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Analysing the Economic Viability of Implicit Demand Response Control of Thermal Energy Storage in Hot Water Tanks

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Abstract: Demand-responsive control of electrically heated hot water storage tanks (HWSTs) is one solution, already present in the building stock, to stabilise volatile energy networks and markets. This has been put into sharp focus with the current energy crisis in Europe due to reduced access to natural gas. Furthermore, increasing proportions of intermittent renewable energy will likely add to this volatility. However, the adoption of demand response (DR) by consumers is highly dependent on the economic benefit. This study assesses the economic potential of DR of centralised HWSTs through both an analysis of spot price data and an optimisation algorithm approximating DR control. The methods are applied to a case study apartment building in Norway using current pricing models and examine the effect of the demand profile, electricity prices, heating power and storage capacity on energy cost and energy flexibility. Unit cost savings from DR are closely linked to the variation in unit energy price during the optimisation period. Increasing the storage capacity or the heating power increases the flexibility with a diminishing rate of return. However, increasing storage capacity does not result in cost savings as additional heat losses are greater than the saving from shifting demand, except for during highly volatile electricity price periods. Changing the minimum setpoint temperature improves the cost curve as a greater thermal storage capacity can be achieved without increasing heat loss. Systems utilising a smaller heating power are more economical due to the dominant role of the monthly price related to the peak energy demand of the system.

Keywords: energy storage; energy flexibility; domestic hot water; demand side management; real time pricing

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1. Introduction

The European energy market has experienced an extreme period of high prices and price volatility between 2021 and 2022, initially due to economies reopening after the COVID-19 pandemic and then due to the supply squeeze of natural gas as a biproduct of the Russia–Ukraine war [1]. In response, there are increased calls to transition from fossil fuel-derived energy to renewable sources [2]. However, the increased intermittency of renewable energy, particularly solar and wind, requires greater energy flexibility to balance supply and demand within energy grids [3]. The energy system must move from one where supply matches demand (supply side management) to one where demand matches supply (demand side management). Shifting energy demand to another point in time, termed demand response (DR), has the potential to both mitigate the current volatility in the energy market and balance the future energy grid powered by renewables. DR is achieved through either directly shifting processes or by short-term storage of energy for later use. Traditionally, DR has been managed centrally by energy companies in order to balance the energy grid. Shifting of processes is administered via contracts with large industrial and office buildings. Storage is provided by a centralised energy storage, such as pumped hydro, thermal storage pits and, increasingly, grid batteries. Direct management of residential buildings, with their many units and small demands, has not been practical [4].

The marketisation of the electricity market and the introduction of smart meters improves the feasibility for smaller scale DR. The wider adoption of small-scale DR could potentially reduce CO_2 emissions from energy generation, as high energy prices often represent periods of higher demand than supply, which require the use of peaking power plants or importing electricity, often with higher CO_2 emissions [5]. Similarly, DR can take advantage of periods of excess renewable energy generation, where energy prices are low. There are already examples of explicit DR where suppliers manage certain appliances on behalf of their customers, such as domestic hot water tanks [6]. The supplier acts as an aggregator of many customer demands passing on a portion of the savings [7]. Implicit DR is also possible with individual consumers responding to real time pricing (RTP), shifting their energy use to when energy is cheaper [8]. For implicit DR to be widely adopted, there must be a clear financial benefit to the consumer [9]. Where RTP is used, DR can help to reduce electricity bills, which have received a greater focus due to recent increases in energy prices. Additionally, incentives for DR could be offered by energy companies as paying for consumer DR could be more cost effective than centralised storage [10] or peaking power plants [9].

Consumer RTP requires a market-based power system and smart meters to measure energy use in smaller timesteps, commonly one hour. The smart meter roll-out across the EU has been uneven, with only Spain, Italy, Estonia, Finland, Sweden and Norway at or near 100% coverage [11]. Norway was the first country to implement a market-based power system in 1991 [12] and completed the installation of smart meters in all properties in 2019 [11]. This has been accompanied by a wide availability of "spot price" electricity contracts which charge the consumer the cost of electricity based on the hourly RTP of the Nord Pool electricity exchange. Over 75% of households are now on this type of contract [13]. Furthermore, some electricity providers are encouraging manual load shifting by providing alerts to customers via their apps for periods of high prices [14,15]. Therefore, Norway is well positioned to be a testbed for innovative technologies within DR.

Consumer DR requires more intelligent controls such as rule-based control (RBC) and model predictive control (MPC) than the widely used PID (proportional–integral–derivative) control [16]. PID control is a responsive control, which steers a system towards a setpoint value based on formulas that use measured values as inputs. The combination of proportional, integral and derivative terms in the formula minimises the delay and overshoot of the response. RBC utilises a set of predefined rules with upper and lower setpoints, allowing for different responses depending on input data. MPC is a predictive control, employing a dynamic building model, which can generate an optimised control strategy that takes the future state of the system into account. The future state is modelled using the current state of the system and forecast information such as weather, occupancy and energy pricing [17]. Electricity pricing is a good proxy for the level of imbalance between supply and demand within the energy grid. The optimisation can be for a combination of factors, such as thermal comfort and energy cost, and can include constraints on the controlled variables. Due to dependency on simulation and the computing power required, the practical use of MPC has only become relevant during the past decade [18].

Energy storage within residential buildings offers greater DR potential than the direct shifting of demands as these are limited to deferable loads (appliances where the time of operation can be shifted without negatively impacting the resident), such as fridges, freezers, dishwashers and washing machines. Consumer management of these loads has been shown to produce insignificant results [19], while automated control may not suit all residents [20]. In addition, the potential savings to the individual are small as the shifted energy use is relatively small. Electricity can be stored either chemically or as thermal energy. The economic feasibility of chemical storage (batteries) is highly dependent on the initial costs of batteries, which are currently too high [21]. The batteries in electric vehicles could be utilised instead, as they stand idle for long periods [4]. However, the pricing model and technology are still in development. The extra wear placed on the battery through increased charging and discharging cycles could mean that price responsive charging of the vehicle is preferred by most owners, which can offer similar savings through load shifting.

In heating dominant climates such as Norway, space heating and domestic hot water (DHW) represent the largest proportion of energy demand, meaning thermal energy storage (TES) offers considerable potential for DR in residential buildings. Thermal energy can be stored in hot water storage tanks (HWSTs) or in the building's thermal mass [22]; however, they are not optimised for DR. In northern Europe, HWSTs are a common element in DHW systems and as buffering elements in heating systems, especially those utilising solar collectors, heat pumps or district heating [23]. The heating element can be a separate element or integrated in the HWST [24]. HWSTs are currently sized according to rules-of-thumb. Thermal mass is present in all buildings but usable storage depends on the type of construction and the level of envelope insulation [25]. The utilisation of thermal mass is limited by thermal comfort requirements and higher heat losses [22]. Additionally, DR of thermal mass requires a more complicated control which accounts for thermal comfort and the heating system [26].

HWSTs buffer heating and DHW demand peaks, reducing the required capacity of the heating source and allowing more efficient operation for longer periods at the nominal power [27]. HWSTs are also good stores for the unregulated supply from solar thermal collector systems [28] and offer the most cost-effective form of storage for excess electricity produced by photovoltaic panels, increasing self-consumption [29]. HWSTs have greater DR potential than building thermal mass due to their higher thermal capacity by volume [22]. By charging the tank (increasing its temperature), it is possible to store energy for later use. Tank stratification and mixing values allow for the average tank temperature to vary without affecting the output temperature delivered to heating or DHW, minimising the impact of DR on the consumer. The variation of setpoint temperature of HWSTs would not affect the end user as is the case with setpoint variation of room temperatures, where thermal comfort has to be factored in [30]. Therefore, the control for HWSTs only needs to meet the energy required for heating and DHW, simplifying the model. Furthermore, where HWSTs are heated by electrical heaters, they offer a significant demand–flexibility potential, with the current stock of electric water heaters in Europe estimated to have a flexible capacity equivalent to the entire installed power generation capacity of the Czech Republic [31]. In Norway, the historically low electricity prices have resulted in almost 100% of water heaters being electric, the highest in Europe.

Research into the control of electrically heated HWSTs has focused on the accuracy of the tank model and the correct functioning of the control. Kepplinger et al. [32] developed and simulated a DR control for an electrically heated HWST which showed cost and energy savings of up to 12% relative to conventional operation. This was then field tested over 18 days, resulting in 3.6% energy cost savings without affecting user comfort [33]. The control used a bulk model for the HWST which was shown to be robust enough when used with a stratified HWST. More recently, Ritchie et al. have developed more detailed models of the HWST which better account for predicted demand and legionella prevention while minimising energy use [34].

Several studies have investigated DR control of HWSTs using RTP in Norway. Olivera et al. [35] found DR control strategies provided worthwhile savings over a constant setpoint strategy especially where hourly prices become more volatile. As the energy price pattern had predictable peaks and troughs, a less complicated control could achieve similar savings with a control strategy to charge during the night resulting in similar savings to a complex strategy. The study used spot prices from February, which are often higher than the rest of the year, potentially leading to a favourable result. Furthermore, the study just used spot prices, as consumer RTP contracts were not available when the research was undertaken. Nord et al. [36] showed that the cost optimal tank size for price responsive control is highly dependent on the additional fees that make up electricity pricing. A strategy with a fixed grid fee had a cost optimal tank three times the reference size. A strategy with a variable fee, based on the system's peak power, had a cost optimal tank six times the reference size. The study used measured DHW profiles recorded for 50 days. Sørensen et al. [37] further developed this research by applying four rule-based control strategies to the measured data using a simplified tank model based on energy capacity. The four control strategies were peak power limitation; spot price saving where each day was divided into low, medium and high price periods; flexibility sale with no heating in peak periods; and maximising self-consumption of a photovoltaic system. The reduced peak power and flexibility-sale strategies were effective in reducing cost, although the price paid for flexibility was purely hypothetical as no such schemes exist in Norway. Spot prices provided limited savings when using 2019 prices, matching when the measured data were recorded. The savings were improved when using price data from 2021 showing a need to analyse year-on-year variation. Furthermore, Sørensen et al. noted that spot price savings could have been improved by using an MPC.

All these studies are successful in showing the marginal benefit of DR over an existing reference case but have not fully investigated the parameters which impact the economic viability of the technology in the current electricity market. The parameters include the demand profile, energy price profile, heating power capacity and the storage capacity. Furthermore, there is a need for a better understanding of electricity price patterns over multiple years. This is particularly important for DR with TES, as the total energy use is often higher due to the additional heat losses from energy storage [38]. To the authors' knowledge, there is also a lack of simple analysis tools which can be used to quickly assess the feasibility of DR in an electricity market before investing time in the technical development of the control. Such tools would also help in developing future price structures to increase the use of DR.

The focus of this research is on assessing the economic potential of implicit DR of HWSTs under current pricing policies by approximating the savings achieved by an optimal control using a simplified analysis method. An optimal control strategy represents a best-case scenario for DR. A pair of algorithms were written to create a charging profile to minimise the unit cost of energy which was then adapted to the available capacity of HWSTs. Each analysis used a full year of historic electricity prices, including fees and taxes split into 24-h periods, as this is the availability of price data from the day-ahead Nord Pool market. The past nine years of electricity spot prices were compared to determine the potential variation in savings. Based on this analysis, three years were chosen to represent average spot prices (2019), volatile spot prices (2018) and highly volatile spot prices (2021). Three different demand profiles were optimised to three different years of electricity spot prices for a range of heating powers. The resulting charging profiles were then used to parametrically study the effect of varying the number of HWSTs and their minimum setpoint temperature. The energy cost and energy flexibility in each case were calculated against a reference system for the demand profiles. The results of this study are used to discuss the effect of each parameter on the potential cost savings from DR and the measures to improve the economic viability of DR.

