OPERATIONAL OPTIMISATION OF A HEAT PUMP SYSTEM WITH SENSIBLE THERMAL ENERGY STORAGE USING GENETIC ALGORITHM

by

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Heating and cooling account for 50% of global energy consumption and 40% of energy related CO_2 emissions. Progress towards renewable heating has been slow, and Ireland is expected to miss European Union 2020 emission reduction and renewable energy targets. While increased wind penetration since 2005 has reduced the carbon intensity of Ireland's electricity by 29%, carbon intensity per used floor area is more than twice the European average, amplifying air pollution, climate change, and energy security issues. The heating and electricity sectors can benefit from the successful transition to cleaner, lower carbon electricity by electrifying heating. Electricity-driven heat pumps deliver 3-4 units of heat per unit of electricity consumed, thereby offering a 76% emission reduction compared with fossil-fuelled heating. This research offers an opportunity to minimise both running cost and emissions, assisting the end user and the environment. This is achieved using the smart grid to charge a thermal store during favourable low-cost times and discharge as required later. Smart, information and communication technology-integrated, adaptive control with artificial intelligence optimises the heat pump schedule based on information from forecasting services and/or predictions of heat demand, heat pump source quality, stored heat and day-ahead electricity prices. Another opportunity is the potential to assist the electricity grid by reducing peak electricity demand as smart control favours low electricity prices and low CO_2 intensity that coincide with the availability of cheap (wind) electricity. Demand is shifted from expensive peak demand periods, enabling the electrification of heating in a smart energy system.

Key words: *electrification, smart energy, heat pump, demand flexibility, thermal storage, optimisation*

Introduction

How can buildings be heated to great levels of comfort, using affordable and clean energy, without polluting air and surroundings, and without affecting the planet's sensitive climate system? Moreover, which synergies can be exploited in a smart energy system to assist the end user, the grid operator, and the environment? One potential pathway to answer this question is the main topic of this study. It will be shown that an intelligently controlled heat pump with thermal energy storage (TES) has the potential to supply the entire heat demand of various applications with renewable energy fractions of up to 100% at low operational cost and demand flexibility benefits to the national grid.

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Since the discovery of fire, combustion has been the dominant means of supplying heat for millennia, initially sourced from biomass and later from fossil fuels such as coal, peat, oil, and gas. Worldwide, heating and cooling applications account for 50% of final energy consumption [1]. The sector is responsible for 40% of energy related CO_2 emissions [2]. In Ireland, 78-91% of central heating systems are still based on combustion, with gas being the prevalent source in urban areas and oil in rural areas with no access to gas pipeline networks [3]. Ireland's CO_2 emissions per used floor area, including carbon emissions from electricity generation, are Europe's highest, and at 120 $kgCO_2/m^2$ twice the European average [4]. Apart from emitting GHG this leads to poor air quality. The European Environmental Agency attributed 520000 premature deaths in Europe in 2014 to air pollution from particulate matter, nitrogen dioxide and ozone alone [5]. Furthermore, it leads to decreased energy security and curtailed trade surplus as Ireland's energy dependency at 88% cost the economy €4.6 billion in 2015 [6]. The availability of sufficient solar energy is out of phase with the heating period, biofuels should not be used for low temperature heat [7], and micro wind turbines are impractical in most urban applications. It follows, that the sustainable divestment from fossil fuels for heating mandates the electrification of the heating sector. The electrification of the heating sector is also a cornerstone of scenarios for 100% renewable (smart) energy systems that take a holistic approach and integrate the traditionally separated electricity, heat, and transport sectors for better overall system efficiency and lower cost [8].

