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Electric water heater flexibility potential and activation impact in system operator perspective – Norwegian scenario case study

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ABSTRACT

Simultaneous activation of demand side flexibility on thermostatically controlled loads will cause adverse impacts later in the form of rebounds. Distribution system operators must know the characterisation of the impact, as they are responsible for voltage quality of power delivery and suffer the loss of lifespan of network components due to overloading. In this paper, characterising parameters for flexibility activation on electric water heaters (EWHs) are proposed and flexibility potentials are computed considering smart activation methods for the Norwegian scenario. The proposed parameters are rebound percentage, delay, ramp rates, second peak distance, activation error, flexible power, and temperature deviation. Four scenarios with different levels of flexible power and activation time are developed in the Norwegian context for quantification of the flexibility potentials and the parameters. The highest average flexible power potential is 53.9% at 8:00 a.m. for a duration of 61 min. EWHs flexibility activation can serve as Frequency Containment Reserves (FCR) at peak demand hours with high ramp-up and ramp-down rates of 48.5% and 23.8% per minute and as Frequency Restoration Reserves (FRR) during non-peak hours.

1. Introduction

1.1. Background

Increasing electricity demand and rise in the share of fluctuating renewable energy sources (RES) drive distribution system operators (DSOs) to look for flexibility at demand side [1]. The demand side flexibility can be evaluated as an alternative to network reinforcement to provide reliable utility services [2]. In the domestic segment, electric vehicles (EV) [3], and thermostatically controlled loads (TCLs) such as space heaters (SH) and electric water heaters (EWH) [4], are promising candidates for flexibility services, as they are power-intensive gadgets [5]. In addition, TCLs have thermal inertia by which their service interruption for a shorter duration will not be noticeable by the end user [6]. In the residential sector, a section of white goods that are shiftable loads are called atomic loads [7]. The loads which have 'atomicity' are classified as atomic loads. Non-interruptibility and non-throttleability of energy consumption patterns specific to their operations are defined as atomicity [8]. Other devices such as freezers, fridges, and shiftable atomic loads are less interesting as their power rating is low [5]. For shiftable atomic loads, the activation has never been conceived to be direct control rather through implicit mechanisms like price signals. In such aspects, TCLs can be interrupted at any time unless they are heat pump type.

1.2. Related work

1.2.1. TCL models and DR applications

The demand response (DR) and flexibility potential of TCLs are studied and presented in many papers [9–12]. Reference [9] presents a systematic review of motivations and barriers to engage the residential consumer to participate in a demand response program. The indication suggests residential user engagement is not simple. Though financial motivations are important in enrolment, but user engagement appears to play key role. Demand response may be reached if it is less disruptive to existing routines. The user experience is different for different users. User engagement is influenced by multiple aspects like familiarity, trust, perceived risk, and perceived control over characteristics of demand response products and services. Reference [10], concludes direct load control of devices is preferred most and financial incentives motivates to

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Abbreviations

BRP	Balance Responsible Party
DSO	Distribution System Operator
DR	Demand Response
ESS	Energy Storage System
EV	Electric Vehicle
EWH	Electric Water Heater
FCR	Frequency Containment Reserve
FRR	Frequency Restoration Reserve
HVAC	Heating Ventilation and Air Conditioning
ICT	Information and Communication Technology
ISE	Integral Square of Error
NISE	Normalised ISE
RC	Resistance Capacitance
RES	Renewable Energy Resource
SH	Space Heater
TCL	Thermostatically Controlled Load
TSO	Transmission System Operator

Symbols in equations

AD_{flex_end}	Actual demand at end of flexibility activation
ARP	Absolute rebound percentage
C^k	Thermal capacitance of EWH (k)
$DAFA$	Demand after flexibility activation
FAD	Flexibility activation delay
E_{aEWH_ON}	Aggregated energy of all water heaters which are ON
N	Total number of EWHs
N_{ON}	Number of EWHs which are ON
ND	Nominal demand
ND_{flex_start}	Nominal demand at the beginning of flexibility activation
ND_{flex_end}	Nominal demand at the end of flexibility activation
$NISE$	Normalised ISE
P_{nom}	Nominal power rating of an EWH
P_m^k	Rated power consumption of EWH (k)
R^k	Thermal resistance of EWH (k)
RDR	Ramp down rate in % per minute
RPP	Rebound peak power
RRP	Relative rebound percentage
RT	Rebound time in minutes
RUR	Ramp up rate in % per minute
S^k	ON OFF control of EWH (k)
t_{act_max}	Maximum possible flexibility activation time
t_{flex_act}	Actual flexibility activation time for the analysis
t_{ST}	Start time of flexibility activation
T_a	Ambient temperature
$T^k(t)$	Water temperature of EWH (k) at any time t
T^k_{min}	Minimum temperature threshold of EWH (k) at any time t
T^k_{max}	Maximum temperature threshold of EWH(k)

participate in DR programs more than the power tariff change. The energy flexibility potential of a hot water-based heating system in smart buildings is studied in Ref. [11]. The authors propose an economic model predictive control method to provide flexible services to power systems. A price signal from a day-ahead electricity market is used to drive the control strategy for heat pump coupled with thermal energy storage along with the thermal model of building and heating systems. The challenges in implementing an economic model predictive control for heating systems are detailed in Ref. [12] using an experimental study in a family house where a control system (smart house) is installed. The TCLs can be modelled by many modelling approaches which can be broadly classified as white-box, grey-box, and black-box methods [13]. The order of the model to be used is decided by the dynamics to be captured. For example, grey-box modelling of heat dynamics of buildings is presented [14–16], which uses models higher than first-order. Reference [16] presents the complications in finding parameters for higher order models. More detailed data representing temperature at different zones, climate data, location information and controlled heat input are important create a model close to reality. The simplest and most used model is a first-order model to represent EWHs [17,18].

DR activation on TCLs to provide different power system services are studied in detail in Refs. [19–22]. In Ref. [19], the authors propose a virtual flow meter-based model for heating ventilation and air conditioning (HVAC) system in buildings to activate DR to provide smart grid services. The DR potential of an individual building or household is negligibility small in comparison with the total capacity of the subnet in the distribution network. Therefore, the general approach is by aggregating the controllable demands and activating DR for power system services [23,24]. The aggregated model of fast-acting DR and control based on real-time pricing from the market is studied in Ref. [20]. In Ref. [21] the authors propose optimized control of community heating system to mitigate over voltage problems in a community with RES penetration. A power to temperature sensitive model is proposed which uses average temperature change by omitting other thermodynamics. A Continues demand response of building HVAC is proposed in Ref. [22] for frequency regulation in smart power grids. The authors considered both financial rewards and thermal comfort for the control strategy. In an unbundled electricity market, a domestic customer is free to choose any electricity retailer [25]. Similarly, if there are multiple aggregators, the end-user is free to choose any aggregator of their preference. In a situation where the DR is performed based on market incentives, the DSO will not know about DR activation and its consequences.

1.2.2. Flexibility potential and impact of flexibility activation

The operation of TCLs is synchronised due to the typical daily routines of individual houses and their overlapped demand profiles [26,27]. Unlike space heaters, EWH operations are dictated by hot water demand by the user which strongly depends on the lifestyle [28]. In Norway, the flexibility potential of domestic water heaters is 600 MWh/h during morning system peak hours even if half of the consumers are flexible [4]. As part of the digital transformation in the power sector, smart home control is being offered as a service by electricity retailers in Norway [29]. The cost of a control solution starts from ca. € 100. An average household in Norway has the potential energy saving of up to 1073 kWh using automatic control [30]. The average total cost of electricity in Norway is 0.12 €/kWh [31]. With the current average total cost of electricity, the cost of control can be recovered within one year from the energy savings.

With the present technology, EWHs can be forced to turn off by disconnecting their power supply. Uncontrolled or blind flexibility activation, which is the only possibility with the current technological infrastructure, can cause rebound [32] and the rebound peak may worsen the situation by causing voltage and network congestion problems, and frequency problems [33,34]. Reference [34] proposes a battery energy storage system to mitigate demand rebound due to EWH. The DSO should have the necessary knowledge about the maximum duration for which the DR can be activated on all EWHs with blind activation to activate maximum power reduction and the rebound consequences of DR activation. Also, the DSO should have knowledge of rebound reduction techniques and their sensitivity to flexible power and duration of flexibility activation. Although there is significant research available on system modelling, methods for load shifting, demand prediction, closed-loop control of demand, and use of flexibility to provide power system services, the methods to assess flexibility potential, characterisation of the impact of flexibility activation and methods for rebound reduction in terms of the DSO perspective are not studied thoroughly.