2. Methodologies

2.1. Inputs

2.1.1. Electricity Prices

The electricity price varies for each hour based on the Nord Pool energy market. The end-user price consists of the spot price, grid tariff, electricity tax and VAT. In addition, there can be small fees for the electricity provider and electricity certificates. The electricity provider fee can be applied as a monthly fixed cost, a fee per kWh or a combination of both. The electricity certificate fee is a fixed fee applied per kWh. These fees are dependent on contracts and represent a very small component of the electricity price. Therefore, they were not included in this analysis. The build-up of the unit cost of electricity is shown in Table 1 using the 2021 energy tax. Hourly spot prices for the Oslo region for the nine years between 2012 and 2021 were acquired from Nord Pool [39]. The grid tariff varies seasonally, and the spot price fluctuates hourly. In addition, there is a monthly cost comprising a fixed grid tariff and a variable grid tariff based on the peak electricity demand in that month, shown in Table 2. Small private customers currently pay a lower fixed cost price and no variable part, although this is changing from 1st of July 2022 [40]. As the case study's heating system is a large centralised system, a business grid tariff for 2021 is used.

Table 1. Unit cost model for 1 kWh of electricity. 1 NOK ≈ 0.1 EUR.

	Spot Price	Grid Tariff	Energy Tax	VAT
Electricity	Hourly spot price	0.070 NOK (November through March) 0.039 NOK (April through October)	0.1669 NOK	+25%

Table 2. Monthly cost model for electricity [41]. 1 NOK ≈ 0.1 EUR.

Period	Fixed Cost/NOK	Peak Cost (Max kW in the Month)/NOK/kW
December through February	340	120
March and November		67
April through October		22

2.1.2. Thermal Energy Demand Profile

For the purpose of this study, the demand profiles were taken from a building energy simulation of a proposed affordable apartment complex in Sørumsand (59°58′54″ N, 11°14′25″ E), Norway, roughly 20 km east of Oslo. It is proposed that four blocks will be built, four floors high, providing 68 units and a total of 3450 m^2 of heated living area. Figure 1 shows their arrangement. The blocks are built on top of an unheated basement which contains parking and the technical room for the buildings. Three thermal energy profiles were generated using the building energy simulation software *SIMIEN 7* [42], which meets European Standard EN ISO 13790 [43] and is validated according to EN 15265 [44].

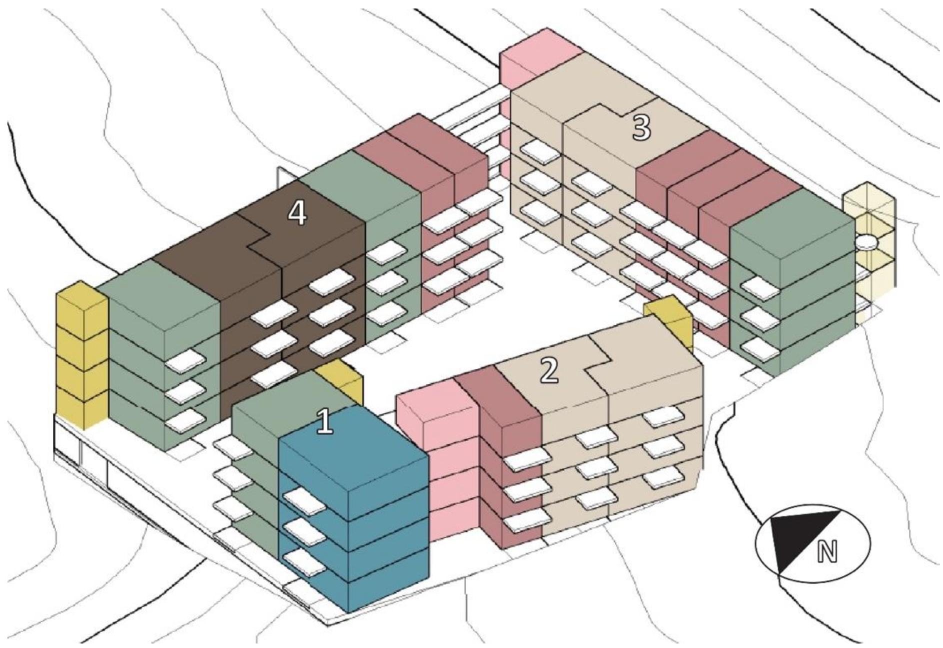

Figure 1. Perspective view of BoKlok Sørumsand development from the southeast. Image provided by BoKlok Norway.

Two heating strategies based on NS 3431 (Norwegian standard) were examined: a variable setpoint strategy, with a setpoint of 22 °C (7:00 to 23:00) and setback of 20 °C (23:00 to 7:00); and a constant setpoint of 22 °C. The heating system was deactivated during the summer (19 May to 8 September). The resulting demand profiles are shown in Figures 2 and 3. The DHW profile is according to Norwegian energy simulation standard SN-NSPEK 2020:3031 [45] and is the same for each 24 h period. The demand profile is shown in Figure 4. Similar standardised profiles have been shown to be accurate where the demands of multiple residential units were combined [46]. The resulting monthly demand profiles of the heating strategies and DHW are shown in Figure 5. All the profiles include the energy required for the simulated distribution losses.

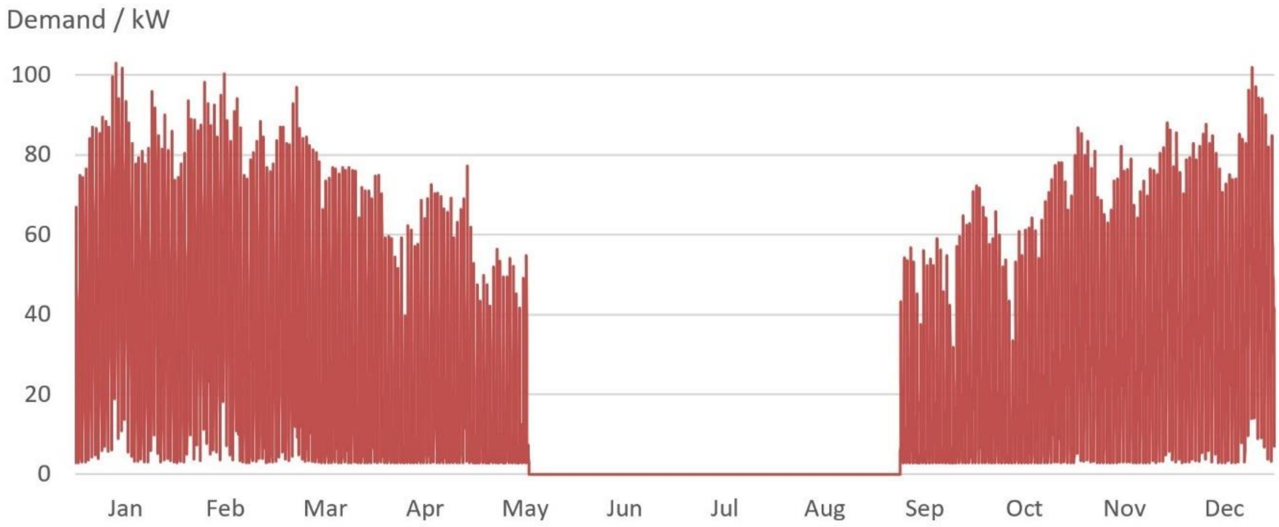

Figure 2. Annual demand profile of heating with a variable setpoint temperature from annual simulation.

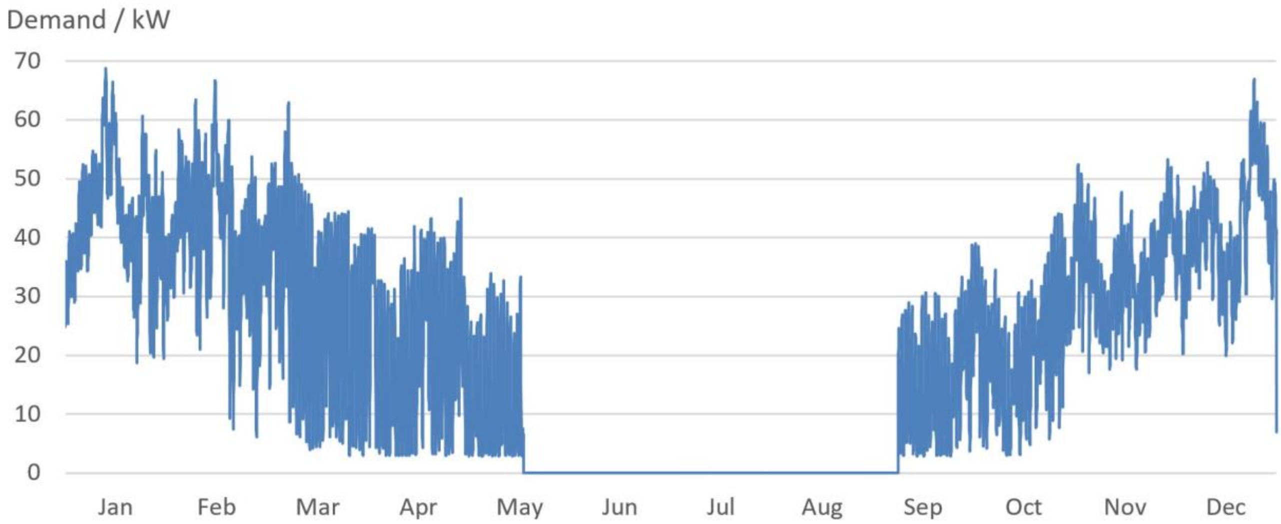

Figure 3. Annual demand profile of heating with a constant setpoint temperature from annual simulation.

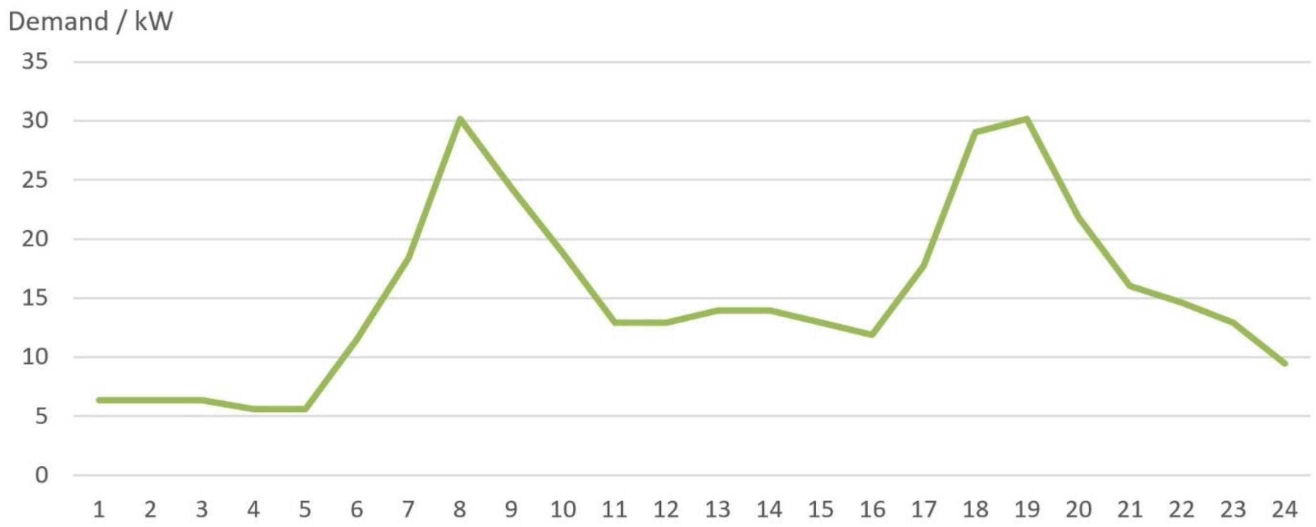

Figure 4. Hourly demand profile for domestic hot water for 24 h (repeated).