Heat pumps convert one unit of electricity to yield approximately three units of heat, and thus, represent the most efficient means of converting electricity to heat. The supplied heat is cheaper than heat from either oil or gas, especially when availing of night time rates. Its generation also requires significantly lower emissions, which depend on the fuel mix of electricity generation. For instance, if the heat pump coefficient of performance (*COP*) is three, and 25% of the generated electricity is from renewables, then 75% of delivered heat can be classified renewable. Emissions converge to zero, when 100% of the electricity is generated from carbon neutral sources. Heat pumps link the electricity sector to the thermal sector and therefore cheap thermal storage. This offers flexibility to the electricity grid and facilitates integration of more intermittent and fluctuating renewable energy sources. It also creates the opportunity to shift emissions to the EU emissions trading system (ETS) sector from the non-ETS sector. The European Commission is committed to accelerating the deployment of smart meters and ensuring access to dynamic electricity price contracts. Figure 1 displays the correlation between low variable electricity market prices and high fractions of demand covered by wind generation in Ireland for a week in January and for a week in July. Increased fractions of renewable electricity (REF_{EL}) generally result in decreased system marginal prices (*SMP*). The carbon intensity of generated electricity decreases analogously. A system that exploits low electricity prices in a dynamic electricity market can thus operate at low cost while maximising the renewable part of energy converted and minimising emissions. A thermal system with a heat pump can further amplify this effect for the delivered heat with the *COP* as a multiplier. Since the *COP* is a function of the temperature differential between source and sink, it is favourable to operate the heat pump when the (air) source temperature is high and the TES sink temperature is low.

This study seeks to exploit variable electricity tariffs and high *COP* to store heat from an air source heat pump to a sensible thermal energy store during favourable periods, and discharge the store later, when heat is needed. Such a system considers day-ahead variable electricity prices, temperature forecast, and heat demand profile. This principle may lend itself to different applications at different scales such as residential, commercial, district heat-

ing and low-temperature industrial. Recent research on the role of heat pumps in smart grids or smart energy systems has been reviewed by Fischer and Madani [9], who categorise the available literature into research pertaining to:
– the stable and economic operation of power grids,
– the integration of renewable energy sources in the power grid, and
– their operation under variable electricity prices.

They found, that heat pumps and TES coupled with appropriate control strategies can assist the transition of an energy system towards large shares of renewables and prosumers in a decentralised energy system. It was found, that scheduling heat pumps according to day-ahead pricing leads to the shift of heat pump operation towards cheap night time rates resulting in savings of 7-35%. It has further been observed, that cost optimisation may lead to decreased heat pump efficiency due to lower source and higher storage temperatures, and increased electricity imports. Price volatility and forecast quality were identified as important parameters affecting the actual performance [9].

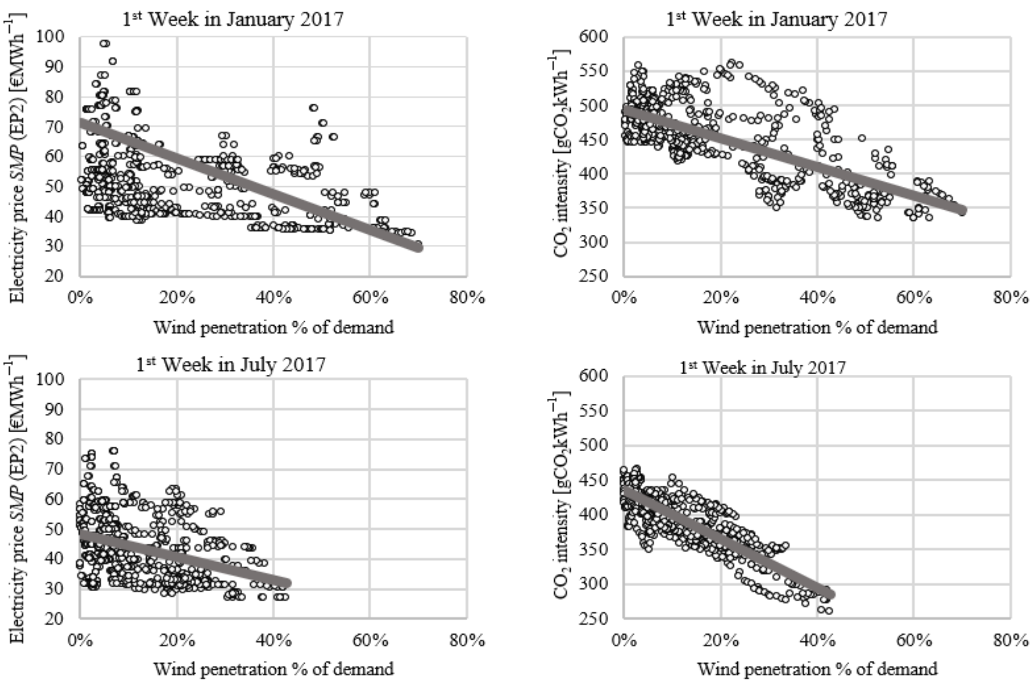

Figure 1. Regression analysis of wind penetration of demand against *SMP* and carbon intensity of electricity generation for weeks in January and July 2017

