility as opposed to energy consumption. Finally, in most existing literature, a common challenge has been the exact definition and quantification of energy flexibility. To address this, a set of unifying definitions has been proposed recently in the context of the IEA Annex 67 on energy flexible buildings [30]. However, this remains a work in progress, especially owing to the large number of factors which influence flexibility in the first place.

2. Contributions

This paper adds a missing link to existing research exploring the determinants of energy flexibility of residential hot water systems. More specifically, the focus of this research is on the available energy flexibility of a single device type: a modern air source heat pump (ASHP) connected to a 200L hot water buffer operating in a multitude of different situations. This focus allows for the link to be established between energy flexibility and the most important internal and external variables, irrespective of device specific variations.

The data necessary for this quantification arose in the context of a European Horizon 2020 project, REnnovates ¹. This project entailed, among other things, the renovation and smart control of hundreds of social houses in The Netherlands. Each of the refurbished houses was designed to be a net-zero energy building, equipped with identical hot water systems. Data gathering and smart control were carried out using the EEBUS interface², which enabled standardized communication between the local gateways installed in households and a central server gathering and analyzing data. Moreover, the project also had partners from Spain and Poland to investigate the replication potential in other climate conditions.

As shown in Fig. 1, the heat pump is responsible for both space heating and hot water production. However, the decision to focus solely on the hot water production system in this paper was based on the net-zero energy status of the considered buildings. Owing to deep refurbishment, these buildings had a very high thermal inertia which meant only minimal transmission losses. Likewise, infiltration and ventilation losses were minimized by treatment of thermal bridges and the installation of a heat exchanger system in the buildings. Taken together, these caused the building to retain any injected energy for a substantial period of time, leading to relatively low energy flexibility of the building's thermal mass. As a concrete example, it was observed that starting from an indoor temperature of 20°C, the indoor temperature in most considered buildings fell by less than 3°C after an entire day when the average outdoor temperature was around 0°C. The hot water vessel, on the other hand, displayed both higher thermodynamic losses (on average, the temperature dropped by more than 6°C in one day without any hot water consumption) and mixing losses (caused by hot water draws which replenish the available flexibility periodically). The higher losses were likely caused by the higher average temperature in the storage vessel and possibly a lower efficiency envelope (when compared with the building).

¹<https://rennovates.eu/>

²www.eebus.org

Figure 1: Sensor setup present in each house on all sites: 1. Outside temperature, 2-3. Water temperature at the outflow and in the tank, 4. Flow meter, 5. Smart meter, 6. Heat pump operation mode

The large number of households available for testing enabled the collection of a lot of different hot water consumption profiles as well as helping understand the behaviour of the hot water system when faced with these different demand patterns. To do so, the data gathered from these hot water systems was used to learn detailed data-driven models for the two components of the hot water system: the storage vessel and the heat pump. By combining these models with observed user behaviour and ambient conditions, the effect on available flexibility in terms of established metrics (energy capacity, efficiency and the recovery period) was quantified.

More concretely, this paper demonstrates the extent to which different factors affect the hot water system’s available flexibility which can be made available to the grid. It also identifies the conditions when this flexibility is at its highest or lowest, and provides exact quantification of how much flexibility can be elicited from the considered hot water system in real world conditions. The determinants of flexibility considered in this paper include occupant behaviour, ambient conditions (diurnal, seasonal and geographical variations) and the choice of control strategy. The paper shows that these factors influence energy flexibility in a way that is markedly different than their influence on energy consumption. Finally, this analysis brings to light important considerations about the practical use of such systems for grid supporting behaviour in terms of the actual available flexibility.

3. Methodology

The quantification of available flexibility requires a number of prerequisites to be met. A model of the system has to be available which describes device behaviour in all possible real world conditions accurately. With this model, different scenarios likely to arise in the real world can be simulated to derive system response, thereby better understanding the effect of influencing variables on flexibility. Formal definitions of energy flexibility in terms of quantifiable metrics are also required, and presented in this section.