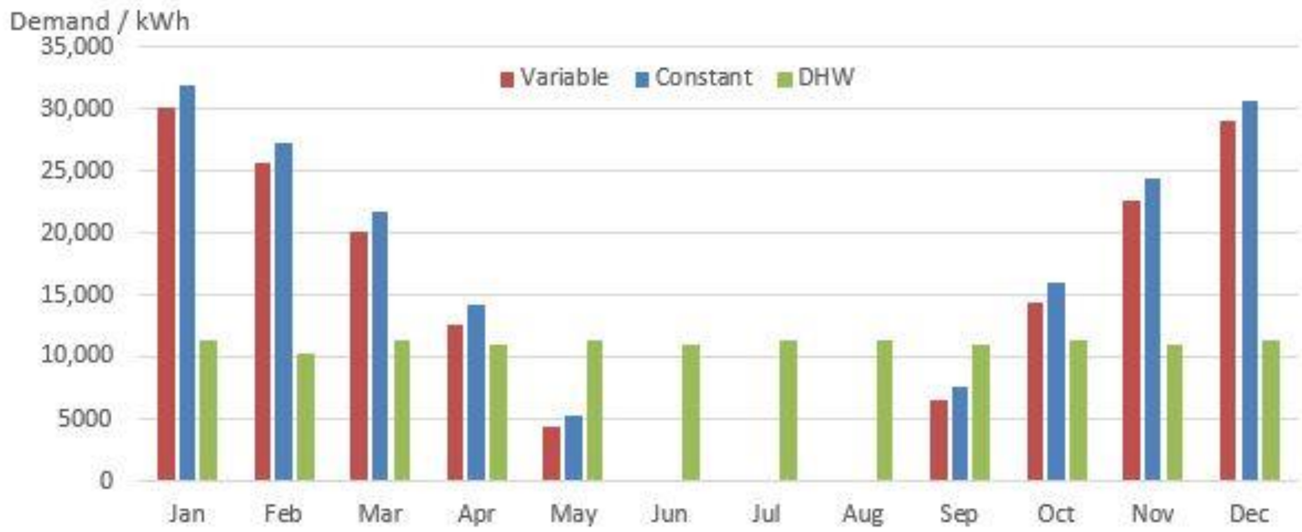

Figure 5. Monthly demand profile from annual simulation of the three tested demands.

2.1.3. HWST

The number of tanks and the setpoints were varied from starting conditions based on common praxis for the project. For heating, this was one 1000 L tank with a 55 °C setpoint. For DHW, this was three tanks with a 65 °C setpoint. Tank sizes were varied in 1000 L increments and setpoints ($T_{setpoint}$) were decreased in 5 °C increments down to 45 °C for heating and 55 °C for DHW. A maximum tank temperature of 95 °C was assumed. The heating elements supplying the system were varied in 5 kW increments. The initial cost of one 1000 L HWST (including electric heating element) according to the Norwegian Pricebook was 42,000 (≈4200 EUR) with a 20-year lifetime [47].

The key parameter for determining the charging profile is the heat loss associated with the storage of energy. A high heat loss makes load shifting difficult over long time periods. The HWST was based on a commercially available 1000 L tank, modelled as a cylinder 2.2 m high and 1 m in diameter. It was assumed to have 100 mm of insulation with a thermal conductivity of 0.037 W/(m·K). The internal dimensions were thus 2 m high and 0.8 m in diameter. The resulting surface area was 6.03 m^2. In addition, a 0.2 W/K loss was assumed for each of the four connection points based on the findings of Steinweg et al. [48]. The specific heat loss, H_s, for each tank was therefore 3.03 W/K. The heat loss of storing an additional kWh of thermal energy was calculated as:

$$\frac{H_s \cdot (T_s + 1 - T_a) - H_s \cdot (T_s - T_a)}{C_{T+1} - C_T} = \frac{H_s}{C_{T+1} - C_T}, \quad [\mathrm{W/kWh}], \tag{1}$$

where T_s is the tank temperature and T_a is the ambient temperature around the tank (assumed constant at 18 °C). The volumetric heat capacity of water (C_T) was defined as:

$$C_T = \frac{c_{p,w} \cdot \rho_w}{3600}, \quad \left[\mathrm{kWh/(m^3 \cdot K)}\right]. \tag{2}$$

The values used for the heat capacity ($C_{p,w}$) and density (ρ_w) of water are those for a constant pressure equivalent to atmospheric pressure at sea level. As $C_{p,w}$ and ρ_w vary with temperature, the resulting range of heat loss within the working range of 45 °C to 95 °C was from 2.99 W/kWh to 3.27 W/kWh. In order to simplify the model, a heat loss of 3.13 W/kWh (equivalent to 65 °C) was taken as the first value. The effect of this simplification has been expanded upon in the discussion section.

2.2. Cost Saving Analyses

The potential economic benefit of DR of HWSTs was examined through two analyses, outlined in Figure 6. The first was a simple analysis of energy price data. The second utilised a set of algorithms that created an HWST charging strategy to minimise unit energy cost based on electricity price, heating power and a thermal energy demand profile, which was then adapted with a second algorithm to the available storage capacity. Although an optimal strategy is unlikely in practice, this simplified model delivers a best-case result to quickly evaluate the potential economic benefit. It is then possible to further analyse chosen scenarios in detail using simulation of a control system.

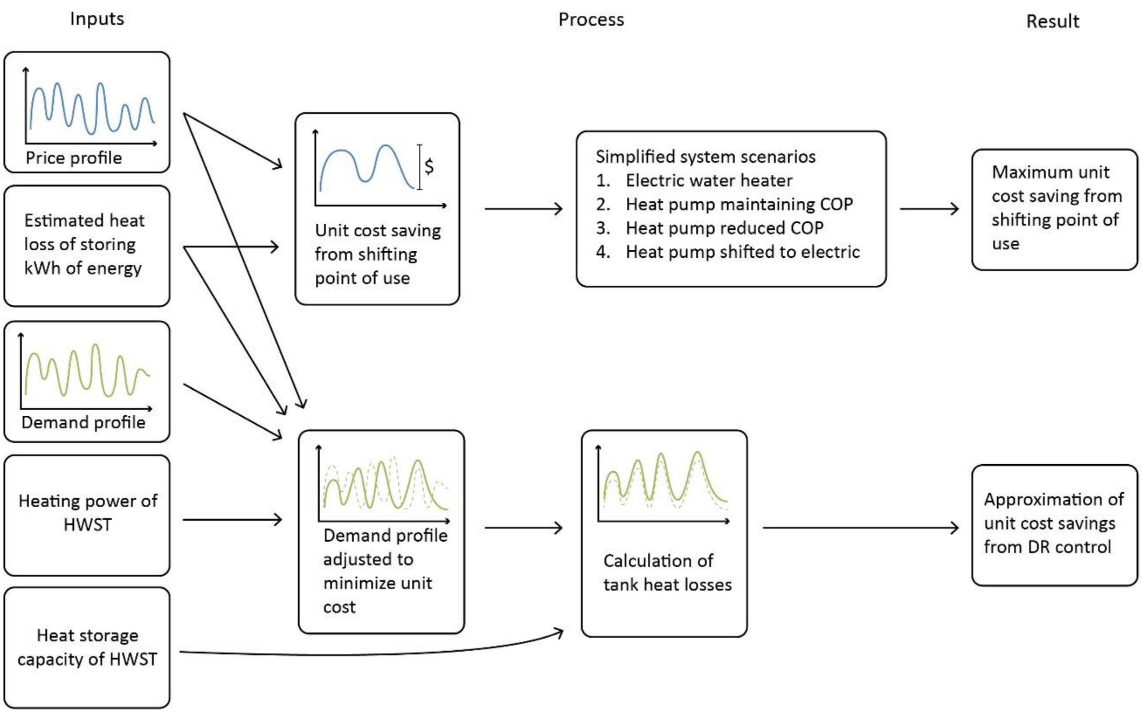

Figure 6. Flowchart of cost saving analyses.

Both analyses worked on an end-of-day time horizon with price information available from 14:00 on the previous day. The Nord Pool auction closes at 12:00 with price data available within the following hour [12]. An additional hour was assumed to mitigate potential communication problems. This meant that the charging profile would be optimised in 34-h iterations. Both analyses worked on the principle that the control would only charge the tank when necessary, preloading it with the required energy to meet the heating demand for future hours. Otherwise, the HWST was kept at the lower setpoint temperature to minimise heat loss.

2.2.1. Analysis of Unit Cost Savings Using Electricity Price Data

A simple analysis of the electricity price data was first undertaken to assess the potential for savings from DR. The last nine years of electricity price data were analysed to find the possible year on year variation. The analysis did not consider any system limits for the heating element or HWST capacity. Therefore, the results represent the maximum energy savings possible from shifting heating energy within the time horizon. For each timestep, the electricity price was compared to the price in the preceding hours until 14:00 the previous day. The price for each preceding hour was calculated as:

$$Price_{0-n} = Price_n \cdot Additional\ Heat\ Loss^n, \text{[NOK/kWh]}, \tag{3}$$

where n is the number of hours preceding the current timestep. The price for each preceding hour factors in the additional heat loss from the longer storage. The potential saving was then found by subtracting the lowest found price from the timestep price. The process was repeated for each timestep. The resulting timestep savings were then multiplied by the hourly thermal energy demand profile. Four scenarios for the delivery of the demand were analysed which represent common electric heating solutions:

- Scenario 1: Electric water heater.
- Scenario 2: Shifting from heat pump to heat pump, maintaining COP. Unit cost savings are divided by the heat pump COP. For both heating profiles, a COP of 4 was used. For DHW, a COP of 3 was used. These values were fixed and based on measured seasonal values [49] as a simplification for this analysis.
- Scenario 3: Shifting from heat pump to heat pump with reduced COP. As the storage of thermal energy for later use often requires higher tank temperatures, the performance of the heat pump will likely be reduced. The reduced COP is half of those used in scenario 2.
- Scenario 4: Shifting from heat pump to electricity. Extending scenario 3 to a situation where the heat pump is no longer able to provide hot enough water temperature to charge the HWST and so an electric heating coil must be used. In other words, the COP is reduced to 1.

2.2.2. Approximation of an Optimal DR Control to Minimise Energy Cost

An algorithm was written to create a charging profile to minimise unit energy cost according to the available heating power, the demand profile and the electricity price over the 34-h iteration time. The algorithm was limited to heating systems with a constant system efficiency independent of the outside conditions or load on the system. Based on the analysis of historic electricity spot prices, three years were chosen to represent average electricity prices (2019), volatile electricity prices (2018) and highly volatile electricity prices (2021).

The potential cost saving for each timestep was found by multiplying the timestep's demand by each of the electricity prices for the timestep hour and the preceding hours until 14:00 the previous day, using Equation (3). These were ranked ($Rank_{timestep}$) by cost saving. This was repeated for all 24 timesteps in the iteration, which were ranked ($Rank_{hour}$) by their maximum cost saving.

The demand for the highest $Rank_{hour}$ was then placed at the timestep which had the highest $Rank_{timestep}$ for that $Rank_{hour}$. If this exceeded the capacity of the heating power, the demand to fill that capacity was placed at the highest $Rank_{timestep}$ and the remaining demand was placed at the next highest $Rank_{timestep}$. This process was repeated for each hour in descending order of $Rank_{hour}$, as shown in Figure 7. The available heating power at each timestep was equal to the maximum capacity of the heating element minus any demand assigned to that timestep. This included the demands assigned in the previous iteration which overlap the first 10 h of the 34-h optimisation period. Where it was not possible to distribute all of an hour's demand within its preceding timesteps, any remaining demand was added to the next proceeding timestep which did not create a deficit in the energy balance. This, in essence, moves a higher ranked hour's demand to a later point to make space for the lower ranked hour's demand.