1.3. Contributions

In this paper, 1. a simplified method to assess the flexibility potential and to calculate flexibility activation duration, and flexibility potential at different hours of the day from a group of water heaters are computed and presented, 2. the impact of flexibility activation is characterised, 3. four different scenarios for rebound reduction, their characteristics are classified and their suitability for different power system ancillary series discussed. A simple first-order model of EWH with lumped parameters is used to represent its operation in family houses. The model is used to calculate power consumption profiles and temperature deviations along with hot water usage profiles from real households to create real-life scenarios. The blind flexibility activation is applied to the created scenario for the impact analysis. The impact of blind flexibility activation is quantified with their rebound peak, rebound peak occurrence time, ramp up and ramp down characteristics, and the second peak and its occurrence time. A simple rebound reduction technique by controlling flexible power and flexibility activation duration is proposed. The proposed rebound reduction method is applied to the base scenario and the results are compared. The rest of the paper is structured as follows: Section 2 describes the method for flexibility activation time calculation and rebound reduction technique. Further, section 3 presents the base scenario of a group of 1000 water heaters' operation with a simple first-order resistor-capacitor (RC) model. Section 4 compares and discusses the numerical results of different rebound reduction cases with the base case scenario and section 5 provides the conclusions and scope for future research.

2. Methodology

In this section, the working principle of EWH, first-order differential equation-based EWH model, a method to calculate flexibility activation time based on the energy content, and a correction for flexibility activation duration based on the number of active EWH in the total population are presented.

2.1. EWH operation and flexibility

EWH operates between two temperature bounds, namely higher and lower thresholds. When the temperature of the water drops below the lower threshold, the thermostat switches the heater ON, and the stored water is heated up. As soon as the temperature reaches the upper threshold, the thermostat switches the heater OFF. The water temperature drops due to two reasons. First, due to the natural heat loss to the surrounding through the hot water tank wall as the surrounding is at a lower temperature, and second, due to users' daily hot water demand. The hot water consumption brings fresh cold water to the tank and the overall temperature of the water in the tank decreases. The flexibility offered by the EWHs such as load shifting (from peak load periods to low peak periods) is made possible due to the total heat capacity of stored water and temperature bands. The heat energy stored between the higher and lower temperature threshold provides the thermal inertia which allows the EWH to provide power system services by reducing the electrical load in peak load periods and shifting the electricity consumption to off-peak periods, without reduced comfort for the customer. According to Ref. [4], EWHs and other heating systems with storage capacity can be disconnected for a few hours without any discomfort or cost to the customer.

If the capacity of all EWHs, their temperature limits, and hot water demand are known, the energy capacity at any time can be calculated. Further, the maximum flexibility activation duration can be calculated as shown in Eq. (1).

$$t_{act\_max} = \frac{E_{aEWH\_ON}}{P_{nom} \times N} \quad \text{in (min)} \qquad 1$$

where, t_{act_max} is the maximum possible flexibility activation time, which is the maximum time an EWH can be disconnected without any discomfort or cost to the customer (maximum disconnection time can be in the range of 2–6 h [4,35,36] depending on the size and hot water demand), E_{aEWH_ON} is aggregated energy of all water heaters which are ON, is the nominal power rating of the water heater and N is the total number of water heaters considered for flexibility activation. Here, for aggregated energy, the stored energy in the active EWH (those which are ON) are considered, as the rest are already OFF due to their thermostatic cycle. At the time of flexibility activation removal, the EWH, which are already OFF due to their thermostatic cycle, also contribute to rebound. Therefore, the power capacity of the total population is considered for flexibility activation time calculation.

2.2. Water heater model

A simple first-order water heater model is considered for the work presented in this paper as shown in Fig. 1. The model is adopted from Ref. [37] and extended with an external flexibility activation switch. The heat capacity of the EWH is represented as C^k and the thermal insulation of the EWH is represented by R^k. The heating element is represented with a heat source P^k_m. During normal operation, when there is no flexibility activation, the flexibility activation switch is in the closed position. When the water temperature T^k is below T^k_{min}, the thermostat will be ON ($S^k = 1$) and the water will be heated. When the temperature T^k reaches the upper threshold T^k_{max}, the thermostat will be OFF ($S^k = 0$). The thermostat has a hysteresis between the temperature range T^k_{min} and T^k_{max}.

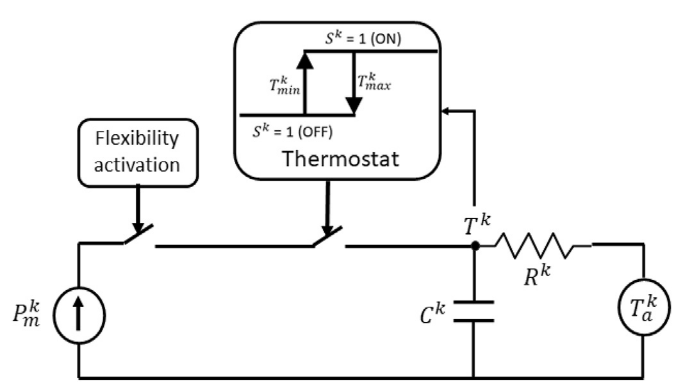

Fig. 1. First-order model representation of EWH.

The normal operation of the model is represented by the following equations Eq. (2) and Eq. (3) [37].

$$\frac{dT^k(t)}{dt} = \frac{1}{C^k R^k}\left(T_a(t) - T^k(t) - S^k(t) R^k P_m^k\right) \text{ in } (C_\circ/\text{min}) \quad 2$$

$$S^k(t) = \begin{cases} 1, \text{ if } S^k(t-1) = 0 \text{ and } T^k(t) \le T_{min}^k \\ 0, \text{ if } S^k(t-1) = 1 \text{ and } T^k(t) \ge T_{max}^k \\ S^k(t-1) \end{cases} \quad 3$$

where:

$T^k(t)$ is water temperature of EWH (k) at any time t in °C.
$T_a(t)$ is ambient temperature of EWH (k) at any time t in °C
C^k is thermal capacitance of EWH (k) in kWh/°C
R^k is thermal resistance of EWH (k) in °C/kW
P_m^k is rated power consumption of EWH (k) in kW.
S^k is ON OFF control of EWH (k).
T_{min}^k is minimum temperature threshold of EWH (k) at any time t in °C
T_{max}^k is maximum temperature threshold of EWH(k) at any time t in °C.

In Norway, EWH in a family house consumes at a power rating $P_m = 2-3$ kW [4]. A data collection of energy consumption metered for EWH from multiple households in Norway as a part of the research project 'Electricity Demand Knowledge' [38] for a duration of 285 days for the months between March 2016 and February in 2017, and its analysis, reveals that a typical EWH at a family house kept at an ambient temperature (T_a) 24 °C has a lower temperature threshold (T_{min}) 70 °C and an upper temperature threshold (T_{max}) of 75 °C. It consumes 1.667 kWh every 20 h when there is no water usage. From the energy consumption and time constant for temperature discharge, the EWH parameters are calculated as C = 0.335 kWh/°C and R = 600 °C/kW. The average demand profile for 24 h period from the metered data is shown in Fig. 2.

For the simulation, a population of 1000 households with one EWH in each household is considered. Each EWH has a rating of P_m = 2 kW and a capacity of 200 L. The temperature threshold limits are T_{min} = 70 °C and T_{max} = 75 °C. The initial temperature of the water is between 70 °C and 75 °C. The initial water temperature for the individual EWH is selected using a uniform distribution with 70 °C and 75 °C as limits for the population of 1000 EWH. In this way, none of the EWHs will have the same initial temperatures. The average demand profile for 24-h periods from the meter data as shown in Fig. 2 is considered for simulation. The demand peak for individual users is assumed to have a 1-h variation with uniform distribution for the given population with a 20% variation. The ambient temperature T_a at every household is assumed to be between 21.6 °C and 26.4 °C (24 °C ± 10%). The ambient temperature for the individual household is selected using a uniform distribution with 21.6 °C and 26.4 °C as limits for the population of 1000 houses. In this way, none of the households will have the same ambient temperatures. The ambient temperature for the individual water heaters is constant throughout the simulation, and the initial switch state for the population is decided with 0.5 probability and uniform random distribution. Therefore, 50% of the EWH population is ON and the rest is OFF. The water heater's power consumption and temperature profile are simulated for 4 days to allow the aggregated power consumption to settle to a steady state value. The steady state value at the end of the 4th day of simulation is considered as the initial conditions for further study.

