Grid-edge technology - Exploring the flexibility potential of a heat pump and thermal energy storage system

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Abstract. Grid-edge technologies (GET) enable and amplify the impact of three emerging energy system trends: electrification, decentralisation, and digitalisation. Smart grid integrated heat pumps with thermal energy storage enable both the electrification of heating and decentralised demand response. Such power-to-heat technologies simultaneously decarbonise heating and facilitate the grid integration of more variable renewable electricity in a cost-effective manner. This may help to explore and exploit untapped wind generation potential. This study explores the flexibility potential of a domestic scale heat pump with thermal energy storage in a typical Irish home in December. The system is simulated to investigate demand-side flexibility and sensitivity to both heat pump and thermal storage capacities for three days with wind energy shares of 7%, 25%, and 60%. Using real-time electricity prices and optimising for operational cost, the implicit demand flexibility potential is quantified with different combinations of heat pump power and storage capacity. The results suggest that 33-100% of critical loads can be shifted dynamically to low-cost periods. Optimised system design depends on local climate, heat demand profile, optimisation horizon, and the type of heat pump. Optimisation with genetic algorithm yielded near-global optimal results approximately 40 times faster than with exhaustive enumeration.

1 Introduction to grid-edge technology and smart heat

Electrification, decentralisation, and digitalisation are key emerging energy system trends. The increasing share of variable renewable electricity capacity on the grid will necessitate an increasing share of demand flexibility and energy storage. Instead of the traditional centralised generation that follows predicted electricity demand, next-generation electricity grids must accommodate intelligent balancing of demand and supply in a decentralised flexible manner [1,2]. Unusually, and to a large extent, electricity demand will have to follow electricity generation, requiring temporal flexibility to incite or curb demand. In this context, the electrification and decarbonisation of heat and transport offer huge potential by providing additional flexible loads. For instance, heat may be added or removed from a thermal store (Power-to-Heat), car batteries may be charged (Vehicle-to-Grid), or hydrogen produced through electrolysis (Power-to-Gas) during periods of surplus low-carbon electricity generation. This defines both the opportunity and the challenge.

One example of how electricity demand may follow generation is the common practice of industrial demand response. Large electricity users enter mutually beneficial agreements with their energy retailers to switch large loads at short notice from the grid operator to help balance the electricity grid. Smaller loads may be aggregated in a pool by third-party aggregators to scale up to a significant switching capacity [3]. In some jurisdictions with limited supply-side flexibility, electric water heaters have been used as a source of flexibility for many years.

The potential for residential demand-side flexibility remains largely untapped. The total power of switchable loads such as heat pumps, electric resistance heaters, and electric car chargers generally only adds up to several kilowatts per household. This power is too small to be traded on the capacity markets. Hence, in conventional energy system thinking, aggregation is often regarded as the solution. However, this generally means that control over the heat pump must be yielded to the aggregator.

In Ireland, 50,000 heat pumps are projected to replace domestic boilers by 2020. It is estimated to increase to 200,000 by 2030 [4]. This adds circa 150-600 MW of flexible loads to the electricity grid. In Ireland, the average electricity demand during 2017 was 3.2 GW peaking during winter at 5 GW. Thousands to hundred-thousands of households would be required to absorb surplus electricity generation at the mega or gigawatt-scale. In Europe, the number of heat pumps could increase from 1.6 million to 10 million between 2020 and 2030 [5].

Incentives for consumers and user-friendly automated control systems must be in place to motivate consumer participation. The roll-out of smart meters and real-time pricing (RTP) electricity tariffs should be accelerated, as

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mandated by the European Commission. Time-of-use-tariffs are the first step into providing these incentives. Customers may avail of cheap night-time electricity to store heat for space heating and sanitary hot water. Furthermore, a peak tariff encourages the avoidance of electricity use during peak demand hours. In some European countries such as Germany and the UK, heat pump tariffs are offered, where the electricity provider reserves the right to block heat pump operation for a period of 30-120 minutes. In exchange, the customer profits from cheaper electricity rates.

However, waiving switching authority to a third party, also known as explicit demand response, may neither be desirable for domestic customers nor is the inconvenience due to the violation of occupant comfort levels [6]. A more discrete and decentralised approach is offered through implicit demand response, i.e. the automatic reaction to variable price signals. Variable electricity tariffs reflect the cost of generation and vary as a function of supply and demand throughout the day. Smart meters and variable electricity tariffs can thus economically incentivise the shift of electricity use from prohibitive high-cost peak periods to low-cost periods with surplus (renewable) electricity. The ultimate decision on how to react to these price signals remains with the end-user.

Apart from end-user financial benefits, this mechanism benefits the distribution system and transmission system operators. It can be utilised as a decentralised congestion management balancing tool. Generation, demand, and storage could be balanced at a local grid level. Its net effect could then be further escalated to regional, national, and international levels. Speculating further, the future energy system may consist of decentralised generators, consumers, storage providers, and the grid, trading energy on a peer-to-peer basis. Each participant can optimise their market engagement according to their own objectives.