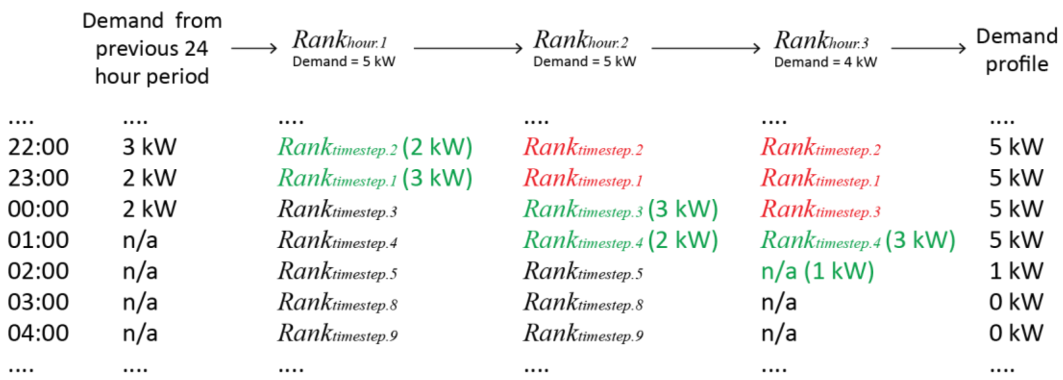

Figure 7. Graphical representation of demand profile optimisation for a simple example of a heating element with a 5 kW capacity. Green shows placement of an hour's demand at that timestep. Red shows where demand placement is not possible as the capacity of that timestep has already been reached.

The resulting charging profile was then applied to a second algorithm which adjusted the charging profile according to the available heat storage capacity and resulting heat losses. The energy stored in the HWSTs at each timestep (q_{tank}) was calculated using the following formula:

$$q_{tank,n} = q_{tank,n-1} + \left(Q_{charge,n} - Q_{discharge,n}\right), \ \ [\text{kWh}], \tag{4}$$

where Q_{charge} is the heat added according to the optimised charging profile and $Q_{discharge}$ is heat used according to the demand profile. For the reference system, it is assumed that Q_{charge} was equal to $Q_{discharge}$ at each timestep. The temperature and additional heat losses of the HWSTs for each timestep were calculated as:

$$T_{tank} = T_{min} + \left(\frac{q_{tank}}{q_{max}} \cdot (T_{max} - T_{min})\right), \ \ [^\circ\text{C}]. \tag{5}$$

The maximum temperature (T_{max}) is set at 95 °C. The minimum temperature (T_{min}) is defined from the starting condition and decreased in 5 °C increments. Here, the relationship between energy storage and the water temperature is simplified to a linear correlation. The energy storage capacity of the tank (q_{max}), defined in kWh, is calculated based on the temperature range and number of tanks:

$$q_{max} = V_{tank} \cdot ((T_{max} \cdot C_{T,max}) - (T_{min} \cdot C_{T,min})), [\text{kWh}], \tag{6}$$

where C_T is calculated according to Equation (2). The heat capacity ($c_{p,w}$) and density (ρ_w) of water are set based on the minimum and maximum tank temperatures. Finally, the heat loss at each timestep was calculated as:

$$q_{S,Loss} = H_S \cdot (T_{tank} - T_a) \cdot n_{tank}, \ \ [\text{W}], \tag{7}$$

where H_S is the specific heat loss for each 1000 L tank (3.03 W/K) and n_{tank} is the number of tanks. The heat loss was then added to the charging profile. In hours which were already utilising the maximum heating power, the heat loss was placed at the next hour with available heating power. When the available storage capacity was full, any additional charging of the tank was placed at the next available hour. These simplifications were chosen to allow variation of the tank size and temperature without having to run the first algorithm again. A potential impact is that in cases with small storage capacity and heating power it is possible that the resulting demand profile is slightly suboptimal.

2.3. Performance Indicators

According to Pallonetto et al. [50], three different dimensions need to be considered in the assessment of energy flexibility: technical (volume of energy shifted or available instantaneous capacity), economic (operational cost) and environmental (carbon dioxide emissions or primary energy). The specifics of these dimensions are dependent upon the chosen perspective studied (supplier, grid operator or consumer). These indicators show the difference in a chosen parameter between the altered energy demand profile and its reference.

The amount of shifted energy was quantified in line with the that proposed by IEA EBC Annex 67 for available electric energy flexibility (AEEF) [50]:

$$AEEF = \int_0^T |P_{e,DR} - P_{e,R}| \cdot dt, \text{[kWh]}, \quad (8)$$

where $P_{e,DR}$ is the optimised profile, $P_{e,R}$ is the unoptimised profile and T is the length of the optimisation period, which was 8760 h in this study. AEEF was then averaged to an hourly value for comparison.

The economic benefit was calculated by multiplying the optimised profile by the electricity price data. The monthly peak power was also found to calculate the monthly fees. These were then compared with the cost of the unoptimised profile.

$$Unit\ cost\ savings = \sum_{n=0}^{T} Price_n * (P_{e,DR.n} - P_{e,R.n}),\ [NOK]. \quad (9)$$

$$Monthly\ cost\ savings = \sum_{Jan}^{Dec} Monthly\ cost * (P_{e,DR.max} - P_{e,R.max}),\ [NOK]. \quad (10)$$

For this study, no assessment of primary energy or carbon dioxide was undertaken, due to the DR of a single building having little effect on macro energy decisions. Furthermore, the CO_{2eq}. intensity in the Oslo regional grid is low with minimal variation [5]. It is unclear if DR would help to reduce carbon dioxide emissions in Norway, as the correlation between price and CO_{2eq}. intensity has been shown to be the opposite of most other countries, with higher intensities at low prices. This is because Norwegian hydropower favours operating at higher prices during energy peaks and so more energy is imported (with higher CO_{2eq}. intensity) when prices are low.

3. Results

3.1. Analysis of Spot Prices

The past nine years of electricity price data were analysed for price distribution over the year, shown in Figure 8, and price variation in a 24-h period, shown in Figure 9. Prices are given in NOK (1 NOK ≈ 0.1 EUR). Box plots in Figure 9 show the 1st, 2nd and 3rd quartile of the 365 values for each year. Whiskers show the range of values within 1.5 times the interquartile range below the 1st quartile and above the 3rd quartile. Dots are values outside this range. For 2016, there are three points which lie beyond the chart range (1.23 NOK, 1.28 NOK and 1.82 NOK). For 2018, there is one point (2.08 NOK). For 2021, there were 26 points with a maximum difference of 4.07 NOK on the 22nd of December. The general variation of prices was less than 0.1 NOK in all years except for 2018 and 2021. This small variation is due to the high proportion of hydropower in the Norwegian electricity mix, as it is possible to regulate the generation capacity of hydropower without affecting efficiency.

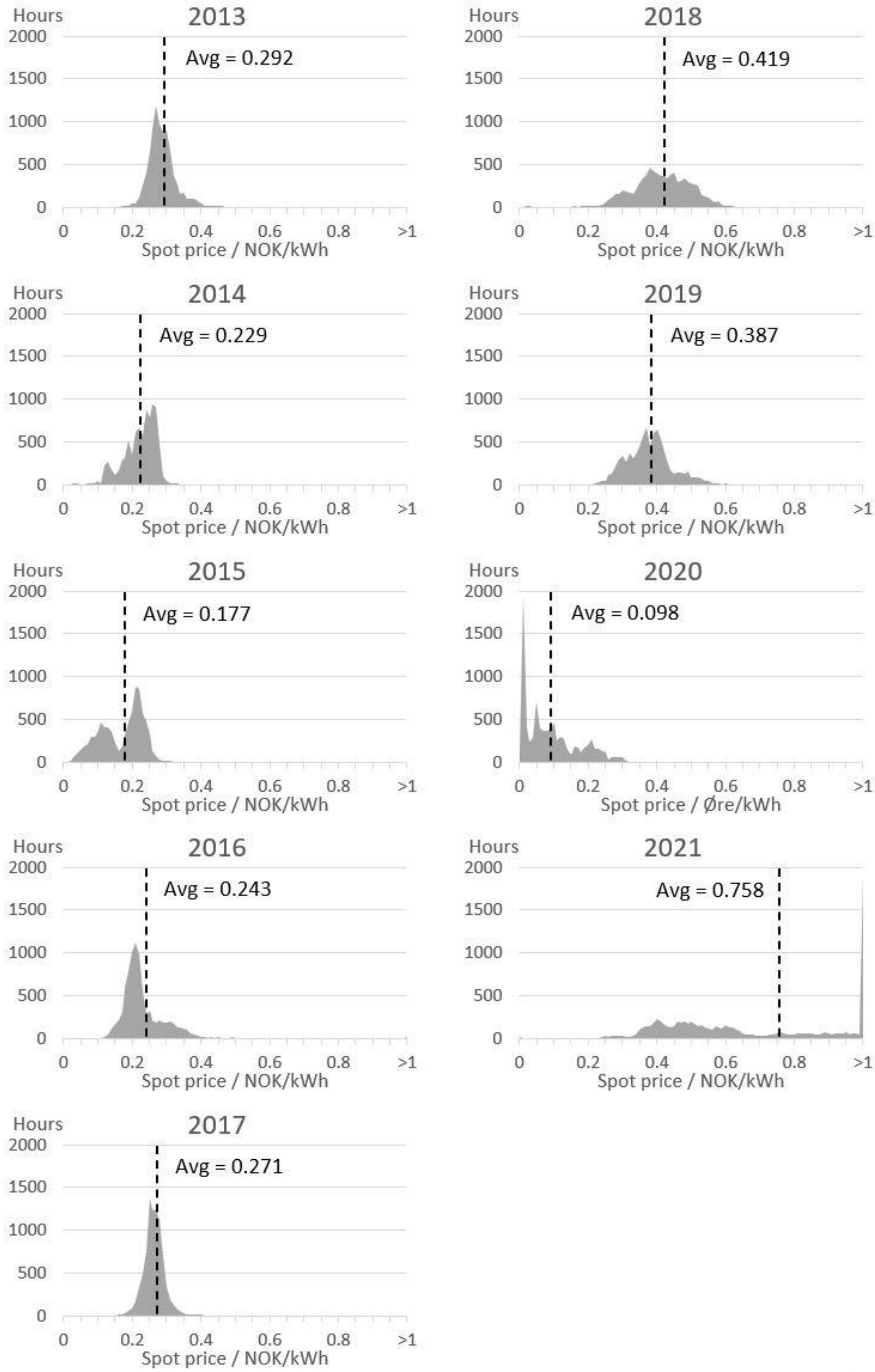

Figure 8. Distribution of Nord Pool spot prices for the Oslo region for the last nine years. Average spot price indicated by the dashed line. 1 NOK ≈ 0.1 EUR.