2.3. Energy content and flexibility activation time

From the initial conditions generated as explained in the previous section, the base profile of water heaters without any flexibility activation is generated to compare with further cases which have flexibility activation. As the temperature of the individual water heaters is known through the model, the energy stored in the water can be calculated from the temperature and heat capacity of the tank. The aggregated power of the EWH population at any time is the available power for up-regulation, and the aggregated energy of those water heaters which are ON is the available energy for up-regulation, as they can provide a similar impact of producing additional generation by their demand reduction [39]. Similarly, the energy available in the water heaters which are already OFF is the available energy for down-regulation and their aggregated power capacity is the available power for down-regulation if they can be switched ON. Fig. 3 shows the aggregated power with its up and down regulation limits and Fig. 4 shows the aggregated energy for up and down-regulation with no flexibility activation.

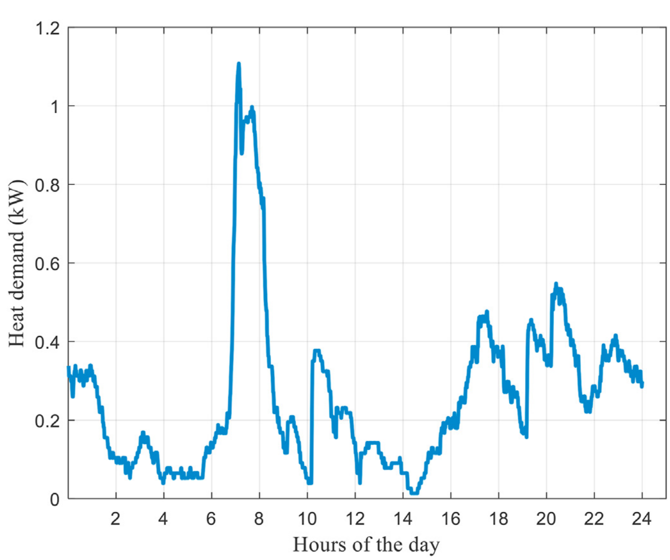

Fig. 2. Average heat demand from the EWH over different hours of a weekday.

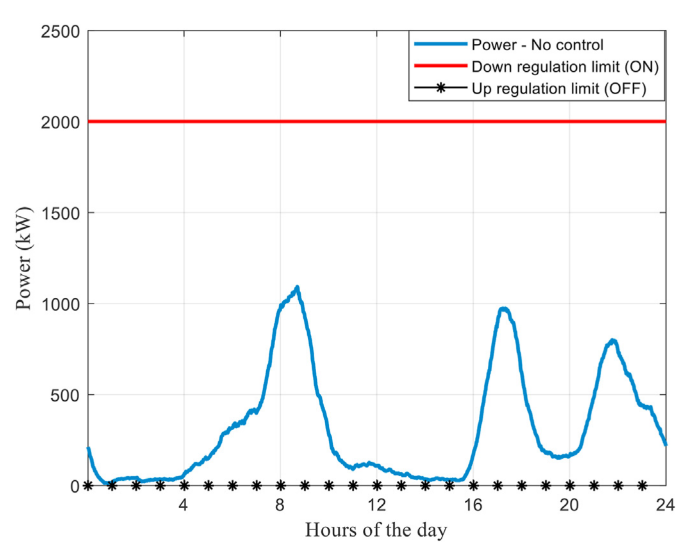

Fig. 3. Aggregated power of water heaters with up and down-regulation limits.

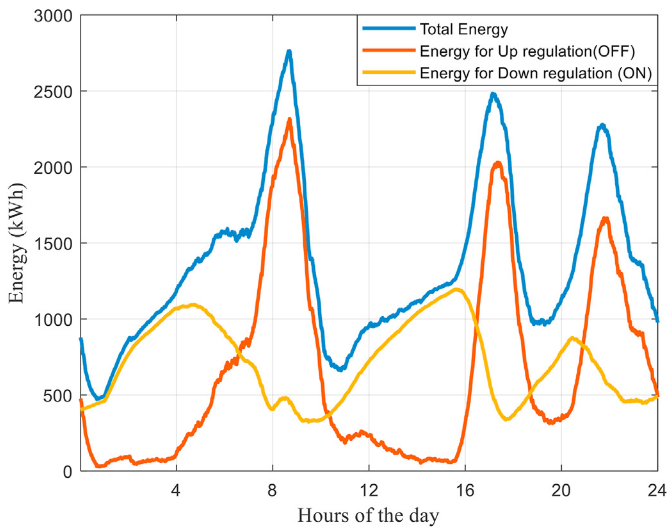

Fig. 4. Aggregated energy available for up and down-regulation.

2.4. Duration for flexibility activation

As the simple and straightforward option for flexibility activation is by switching OFF all water heaters in the selected population through broadcast signal (Fig. 5), the flexibility activation time must be defined based on the available energy to minimise user discomfort.

In the total population of EWHs, only those which are ON can provide flexibility and the duration for activation can be defined as represented by Eq. (1). The EWHs which are already OFF due to their thermostatic cycle will go ON after their temperature reaches a value below T_{min}. They cannot be kept off for a longer duration, as the water temperature reduces to the level of user discomfort, which is below 50 °C [40]. Therefore, a correction factor is added to Eq. (1) as shown in Eq. (4).

$$t_{flex\_act} = t_{act\_max} \times \frac{N_{ON}}{N} \quad \text{in (min)} \tag{4}$$

where, t_{flex_act} is actual flexibility activation time for the base case analysis, E_{aEWH_ON} is the aggregated energy of all water heaters which are ON.

2.5. Impact quantification

2.5.1. Rebound

After removing flexibility activation on TCLs, especially a direct load control, the load rebound occurs as the gadget compensates for the previous outage or resets the load state, e.g., resets the temperature to its predefined value which is in between the upper and lower thresholds [32]. The rebound effect is measured in percentage by considering the power consumption with no flexibility activation as the base.

The flexibility activation is characterised by the following parameters:

a) *Rebound percentage* - Rebound percentage can be classified as relative and absolute. The relative rebound percentage (RRP) is the ratio between the difference between actual rebound peak power (RPP) and expected aggregated power without flexibility activation (normal demand) and the normal demand (Fig. 6). The absolute rebound percentage (ARP) is characterised by the total capacity. ARP and RRP can be calculated as shown in Eq. (5) and Eq. (6).

$$ARP = \frac{RPP}{P_{nom} \times N} \times 100 \quad \text{in} \quad (\%) \tag{5}$$

$$RRP = \frac{RPP}{ND_{flex\_end}} \times 100 \quad \text{in} \ (\%) \tag{6}$$

where ARP is the absolute rebound percentage, RPP is the rebound peak power, RRP is the relative rebound percentage, ND_{flex_end} is the nominal demand at the end of flexibility activation, P_{nom} is the nominal power rating of the water heater, and N is the total number of independent water heaters considered for flexibility activation as shown in Fig. 5. In an unbundled electricity market, there are multiple stakeholders with different responsibilities. Although the DSO delivers power to the end-users, the retailers procure them in the electricity market with a committed consumption quantity [41]. Any deviation in the consumption will cause an imbalance in the system and the cost for the imbalance settlement will be charged to the retailer through the balance responsible party (BRP). The relative rebound provides an indication of the deviation from the predicted demand due to flexibility activation.

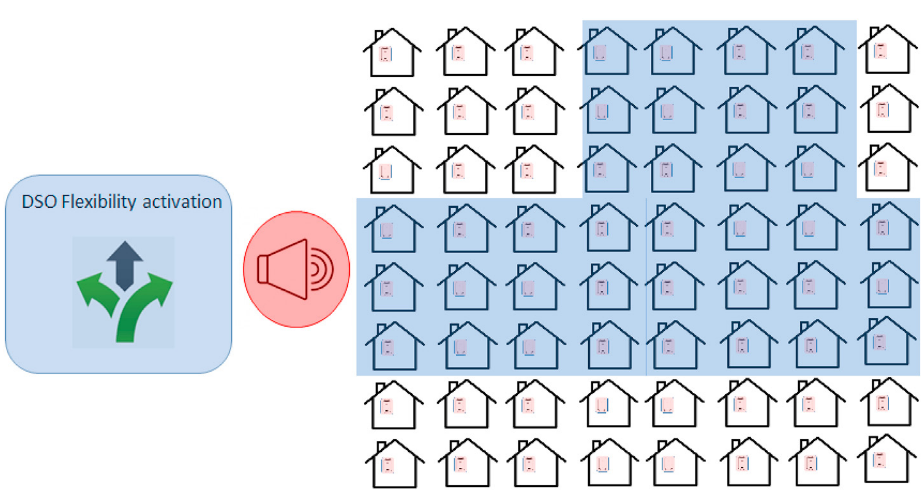

Fig. 5. Flexibility activation on a selected population of EWHs through a broadcast signal.