3.1. Modelling the hot water system

A model describing the systems dynamics can be used to quantify its potential flexibility. This can be learned either offline or in a data-driven fashion. Offline modelling of thermal systems involves either white- or grey-box modelling techniques and relies mostly on the expertise of a human domain expert [13], [31]. Data-driven techniques, on the other hand, learn system dynamics using available sensor data [32]. Due to the large amount of data gathered in the REnnovates project, and the ability of data-driven models to generalize better to new types of devices, data-driven modelling was used in this paper.

Before describing the data-driven model in detail, it is important to note a few important characteristics of the system under consideration. Each heat pump under consideration came equipped with an inverter scroll compressor which can vary in power to minimal part load of about 40% in a couple of steps. The heat pump consumes, on average, 1 to 2 kWh of energy to reheat the storage vessel by 5 to 10°C. However, this is strongly dependent on both the ambient and inlet temperature, and can, in extreme cases, exceed even 5 kWh. The time required by the heat pump to reheat the vessel completely (i.e. from a completely drained state to a completely charged state) is over 2 hours; although this too varies with ambient temperature. The average coefficient of performance (COP) of the heat pump is between 2 and 4 for reheating the vessel from 45 to 50°C by 5°C with an ambient temperature between 0 to 10°C. The heat pumps are also equipped with an additional booster heater which is not controllable remotely, and is only employed when the heat pump cannot sufficiently reheat the vessel (this happens when the target temperature is above 55°C or when ambient temperature falls below -10°C in winter). This information is only for descriptive purposes and is not used in the modelling process, as the data-driven models are expected to learn device behaviour without any device specific information.

It is well-known that the quality of black box models improves with the amount of gathered data, provided the model has sufficient capacity to model the system dynamics [32]. In the limit, when the model has learned device behaviour accurately, additional data has no effect on the model. This happens when the gathered data is sufficient to describe the device behaviour to an arbitrary accuracy, or is only limited by the level of noise inherent to device behaviour (caused by stochasticity, partial observability or both).

For the modelling of the hot water system under consideration, two models were learned with available data that amounted to roughly 20 data-years of device behaviour. While not feasible with a single device, this data set was created by aggregating data from different households using identical hot water systems. The first of these models, the storage vessel model, learned the temperature distribution in the storage vessel as a function of its height. This was then used to estimate the state of charge with respect to a reference temperature. Likewise, the heat pump model was learned in a way that it would output the energy consumed by the heat pump to reheat the storage vessel from some state of charge to a target state of charge, given some ambient conditions.

The inputs to both models were features extracted from the raw time series data (observed via the sensors shown in Fig. 1). These raw time series corresponded to data from a temperature sensor installed mid-way in all the storage vessels as well as an ambient temperature sensor, a hot water flow meter and an energy meter measuring the heat pump's

electrical consumption. Feature extraction reduced the input dimensionality and considerably simplified the learning problem. These features corresponded to (1) the initial state of the storage vessel, (2) user hot water consumption since the last reheat cycle (which identifies user behaviour), (3) time elapsed since the last reheat cycle (which identifies thermodynamic losses), (4) the ambient temperature, and (5) the target reheat temperature. The last two features were used only by the heat pump model. For training purposes, over 600,000 samples were available for the storage vessel model, while the heat pump model had access to 24,000 samples. The large difference in training sample sizes for the two models was caused by the fact that while observations for storage vessel state are made every 15 minutes, there are only one to two reheat cycles every day, severely limiting the amount of data available for the heat pump model. 67% of available samples were used for training the models, and the remaining constituted the validation set.

The models themselves were deep neural networks that were trained with the available samples using stochastic gradient descent [14]. This corresponded to solving a supervised learning problem to identify weights which would minimize the mean absolute error of the predictions and was carried out for both the storage vessel and the heat pump to yield two separate models. The model parametrisation which minimized the prediction error was then selected for subsequent analysis.