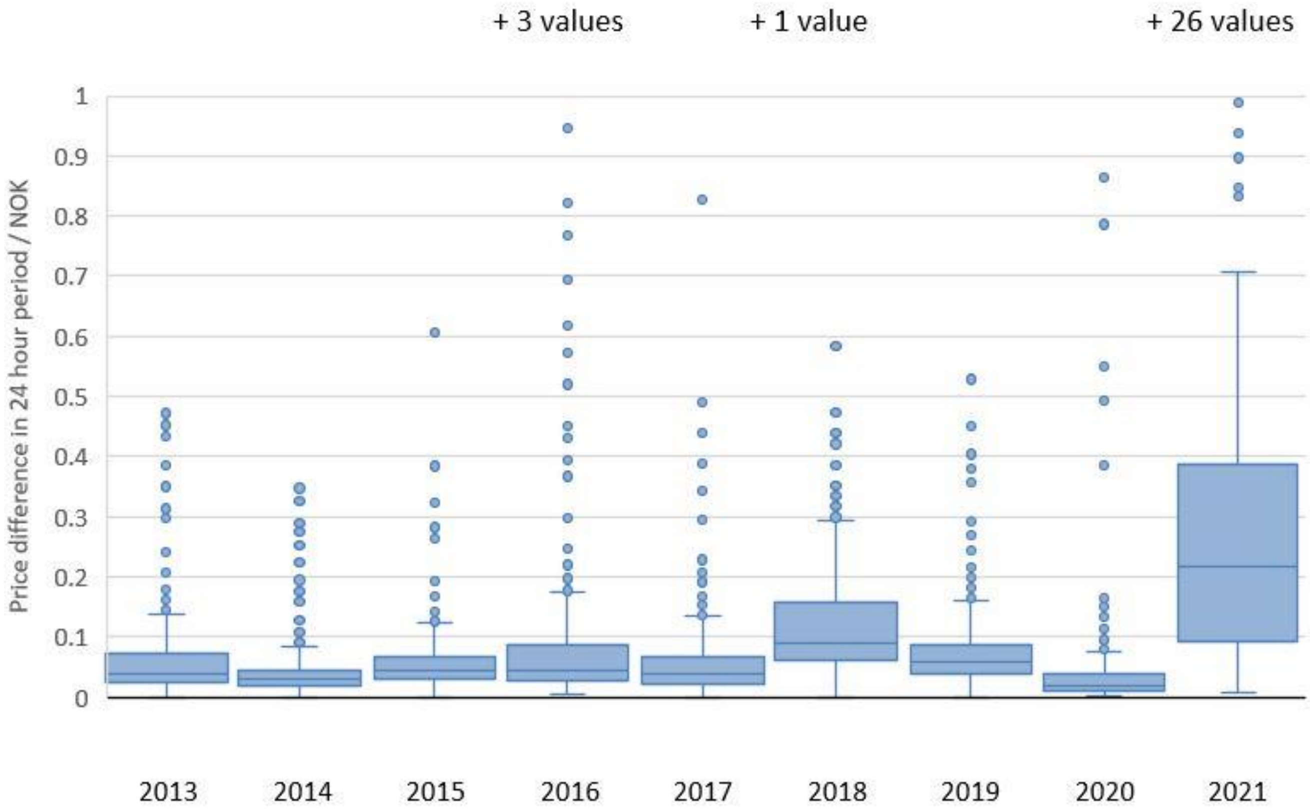

Figure 9. Distribution of the price difference between the highest and lowest spot price in each 24 h period in a year, for the last nine years of spot price data. 1 NOK ≈ 0.1 EUR.

The electricity price has had greater variation in the past four years. Average prices and price variation were higher than average in 2018, due to a lack of precipitation constricting the supply of hydropower combined with increased prices for imported energy due to higher CO_2 taxes [51]. Prices were also slightly volatile in 2016, although this was due to a few extreme 24 h periods, of which three were over 1 NOK in difference (outside the range of Figure 9). The interquartile range and mean spot price for 2016 were similar to the other "normal" years before 2018, with a mean spot price of around 0.25 NOK/kWh. There was increased variation in 2019 due to the increasing number of grid interconnections [12]. When prices are high in other countries, it is appealing for Norwegian energy producers to sell their electricity abroad, in turn raising prices nationally. As both CO_2 taxes and grid interconnections will exist in the coming years, 2019 is considered a good example of a typical year. Electricity prices were extremely low, sometimes below zero, in 2020 due to the depressed demand caused by the coronavirus pandemic. There were significantly higher prices in 2021, due to the combination of high demand from economies reopening from the pandemic and a shortage of fossil fuels [52]. During 2021, Norway exported large quantities of energy at peak times which resulted in significantly more price variation within a 24 period than in the preceding nine years. There was also the largest range in prices over the year with a minimum of 0 NOK and a maximum of 6.12 NOK.

3.2. Potential Unit Cost Saving

The maximum potential unit cost savings from shifting the energy for all nine years was calculated using Equation (3). The results are shown in Table 3 for the three demand profiles and four scenarios. For comparison, the leap day was removed from 2020 and 2016 data.

Table 3. Annual savings in unit energy cost from shifting demand to lowest price within a 24 h period. Prices in NOK. 1 NOK ≈ 0.1 EUR.

	2013	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Scenario 1: Shifting from electricity to electricity									
Constant	3665	3714	3924	7596	4026	8859	4540	3477	35,835
Variable	4564	4435	4737	9144	4927	10,916	5646	4003	40,291
DHW	4125	2650	4107	5402	3798	9154	5049	2092	25,272
Scenario 2: Shifting from heat pump to heat pump maintaining COP									
Constant (COP = 4)	916	929	981	1899	1006	2215	1135	869	8959
Variable (COP = 4)	1141	1109	1184	2286	1232	2729	1412	1001	10,073
DHW (COP = 3)	1375	883	1369	1801	1266	3051	1683	697	8424
Scenario 3: Shifting from heat pump to heat pump with reduced COP									
Con. (COP: 4 →2)	10	0	1	203	5	98	12	38	709
Var. (COP: 4 → 2)	11	0	2	244	5	130	14	44	827
DHW (COP: 3 → 1.5)	14	0	2	156	4	122	17	24	818
Scenario 4: Shifting from heat pump to electricity									
Con. (COP: 4 → 1)	0	0	0	10	0	3	0	0	18
Var. (COP: 4 → 1)	0	0	0	14	0	4	0	0	16
DHW (COP: 3 → 1)	0	0	0	53	0	16	0	0	126

The results indicate that the variable setpoint heating schedule had the most to gain from DR. The constant setpoint heating and DHW schedules produced similar savings, but neither was consistently better than the other over the nine years. There was no clear correlation between the price distribution and the difference between these schedules. For all three schedules, there was a good correlation between the price variation over a 24 h period (Figure 9) and the energy savings for scenario 1 and 2. The correlation for scenario 1 is shown in Figure 10. Scenario 2 has the same R^2 value as the savings are scaled. The high price variation in 2021 resulted in the largest savings. The low price variation in 2014 and 2020 resulted in the lowest savings. Under scenarios 3 and 4, these patterns were skewed in favour of years with large price variations (2016, 2018 and 2021), due to the decreased COP requiring a greater electricity price saving to warrant shifting energy.

The potential savings were greatest for scenario 1. Where a heat pump is used for DR, maintaining its COP (scenario 2), the possible savings were divided by that COP. In Table 3 the savings are a quarter of the electricity savings, as the COP is 4. Therefore, the higher the heat pump COP, the lower the potential savings from load shifting. This was even more pronounced for scenarios 3 and 4, where the COP at the shifted time is reduced. As the energy has to be stored, it will likely require a higher temperature than at the point of demand, reducing the COP of the heat pump. Under these scenarios, the savings are reduced to a few hundred NOK. Under scenario 4, there were no savings in six of the nine years.

The savings mirror the potential benefit to the electricity grid. As the COP of the heat pumps already reduces the load on the grid, shifting it to another point in time has less benefit. Flexibility control should therefore be focused on direct electrical systems. These are well suited to control as they can be started and stopped nearly instantly with little energy loss.

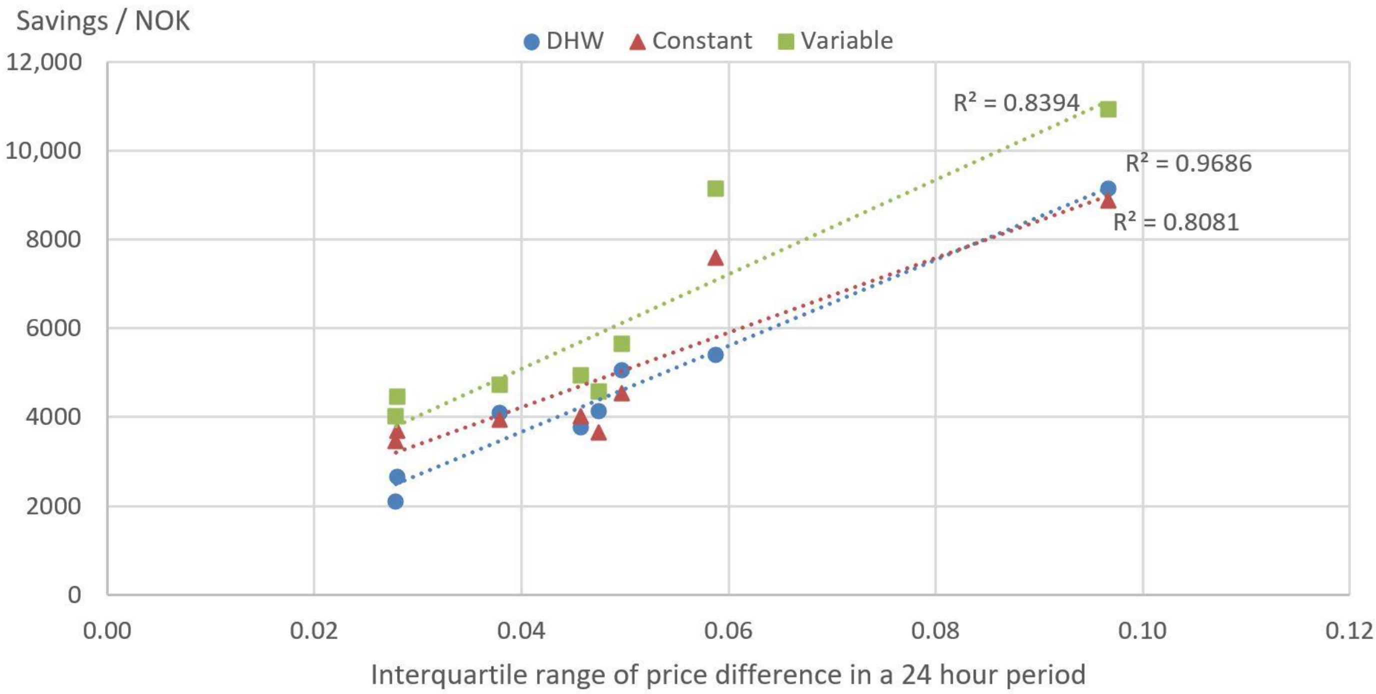

Figure 10. Correlation between price variation over a 24 h period and savings for scenario 1, excluding 2021. 1 NOK ≈ 0.1 EUR.

3.3. Demand Profile Optimisation

The potential for electrical systems was further analysed, accounting for the power of the electric water heater and the HWST characteristics. The monthly cost for the electrical peak power was also considered. Based on the analysis of historic electricity spot prices, three years were chosen to represent average spot prices (2019), volatile spot prices (2018) and highly volatile spot prices (2021).

The energy flexibility as a function of the tank volume for the three demand profiles at different maximum heating powers is shown in Figure 11, using 2019 spot prices. The flexibility increases with tank size and heating capacity; however, both factors are subject to a diminishing rate of return as shown by the plateauing of flexibility as the tank size increases. The variable heating schedule had the highest flexibility potential and DHW had the lowest. As the metric is created by the difference between the optimised charging profile and the reference demand profile, it is affected by the amount and distribution of the reference demand. The lower potential of DHW is in part due to the lower total demand. DHW requires 133 MWh annually compared to 179 MWh for constant setpoint heating and 165 MWH for variable setpoint heating. Conversely, the higher total demand of the constant heating does not lead to more flexibility due to the distribution of the demand which is fairly constant over a 24-h period. The peaks of the DHW and variable demand coincide with the daily peaks in electricity prices. Therefore, this demand is often shifted and so leads to a higher flexibility result. Part of the increased flexibility score with the increased number of tanks is due to the higher energy use due to additional heat losses from more tanks.

Changing the minimum setpoint temperature alters the energy storage capacity of each HWST. This affects the steepness of the flexibility curve but has little effect on the maximum level of flexibility achieved, as shown in Figure 12.

The unit cost savings curves as a function of the tank volume for the three demand profiles at different powers and minimum tank temperatures using 2019 spot prices are shown in Figures 13–15.