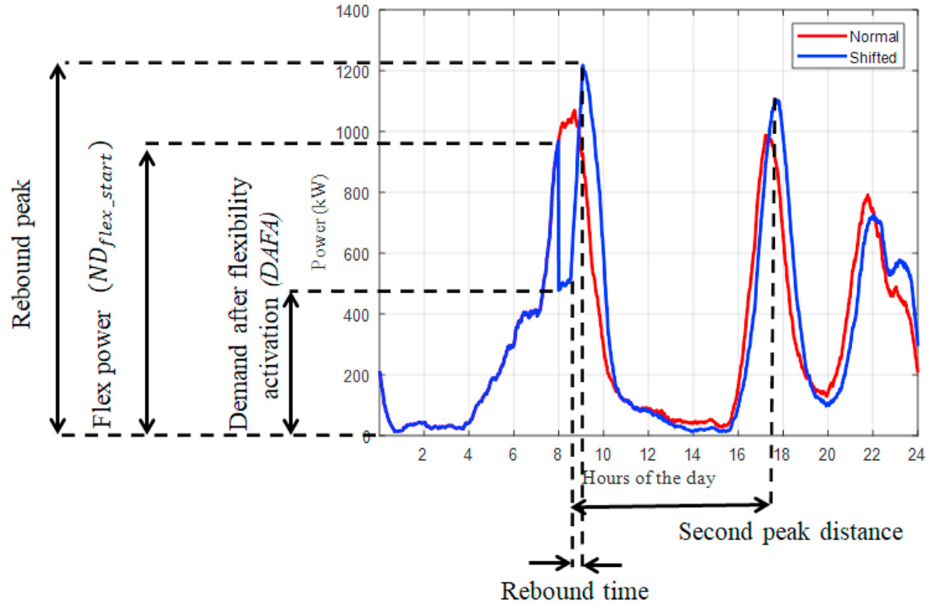

Fig. 6. Rebound characteristics.

b) *Rebound delay* — The rebound delay is defined as the duration after which the rebound peak occurs when EWHs go back to their normal operation after the flexibility activation period. During the rebound delay, the DSO can plan for alternative flexibility activation on another group of EWHs to mitigate the rebound.

The balancing power market perspective: *"Up-regulation refers to an increase in generation or reduction in consumption. Down-regulation refers to a decrease in generation or increase in consumption"* [39]. Therefore, the ramp-up and ramp-down rates similar to generation characteristics can be defined as follows:

c) *Ramp-up rate (RUR)* - The ramp-up rate is defined as the ratio of the difference in aggregated nominal demand at the time of flexibility activation (ND_{flex_start}) and its minimum value demand after flexibility activation (*DAFA*), to the time it takes to reach the minimum value. In the simulation the time taken is 1 min and, in real-time activation, it will vary depending on the delay characteristics of information and communication technology (ICT), which can be described as flexibility activation delay. RUR can be calculated as shown in Eq. (7).

$$RUR = \frac{ND_{flex\_start} - DAFA}{P_{nom} \times N \times FAD} \times 100 \quad \text{in } (\%/\text{min}) \tag{7}$$

where *RUR* is the ramp-up rate in percentage per minute of total EWH power capacity, ND_{flex_start} is the actual power at the start of flexibility activation, *DAFA* is the minimum demand after flexibility activation, *FAD* is the flexibility activation delay in minutes, P_{nom} is the nominal power rating of the water heater, and *N* is the total number of water heaters considered for flexibility activation. ND_{flex_start} and *DAFA* are illustrated in Fig. 6.

d) *Ramp-down rate (RDR)* - The ramp-down rate is defined as the ratio of the difference in aggregated power at the time of flexibility activation removal and its maximum value due to rebound to the time it takes to reach the maximum value as shown in Fig. 6. RDR can be calculated as shown in Eq. (8).

$$RDR = \frac{RPP - ND_{flex\_end}}{RT} \times \frac{100}{P_{nom} \times N} \quad \text{in } (\%/\text{min}) \tag{8}$$

where *RDR* is the ramp-down rate in percentage per minute of total EWH power capacity, *RPP* is the rebound peak power, ND_{flex_end} is the actual power at the end of flexibility activation, *RT* is the rebound time in minutes, P_{nom} is the nominal power rating of the water heater and *N* is the total number of water heaters considered for flexibility activation.

e) *Second peak distance* - The second peak restricts the next flexibility activation at the time of occurrence. It is the time difference between the second rebound peak and time of flexibility activation removal, as shown in Fig. 6.

f) *Activation error* - The activation error can be defined as the difference between the targeted power reduction and the actual power reduced by the flexibility activation. The deviation is characterised by the integral square of error (ISE) and normalised with the total capacity and duration of activation. Normalised ISE can be calculated as shown in Eq. 9

$$NISE = \frac{1}{P_{nom} \times N \times t_{flex\_act}} \int_{t=ST}^{t_{ST}+t_{flex\_act}} (TP - AP_t)^2 \quad \text{in } (\text{kW}) \tag{9}$$

where *NISE* is the normalised ISE, *TP* is the targeted power reduction, AP_t is the actual power reduction at any point of time, and t_{ST} is the start time of flexibility activation.

g) *Average flexible power* - The average available flexibility is the average power consumption for the given activation duration of different hours of the day. It is represented as a percentage of the total capacity.

h) *Peak flexible power* - The peak power in the given activation duration is considered as the peak value of available flexible power. It is represented as a percentage of the total absolute capacity.

i) *Temperature deviation* - The minimum temperature of the water heater population at different scenarios of activation at different hours of the day are listed in °C. It is the qualitative indicator of the discomfort caused to the consumer for different activation scenarios.

2.5.2. Scenario definition

The base case scenario is created by activating the flexibility by switching OFF all EWHs for the duration of t_{flex_act} mentioned in Eq. (4) at different hours of the day. Base case flexibility activation will cause maximum possible rebound, temperature deviation, highest possible ramp rates and minimum rebound delays. The rebound reduction scenarios are defined by different levels of flexibility activation in terms of power and duration of activation as shown in Fig. 7. The base case will serve as a baseline to compare the impacts in other scenarios. The base case and rebound reduction scenarios are defined as follows:

Base case: 100% activation for 100% of the activation time and no desynchronisation.

Scenario 1: 100% activation for 25% of the activation time and 75% of the activation time for desynchronisation.

Scenario 2: 50% activation for 50% of the activation time and 50% of the activation time for desynchronisation.

Scenario 3: 25% activation for 75% of the activation time and 75% of activation time for desynchronisation.

Scenario 4: Block approach: 33% activation for each 1/3rd of the activation time.

During the desynchronisation time, EWH is selected randomly and the EWHs are uniformly distributed in the desynchronisation time. Fig. 7 presents the base case and 4 flexibility activation scenarios.

3. Results and discussion

3.1. Activation time

The flexibility activation time for different hours of the day for the base case and scenarios 1–4 are plotted in Fig. 8. The activation time is high at the early hours of the day although the number of active EWHs is low as represented by the aggregated power of EWH population as shown in Fig. 3. This is due to low hot water usage during the early hours of the day. The activation time decreases as the hot water demand increases.

The hot water demand is high between hours 6 and 8. As the hot water demand increases, a greater number of EWHs will be ON and their aggregated power will also be high. But the activation time is low. The maximum possible activation time for the base case is 131 min and its occurrence is at hour 1. The minimum possible activation time is 61 min, and its occurrence is at hour 8. The activation time for other scenarios is derived from the base case and the maximum and minimum values and time of occurrence are presented in Table 1.