Technology that automates the exploitation of variable electricity tariffs can be categorised as grid-edge technology. Grid-edge technology enables and amplifies the emerging energy system trends of electrification, decentralisation, and digitalisation as shown in Fig. 1. These three trends are seen to be acting in a so-called virtuous c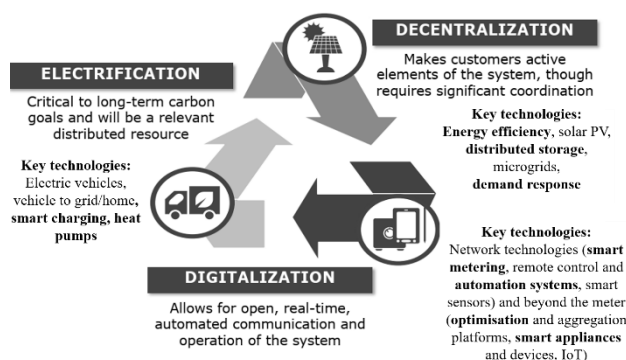ycle, enabling, amplifying and reinforcing developments beyond their individual contributions [7]. Electrification of heat by means of heat pumps enables the decentralisation of demand response through digitalised, automatic real-time optimisation of consumption.

The low cost of converting electricity to heat and the low cost of heat storage make power-to-heat (P2H) technology a particularly promising flexibility option. The electrification of heat can simultaneously facilitate the decarbonisation of the heating sector and the power system integration of more variable renewable electricity generation in a cost-effective manner [8]. Heat pumps can already outperform fossil fuel-based heating economically and ecologically as illustrated in Fig. 2 for Ireland.[1] Both emissions and cost have the potential to be further improved through grid-edge technology. The preferential use of low-cost electricity reduces operational cost. Since low-cost electricity often coincides with large shares of renewable electricity generation on the grid, the CO_2 intensity of the utilised electricity also decreases.

The ambition of this research is to exploit this triple boon of low-cost, low-emission heat and increased use of renewable electricity through flexibility. The automatic real-time optimisation of a domestic scale air source heat pump (ASHP) and thermal energy storage (TES) offers decentralised demand response to the grid. The heat pump is scheduled to satisfy demand over the optimisation horizon, and it is optimised for day-ahead electricity prices. This requires knowledge about both the expected heat demand of the application and future energy prices. The temperature forecast is required because heat demand and efficiency of the ASHP are sensitive to ambient air temperature. A model of the heating system is simulated to quantify system operational cost and energetic performance.
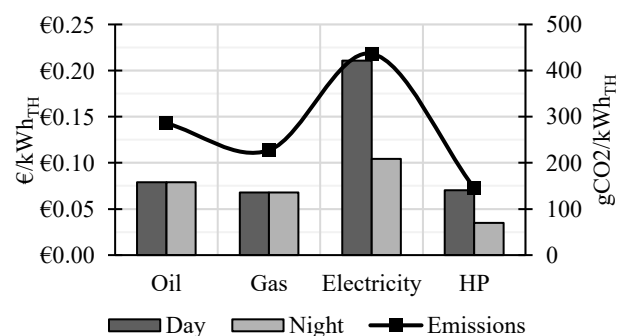
Fig. 2. Cost and CO_2 emissions of supplied thermal energy for space heating from different energy carriers

The remainder of this article explores different aspects of this heat-pump based grid-edge technology. The approach is optimised for a detached house in Ireland with a C2 energy rating on three consecutive days in December with varying shares of variable renewable electricity of 7%, 25%, and 60% on the grid. This is mainly from wind. The flexibility potential is quantified for these scenarios in terms of load shifting capacity. Sensitivity to heat pump power and thermal energy storage capacity was tested with ranges of 5-10 kW and 550-1,000 litres of water

Fig. 1. The virtuous cycle of electrification, decentralisation, and digitalisation [7].

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[1] Heat Pump COP=3, Oil and Gas Boiler η=0.9

respectively. Finally, quasi-optimal results were obtained using genetic algorithm and compared to global-optimal results obtained through exhaustive calculation.

The next section briefly describes the simulated model and optimisation approach, followed by a section that discusses the acquired results in the context of the study's limitations leading into some concluding remarks and suggestions for further research.

2 Model description

The system depicted in Fig. 3 consists of an air source heat pump and sensible thermal energy storage. It is controlled by supervisory control. The system is optimised on the thermal energy supply side excluding the heating distribution system or modelling of room temperature. The availability of thermal energy at a minimum distribution temperature in the TES is assumed to be enough to maintain appropriate room temperatures for every 60-minute time step. This may be achieved by thermostatically controlled circulation pumps on the distribution side.