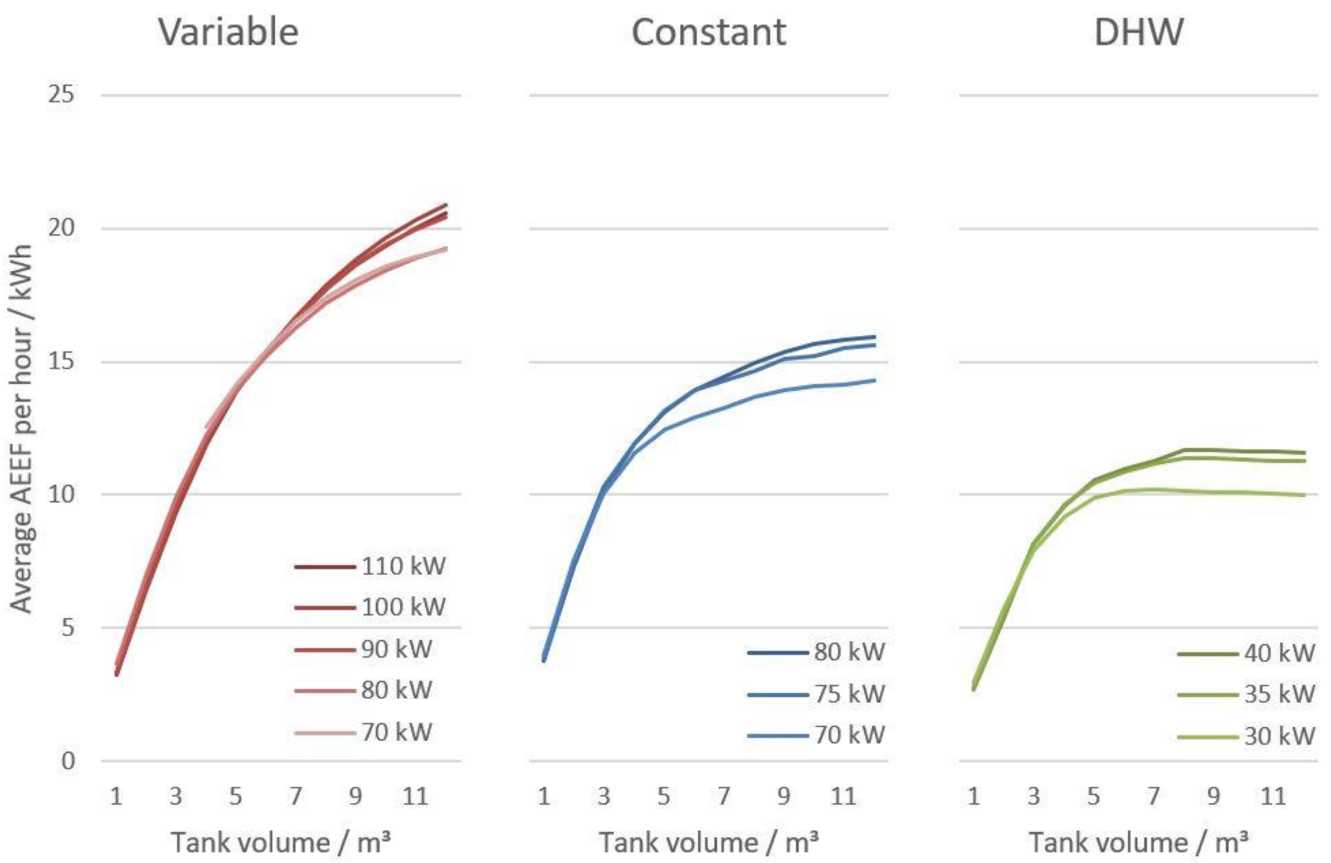

Figure 11. Average AEEF per hour as a function of tank volume for the three demand profiles at different maximum heating power using 2019 spot prices.

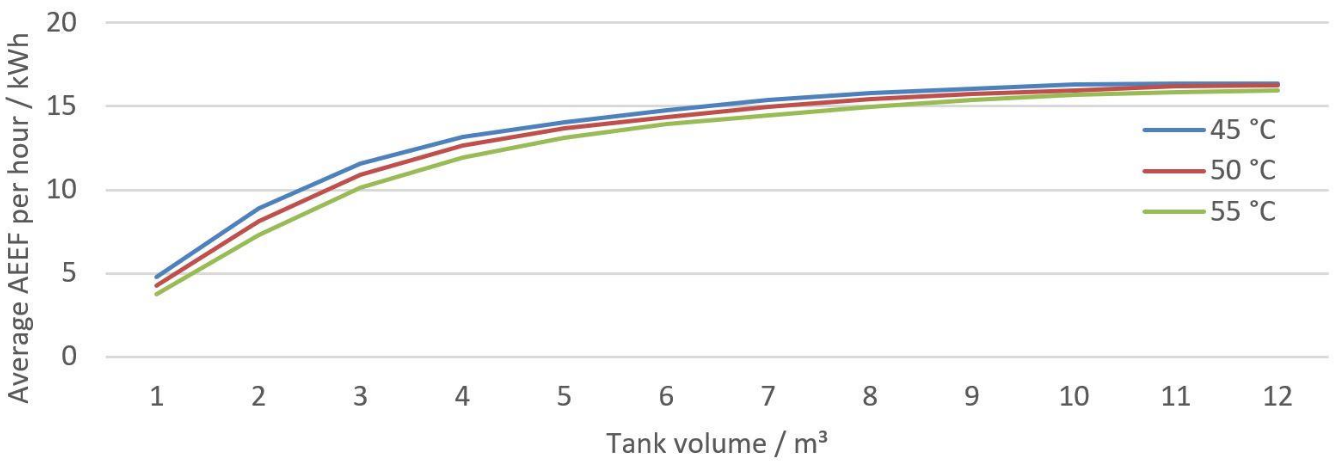

Figure 12. Effect of minimum setpoint temperature on AEEF as a function of tank volume. Result for constant setpoint heating and 80 kW heating power using 2019 spot prices.

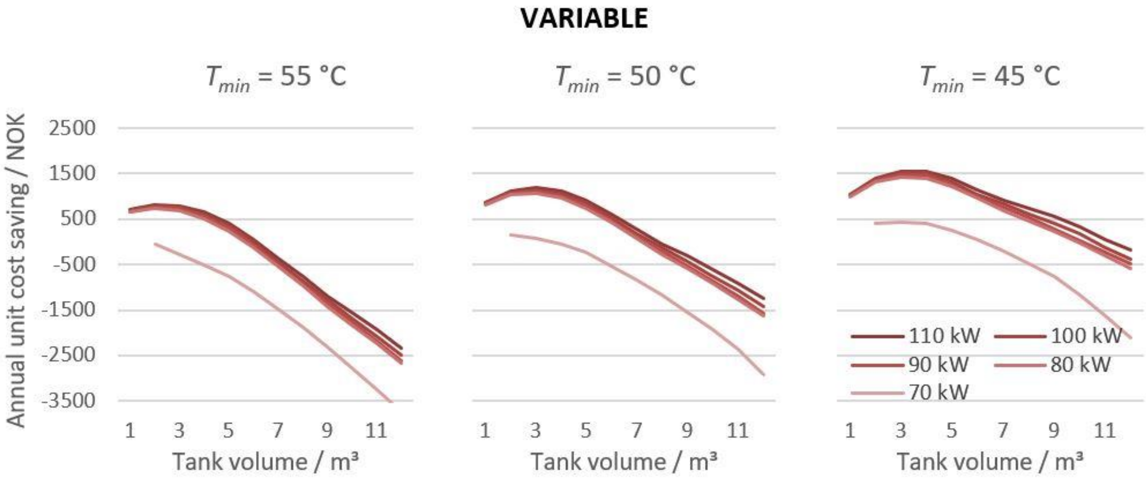

Figure 13. Unit cost saving as a function of the tank volume for variable setpoint demand profile at different maximum heating power and minimum tank temperature using 2019 spot prices. 1 NOK ≈ 0.1 EUR.

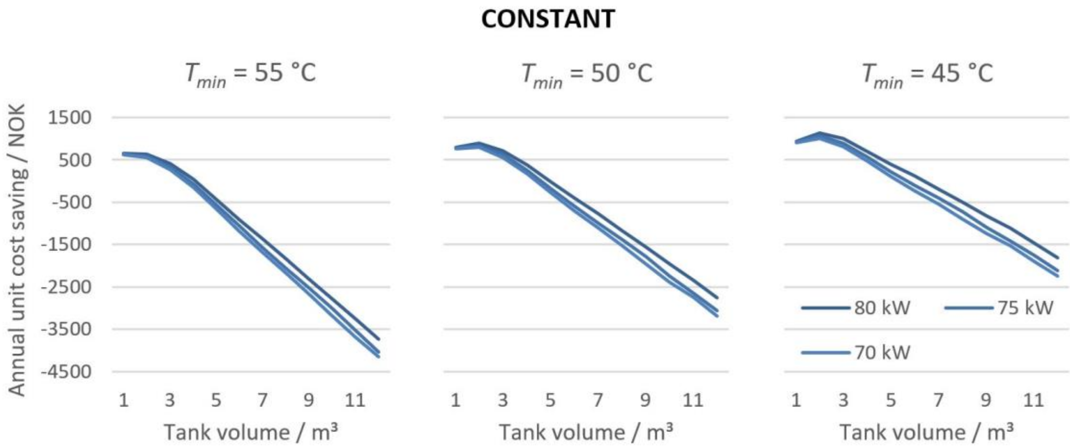

Figure 14. Unit cost saving as a function of the tank volume for constant setpoint demand profile at different maximum heating power and minimum tank temperature using 2019 spot prices. 1 NOK ≈ 0.1 EUR.

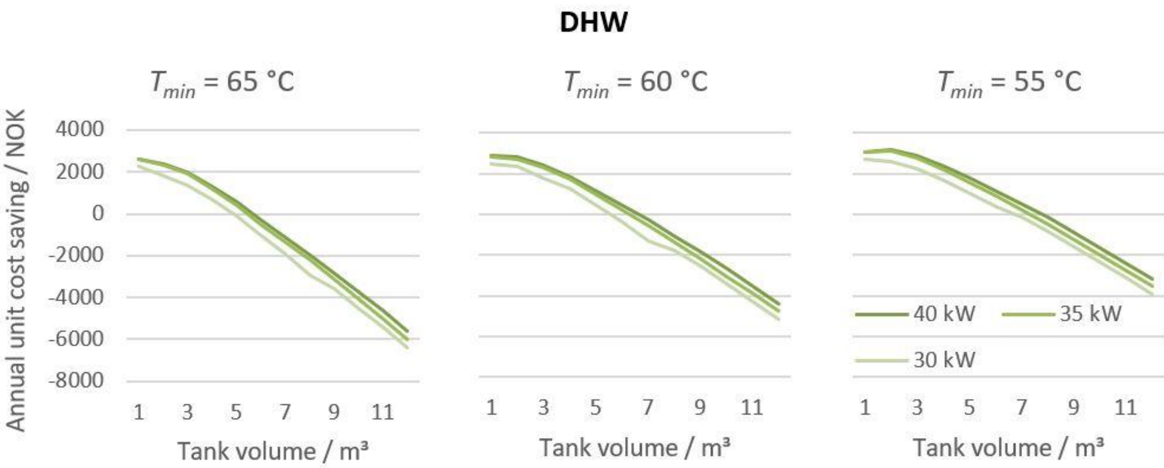

Figure 15. Unit cost saving as a function of the tank volume for DHW demand profile at different maximum heating power and minimum tank temperature using 2019 spot prices. 1 NOK ≈ 0.1 EUR.

Increasing the heating power increases the unit cost savings but with a diminishing rate of return, as shown with the flexibility. However, increasing the storage capacity by increasing the number of tanks results in lower cost savings as the additional heat losses more than outweigh the gains from greater flexibility. Increasing the storage capacity by lowering the minimum tank temperature shows improved cost savings, as storage capacity is increased without increasing heat losses. The AEEF and unit cost savings for 2018, 2019 and 2021 are compared in Figures 16 and 17, respectively.