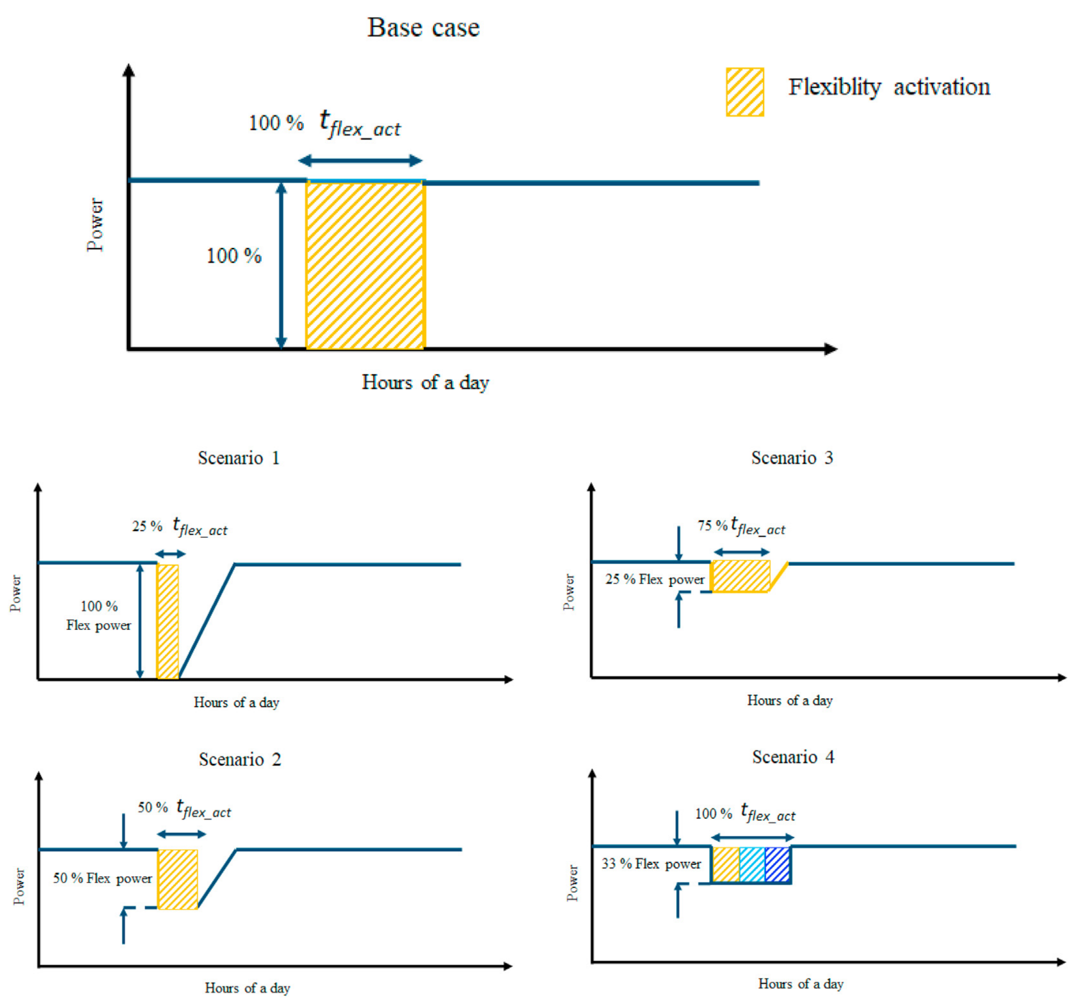

Fig. 7. Scenario definition for rebound impact analysis.

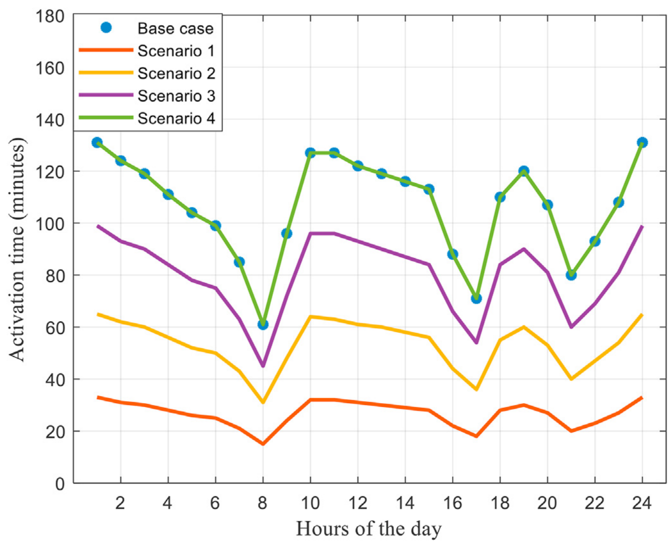

Fig. 8. Change in activation time for different scenarios.

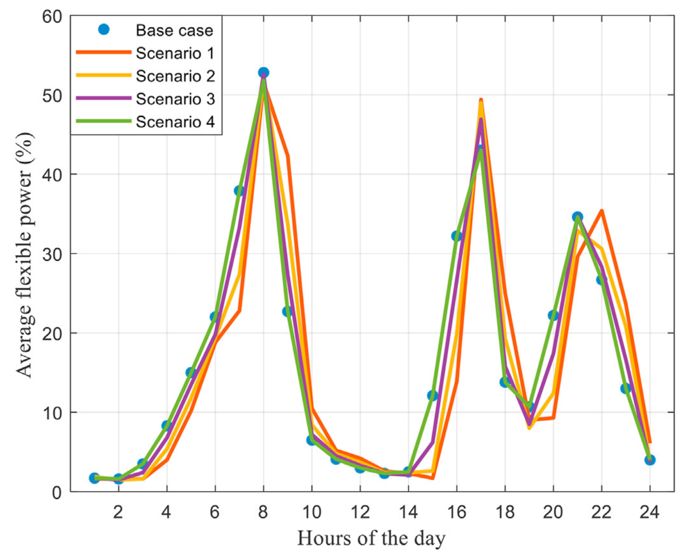

Fig. 9. Average flexible power at different hours of a weekday.

3.2. Available flexible power variation

The available flexible power for flexibility activation can be classified as average flexible power and peak flexible power. The average flexible power is the average aggregated power within the flexibility activation duration. The flexibility activation window varies for different scenarios. Fig. 9 shows the variations in available average flexible power in the different hours of the day. The average flexible power stays in the same range for all scenarios at different hours of the day, though their activation window changes. The number of EWHs which are ON have uniform distribution during the whole activation period. The average flexible power plots for the base case and scenario 4 overlap each other. The base case and scenario 4 have the same duration of flexibility activation t_{flex_act} and the activation interval. Since the flexibility activation interval is the same, the average flexible power in the given duration is the same for both cases. Therefore, their values overlap in the plots in Fig. 9. The average flexible power has a maximum value in the range from 52.8% to 51.5% of the aggregated rated capacity. The maximum average flexible power is at hour 8. Similarly, the minimum value of average flexible power is at hour 2 for the base case and all scenarios except scenario 1. The minimum value for scenario 1 is attained at hour 1. The minimum average flexible power value ranges from 1.5% to 1.6% of the total aggregated rated capacity.

The maximum and minimum values of average flexible power for the base case and all scenarios and their hour of occurrence, are presented in Table 2.

The peak flexible power in the flexibility activation duration for the base case and the different scenarios are shown in Fig. 10. Similar to the average flexible power, the peak flexible power of the different scenarios follows the same trend as the base case. The peak power does not differ to a greater extent in comparison with the average flexible power. Similar to the average flexible power plots for the base case and scenario 4, the available peak power for the base case and scenario 4 overlap with each other, shown in Fig. 10. The base case and scenario 4 have the same duration of flexibility activation t_{flex_act}. Since the flexibility activation interval is the same, the available peak within the interval is also the same for both cases. Therefore, their values overlap in the plots in corresponding plots in Fig. 10. The maximum and minimum values of average flexible power for the base case and all scenarios and their hour of occurrence, are presented in Table 3.

3.3. Rebound percentage

As discussed in section 2.5.1, TCLs exhibits rebound in power consumption due to their synchronised operation. The temperature hysteresis causes synchronisation in the operation of EWHs, and the absolute rebound represents the share of EWH in the population that synchronises after flexibility activation removal. Fig. 11 shows the absolute rebound for the base case and the different scenarios. The rebound is more dominant in activating flexibility during the hours when the hot water demand is high. The peak demand increases to 69% during evening hours due to flexibility activation in contrast to the morning peak, which is around 50%. If the flexibility activation is performed by a third party such as aggregators, the DSO as a system operator must have the knowledge about the absolute rebound as it will affect the power quality and reduce the grid assets' life for which they are responsible.

The rebound peak is proportional to the power reduction even though the duration of activation is less. The absolute rebound maximum is 69% and it occurs for the base case scenario at hour 16. Scenario 3 exhibits the lowest rebound which is 15% and it occurs at hour 16. Though the power reduction is less for scenario 4 (33%) in comparison with scenario 2 (50%), the rebound for scenario 4 is

Table 1
Flexibility activation time for the base case and scenarios 1–4.