The supervisory control retrieves data about the current state of charge of the TES, the forecasted ambient air temperature, the expected heat demand profile, and the day-ahead electricity prices. Based on this data, it generates a schedule that ensures sufficient thermal energy to be available in the TES at every time step at the lowest operational cost. The temperature forecast is available through standard web-services from the meteorological service office and may be used to derive the expected heat demand profile and heat pump performance. Day-ahead electricity prices are derived from spot market prices (SMP). As Ireland has not implemented real-time electricity tariffs yet, these spot market prices are scaled to approximate more realistic end-user prices. Here, the ratio of instantaneous spot market price to annual average is multiplied by an assumed base electricity rate of €0.10/kWh.

The state of charge (SOC_t) of the thermal energy storage is the energy content available at the end of the previous interval SOC_{t-1} plus heat added from the heat pump $Q_{HP,t}$ minus heat demand $Q_{D,t}$ and storage losses $Q_{L,t}$ (eq. 1). The minimum storage temperature is set to the minimum useful supply temperature of 45 °C for a typical hydronic radiator-based distribution system ($T_{TES,min}$). At this temperature, the TES is considered to contain zero useful energy. After heat has been added, the TES temperature $T_{TES,t}$ increases from the previous storage temperature by the ratio of added heat to the product of storage mass (m) and specific heat capacity (C_p) (eq. 2).

A maximum TES temperature constraint was found to be redundant in a previous study due to the fact that high storage temperatures result in low coefficients of performance (COPs), which in turn increase operational cost. As a result, the economic optimisation has the effect of self-regulating TES temperature [9]. In this study 60 °C was the highest observed TES temperature allowing the heat pump to perform with a reasonable COP of 1.5-2.8 assuming an ambient air temperature range of ± 20°C.

The thermal capacity of the heat pump is taken as constant. The electricity input varies according to the heat pump's COP, which is a function of sink and source temperatures. The heat demand profile is synthetically created using the heating degree method for the typical annual space heating demand of a detached Irish house with a C2 energy rating (~93 kWh/m^2/annum) and a floor area of 156 m^2. Thermal storage losses from the
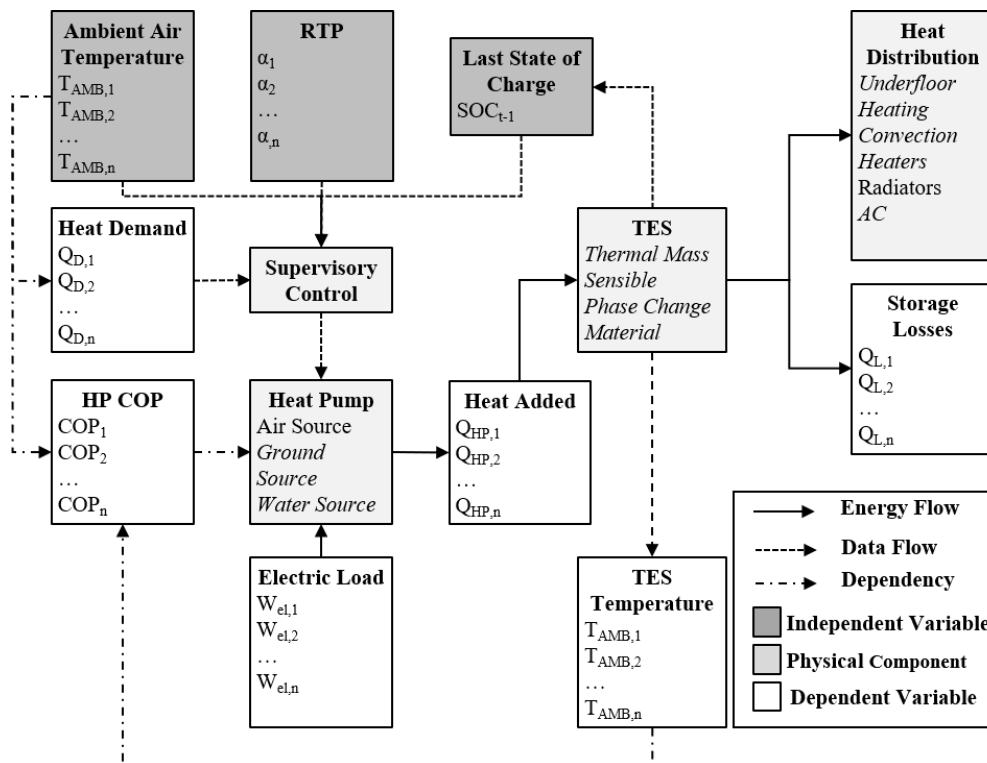

Fig. 3. Schematic showing system components, energy flows, data streams and dependencies of optimised HP and TES control

completely mixed hot water tank are calculated multiplying the thermal transmittance (U) and heat loss area of the thermal envelope of the storage vessel (A) with the temperature differential between the TES and its surroundings (ΔT) (eq. 3).