3.2. Defining influencing variables

The models thus obtained allowed the hot water system to be simulated extremely accurately in a multitude of observed and unobserved conditions. In this section, we define the factors we use as input for the simulation besides the learned models:

3.2.1. Occupant behaviour

Occupant behaviour is defined as the hot water consumption over time by a household. The water flowing out of the vessel is constrained to be above 45°C at all times although the user can obviously mix it with cold water. The hot water flow is not sub-metered by load (e.g. for showers or dish washing etc.), but is rather given as an aggregated time series for each household representing water flow in litres. The sampling interval of this time series is 15 minutes and the observation period is a year for all houses considered in the analysis.

More concretely, occupant behaviour is not modelled in a data-driven manner, i.e. data-driven models are learned only for the hot water system. Rather, in subsequent simulations, the observed hot water draws for each household are sampled randomly from historic data observed for that particular household, according to the season under consideration. This ensures that the simulations actually refer to real world hot water consumption, as previous research has shown that predicting hot water consumption accurately can be a challenging problem in itself [13]. As the sample set is fairly large and sampled randomly, it can be considered representative of Dutch households in general.

3.2.2. Ambient conditions

Ambient conditions refer to the temperature in the geographical location the hot water system is being operated in. This can affect hot water system operation as the COP of

Figure 2: Weather data for the three considered locations: Amsterdam (The Netherlands), Krakow (Poland) and Bilbao (Spain)

the heat pump is strongly dependent on the ambient temperature (the storage vessel remains largely unaffected by the ambient temperature as it is contained within a conditioned space). These ambient conditions vary over the course of a day (diurnal variations) and a season (seasonal variations). Furthermore, geographical variations also influence ambient conditions, i.e. the winter day-time temperature in The Netherlands is different from both Poland and Spain. The ambient temperature for all three locations was obtained from the EnergyPlus website³, and is visualized in Fig. 2. As the learned models incorporate the ambient conditions as their input features, it was possible to understand their effect on energy flexibility. Since the hot water profiles for Poland and Spain were not available, the Dutch hot water profiles were also used for this case. As there is substantial variability in the observed hot water profiles, this should theoretically not lead to a large effect, however further work is required to test this assumption.

3.2.3. Control algorithm

While numerous controllers can be envisioned, two distinct controllers were employed in this analysis which have been adapted from previous analysis conducted by [13]. While both controllers can be simplified to a rule-based form to keep the analysis simple, one was designed to mimic default device behaviour and the other was a just-in-time controller to improve device efficiency.

The **default controller** operated according to a predefined threshold on the water temperature at the mid-point in the storage vessel. Every time this temperature dropped below a certain threshold, the heat pump was activated to reheat the storage vessel in a non-interruptible manner. This controller, while sub-optimal, requires minimal state estimation

³<https://energyplus.net/weather>

Figure 3: Control logic of rule based controller which operates on a fixed threshold (left) and energy efficient controller which operates on the storage state of charge (SOC) (right); mode 1 in both flowcharts corresponds to the initiation of a reheat cycle while mode 0 identifies the heat pump’s idle state

and processing power.

The **energy efficient controller**, on the other hand, used the vessel model learned previously to minimize its energy consumption. It employed a just-in-time controller which compared the available hot water in the vessel with the predicted user consumption. It reduced energy by postponing the reheat cycle as much as possible without compromising occupant comfort, which had the effect of lengthening the duration between reheat cycles. Additionally, a backup controller was implemented with this energy efficient controller to ensure no loss of occupant comfort.

These strategies are illustrated in the flow-chart in Fig. 3.

3.2.4. Hot water system

The nature of a hot water system determines its flexibility. However, there is a bewildering variety of hot water systems and, as it is not possible to analyze all these systems in detail, we focus on a single system to quantify the effects of other influencing variables. Therefore, differences in the hot water system are not considered further in the paper.