In a system with changing conditions, such as price structures and demand profiles, Thieblemont *et al*. [10] suggest the implementation of predictive features in the control of building's active or passive thermal storage to achieve a better performance than rule-based control approaches could offer. Commonly used model predictive control approaches with various levels of detail have been found to outperform non-predictive control strategies. Increasing levels of detail range from black-box to white-box models with increasing computational complexity. Moreover, computation time due to the optimisation process is one of the main challenges. Ooka and Ikeda [11] reviewed optimisation techniques and categorised them into mathematical methods such as dynamic programming or mixed integer linear programming, and meta-heuristic methods including genetic algorithm (GA) or particle swarm optimisation. While deterministic methods can provide an exact mathematical solution, this comes at a cost of either computational complexity or simplification and linearization of non-linear behaviour which may explain the wide spread of reported results. Meta-heuristic optimisation methods, on the other hand, have been used successfully to easily yield approximate, quasi-optimal solutions at low computational load in the case of uncertain or poorly defined problems. The exact methods are very unlikely to provide solutions within an acceptable period of time for problems, that are possibly subject to random perturbations or for which the search for solutions might evolve toward the combinatorial explosion [12].

This study's optimisation problem is in the order of 2^{24}, equating to more than 16.7 million possible permutations of the heat pump being switched on or off each day of the year. Each permutation results in a unique heat pump performance according to source quality profile, electricity cost profile and resulting TES temperature profile with dynamic *COP*, bound by the constraint to satisfy demand at any time. To deal with this complexity and probable non-linear system behaviour, a GA is employed as suggested by Dimache and Lohan. They developed a method for the optimal design of heat pump-based thermal hybrid energy systems (THRES) that is sensitive to local climate conditions. Employing a novel hybrid artificial intelligence technique including artificial neural network (ANN) and GA they used series and parallel optimisation to simultaneously optimise design and operation of THRES [13]. Their optimisation strategy followed a demand matching approach. Thus, they did not utilise means of heat storage. Loesch *et al.* [14] achieved a higher degree of freedom for scheduling heat pumps based on overheating the hot water storage employing GA and considering a six-hour optimisation horizon. While achieving significant electricity cost reductions compared to hysteresis control they noted a decreased *COP* due to the increased storage temperature and thus less efficient use of electrical energy. Meta-heuristic optimisation methods discover optimal solutions iteratively by trial and error. Their advantage is their capacity to obtain solutions easily and with low computational load compared to mathematical programming methods. However, a solution obtained with meta-heuristic methods is only an approximate solution and multiple optimisations under identical conditions will lead to different *optimal* solutions. Moreover, the performance of the algorithm is sensitive to search parameters including population size, mutation rate and crossover point.

This study aimed to accrue the greatest benefit to the grid operator in terms of assisting uptake of renewable electricity, to the heat pump owner by reducing operating cost and to the environment by minimising heating related CO_2 emissions.

Model description

The purpose of the conducted analysis is the model-based evaluation of an optimised heat pump operation schedule to be compared to a conventional load following reference model. The system consists of a 15 kW_{TH} monovalent air-to-water heat pump and a thermal energy store. This study focuses on decoupling of thermal energy supply and demand and the interaction between the heat pump and TES considering the local weather conditions and variable electricity tariffs. During the design of this model, a set of good practice guidelines and steps for energy system optimisation models, suggested by DeCarolis *et al.* [15] was taken under advisement. While their focus was mainly on modelling large energy systems, several elements of their approach lend themselves to the modelling of smaller energy systems including, for instance, transparency, consistency, and repeatability.

The goal of this project is to test, if the optimised control strategy performs better than the reference strategy in terms of operational cost ($C_{\mathrm{OPERATIONAL}}$), and renewable energy fraction of the heat supplied (REF_{TH}). The developed model is a deterministic, quasi steady--state model that facilitates the analysis of both, optimised and reference control architectures.