Quasi-steady state performance map models are used to approximate the heat pump COP_t as a function of source and sink temperatures (eq. 4). A two-layer, feed-forward neural network with seven sigmoid hidden neurons and linear output neurons was trained with manufacturer data for the Mitsubishi Ecodan range (based on EN14511) using the Levenberg-Marquardt backpropagation algorithm. Perfect forecast of ambient air temperatures is assumed using historical data from the Irish Meteorological Service (MET Éireann).

$$SOC_t = SOC_{t-1} + Q_{HP,t} - Q_{D,t} - Q_{L,t} \qquad (1)$$

$$T_{TES,t} = T_{TES,min} + (SOC_t/mC_P) \qquad (2)$$

$$Q_{L,t} = UA\Delta T_t \qquad (3)$$

$$COP_t = f(T_{AMB}, T_{TES}) \qquad (4)$$

Figure 4 shows key power system statistics for the period of 4th-6th December 2017 during which the heat pump and TES system was simulated. The shares of electricity demand generated by wind energy were recorded as 7%, 25% and 60% for the three days respectively. During 2017 the wind energy share of electricity demand was approximately equivalent to the renewable energy fraction of generated electricity and will from now on be referred to as the renewable energy fraction of electricity REF_{EL}. The ambient air temperatures and thus heat demand profiles for these days were almost identical with mean temperatures of approximately 6 °C fluctuating from 5-8 °C. The system was modelled over the optimisation horizon of 24 hours with hourly time steps. This is consistent with input data resolution. However, longer optimisation horizons and higher resolution are possible, but such models also require longer simulation and optimisation run-times. Also, minimum heat pump run-times of generally 15 minutes must be accommodated.
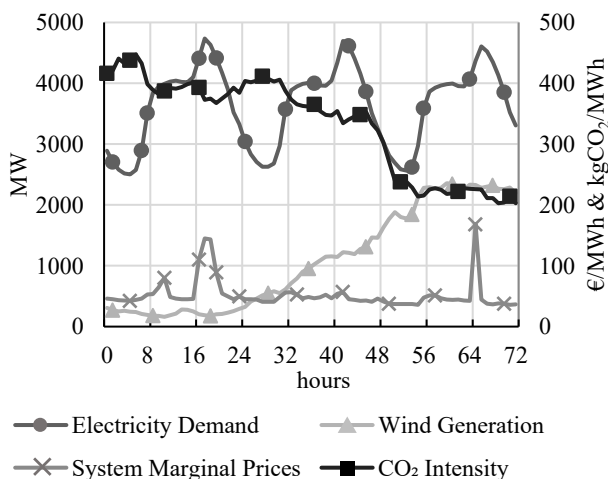

Fig. 4. Key power system statistics from 4th-6th December 2017 sourced from Ireland's TSO Eirgrid

3 Optimisation approach

The optimisation objective was defined as meeting heat demand with minimum operational cost. Other optimisation objectives such as minimum imported electricity or maximum share of renewable heat have yielded similar results to cost minimisation in a previous study [9].

The objective function (J_e) quantifies operational cost over the optimisation horizon as the sum of electricity cost for every time step (t) (eq.5). Electricity cost is the product of electricity quantity ($W_{el,t}$) and unit price (α_t) (eq. 6). The quantity of electricity is the thermal energy supplied by the heat pump ($Q_{HP,t}$) divided by the COP_t. Perfect unit price forecast is assumed using scaled historical spot market price data from the Irish Single Electricity Market for Ireland and Northern Ireland.

$$J_e = \sum W_{EL,t}\alpha_t \qquad (5)$$

$$W_{EL,t} = Q_{HP,t}/COP_t \qquad (6)$$

The magnitude of the optimisation problem depends on the number of values that the decision variable can assume (Z) and the number of time intervals over which the system is to be optimised (T) yielding Z^T permutations. Computation time further depends on model complexity and on the selected optimisation method.

In this study exhaustive search was used to systematically enumerate all possible solution candidates to find the global optimum. The results were then compared to a meta-heuristic approach using genetic algorithm. The focus was on run-time and optimisation error. System model, exhaustive enumeration and genetic algorithm were programmed in the programming language PYTHON. The parameters yielding satisfactory genetic algorithm performance were a population of 60, a mutation rate of 2.5%, single cross-over point, elitist selection truncated at 40%, and a maximum of 5,000 trials.

4 Results and discussion

As a reference case, a model of a variable speed heat pump is simulated to exactly match heat demand at every time step. For the reference case, a distribution temperature of 45 °C is assumed to calculate dynamic COPs. This demand-following operation of the heat pump does not offer any demand flexibility to the grid and would exacerbate the grid's peak electricity demand periods. This is especially the case in the evening when ambient air temperatures decrease, and people return from work. The morning peak is also affected where daily minimum temperatures are experienced, and people get up for work.