3.3. Flexibility metrics

So far, the factors influencing energy flexibility and data-driven models to quantify it have been presented, without formally defining the metrics characterizing this flexibility. In this section, the metrics used to quantify flex are defined, which build upon [33]. The

flexibility of the device is requested during an automatic demand response (ADR) event. The ADR events were simulated as a positive infinite flexibility request with daily frequency for a given hour. This meant every heat pump, regardless of the vessel state, was requested to turn on at a specified hour, every day of the year. The one-year long simulation resulted in the mean maximum flexibility for that hour for every given house. This one-year long simulation was rerun 24 times with different ADR event times (i.e. for all hours of the day for every single house). These results were then analysed in individual or aggregated form. In reality, the ADR event need not be activated with a fixed 24 hour sampling interval, i.e. other sampling intervals - both longer and shorter - are also possible. The minimum duration between ADR events will be addressed in subsequent sections.

3.3.1. *Type of flexibility*

As the hot water system is considered to be a thermal storage system, the focus of this research is on using the heat pump as a means to consume more power (i.e. to provide up-regulation). Providing down-regulation to the grid, or consuming less energy at any given time, would require a much larger population of heating devices which would need to be on at any given time. While this is true in winter time when the heat pumps are used for space heating, it is definitely not true over the course of an entire year especially for hot water operation [28]. Therefore, for down-regulation to be feasible in any meaningful sense of flexibility, thousands of hot water systems would be required. For this reason, the subsequent sections focus on providing only up-regulation to the grid using hot water systems (whereby the hot water systems are requested to consume more energy than a default baseline after an ADR event).

3.3.2. *Capacity*

The capacity of a flexibility bearing device is the amount of energy that can either be stored in or drawn from it at any given time, and is measured in kilowatt-hours. The capacity is a function of the storage mechanism, which in this case is the hot water storage vessel.

The amount of energy that can be injected into the storage vessel is limited because of hardware constraints (i.e. the heat pump cannot heat the storage vessel water beyond a certain limit). Furthermore, as the energy is stored as heat, no electrical energy can be retrieved. This energy is also lost to ambient over time due to thermodynamic losses. However, by preheating the storage vessel, it is possible to change the time and duration of energy consumption. Furthermore, due to thermodynamic losses, the storage capacity is automatically regenerated over time. Occupant behaviour can further accelerate this regeneration: this is discussed further in the section on recovery period.

More concretely, this metric defines the available structural storage capacity for active demand response (C_{ADR} [kWh]) as the amount of electrical energy that can be added to the storage element in the form of heat during an ADR event, without jeopardizing occupant thermal comfort. The available storage capacity is given by the integral of the difference between the electric power used for heating during an ADR event (Q_{ADR} [W]) and the power consumed in normal operation (Q_{Ref} [W]):

$$C_{ADR} = \int_0^{l_{ADR}} (Q_{ADR} - Q_{ref}) dt \quad (1)$$

3.3.3. Activation

Device activation is, unlike capacity, a temporal measure of the power that can be provided to the grid or consumed from it at any given instant. As the heat pump can only consume electrical energy (and not generate it), the majority of flexibility offered by a heat pump is in the form of upwards regulation, as mentioned previously. In general, the power shift (Q_δ [W]) is defined as the difference between the heating power during the ADR event (Q_{ADR} [W]) and the reference heating power (Q_{Ref} [W]) during normal operation. Starting with the vessel in a given state, the thermal response of the vessel is activated and the change in the heating power is estimated using the learned model.

$$Q_\delta = Q_{ADR} - Q_{ref} \quad (2)$$

3.3.4. Efficiency

As alluded to already, flexibility can frequently come at the cost of energy efficiency. By activating the heat pump to preheat the building or storage vessel, thermodynamic losses increase. These losses drive down energy efficiency in the long run. The relationship however is more complicated in reality as complex interactions between energy losses and occupant demand can lead to unexpected behaviour. These effects are documented in greater detail in the results section.