Activation time	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Maximum duration value (minutes)	**131**	33	66	99	131
Hour of maximum value	**1**	1	1	1	1
Minimum duration value (minutes)	**61**	15	30	45	61
Hour of minimum value	**8**	8	8	8	8

Table 2
Average flexible power for the base case and 4 scenarios.

Average flexible power	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Maximum value (%)	52.8	51.5	52.1	52.6	52.8
Hour of maximum value	8	8	8	8	8
Minimum value (%)	1.6	1.6	1.5	1.5	1.6
Hour of minimum value	2	1	2	2	2

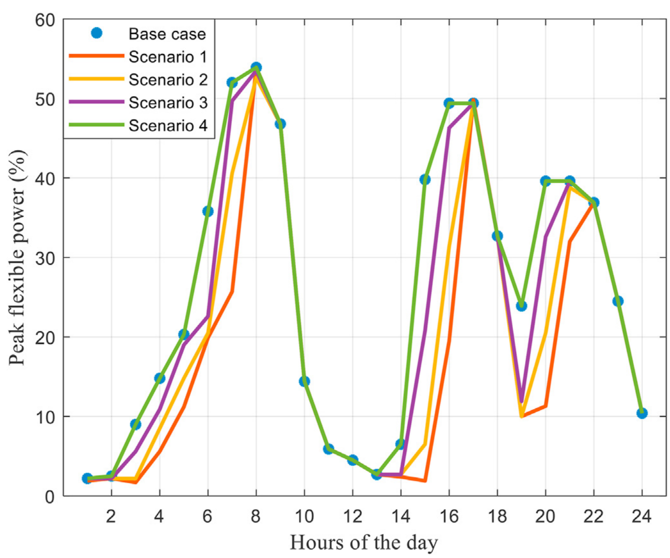

Fig. 10. Peak flexible power at different hours of a weekday.

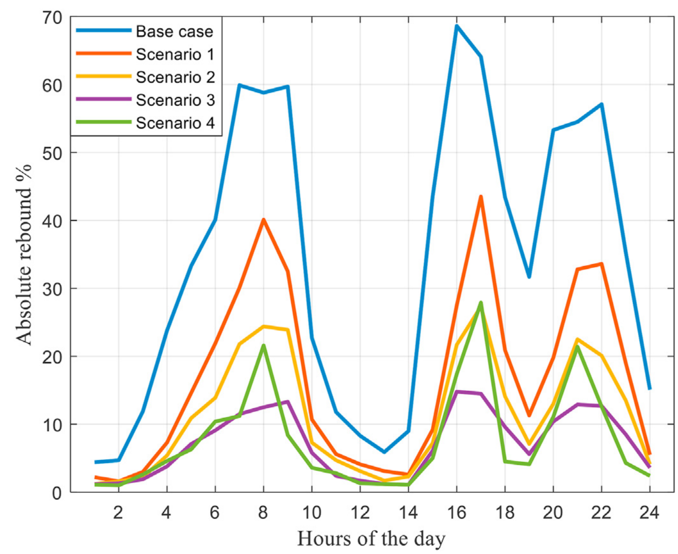

Fig. 11. Absolute rebound at different hours of a weekday.

higher. This is due to the insufficiency in time for desynchronisation. The rebound effect has a minimum value of 1% which occurs during the early hours of the day and noon when the hot water demand is less. The maximum and minimum values of the absolute rebound and their hours of occurrence are listed in Table 4.

The relative rebound for the base case and scenarios 1–4 is shown in Fig. 12. Relative rebound is calculated with nominal demand as a base. The relative rebound represents the imbalance created due to flexibility activation.

In an unbundled market, the imbalance is avoided by trading in the intraday market at a higher price than the day-ahead price. The electricity retailer avail EWH flexibility to avoid short term imbalances and they can plan the intraday energy purchase volume based on the relative rebound caused by flexibility activation, as the imbalance penalty is higher than the intraday market price. If the DSO avails flexibility as a solution for congestion management, the relative rebound can provide an indicative figure about the future congestion due to flexibility activation. Also, they can avoid or reduce the penalty for their share of imbalance which is compensated by the balance supply parties (BSPs) activated by the transmission system operator (TSO). The relative rebound attains the maximum for the base case scenario at 23 h and the minimum value for scenario 3 at 14 h. The maximum and minimum values of relative rebound for the base case and other scenarios are given in Table 5.

3.4. Rebound delay

The rebound during different hours of the day is shown in Fig. 13. The rebound delay for scenario 1 is high in comparison to others, as the desynchronisation time is high for scenario 1. The rebound delay for scenario 4 is low, though there is a desynchronisation time for the first 2 blocks of EWHs activated for flexibility. At the same time, the rebound delay for the base case falls in between scenario 1 and 4, though there is no desensitisation time for the base case. In scenario 4, the EWHs which are delayed in the first 2 blocks to avoid rebound, synchronises with the last block of EWHs which does not have any desynchronisation delay. The rebound delay has the highest value of 116 min for scenario 1 and occurs at hour 15. The minimum value for rebound delay is 2 min which occurs for scenario 4 at h 6. The rebound delay and rebound peak have an impact on ramp-down characteristics, which discussed in the further sections.

The rebound delays maximum and minimum values for different scenarios and their hour of occurrences are listed in Table 6.

Table 3
Peak flexible power for the base case and 4 scenarios.

Peak flexible power	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Maximum value (%)	53.9	53.9	52.6	53.5	53.9
Hour of maximum value	8	8	8	8	8
Minimum value (%)	2.2	1.7	2.2	2.2	2.2
Hour of minimum value	1	3	1	1	1

Table 4
Absolute rebound for the base case and 4 scenarios.

Absolute rebound	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Maximum value (%)	69	44	27	15	28
Hour of maximum value	16	17	17	16	17
Minimum value (%)	4	2	1	1	1
Hour of minimum value	1	2	1	14	2

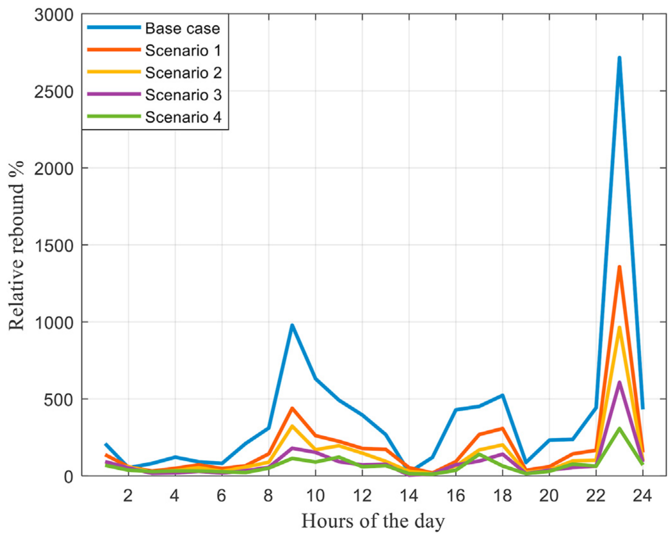

Fig. 12. Relative rebound at different hours of a weekday.

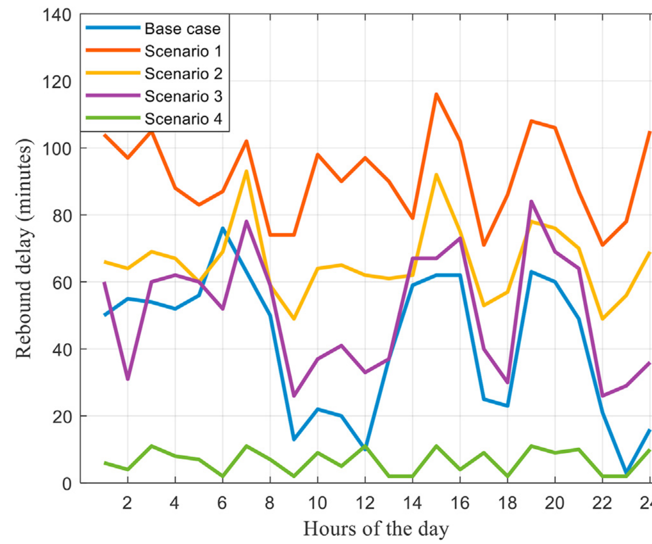

Fig. 13. Rebound delay at different hours of a weekday.

3.5. Ramp-up rate

Ramp rates bring a value to the DSO or the aggregator who activates flexibility when they serve the frequency requirement for TSO. The ramp-up rate explains how soon the demand can be reduced to bring the dropped system frequency to normal. Though the objective of this paper is not to characterise ramp rates, the ramp rates quantified for the different scenarios indicates how the system frequency will be affected, if the system inertia is known.