The results of this explorative study offer a snapshot of the load shifting potential of implicit demand response with optimised control schedules for different heat pump and TES capacities. Further simulation over an entire heating season will be required in order to provide more meaningful insights. However, certain trends can be

observed, and the reader may be referred to a previous study indicating operational cost savings and share of renewable heat for an entire heating season [9].

4.1 Flexibility potential

All optimal schedules reveal successful load shifting away from high price periods, as may be expected when carrying out an optimisation for low operational cost. As high prices indicate supply-demand bottlenecks, the temporal shift of heat pump loads to low-price periods effectively facilitates price induced balancing of the grid supply and demand. It may be noted that grid bottlenecks exist both on a national grid scale and on a more local distribution grid scale. Therefore, local congestion problems may be tackled by using regional or nodal real-time pricing schemes to balance supply and demand from micro-grid level up to (inter-)national grid level.

The flexibility potential of implicit demand response is not as easily quantified as for explicit demand control. Explicit demand-side flexibility can be measured in terms of available switchable power, time-frame, and thus energy. This resource can then be used to offer services to the grid. It can provide dispatchable and reliable capacity, balancing and ancillary services to Transmission and Distribution System Operators. In implicit demand response, there is no firm commitment of the consumer to react to price signals. However, it can be assumed, that above-average prices imply a reduction of electricity use through the use of grid-edge technology. With increasing consumer participation, it can be expected that predictability and reliability of implicit demand flexibility can be enhanced [10].

In this study, the flexibility potential of implicit demand response is quantified as the share of electrical load that is shifted from above average price periods, which imply demand-supply bottlenecks, to low-cost periods. Figure 5 illustrates how optimised GET control organises heat pump operation accordingly. The black columns represent the load-following reference case (LF) and thus simultaneously the heat demand. The diagonally striped columns mark heat demand periods that coincide with above-average electricity price periods. The GET heat pump schedule is represented by the grey columns. If a grey column is located behind a striped column, it means that the heat load could not be shifted from the above-average price period. The black and grey lines show the electricity cost profiles and the stored heat respectively. Note that the store was assumed to be empty at the beginning of each day and retains unused thermal energy at the end of the day. The displayed results belong to the 7kW.1000L scenario, i.e. the combination of a 7 kW_{TH} ASHP and a 1,000 litres sensible TES.

Figure 5a) illustrates an exemplary demonstration of the intended effect of the implicit demand response. Heat is stored in the TES before above-average electricity cost periods. In the diagram, this is revealed by the grey SOC curve leading the black electricity cost curve. The optimised GET schedule entirely avoids heat pump operation during the above-average cost periods from 9-11am and 16-20pm. Thus, on the day with 7% REF_{EL},

100% of the electric load of 0.94 kW per HP and TES system is shifted from high-cost periods to low-cost periods. The same flexibility potential is realised on the day with 60% REF_{EL} (Fig. 5c).

Conversely, during the 25% REF_{EL} day, the GET control scheme shifted only 67.3% of the electrical load from above-average cost periods (Fig. 5b). During six high-cost periods, the electrical load was reduced by 0.95 kW. However, in three cases the GET control increases the electrical load by a factor of approximately 2.5. The reason for this reveals itself in the nature of fluctuations of the electricity price profile. The electricity price profiles for 7% and 60% REF_{EL} follow typical working day residual load profiles with morning and evening peaks. The 25% REF_{EL} profile, on the other hand, is characterised by more frequent fluctuations at smaller amplitudes. The resulting optimal schedule, thus, only has one intense charging period before the morning peak. Subsequently, the system schedule is following the multiple minor price fluctuations and alternates between
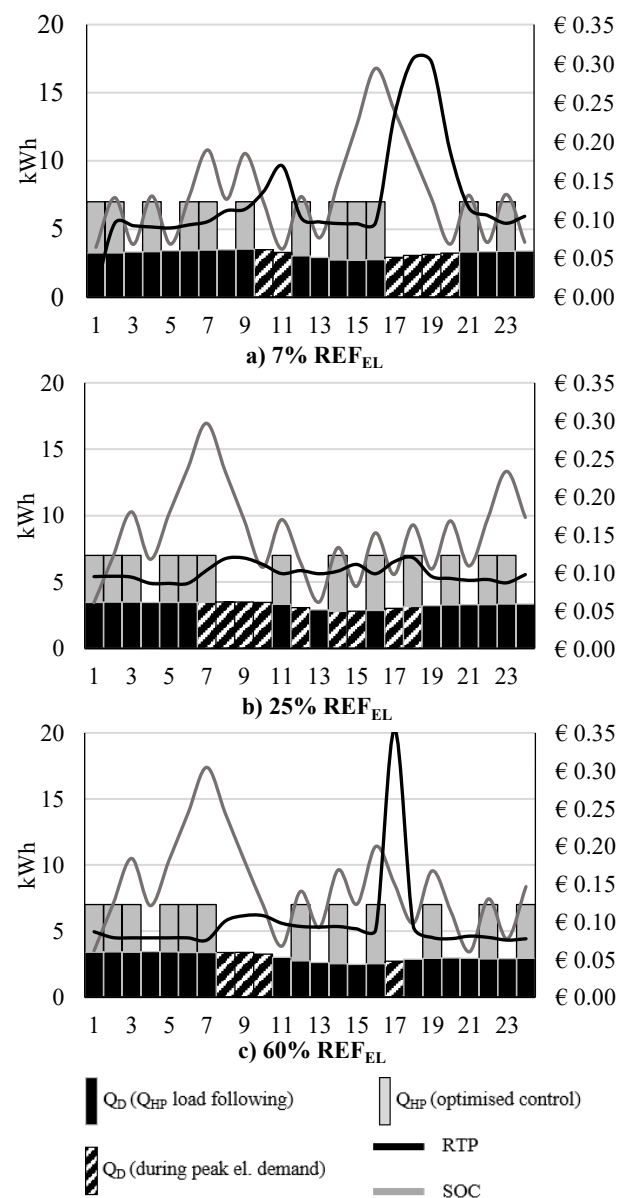
Fig. 5. Optimised GET Smart Heat schedule illustrating the charging of TES according to real-time electricity cost