The storage efficiency (η_{ADR} [-]) is defined as the fraction of the heat that is stored during the ADR event that can be used subsequently to reduce the heating power needed to maintain thermal comfort. The efficiency is calculated using the same simulations that are used to quantify the storage capacity. Given these simulations, the efficiency is calculated as:

$$\eta_{ADR} = 1 - \frac{\int_0^\infty (Q_{ADR} - Q_{ref}) dt}{\int_0^{l_{ADR}} (Q_{ADR} - Q_{ref}) dt} \quad (3)$$

The integral in the denominator is equal to the heat stored in the storage element during the ADR event (i.e. the available storage capacity (C_{ADR})). A part of this heat can be used after the ADR event to reduce the heating power needed to maintain occupant comfort. The numerator represents this fraction of the heat stored during the ADR event that is not recovered over a long period.

3.3.5. Recovery

Once flexibility has been requested from a storage mechanism, there is a subsequent recovery period during which time additional flexibility cannot be offered. While this can be either because of device or occupant comfort constraints, it is important to quantify the time period during which the device cannot be activated again. Once this time period has elapsed, the flexibility is available once more. Formally, the recovery period is defined as

Figure 4: Estimation error for the two learned models: (left) storage vessel model, (right) heat pump model

the time duration it takes for the storage tank to return to normal operation after an ADR event, i.e. $Q_\delta = 0$.

4. Results

4.1. Model accuracy

In this section, we present results of the data-driven model’s accuracy and its general suitability for simulation purposes. The mean and spread of the prediction errors are therefore both vital metrics.

4.1.1. Hot water vessel model

The hot water vessel model is tested using a held-out test data set, as described earlier. While the mean error is reassuringly close to zero, the mean absolute error hovers around 0.5 °C. This is quite close to the precision of the temperature sensor which is also 0.5 °C. The residuals of the model’s temperature prediction are also normally distributed with a standard deviation of less than 1 °C.

4.1.2. Heat pump model

The data acquired for the heat pump is one to two orders of magnitude fewer than the data available to train the storage model vessel. Despite this, the model has learned an accurate representation of the heat pump. The error is, as for the case of the storage vessel, normally distributed, with a mean close to zero. The average error for a single reheat event is, in general, less than 10% of the total energy consumption which means that the model can be used to accurately simulate the behaviour of the hot water system.

A histogram of the error distributions for the storage vessel and the heat pump are shown in Fig. 4.

Figure 5: Effect of user behaviour on available energy capacity [kWh] with different control strategies; individual dots refer to results obtained for different households

4.2. Capacity

As mentioned in the previous section, the capacity of a flexibility bearing device is an indication of its ability to store or provide energy. This section provides a detailed analysis of the effect of different factors on the available capacity of the hot water system.

4.2.1. Occupant behaviour

To investigate the impact of occupant behaviour on available capacity for energy flexibility, we keep the other factors under consideration constant. As a result, it is seen that with increasing hot water demand, the vessel's energy capacity increases up to a certain limit, and then stays constant. The initial increase in capacity with consumption is caused by mixing (or consumption-driven) losses, which lead to the possibility of injecting more energy into the storage vessel. When there is insignificant user consumption, the energy capacity of the vessel is constrained by thermodynamic losses to the ambient. Therefore, the energy capacity of the vessel increases from this baseline when building occupants consume a lot of hot water over the course of a day (approaching or exceeding the vessel capacity).

The effect, while being significant, is not particularly large, i.e. a doubling of water consumption does not lead to a doubling of energy capacity. It was found that capacity fluctuations, as a function of user behaviour, are on the order of 10 to 20% when compared with the baseline. These results are shown in Fig. 5.

4.2.2. Choice of control algorithm

The choice of control algorithm also plays an important role in determining the flexibility of the device under consideration. As explained earlier, two distinct controllers are considered to simplify the analysis. The efficient controller tries to postpone reheat cycles as much as possible, thereby minimizing thermodynamic losses and improving heat pump efficiency (by reducing the average temperature of the water at the inlet). However, it also influences the available capacity of the storage vessel as is evident from Fig. 5, and results

Figure 6: Effect of diurnal ambient condition variations and control algorithm on available energy capacity [kWh]; transparent traces represent the behaviour of individual households while bold lines indicate the averaged behaviour

in an increase of available capacity by an average of 20%, irrespective of user behaviour. However, as will be explained later, this also has important repercussions for other aspects governing device flexibility.