Spatio-temporal boundaries

The spatio-temporal boundaries for this model are defined considering the subject of optimisation and the resolution of available data. Moreover, limitations due to computational complexity must be addressed. The system under consideration consists of an air-to-water heat pump and a thermal energy store serving a commercial office space heating demand in the cool Irish maritime climate. This system exchanges energy flows and information streams

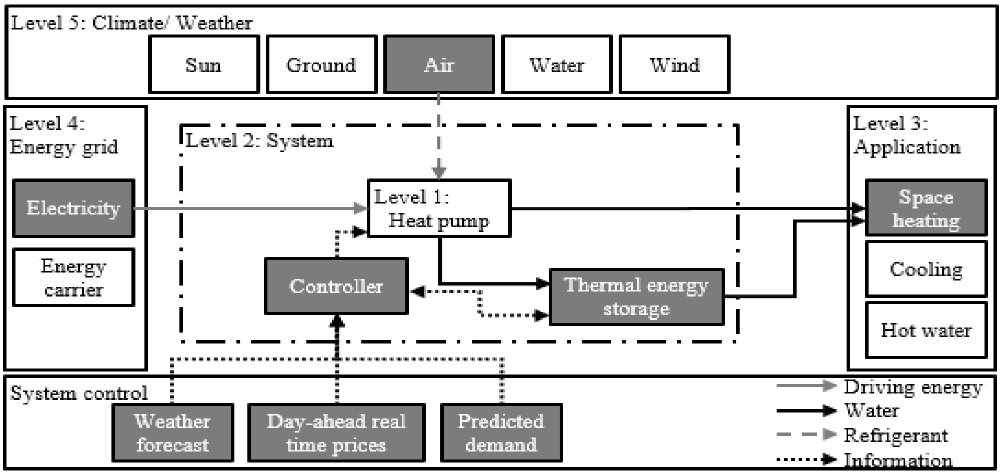

Figure 2. Energy and information flows optimized at Level 2 (adapted from Carbonell *et al.* [16])

across its boundary as shown in fig. 2. Energy flows to the system are thermal energy from the ambient air and electrical energy from the grid. Energy flows from the system consist of the thermal energy that supplies the heat demand to the distribution system and losses from the TES. The information flows from and to the system include a controller signal to switch the heat pump on and off and TES temperature to represent the state of charge (*SOC*). The controller furthermore receives information from web services, including day-ahead variable electricity prices and temperature forecast. The temporal boundaries for this study are the resolution of the model and the period over which the system is simulated. Systems with a high share of variable renewable energy require high spatio-temporal resolution [15]. Commonly, a resolution of hourly time steps is chosen, which is consistent with the available data for day-ahead electricity prices, temperature forecasts and heat demand profile. Moreover, this resolution confines computational complexity to a manageable level. The modelling period spans an entire month in January.

Optimisation problem

Optimisation is the process of finding the *best* solution for a problem, *i. e.* selecting values for input variables to maximise or minimise an objective value under constraining boundary conditions. The heat pump operation schedule in this study is optimised over a temporal horizon, n, of 24 hours for minimum cost, maximum REF of supplied heat (REF_{TH}) or maximum $REF_{\mathrm{TH}}/Cost$. The optimisation variable δ_i represents the on/off state of the heat pump. Thus, the optimisation problem is of the order 2^{24} and consequently, there are more than 16.7 million heat pump on/off permutations for every 24-hour horizon. Moreover, there are 24 temperature, $T_{\mathrm{AMBIENT},i}$, 24 heat demand, $Q_{\mathrm{DEMAND},I}$, and 24 electricity cost inputs, SMP_i. Each permutation results in a unique system performance affecting TES temperature, $T_{\mathrm{TES},I}$, profile and therefore COP_i of the heat pump, storage losses, $Q_{\mathrm{LOSS},i}$, REF_{TH} and operational cost. Also, permutations may be valid or invalid, depending on whether they satisfy demand or not. This is the central constraint that the optimisation algorithm must negotiate. Given the high dimensionality, non-linearity, discontinuity and complex dynamics of the optimisation problem, GA is used due to its numerous advantages over conventional optimisation algorithms.