charging and discharging. To that end, it must be stated that some combinations of price, temperature, and demand profile exist that inherently limit the flexibility potential and occasionally even increase peak electricity demand. Nonetheless, a significant part of the load is shifted, and stronger price signals would mitigate this issue.

4.2   Sensitivity to HP and TES capacity

Figure 6 displays the optimal schedules for different combinations of storage and heat pump capacity for the day with 7% REF_{EL}. Black rectangles represent scheduled heat pump operation.
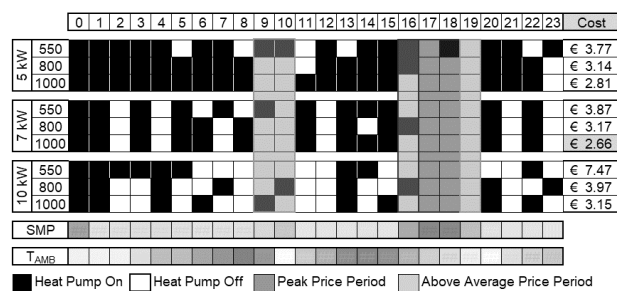

Fig. 6. Optimal schedule for different TES and HP capacity combinations on the 7% REF_{EL} day

The shaded areas display above average price periods, and peak price periods are shaded slightly darker. The different combinations reveal varying degrees of flexibility that can be offered to the electricity grid. For instance, the optimal schedule for the combination of a 5 kW_{TH} heat pump and 550-litre TES system (5kW550L) exhibits a load profile that barely deviates from the load-following reference case. The heat pump is required to operate during restrictive above-average price periods because it is required to satisfy the heat demand profile with a mean of 3.2 kW_{TH} and a peak of 3.5 kW_{TH}. Consequently, the remaining heat pump capacity is not sufficient to charge the TES and offer considerable flexibility. As a result, only 32.9% of the electrical load can be shifted. Combinations of 1,000 litre TES and heat

pump capacities of 5 and 7 kW_{TH} successfully shift 100% of the electrical load at minimal operational cost.

Table 1 summarises the performances of the optimised heat pump schedules. The flexibility of the various system combinations is quantified as the share of the electric load, which can be shifted from restrictive periods to low-cost periods. The associated operational cost of the system is then used to define the flexibility cost indicator (FCI), which represents the ratio of flexibility to operational cost. Consequently, a high FCI indicates high flexibility at low operational cost.

The highest FCIs were observed when the largest storage volume of 1,000 litres was combined with heat pump capacities of 7, 10, and 5 kW_{TH} respectively. The average flexibility offered to the grid amounted to 89%, 87%, and 76%. Only the 10kW550L combination achieved 100% flexibility potential for all three days. However, this resulted in the highest operational cost. When comparing overall operational costs with the load-following reference case, it appears that savings could only be achieved for the day with the lowest share of 7% wind generation. Cost reductions of 6.6% and 1.4% were achieved for scenarios 7kW1000L and 5kW1000L. On one hand, the reference case was 8% more economical to run than the lowest cost scenario GET5kW1000L over the simulated three-day period. On the other hand, no flexibility was offered to the grid and the study neglects the fact that energy remained in the TES, which was discarded at the end of each day.