Fig. 14 shows the ramp-up rate for the base case and the other scenarios. The ramp-up rate is high for the base case and scenario 1, as the demand reduction is 100% within one simulation time step (1 min). It follows the demand curve. Other scenarios have the same pattern with reduced amplitude, as the flexibility activation is a fraction of the base case.

The ramp-up rate is high at hours of peak hot water demand. The ramp-up rate has a maximum value at hour 8 and its value is 48.50% per minute. The minimum value is 0.20% per minute and occurs at hour 1. The ramp-up rate maximum and minimum for different scenarios and their hours of occurrence are listed in Table 7.

3.6. Ramp-down rate

The ramp-down rate shows the rate at which the demand increases after the flexibility activation removal. Similar to the ramp-up rate, the ramp-down rate indicates the rate at which the frequency will drop in the system, if the system inertia is known.

Fig. 15 shows the ramp-down rate for the base case and the other scenarios. The ramp-down rate is high for the base case and scenario 4 compared to other scenarios, as there is no desynchronisation of the EWHs at the end of flexibility activation. The maximum value of the ramp-down rate is 23.80% per minute for the base case and it occurs at hour 6. The minimum value is 0% per minute for scenarios 1, 2, and 3 as there is desensitisation in the flexibility activation removal phase. The minimum value occurs at hour 6. The ramp-down rate maximum and minimum for different scenarios and their hours of occurrence are listed in Table 8.

3.7. Second peak distance

One flexibility activation causes more than one rebound within 24 h. The second rebound is smaller in amplitude compared to the

Table 5
Relative rebound for base case and 4 scenarios.

Relative rebound	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Maximum value (%)	2715	1357	964	607	307
Hour of maximum value	23	23	23	23	23
Minimum value (%)	22	19	15	4	11
Hour of minimum value	14	15	15	14	15

Table 6
Rebound delay for the base case and 4 scenarios.

Rebound delay	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Maximum value (min)	76	116	93	84	11
Hour of maximum value	6	15	7	19	3
Minimum value (min)	3	71	49	26	2
Hour of minimum value	23	17	9	9	6

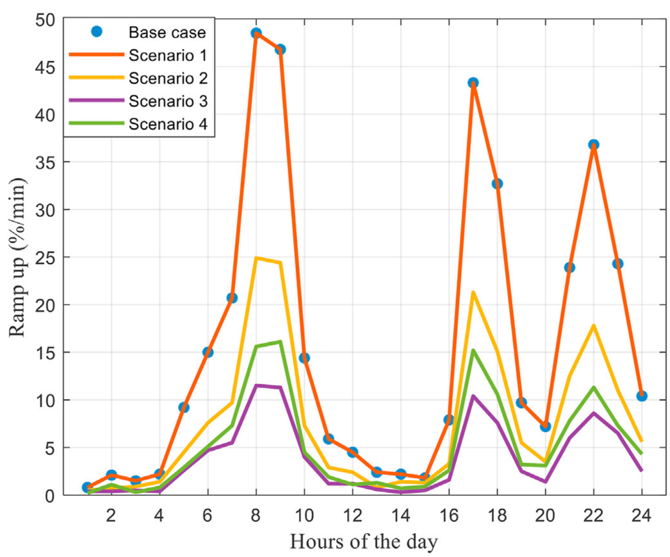

Fig. 14. Ramp-up rate at different hours of a weekday.

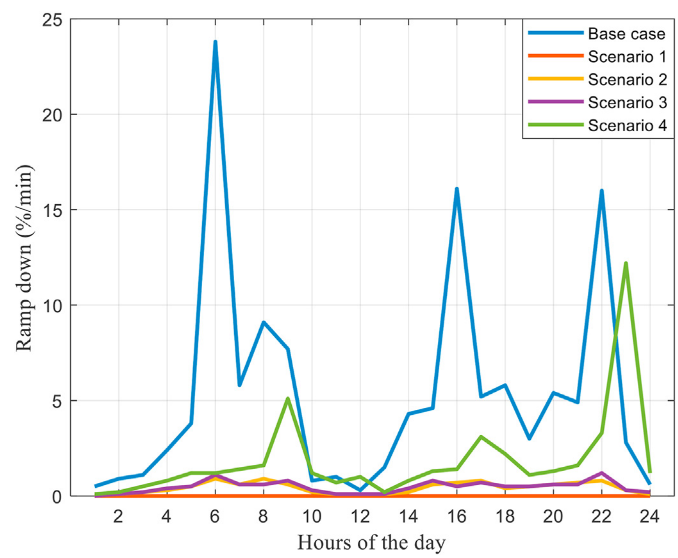

Fig. 15. Ramp down rate at different hours of a weekday.

first rebound. The second rebound indicates the synchronisation in the EWH population and reduced energy capacity for any flexibility activation. Fig. 16 shows the second peak delay in minutes from the flexibility activation removal. The flexibility capacity during the hours of peak hot water demand is affected by the flexibility activation which happened 15 h earlier. Therefore, the flexibility activation will increase the peak demand forecast for the next horizon of 13–15 h and it can cause congestion in the DSOs operational perspective, cause an imbalance in TSO's and BRP's perspectives, and an additional demand purchase in the retailers' perspectives.

The maximum value of the second peak distance is 899 min for scenario 1 which occurs at 17 h which will affect flexible energy capacity for the next day morning demand peak. The minimum value occurs at hour 2 for scenario 3 and its value is 328 min of delay. The maximum and minimum values of second peak delay and their hours of occurrences are listed in Table 9.

3.8. Activation error

The targeted flexible power may not be achieved when only a part of the EWH population is engaged in flexibility activation. If the temperature of most of the EWHs in the selected set in the population are close to T_{max} due to their thermostatic cycle during the flexibility activation time, the achieved power reduction will be more than the targeted power reduction. Similarly, the achieved power reduction will be less than the targeted power reduction when the temperature of most of the EWHs are close to T_{min}. To avoid the cancellation of negative and positive errors, the flexibility activation error can be quantified by ISE and can be normalised to the total aggregated capacity of the EWH population. There is no activation error when the whole population of EWH is switched OFF.

Therefore, the base case and scenario 1 do not have flexibility activation error characterisation. The flexibility activation error for scenarios 2 to 4 are shown in Fig. 17. Scenario 4 exhibits the highest activation error in comparison to the other two scenarios. This is due to the rebound in the first two blocks when their flexibility activation is removed. The normalised ISE is higher for scenario 3 in comparison to scenario 2 as the share of uncontrolled EWHs in the total population is higher for scenario 3 in comparison to scenario 2. In general, the ISE is dominant during the longer hours of higher hot water demand than the intense hot water demand for a short duration. The maximum and minimum values of activation error for scenarios 2 to 4 and their hours of occurrence are listed in Table 10. The activation error has a maximum value of 222.6 for scenario 4 at h 16. The minimum value is 0.7 for scenario 2 at h 19.

Table 7
Ramp-up rate for base case and 4 scenarios.

Ramp-up	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Maximum value (%/min)	48.50	48.50	24.90	11.50	16.10
Hour of maximum value	8	8	8	8	9
Minimum value (%/min)	0.80	0.80	0.50	0.30	0.20
Hour of minimum value	1	1	1	14	1

Table 8
Ramp-down rate for base case and 4 scenarios.

Ramp down	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Maximum value (%/min)	23.80	0.00	0.90	1.20	12.20
Hour of maximum value	6	1	6	22	23
Minimum value (%/min)	0.30	0.00	0.00	0.00	0.10
Hour of minimum value	12	1	1	1	1

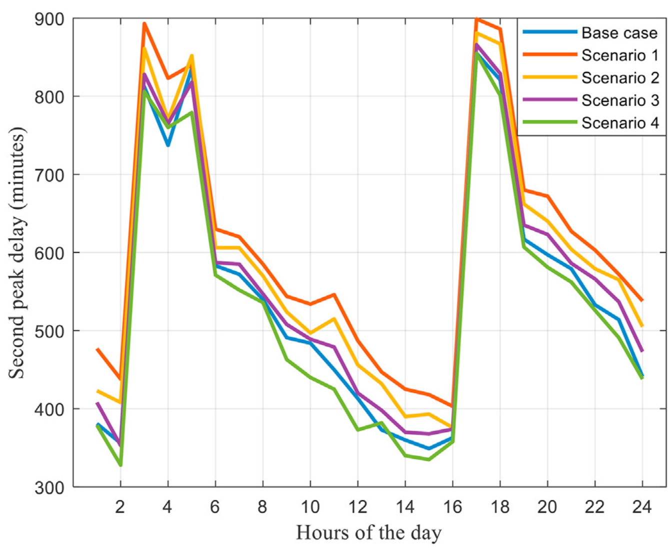

Fig. 16. Second peak delay at different hours of a weekday.