The operational cost to be minimised during economic optimisation is a function of electrical energy supplied to the heat pump W_{EL} and the unit cost at any given time step as shown in eq. (1):

$$\min Cost = \min\left\{\sum_{i}^{n}\delta_i W_{\mathrm{EL},i} SMP_i\right\} \tag{1}$$

The schedule is also optimised for ecological performance by maximising REF_{TH} as shown in eq. (2). REF_{TH} is the renewable fraction of the delivered thermal energy and consists of the ambient energy sourced by the heat pump and the fraction of renewable electricity. If the heat pump delivers three units of thermal energy for one supplied unit of electricity with 25% from renewable generation, the renewable energy fraction of delivered thermal energy equates to 75%. With increasing shares of renewable electricity generation (REF_{EL}) the REF_{TH} may approach 100%. Ireland's largest contributor to renewable electricity generation is wind energy. For the purpose of this study REF_{EL} is used synonymously for wind penetration of demand. It is corrected for electricity distribution losses using the distribution loss adjustment factor ($DLAF$). REF_{TH} is then divided by the amount of operation hours to incentivise reduction of the latter:

$$\max REF_{\mathrm{THERMAL,AVG}} = \max\left\{\frac{\sum_{i}^{n}\dfrac{COP_i - DLAF_i(1-REF_{\mathrm{ELECTRICITY},i})}{COP_i}}{n}\right\} \tag{2}$$

Finally, to obtain a compromise between the best possible renewable fraction and the lowest operational cost, the quotient of $Cost$ and REF_{TH} is minimised. In this case, the fraction of $Cost$ per REF_{TH} is multiplied with the number of operational hours during optimisation.

Heat pump model

Heat pumps transfer heat from a low temperature source to a high temperature sink and their isentropic performance is a function of their respective absolute temperatures, shown in eq. (3). The coefficient of performance of a heat pump represents the quantity of thermal energy delivered per unit of electricity supplied:

$$COP_{\mathrm{HP,CARNOT}} = \frac{1}{1-T_{\mathrm{L}}/T_{\mathrm{H}}} \tag{3}$$

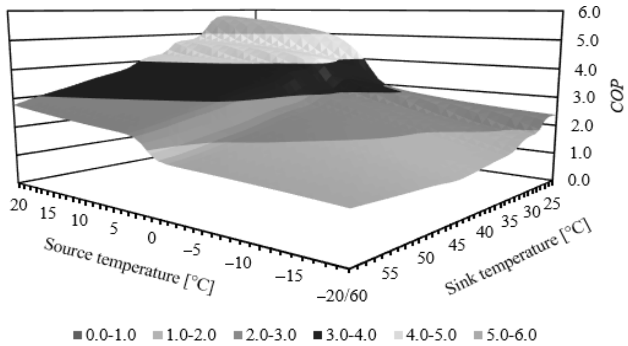

Figure 3. Heat pump performance map model predicted by 8-node MLFN that was trained on manufacturer's data

Dynamic system simulation and detailed modelling requires the consideration of system dynamics and the evaluation of the system under varying boundary conditions [17]. Therefore, the quasi steady-state performance map model, fig. 3, was derived from manufacturer's data that was measured based on EN14511-2011. An ANN was trained to predict the *COP* for varying source and sink temperatures. The 8-node multi-layer feedforward net (MLFN) was trained with 44 data points. During testing, it achieved a root mean square error of 0.045 and outperformed linear regression by a factor of seven.

Thermal energy storage

The TES considered for this study is a dedicated space heating hot water cylinder with a capacity of 3 m^3. It is assumed to be fully mixed and of uniform temperature. The minimum storage temperature is fixed at 35 °C to offer a minimum temperature differential, enabling distribution system heat transfer, and the maximum temperature is 55 °C, maintaining a relatively low sink temperature to enhance heat pump performance. This yields a storage capacity of 69.8 kWh representing 34% of the average daily winter heat load of the commercial building. Storage capacity and sink temperature for various states of charge are calculated based on eq. (4):

$$Q_{\mathrm{STORE,MAX}} = mC_P\Delta T \tag{4}$$

The storage losses are a function of the surface area of the TES, its thermal transmittance or *U*-value, and the temperature differential between the TES and its surroundings. The latter is responsible for varying heat losses at different states of charge of the TES, that are calculated according to eq. (5). For this study, the insulated storage cylinder has a *U*-value of 0.59 W/m^{2}K, surface area *A* of 11.7 m^2 and is assumed to be located within the building and surrounded by air at room temperature:

$$Q_{\mathrm{LOSSES},i} = UA\Delta T_i\Delta t \tag{5}$$

The SOC of the TES at any time step is the previous SOC plus the net heat flux that includes heat added by the heat pump Q_{HP}, heat discharged to the distribution system Q_{DEMAND} and heat losses from the TES Q_{LOSSES} as defined in eq. (6):

$$Q_{\mathrm{STORE},i} = Q_{\mathrm{STORE},i-1} + (Q_{\mathrm{HP},i} - Q_{\mathrm{DEMAND},i} - Q_{\mathrm{LOSSES},i}) \tag{6}$$