Larger storage volumes tend to offer higher flexibility at low cost because TES temperatures increase slower with increasing energy content than with smaller TES volumes. Therefore, system performance can benefit from higher COPs. Higher heat pump capacities allow for more heat to be stored during a given low-cost interval. Therefore, they offer a higher degree of flexibility. However, the increased amount of stored heat increases TES temperature and reduces the COP. This results in the increased need for electricity and thus higher cost for flexibility. In this study, the heat pump was modelled as an on/off system with binary decision variables. The use of a variable speed heat pump could enhance economic storage utilisation and should be considered during

Table 1. The share of electric load shifted from restrictive periods, associated operational cost and resulting flexibility cost indicator

	5kW550L	5kW800L	5kW1000L	7kW550L	7kW800L	7kW1000L	10kW550L	10kW800L	10kW1000L
Flexibility Potential									
04/12	33%	85%	100%	82%	85%	100%	100%	68%	82%
05/12	45%	45%	55%	79%	67%	67%	100%	68%	78%
06/12	48%	75%	73%	48%	75%	100%	100%	73%	100%
Cost									
04/12	€3.77	€3.14	€2.81	€3.87	€3.17	€2.66	€7.47	€3.97	€3.15
05/12	€3.05	€2.81	€2.74	€5.59	€3.25	€3.08	€7.58	€3.45	€3.15
06/12	€2.44	€2.31	€2.25	€3.10	€2.53	€2.43	€5.78	€2.71	€2.48
Flexibility Cost Indicator (FCI)									
04/12	0.09	0.27	0.36	0.21	0.27	0.38	0.13	0.17	0.26
05/12	0.15	0.16	0.20	0.14	0.21	0.22	0.13	0.20	0.25
06/12	0.20	0.32	0.33	0.15	0.29	0.41	0.17	0.27	0.40
Mean FCI	0.14	0.25	0.29	0.17	0.26	0.34	0.15	0.21	0.30

system design. A variable speed heat pump, modelled with integers as decision variables, would enable the system to reduce its output as required, but increases the computational complexity of optimisation. Assuming ten increments of 10% capacity, the number of permutations for optimisation would be increased by an order of magnitude of 17 (10^{24} instead of 2^{24}). The results suggest that the ideal design combination of heat pump and storage depends on the heat demand profile, electricity price elasticity, optimisation horizon and whether a variable speed heat pump is considered.

4.3 General observations and limitations

Table 2 summarises the increased use of renewable electricity, renewable energy fraction of heat, and cost implications when compared with the load-following reference scenario. Shown are the results for this study's best performing combination of 7 kW$_{TH}$ heat pump with 1,000 litre TES. The share of utilised renewable electricity is increased by 6.7% and 3.1% for the low and high wind days respectively. For the medium wind day, it slightly decreases by 1.8%. Operational cost is decreased only for the low wind day by 5.8% and increased for medium and high wind days by 35.2% and 18% respectively. However, the calculated savings in this study heavily depend on the electricity base rate that was assumed to be €0.10 per kWh. Increasing this base rate would lead to more price elasticity and increased cost savings. The share of delivered renewable heat (REF$_{TH}$) in all cases ranges from 67.9% to 88.5%. A more renewable electricity supply will further increase this fraction. The share of renewable heat decreases from the load-following reference scenario. The largest reduction of 6.4% occurs on the day with the smallest share of wind electricity and similarly for the medium wind day. On the high wind day, the share is reduced by only 1.9% as the share of renewable electricity is large throughout the day.

Table 2. Summary of increased use of renewable electricity, the share of delivered renewable heat and operational cost when comparing optimal GET control (7kW1000L) to the load-following reference case

	4/12/2017	5/12/2017	6/12/2017
Fraction of renewable electricity used			
LF	6.7%	24.4%	60.7%
GET	7.4%	24.0%	62.6%
Change	10.1%	-1.8%	3.1%
Fraction of renewable heat supplied REF$_{TH}$			
LF	72.5%	77.7%	88.5%
GET	67.9%	73.0%	86.9%
Change	-6.4%	-6.2%	-1.9%
Operational Cost			
LF	€ 2.85	€ 2.29	€ 2.06
GET	€ 2.68	€ 3.10	€ 2.43
Change	-5.8%	35.2%	18.0%

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[2] Intel® Core™ i3-6100U CPU @2.3GHz and 8GB RAM on a 64-bit Windows 10 Pro OS

The simulation time frame was only three days. The TES retained a charge of 4-10 kWh at the end of each day, which would normally be used during the next optimisation horizon. This is not factored into the results of this study and explains the increased cost and decreased REF$_{TH}$, especially in the context of the short modelling period. Thus, a longer simulation time-frame will result in this energy being used and the optimal control to be more economic as shown in previous work [9].

In this study, optimisation was performed at the beginning of the 24-hour optimisation horizon. In a practical system, a rolling optimisation with a receding horizon would enable the reaction to updated system information and forecasts. The uncertainty of wind energy generation and temperature forecast is smaller for near future events than for distant future events. Thus, the effect of prediction uncertainty can be mitigated by frequent optimisations.