4.2.3. Effect of ambient conditions

There are a number of factors that influence the ambient conditions under which a hot water system operates. These include diurnal and seasonal temperature variations which can influence the heat pump's COP. Additionally, identical devices operating in different countries or regions (i.e. variations in geographical conditions) will also exhibit differences in available flexibility. These effects can be summarized as follows:

1. **Diurnal variations** were observed to increase or decrease the available energy capacity of a hot water system by up to 15%. Generally higher temperatures during the day mean that less flexibility is available during day-time hours even when accounting for occupant behaviour and controller. For countries in North-Western Europe where there is only a small difference in day and night temperatures during winter (such as The Netherlands), this effect is most pronounced in the non-winter months. These effects are highlighted in Fig. 6.
2. **Seasonal variations** have arguably the largest effect on the available energy capacity of a storage vessel. The increase in available device capacity can be up to 50% for the efficient controller from summer to winter, and almost 70% for the rule-based controller. Keeping in mind the diurnal variations, the effect of ambient conditions can be considered even larger. These effects are visualized in Fig. 7.
3. **Geographical variations** has a largely similar effect to the diurnal and seasonal variations in the sense that different countries have very different climates (Fig. 2). Here, we run our simulations for different countries assuming similar hot water consumption

Figure 7: Effect of seasonal ambient condition variations and control algorithm on available energy capacity [kWh]: (a) Rule-based control; (b) Energy efficient controller

profiles as those observed in The Netherlands. While this assumption is not necessarily true, it provides an indication of how the same hot water system would behave in a different geographical location. It is seen that in Poland, the same device has a much higher flexibility potential than in Spain where it is lower by almost 25% throughout the day. This is shown in Fig. 8.

4.3. Efficiency

While all the factors identified and discussed so far have a large effect on the available energy capacity of the storage vessel, it is interesting to also look at their effect on the storage efficiency. Efficiency, in this context, is defined as the amount of usable heat arising from the ADR event. Here, unlike with available energy capacity, the effect is mostly dominated by user behaviour and the control algorithm. These can account for substantial variations of between 30 and 50% in the achieved efficiency of the hot water system. It is important to stress here that this efficiency is not the device efficiency in general but the device efficiency in case of an ADR event. These relationships are shown in Fig. 9. It is obvious from this visualization that the average efficiency hovers below 0.7. This implies that, regardless of user and controller behaviour, an ADR event will cause a substantial loss of energy from the vessel, and marks the inherent trade-off between efficiency and flexibility.

4.4. Power shifting potential

This effect is visualized in Fig. 10 with an ADR activation hour of 6 o'clock. This time of activation is clearly visible as a red vertical line where all heat pumps consume power to reheat the storage vessel, i.e. the ADR activation increases the energy consumption significantly compared to the original behaviour. It is important to note that different heat pumps consume different amounts of power, even when activated at the same time, because of the varying SoC of the storage vessel in different households. A rebound effect is present after the activation, where the Q_{ADR} turns negative for some period. This period is longer in houses with low consumption and gets shorter as water consumption increases,

Figure 8: Effect of geographical ambient condition variations and control algorithm on available energy capacity [kWh]

Figure 9: Effect of occupant behaviour, ambient condition variations and control algorithm on efficiency

Figure 10: Effect of occupant behaviour and control algorithm [left: default controller, right: energy efficient controller] on the power shifting potential of the storage vessel

as anticipated. After the negative period, a second positive peak can be observed, albeit generally much lower than the peak at activation. The same experiment was repeated for all hours of the day with largely similar results.