Heat demand profile

The heat demand profile quantifies the thermal energy (Q_{DEMAND}) required for space heating at any given time step of the optimisation horizon. The decoupling of heat demand and supply is a central theme of this study. To always match demand is the principle constraint of the optimisation. Space heating applications are characterised by high variability due to weather conditions, building characteristics, occupancy profile and occupants' behaviour. The heat demand profile, used for this study, represents heat demand of the Innovation in Business Centre in Galway, a commercial office building with 19 incubation units for start-ups ranging in size from 18-60 m^2. The unique heat demand profiles for every day in January were derived from historical fortnightly gas meter readings of 2015. They were weighted for hourly distribution using the heating degree method, and thus display sensitivity to the daily variation of ambient air temperature.

Electricity cost

This model uses variable electricity unit cost, based on final system marginal prices (*SMP ExPost*2) in Ireland's single electricity market. The European Commission is accelerating the deployment of smart meters and will ensure access to dynamic electricity price contracts. The cost per unit electricity depends on the interplay of demand and generation and it decreases when a large share of demand is covered by renewable electricity. On the other hand, unit rates increase during peak demand periods, especially if they coincide with periods of reduced renewable generation. As a result, the exploitation of cheap electricity unit prices yields both financial benefit to the consumer and benefit the grid operator through implicit demand response.

Genetic algorithm

The optimisation of non-linear, multi-dimensional, non-convex, discontinuous, and complex systems yielding exact solutions is computationally intensive and sometimes cannot be achieved using mathematical programming. Therefore, systems are commonly simplified through linearization of non-linear behaviour. Meta-heuristic methods such as GA on the other hand can be used to obtain quasi-optimal solutions with comparatively low computational resources. Yet, it is difficult to quantify the accuracy of its approximate solutions and multiple optimisations may be executed to indicate the range of these quasi-optimal results. The GA mimics Darwinian principles of natural selection by generating hundreds of potential random solutions that compete with one another and then permitting the fittest ones to pass on their genes to a new generation. Initially, multiple strings of 24 bits called chromosomes are randomly created to represent different permutations of heat pump on/off states for every hour of the day. Every permutation results in a unique system performance which allows to rank the potential solutions based on merit. The best performing, or fittest solutions are then selected as parents and their chromosomes are recombined to yield a new generation in a step called crossover. A degree of randomness is implemented by introducing a low probability of mutation after the crossover step. Every iteration improves the average fitness of all potential solutions and converges towards the quasi-optimal solution.

In this study, EVOLVER from Palisade's Decision Tools Suite provided the GA optimisation functionality. There are no universal rules for the selection of optimisation parameters such as population size, crossover point, mutation rate or stopping conditions. Adequate performance was achieved with a population size of 30, crossover point of 0.5, automatically controlled mutation rate and a maximum of 2,000 trials. The optimisation was performed on an Intel® Core™ i3-6100U CPU at 2.3 GHz and 8 GB RAM, operating a 64-bit Windows 10 distribution.

Results and discussion

The load following reference control strategy and the optimisation strategies were applied to a model to simulate the operation of the heat pump and TES system for the month of

Table 1. System boundary conditions for the modelled system in January 2015

	Hourly heat demand [kWh]	Ambient air temperature [°C]	REF_{EL} [%]	System marginal price (EP2) [€kWh^{-1}]
Min	4.1	−3.6	0.7%	0.003
Max	15.7	13.8	54.2%	0.332
Average	10.0	4.6	32.5%	0.051
Total	7,447.9			

January 2015. The boundary conditions for the modelled system are indicated in tab. 1 and the initial TES temperature is 36-37 °C. It is expected that cost optimisation yields the best economic operational performance by shifting heat pump operation to periods with low electricity costs. Furthermore, periods with high source temperature and low storage temperature should be favoured yielding a high COP and hence, more heat per unit electricity. The decoupling of supply and demand is expected to increase storage losses that are driven by the higher temperatures in the TES, and to increase electricity imports. The optimisation for maximum REF_{TH} is expected to yield a higher share of renewable heat in exchange for higher operational cost while the optimisation for minimum $Cost/REF_{TH}$ should result in a performance representing a compromise between minimum cost and maximum REF_{TH}.