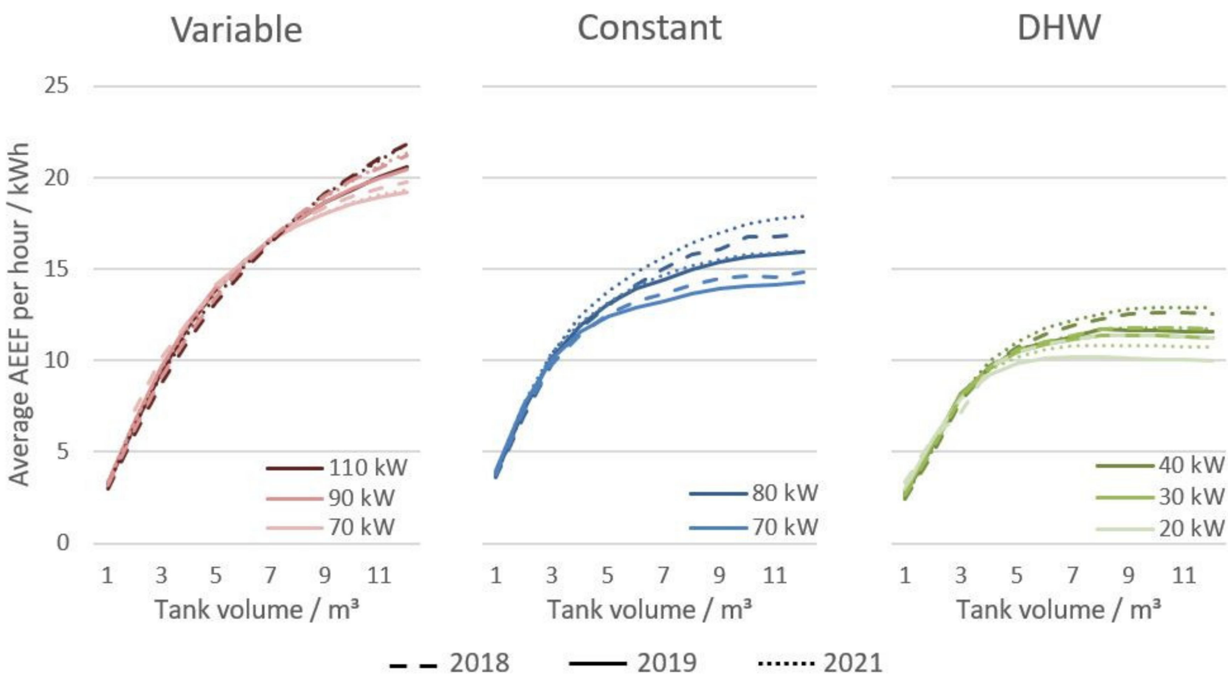

Figure 16. Average AEEF per hour as a function of tank volume for the three demand profiles at different maximum heating power using 2018, 2019 and 2021 spot prices.

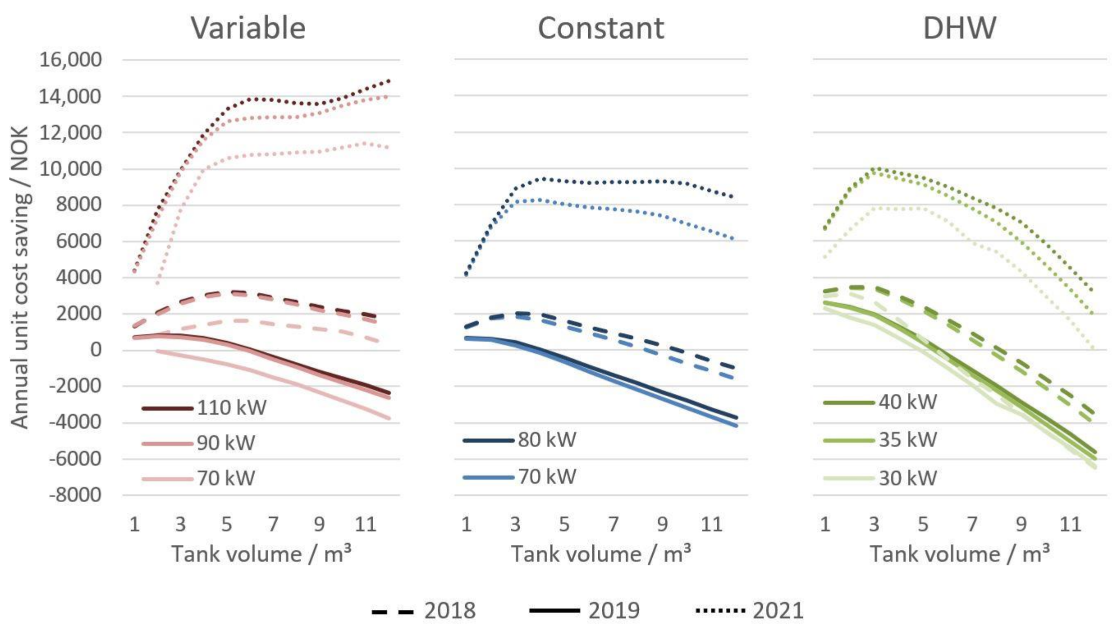

Figure 17. Unit cost saving as a function of the tank volume for the three demand profiles at different maximum heating power using 2018, 2019 and 2021 spot prices. 1 NOK ≈ 0.1 EUR.

The amount of flexibility was similar between the three years, while the unit cost savings varied considerably, correlating to the energy price variation shown in Figure 9. The volatile prices of 2018 resulted in five tanks giving increased unit cost savings for the variable schedule. Here, the benefit of more flexibility outweighs the additional energy cost of heat losses. The high volatility of the 2021 spot prices makes greater tank volumes worthwhile for all three demand profiles when considering unit cost savings. For this spot price, there was a clear optimum tank volume, which increased with higher heating power. For the DHW demand, the optimum number of tanks was three. The optimums for the heating profiles were between three and five tanks. The savings were significantly lower than those predicted using the simple model, as the simple model did not factor in the increased baseline heat losses from the increased storage volume required to maximise the shifted load.

The monthly cost saving is shown in Figure 18. The peak load of each month would equal the defined maximum heating power as the algorithm would always assign the maximum capacity where electricity prices were lowest. For each 10 kW increase in heater power, the peak electricity cost increased by 6480 NOK (≈648 EUR) for DHW and by 5820 NOK (≈582 EUR) for heating (as there is no heating in the summer months).

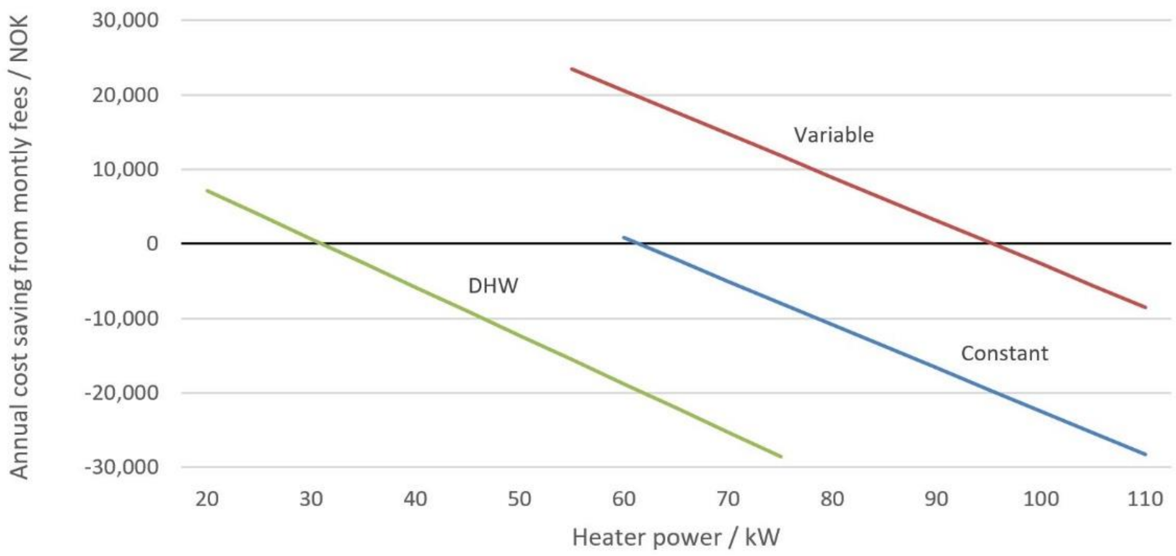

Figure 18. Annual cost saving from monthly fees as a function of maximum heating power for the three demand profiles. 1 NOK ≈ 0.1 EUR.

When the monthly cost and the capital cost of additional tanks are factored in, the unit cost savings are dwarfed and the yearly variation appears minimal. The total cost savings are shown in Figure 19. The capital cost of each tank (42,000 NOK ≈ 4200 EUR) was divided by its expected lifespan (20 years) to give a simple annual cost based on a straight-line depreciation. Under all scenarios, the most cost-effective approach was to minimise the tank volume and heating power. These savings are sensitive to the starting parameters for the number of tanks and tank setpoint. The savings for DHW are relatively high as the reference system consisted of three tanks compared to just one tank for the heating systems. There were little cost savings for the constant profile as this heating strategy already minimises the peak power required. The variable setpoint gives the greatest cost savings as the electric heater size can be dramatically decreased.

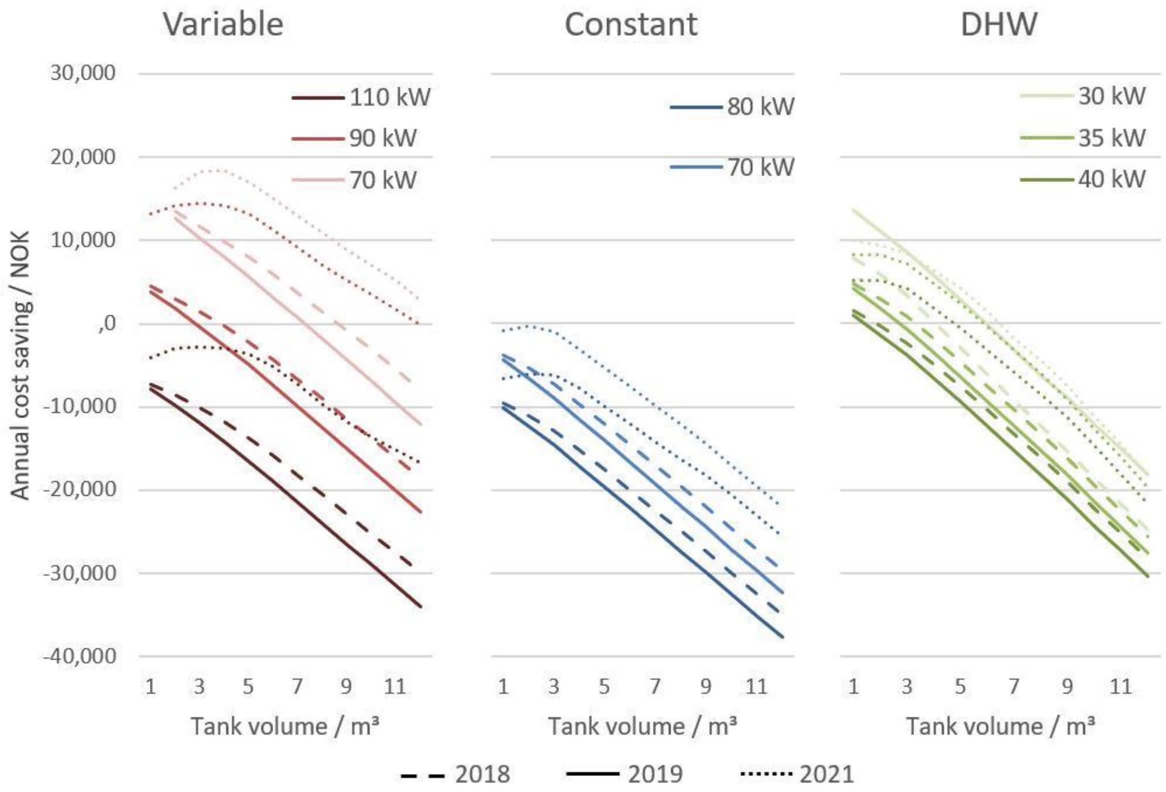

Figure 19. Total annual cost saving as a function of the tank volume for the three demand profiles at different maximum heating power using 2018, 2019 and 2021 spot prices. 1 NOK ≈ 0.1 EUR.