4.5. Recovery

The different factors considered so far influence recovery in a highly inter-connected manner. The energy efficient **controller** lengthens the recovery period by two to three hours, or about 20%, on average compared to the rule-based controller, just as it increases the average time between reheat cycles. Compared to the rule-based controller, this generally longer recovery period can be observed in Fig. 11.

The recovery period is also strongly influenced by the **occupant behaviour**, as higher hot water demand leads to a quicker recovery. In households with very low water consumption (lower than one quarter of the storage capacity on a daily basis) the recovery period can be even higher than 24 hours, which can reduce the amount of flexibility these devices offer considerably as shown in Fig. 11. It is straightforward to see that, at low consumption, the difference in recovery times across controllers are not governed by user behaviour. However, with increasing occupant demand, the recovery period reduces drastically, by a factor of around two for the rule based controller (i.e. from 16 hours to 8 hours) and by almost three for the efficient controller (i.e. from 18 hours to only 6 hours).

Figure 11: Effect of geographical ambient condition variations and control algorithm on available energy capacity [kWh]

Very low recovery periods caused by occupant behaviour can ensure that there is a constant supply of households available to provide flexibility to the grid. On the other hand, high hot water demand substantially increases energy consumption, a topic addressed in a subsequent section. On the other hand, the recovery period is relatively unaffected by ambient conditions such as seasonal or geographical variations. This is largely the case because the ambient conditions mostly affect the heat pump operation while the recovery period is determined by the storage vessel. The storage vessel, as mentioned earlier, is located in a conditioned space, which reduces its exposure to the elements, and the consequent thermodynamic losses.

4.6. Quantifying flexibility

So far, the focus of this study has been on describing the flexibility in relative terms, i.e. how different flexibility metrics are affected by various determinants. To provide grid services, it is also important to quantify the absolute values for flexibility. More concretely, based on results so far, it can be concluded that the considered hot water system can provide energy storage capacity which varies between 600 Wh and 1500 Wh. In general, the highest capacity can be elicited from the system in colder climates with an energy efficient controller and occupants consuming substantial amount of hot water on a daily basis. The activation potential, which identifies the amount of instantaneous power that can be drawn from the electric grid, is, on average, 1 kW but can vary by as much as 25% in either direction. Finally, the recovery period is, on average, close to 10 hours, although this too can vary substantially. In any given population, the more extreme occupant behaviour will be smoothed out. Taken together, the hot water system under consideration can therefore act as a storage medium of roughly 1 kWh / 1 kW that can be activated at least twice every day. Scaling by the number of households equipped with such systems, this provides a remarkable amount of flexibility to the electric grid. In other words, with 100 such hot water systems, it is possible to provide a storage capacity of roughly 200 kWh, while providing activation potential of 100 kW. In many real world contexts, this amount of flexibility can sway the decision in favour

of ADR, rather than (local) grid reinforcement. However, it has to be kept in mind that the use of hot water systems as flexible loads incurs an efficiency loss of around 30%, which means much higher energy consumption than the baseline which does not involve ADR.

4.7. Determinants of energy consumption

So far, the focus of this paper has been to investigate the impact of different factors on the energy flexibility of a hot water system. In this section, a brief overview of how they influence energy demand, and how this differs from the influence on flexibility is presented.

1. **Occupant behaviour** has a disproportionate effect on energy consumption. Increasing average daily hot water demand from, for instance, 100L to 200L increases the energy demand by over 50% on average, keeping everything else constant. Contrast this to the effect on flexibility where a similar change would increase the available capacity by less than 10%. Changes to energy flexibility as a function of occupant behaviour therefore seem to deviate significantly from how energy is consumed by the hot water system. In other words, occupant behaviour appears to primarily define energy consumption. In terms of energy flexibility, it only has a large influence on the recovery period of hot water systems, especially in extreme conditions, i.e. when occupant demand is extremely low or high.
2. **Choice of control algorithm** substantially effects end energy demand, keeping everything else constant. For this particular hot water system, energy demand can be reduced by almost 20% when transitioning from the rule-based controller to the efficient controller [14]. This is broadly in line with the changes observed in the available flexibility, and there indeed exists a causal link between the two (the efficient controller exploits the inherent flexibility in the storage vessel to minimize energy demand).
3. **Ambient conditions** influence the energy demand of the hot water system in a manner fairly similar to how they affect the energy flexibility. More concretely, there is a factor of two difference between summer and winter energy demand for the same hot water demand and control algorithm. This is largely in line with differences observed in available flexibility.