Figure 4 illustrates heat pump scheduling according to the applied control paradigms for a typical working day in January with typical wind generation accounting for 35.5% of electricity demand. Triangular markers represent temperature profiles with low temperatures on the (air) source side and elevated temperatures on the (TES) sink side. The line, marked with circles, represents the wholesale electricity market cost profile for the typical workday and a characteristic peak around 6 PM. The heat pump schedule is represented by the line with square markers and represents the heat pump cycling between 0 (OFF) and 15 kWh (ON).

Figure 4(a) illustrates performance of the load following reference model. Heat pump operation is characterised by continual hourly cycling of the heat pump. In the absence of capacity control more heat is supplied by the heat pump than demanded, leading to the inadvertent charging of the TES with excess heat. Consequently, in the next time step the store is discharged which in this instance suffices to meet demand. Operation is not affected by electricity tariff or favourable source quality, and storage temperatures fluctuate around 36-39 °C. Figure 4(b) corresponds to cost optimised scheduling and reveals sensitivity of the optimisation algorithm to electricity price profile and dynamic *COP*. The first quarter of the day low electricity prices and low sink temperatures induce a period of intense charging that is accompanied by the steady increase of sink temperature and thus, decreasing *COP*. During the following quarter with increased electricity cost, demand is supplied entirely by discharging the thermal store. Before the characteristic spike in electricity peak demand and cost at approximately 6 o'clock in the evening the store is charged again during a relatively cheap period avoiding the two following more prohibitive hours around 17:00-19:00. Heat pump operation then continues to charge the TES at normal cost and mild outside temperatures in preparation for a cold night. The store temperatures fluctuate around 35-48 °C but never reach the maximum temperature of 55 °C. In fact, no maximum SOC constraint has to be applied to the model as the algorithm maintains a low sink temperature.

The control algorithm does not exploit the entire storage capacity which potentially signals a mismatch between optimisation horizon and storage capacity. However, it may be speculated that both the increased storage losses and decreased *COP*, driven by increased TES temperature, negate the cost savings that could be achieved by availing of low-cost electricity periods. Longer optimisation horizons for medium-term storage and/or increased levels of TES insulation may prompt better utilisation of storage capacity. The optimisation maximising the renewable energy fraction of thermal energy delivered, shown in fig. 4(c) yields a schedule that is somewhat similar to load following operation. In this instance, the optimisation routine is indifferent towards operational cost and focusses on maximising REF_{TH} with least heat pump activity. REF_{EL} during the displayed period remains relatively constant with a mean of 35.5% and a standard deviation of 5.7%. Thus, frequent cycling of the heat pump is mainly driven by a feedback loop caused by the fluctuating TES sink temperature and associated fluctuating *COP*. The only two-hour long charging and discharging periods are triggered by particularly low or high TES temperatures respectively. Finally, the optimisation for the best compromise between low operational cost and high REF_{TH} in fig. 4(d) result in the same pattern as the pure cost optimisation.