4. Discussion

When all system factors were considered, the use of DR of HWSTs gave operational cost savings, but this was from minimising the peak power of the heating element and storage volume rather than shifting the load to hours with a lower spot price, as shown in Figure 19. Under this strategy, an intelligent control is required to proactively charge the HWST over several hours at a low power to meet the heating/DHW demand. Even when the monthly cost and tank investment cost are excluded, it was more economical to minimise the storage volume in most cases. The spot prices from 2021 had enough price variation to warrant increased storage volume for all three demand profiles, as shown in Figure 17. Greater unit cost savings were possible through increasing the heating power or reducing the setpoint temperature, as shown in Figures 13–15. Increasing the heating power was subject to a diminishing rate of return and the unit cost savings were outweighed by the dominant role of the monthly price related to the peak energy demand of the system. Reducing the minimum setpoint temperature reduces heat losses while increasing storage capacity. For DHW, this must be balanced with periodically achieving a high enough temperature to prevent the growth of legionella [53]. Furthermore, a lower setpoint decreases the resilience of the HWST to short demand peaks, with an increased risk of not meeting demand. For this study, the minimum setpoint temperature was not reduced below the required supply temperature of the demand profile, to guarantee the quality of heat was always enough. As the algorithm uses the average temperature in the HWST, a stratified HWST could allow for the minimum setpoint temperature to be further reduced as the top of the tank can be hotter than the average.

The results are an indication of the economic benefits of DR of HWSTs; however, they are subject to methodological and practical limitations which mean that real-world returns would likely be lower than found with this method. The algorithms approximate a control with a charging strategy to minimise unit cost, whereas an actual control would deviate from this profile as it responds to other system parameters and unforeseen disturbances.

Additionally, the heating control requires a finer temporal resolution [54] than the hourly values simulated here and a degree of safety to cover these unforeseen disturbances. Although the time horizon was limited by the electricity price data, short horizons on the order of one day are only marginally suboptimal relative to a strategy that is optimal over the entire simulation horizon [55]. Similarly, it has been shown that MPCs can achieve near optimum performance [36]. This study assumed that there were no limits to the amount of energy used to charge and discharge the HWSTs. Measured data shows that large demand variations can occur within the hour for DHW [37], which define the peak discharge and so the minimum system size. Therefore, there is a limit to how much the size of a DHW system can be reduced. Another issue with small storage volumes is a greater temperature fluctuation which requires a control valve to provide consistent delivered temperatures, adding an additional cost to the system. The optimisation is sensitive to the chosen storage heat loss parameter, with a higher value resulting in less shifting. If the average tank temperature is significantly higher or lower than the one used to define the heat loss parameter, the algorithm can deliver a suboptimal charging strategy. Running the optimisation using the upper and lower limits for the heat loss parameter showed a maximum variation of 0.08% in the calculated cost, equivalent to less than 200 NOK (≈20 EUR) in annual savings. This error could be reduced by running several whole-year iterations of the algorithms where the average tank temperature of the previous iteration is used for determining the heat loss value.

The benefit of DR is also dependent on the demand profile. A demand profile with little variation, such as the constant heating profile, benefits less from both the unit cost savings and the monthly cost savings. The savings potential of the variable setpoint heating was the highest of the three demands, as the profile peaks during the morning electricity price peak. Distributing this load to the night before gives good unit cost savings and reduces the peak load to that of constant setpoint heating. However, the practical use of DR for heating is limited. Although electric heating is common in Norway, a large proportion are electrical panel radiators, which limits the flexibility of the energy storage capacity of the thermal mass that does not affect thermal comfort. Where water-based heating is used, central heating systems with heat pumps offer greater savings in energy use and peak power demand than the optimised electrical water heaters in this study. The use of an intelligent control may still be relevant for heat pumps in order to increase the operation of the heat pumps at nominal power. This improves the seasonal COP and can reduce the size of the required heat pumps, reducing costs. If the price variation increased, load shifting would become more relevant for heat pump systems [56,57]. A study of a HWST with a heat pump reached a similar conclusion that the most cost-effective solution occurs at small tank sizes [58].

DR of DHW systems is more practical both for new systems and retrofitting of existing systems. DHW represents an increasing share of the total energy use in low-energy Norwegian apartment buildings [59]. A study of existing HWSTs used for DHW in Norway showed that they are dimensioned with a large margin of safety [60] offering good flexibility potential. DHW systems also have a greater potential to reduce the setpoint temperature than heating systems. Electric heating of DHW is still common as the performance difference between heat pumps and electric heating is smaller due to the higher temperatures required.

There is a degree of uncertainty in the results as the demand profiles were generated through simulation using a typical meteorological year, whereas the electricity pricing is based on historic data. Both heating demand and electricity prices are influenced by the weather with higher energy prices often coinciding with higher heating demand such as in sustained cold periods. Real DHW profiles for Norwegian apartment buildings have been found to be less volatile than the standardised profile [60,61], which could result in smaller cost savings. However, the measured profiles also showed variation seasonally and between weekdays and weekends, which could offer other opportunities for load shifting.

The presented approach allows for a simple economic analysis of the potential for DR control in an energy market. The method is applicable to other building typologies and DR technologies. There was good correlation between the potential energy savings from DR and the simple energy price analysis, shown in Figure 9 and Table 3. However, the results of the algorithmic model were significantly lower than the simple analysis predicted due to the extra heat losses from the additional HWSTs required to shift enough electricity. This discrepancy would be smaller for DR technologies with lower additional losses, for example, shifting of electric vehicle charging. Such simple analysis tools could be further developed to better predict savings and so quickly find the most cost-effective applications of DR based on RTP signals. Smaller systems, such as those in single family houses and apartment-based systems, could also be analysed. However, these would likely give less flexibility and savings, as the higher variation in demand [62] makes prediction more difficult and increases the safety margin required. Furthermore, the control must be inexpensive to be worthwhile in small systems [63].

The results indicate that the current electricity pricing policies in Norway encourage DR to reduce peak power use. The societal benefit of this strategy is a reduced need to expand grid infrastructure. This will be further reinforced by a new grid tariff model in July 2022, where small residential customers pay monthly fees according to the peak power of their energy use [40]. There is little benefit to the consumer from load shifting as electricity prices are relatively cheap with little variation compared to other European countries [64], due to the large proportion of hydropower (and pumped storage) in the Norwegian energy mix, which can respond well to changes in demand [65].

An alternative price model is required, if grid operators and governments want to encourage consumer demand side management in order to balance the more intermittent renewable energy. In Norway, this would require reducing the dominant role of peak pricing, which is particularly present in Norway and the Netherlands [11], in favour of spot prices. Days ahead, electricity spot prices can provide a clear price signal of supply in the grid. However, the cost of electricity for consumers is not determined solely by the wholesale electricity price. A large proportion (averaging 40% across the EU) of the unit cost is made up of fixed price taxes, which blunt the price signal to the consumer [11]. In the studied case, the fixed part of the unit cost averaged 35% for 2018 price data, 37% for 2019 and 26% for 2021. In years with low spot prices, the fixed part exceeded 50%. Regulation of electricity prices to protect consumers from market fluctuations also disconnects consumer prices from the market price signal required for DR. Although not present in Norway, some form of price intervention was present in 13 EU countries in 2018, although it is an aim of the EU commission to phase out such price regulation [66].

In the long term, wide adoption of DR could reduce the clarity of spot prices as the price signal, as more DR devices would stabilise electricity prices, making further adoption less economically attractive [67]. Further price incentives may be required to stimulate load shifting. Peak pricing could be changed so that it acts as a short-term price signal. For example, the peak pricing could be lower at night to encourage greater electricity use in this period. Another possibility is to allow DR devices to trade on the intraday market which can be more volatile than the day ahead market [68]; however, this would require additional metering infrastructure. Alternatively, energy companies can pay a flexibility bonus per kWh of shifted demand. It has been shown that such incentives can greatly improve the return on investment [37,69]. However, too many incentives without regulation can lead to the use of less efficient technologies which offer greater flexibility.

5. Conclusions

The use of demand-responsive electrically heated hot water storage tanks (HWSTs) is one of many interesting solutions to stabilise future energy networks with higher proportions of intermittent renewable energy. HWSTs are already present in a large proportion of the building stock; however, the adoption of demand response (DR) by consumers is highly dependent on the economic benefit. This study assessed the economic potential of

DR of HWSTs under current pricing models which were applied to a Norwegian case study building with three different demand profiles. The analysis found the maximum possible cost savings from shifting electricity within a 24-h time horizon using energy price data and the demand profile as inputs. A charging profile was created for each demand profile and optimised to three different years of electricity spot prices, each representing three levels of price volatility. The optimisation was repeated for different heating powers, varying by 5 kW increments. The resulting charging profiles were then used to parametrically study the effect of varying the number of HWSTs and their minimum setpoint temperature. The energy cost and energy flexibility of each case was calculated against a reference for each of the demand profiles.

Increasing the number of HWSTs or the heating power increased the flexibility with a diminishing rate of return. Increasing heating power also increased unit cost savings with a diminishing rate of return. However, increasing the number of tanks resulted in lower unit cost savings as the cost of additional heat losses was greater than the savings from shifting demand, except for the highly volatile price data from 2021. Changing the minimum setpoint temperature has little effect on flexibility but improves the cost savings, as a greater thermal storage capacity can be achieved without increasing heat loss. Overall, systems utilising smaller heating power and fewer HWSTs were more economical when the monthly price was included, which is related to the peak energy demand of the system in each month. The year-on-year variation in savings is small as the monthly price is dominant over the hourly spot prices. The savings potential from DR is reduced when a heat pump is used, especially when the shifting of energy leads to reduced heat pump performance. The total cost savings are sensitive to the reference system used. Where the reference system utilises several HWSTs, there are greater savings available from using a smaller optimised system.

The possible savings from DR are closely linked to the variation in unit energy price during the optimisation period. The small variation in Norwegian spot prices meant that adopting DR for load shifting offers little economic benefit to consumers, despite Norway being one of the few countries with the infrastructure required to implement it. Cost savings are best achieved from redistributing energy demand to flatten demand peaks and thus minimise the peak heating power required, the pricing of which is dominant in the energy cost under the current price structure. With the current importance of peak pricing, the method presented in this study should be further developed to include all building electricity loads when creating the charging profile. The charging profile can then be used to smooth out the building's demand profile in order to minimise the peak power. Under such a method, the available capacity for heating a HWST would vary throughout the day depending upon other loads. Alternatively, it is possible for energy companies or governments to encourage load shifting by changing this price structure so that the unit cost has greater importance for the total energy cost. This can be achieved by minimising the fixed parts of the unit cost or introducing bonuses for shifting energy use away from certain times.

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Abbreviations

AEEF	Available Electric Energy Flexibility
COP	Coefficient of Performance
DHW	Domestic Hot Water
DR	Demand Response
HWST	Hot Water Storage Tank
MPC	Model Predictive Control
RTP	Real Time Pricing
TES	Thermal Energy Storage

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