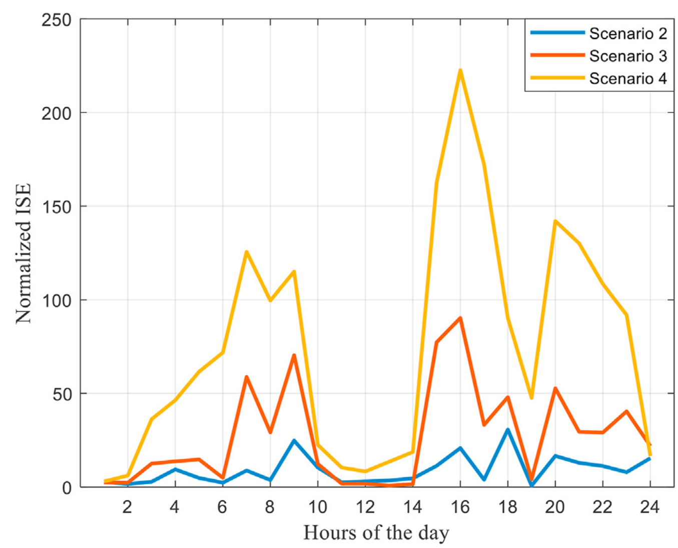

Fig. 17. Normalised ISE of flexibility activation at different hours of a weekday.

3.9. Temperature deviation

The deviation of the average temperature of all EWHs from the lower threshold T_{min} denotes the discomfort caused to the user due to the flexibility activation. Fig. 18 shows the temperature deviation during different hours of the day for the base case and the different scenarios.

The temperature deviation is high during the intense hot water demand, namely morning hours, and the figure above shows that scenario 4 has a lower temperature deviation than the other scenarios. The maximum and minimum temperature deviation for the base case and other scenarios and the hours of occurrence are listed in Table 11.

In scenario 4 the EWHs which engaged in flexibility activation in the first two blocks can relax their temperature profile during the activation period of block number 3. The temperature deviation is minimum for scenario 4 during the early hours between 2 and 5 with a value of 0.4 °C. The maximum temperature deviation occurs at hour 7 for the base case which has a value of 4.4 °C.

The 4 scenarios exhibit different characteristics for rebound, rebound delay, ramping, and error characteristics. Scenario 1 has a quick response in terms of power reduction, high rebound, rebound delay, and has low activation time. These characteristics are suitable for power system services that require a fast response, for example, fast frequency response (FFR). High rebound delay helps provide sufficient time to procure sufficient resources to handle the imbalances due to rebound. On the contrary, scenario 4 has a slow response. At the same time, it can provide stable power reduction for a longer duration. The power system services like congestion management and voltage control require a longer duration of service activation and scenario 4 is suitable for such services. The shorter rebound delay in scenario 4 can be managed by resource procurement during its longer activation time. Scenarios 2 and 3 exhibit intermittent characteristics in comparison with scenarios 1 and 4. Their slow response and shorter activation time make them suitable for short duration services like secondary frequency

Table 10
Normalised ISE for the base case and 4 scenarios.

Normalised ISE	Scenario 2	Scenario 3	Scenario 4
Maximum value (kW)	30.7	90.3	222.6
Hour of maximum value	18	16	16
Minimum value (kW)	0.7	0.8	3.0
Hour of minimum value	19	13	1

Table 9
Second peak delay for the base case and 4 scenarios.

Second peak delay	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Maximum value (min)	855	899	881	866	855
Hour of maximum value	17	17	17	17	17
Minimum value (min)	349	403	376	353	328
Hour of minimum value	15	16	16	2	2

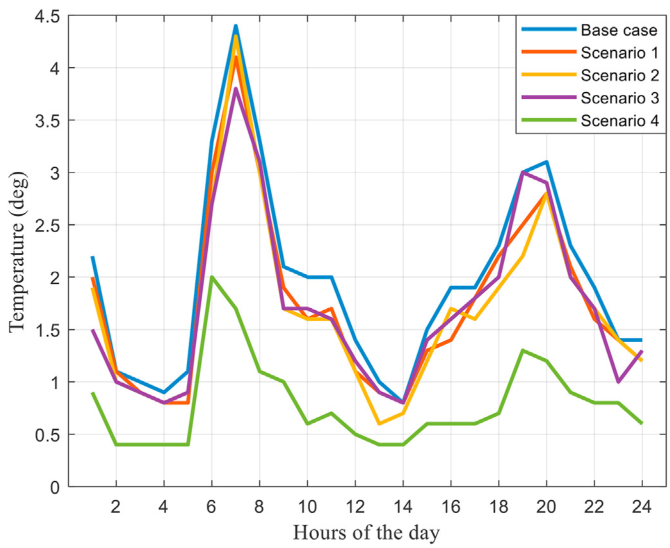

Fig. 18. Temperature deviation on flexibility activation at different hours of a weekday.

Table 11
Average temperature for the base case and 4 scenarios.

Average temperature	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Maximum value (°C)	4.4	4.1	4.3	3.8	2
Hour of maximum value	7	7	7	7	6
Minimum value (°C)	0.8	0.8	0.6	0.8	0.4
Hour of minimum value	14	4	13	4	2

control.

Demand side flexibility activation was only a concept decade before. In today's scenario, it is approaching close to reality. In Norway, electricity retailers already provide smart home solutions for measurement and control at an affordable cost [29]. DSOs are responsible for smart metering and have the information about the consumption, but they do not control it. Pilot studies with consumer participation reveal that Norway has a potential for 600 MW demand reduction only from EWH, even if half of the consumers offer flexibility [4]. Initiatives to facilitate the trade of flexibility as a market product were already taken [42]. In the near future, aggregators in cooperation with other market stakeholders can offer flexible products for power system ancillary services.

4. Conclusion

DSO must have an overview of the impact of flexibility activation on the demand side, as they have the responsibility to operate the power grid safely and reliably, and flexibility activation may bring more adverse effects to the grid. In the domestic segment, power-intensive demands such as EVs and TCLs will be the most important demand side flexibility resources. Flexibility activation of TCLs can cause rebound if proper precautions are not taken. In this paper, the impact of flexibility activation on EWHs in terms of the DSOs perspective for the Norwegian scenario with real-life demand data are analysed and presented. EWHs flexibility potential is highly influenced by the daily hot water demand of the customers. The highest average flexible power potential is 53.9% at hour 8, where the activation duration is lowest, and it can last for a maximum duration of 61 min due to low energy availability. It will cause absolute rebound of around 60% which can be reduced to a value of around 15% by scarifying the flexible power to 13.5%. The user comfort is affected by the reduction of temperature around 4.4 °C which can be reduced to a value around 1.7 °C using scenario 4. Power retailers need to focus on the high absolute rebound hours between 5-10 and 14–23 to avoid a BRP imbalance penalty as the rebound power is high.

The ramp-up and down characteristics indicate the frequency change in the system due to flexibility activation if the inertia characteristics are known. EWHs flexibility activation can serve as a frequency containment reserve (FCR) at peak demand hours with high ramp-up and ramp-down rates of 48.5% and 23.8% per minute, respectively. The flexibility activation can serve as a frequency restoration reserve (FRR) during the non-peak hours. The flexibility activation has high normalised ISE for scenarios 3 and 4 although the flexible powers activated are lower than scenario 2. This signifies the need for higher desynchronisation time. The rebound can be reduced by optimally scheduling the EWHs activation without sacrificing user comfort. In this study, it is assumed that all EWHs will respond to the flexibility activation switching signal. The flexibility activation signal may be rejected in a real-world scenario. A sensitivity analysis on the different characteristics would be an interesting topic to study. Other TCLs such as SHs can complement the EWHs rebound impact. It will be interesting to compare the voltage deviation in the network by optimized flexibility activation and normal activation.

Credit author statement

Venkatachalam Lakshmanan: Conceptualization, Methodology, Formal analysis, Software, Validation, Writing – original draft Hanne Sæle: Project administration, Formal analysis, Resources, Supervision, Data curation, Methodology, Writing- Reviewing and Editing. Merkebu Zenebe Degefa: Methodology, Formal analysis, Writing- Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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