5. Conclusions

This paper has quantified the energy flexibility inherent to hot water systems and investigated its key determinants. While similar to the determinants of energy consumption in a building, there are nevertheless important differences. The most important of these is, rather surprisingly, in the way occupant behaviour influences available flexibility. This section summarizes key findings and highlights important aspects which need to be considered when leveraging the flexibility offered by these devices.

Ambient conditions, including diurnal and seasonal variations in temperature, play a major role in determining the extent to which a hot water system can be operated flexibly to provide value added services. In general, device flexibility is highest during (cold) winter nights and lowest during (warm) summer afternoons. However, time of the day and year

is not the only influencing factor here, and the geographical location in which the system is being operated also substantially effects its available flexibility. The same system, with everything else held constant, has higher flexibility potential in Poland than in The Netherlands and Spain. The unifying theme for this space-time variation of flexibility is of course the ambient temperature conditions. This finding only holds for air source heat pumps, other heating technologies which are not dependent on ambient conditions, such as gas or electric boilers, would not show this strong dependence on ambient conditions. Additionally, the energy flexibility of such devices (in terms of capacity and activation potential) would likely be much higher because of the comparatively low efficiency of these technologies.

The choice of **control algorithm** plays an important role in the available flexibility as well. With a more energy efficient controller, it is possible to elicit higher capacity on average from the same hot water system. However this comes at the cost of a longer recovery period. This suggests at least one additional avenue for optimal control where controllers can be designed based on the grid supportive behaviour that is expected of them. If the hot water systems are expected to only provide large amounts of flexibility infrequently, an efficient controller will work better at providing this flexibility. On the other hand, if limited amounts of flexibility is required often and on a periodic basis, a less efficient controller could very well perform better. The loss of efficiency in this case, leading to higher energy costs, however has to be counteracted by other incentive mechanisms.

Finally, **occupant behaviour** also influences device flexibility, albeit in a rather round-about manner, and much less than it affects energy consumption. There are numerous reasons for this. Primarily, available flexibility is limited by constraints on occupant comfort which ensure that the system can only be operated within certain bounds. Furthermore, occupant behaviour works in tandem with thermodynamic losses to determine the capacity and recovery period of a device. This means that increasing hot water demand for users leads to only somewhat higher capacity, similar to the use of a more efficient controller. However, unlike with the controller, higher consumption also leads to a generally shorter recovery period. This means that households with higher consumption can provide more flexibility to the grid, more often. In conjunction with smart controllers, this difference can be rather substantial with recovery periods varying by a factor of almost three.

Quantification of energy flexibility available via flexible loads remains an active area of research. The fact that different controllers and occupant behaviour influence energy flexibility significantly further complicates its quantification in a standard form by adding yet more degrees of freedom. The energy flexibility of the system under consideration was found to vary by over 25% on all dimensions of interest (capacity, recovery, efficiency and activation potential). Nevertheless, on average, it seems that the considered system can provide over 2kWh's of storage capacity in two separate ADR events over the course of a day.

This analysis of the flexibility of hot water systems also has important repercussions for the use of hot water systems in grid supportive roles. More concretely, in most Northern European countries, hot water systems have been considered as a means to reduce the peak injection of solar production during the summer months. However, the flexibility of such devices is generally at its lowest during this period. This information, and not the average

flexibility of these devices, has to be taken into consideration during operational planning of modern grids. In the more general context, care must be taken to account for these differences in energy flexibility of the same system which can vary by as much as three to four times depending on ambient conditions, occupant behaviour and choice of controller.

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