The reaction to changing electricity prices could be realised within several minutes depending on the optimisation run-time that effectively limits its frequency. Day-ahead electricity prices limit the time scale of flexibility to approximately one day. Availability of price data for longer optimisation horizons could increase the ability of the local system to help the grid experiencing a short 'Dunkelflaute', a period where no electricity can be obtained from wind and solar. Increased foresight regarding electricity prices could enable multi-day flexibility. Longer prediction horizons mean increased prediction uncertainty. Therefore, rolling optimisation with regularly updated forecasts should be used to mitigate adverse effects from prediction error. Longer optimisation horizons and higher resolution also mean that simulation and optimisation require longer run-times.

Finally, the selected minimum storage temperature significantly affects the coefficient of performance of the heat pump. Utilising low-temperature heat emitters such as underfloor heating, fan-assisted radiators or air-conditioning can be expected to enhance system performance further. Thus, heat distribution system design impacts on both the potential of GET Smart Heat and sensitivity of models to system design.

4.4 Optimisation performance

Globally optimal results are obtained for each modelled day and all HP and TES capacity combinations by exhaustive enumeration. This means that all possible decision variable permutations are calculated to find the global optimum heat pump schedule, which satisfies the heat demand at the lowest operational cost. For each day, an average runtime of 36 minutes and 40 seconds was noted[2]. Subsequently, all scenarios were optimised using a Python-based genetic algorithm to benchmark run-time and optimisation error. Limiting the maximum number of trials to 5000 yielded satisfactory results after a run-time of 58 seconds, which represents 2% of the duration of the exhaustive enumeration method. The schedules obtained

by GA optimisation are in most cases identical to the global optimum schedules and resulted in a maximum optimisation error of 0.7%. In two cases a small difference in schedule resulted in an error of approximately 0.2%. While these results are very promising in terms of run-time and convergence to near-global optima, multiple GA optimisations of the same scenario should be run to establish the mean optimum and standard deviation with statistical significance.

5   Conclusions

Flexibility is a key component of future demand-respond energy systems. It is a requirement for the integration of large shares of renewable energy and for the electrification of heating and transport. Part of this flexibility can be offered by buildings' HVAC systems. This study explores the flexibility potential of a heat pump and thermal energy storage as a grid-edge technology. Automated implicit demand response can offer flexibility to the grid while enabling operational cost reductions to benefit the consumer. Demand flexibility helps to accommodate fluctuations in daily wind generation and to balance grid bottlenecks. This facilitates the electrification of heat, the integration of more fluctuating renewable electricity sources, and thus the decarbonisation of the energy system in a cost-effective manner. Furthermore, air-pollution and CO_2 emissions are reduced both at a local and at a national level. Nodal real-time pricing schemes could mitigate congestion problems at distribution level scale. However, as there is no firm commitment of the consumer to react to price signals, increasing consumer participation will demonstrate and help quantify the predictability and reliability of implicit demand flexibility.

The flexibility potential considered in this study was quantified as the share of energy moved from above-average price periods to low-cost periods. Depending on system design and the electricity cost profile, 33-100% of electric loads could be shifted from restrictive periods to times of more favourable grid conditions. The results indicate that the flexibility potential and operational cost are sensitive to system design, i.e. heat pump power and storage capacity. The flexibility cost indicator FCI was introduced to compare different HP and TES combinations for their ability to offer benefits both to the grid and to the consumer. It is the ratio of flexibility to operational cost. In this study, a 7 kW_{TH} heat pump coupled with 1,000 litres of sensible thermal energy storage yielded the best flexibility to cost ratio. The FCI may lend itself to the design for grid flexibility of heat pump and storage systems, which need to be tailored according to heat demand profile, electricity price volatility, optimisation horizon, and type of heat pump.

The genetic algorithm considered in this study yielded near-optimal results with an error smaller than 1%. This was achieved almost 40 times faster than with the exhaustive search. Further research should verify the statistical significance of optimisation error and run-time. This study was explorative as the simulation spanned only three days. The observed trends will be further verified by simulating the system for an entire heating season with rolling optimisations. Variable speed heat pumps will be considered to investigate what effect they have on flexibility and operational cost, and further on optimisation run-time and accuracy of the meta-heuristic optimisation.

A key requirement to achieve residential demand-side flexibility on the grid-edge is the introduction of real-time pricing coupled with automatic real-time optimisation. The roll-out of smart meters and real-time electricity tariffs should be accelerated, as mandated by the European Commission. This will support the decarbonisation and electrification of heat, towards a smart energy system.

6   Abbreviations

ASHP	air source heat pump
COP	coefficient of performance
FCI	flexibility cost indicator
GA	genetic algorithm
GET	grid edge technology
HP	heat pump
HVAC	heating, ventilation, air conditioning
LF	load following
P2H	power-to-heat
REF_{EL}	renewable energy fraction electricity
REF_{TH}	renewable energy fraction thermal
RTP	real-time pricing
SOC	state of charge
SMP	system marginal price
TES	thermal energy storage

7   Acknowledgements

8   Bibliography

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