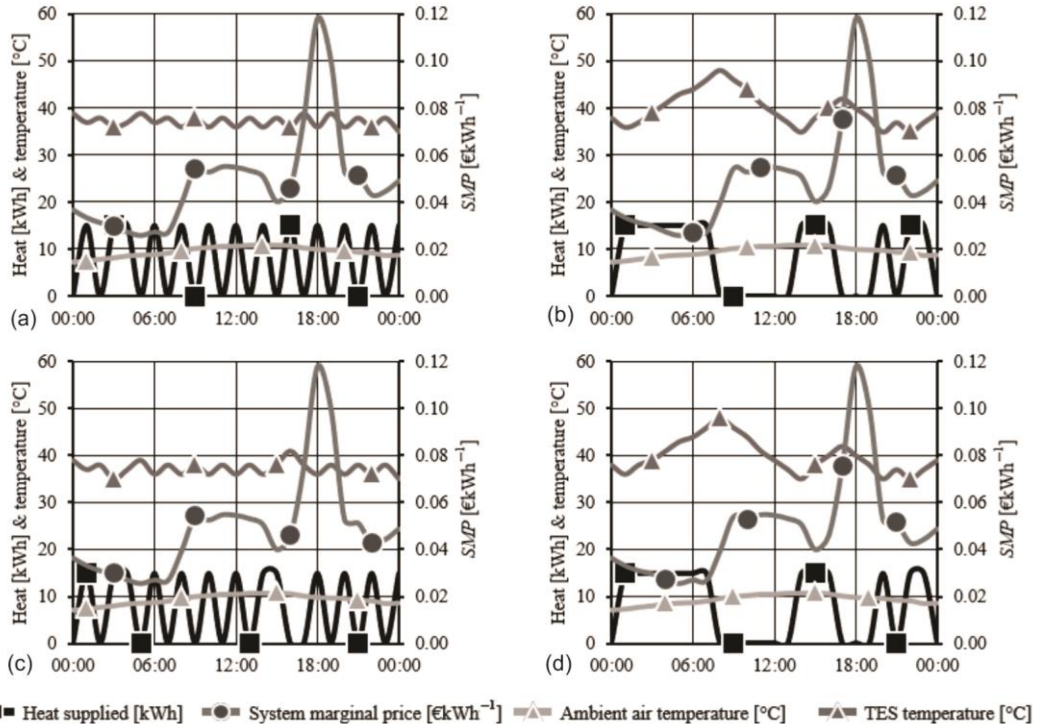

Figure 4. Heat pump schedules for a typical workday with typical average REF_{EL} of 35.5% in January with source and sink temperature and electricity cost profiles for; (a) load following (reference), (b) cost optimised, (c) REF_{TH} optimised, and (d) *Cost*/REF_{TH} control strategies

The heat pump schedule for a particularly cold work day with an average of 1.5 °C and a low REF_{EL} of 5.1%, resulting in 20.9% increased average *SMP*, displays similar characteristics as operation on the warmer and windier day. Analogously to the optimisation results for the windy day, cost optimisation strategies (b) and (d) reveal sensitivity to the *SMP* profile while the load-following and REF_{TH}-focused operation strategies are most affected by TES temperature.

Table 2 displays results from the analysis of correlation patterns between daily averaged ambient air temperature, REF_{EL}, *SMP* and daily cost for all optimisation strategies that reveal a very strong negative relationship of temperature to cost. The analysed data suggests, that

Table 2. Correlation coefficients of daily mean ambient temperatures (T_{AVG}), REF_{EL}, SMP, and *Cost*

Cost	T_{AVG}	$REF_{EL,AVG}$	SMP_{AVG}
Load following	−0.816	−0.676	0.774
Cost optimised	−0.804	−0.634	0.701
REF_{TH} optimised	−0.792	−0.636	0.757
$Cost/REF_{TH}$ optimised	−0.801	−0.626	0.717

sink temperature and *SMP* have the strongest impact on the heat pump schedule, but more sensitivity analysis may be needed to correct for the heat demand that is sensitive to ambient air temperature. A very strong positive relationship reveals itself between *SMP* and *Cost*, especially for the load following and REF_{TH} optimised schedules. Naturally, this relationship is weaker for the cost-optimised control patterns. The average REF_{EL} has a strong negative relationship with operational cost for all tested strategies due to the decreasing cost of electricity with increasing wind electricity generation.

Figure 5 summarises the optimisation results for January 2015 comparing operational cost, renewable energy fraction, storage losses and electricity supplied. It can be seen, that all operation modes have a high renewable energy fraction of more than 79% in common, during a month in which 32.5% of electricity demand was covered by wind generation subject to a standard deviation of 14.7%. Cost optimisation offers the greatest reduction of 17.4% in operational expenditure compared to the reference case, closely followed by $Cost/REF_{TH}$ optimisation with savings of 17%. This is achieved through the successful shift of heat pump operation towards low cost periods while avoiding prohibitive (peak) times and taking advantage of good *COP*. In both cases this requires an increased supply of electricity which leads to a reduction of REF_{TH} by approximately 1% and an increase of storage losses by 19-21% due to higher TES temperatures. The optimisation for REF_{TH} only resulted in a miniscule 0.1% increase of REF_{TH}, accompanied by a cost reduction of 2.3% and 4% more storage losses. The required electricity is decreased by 6.1%.

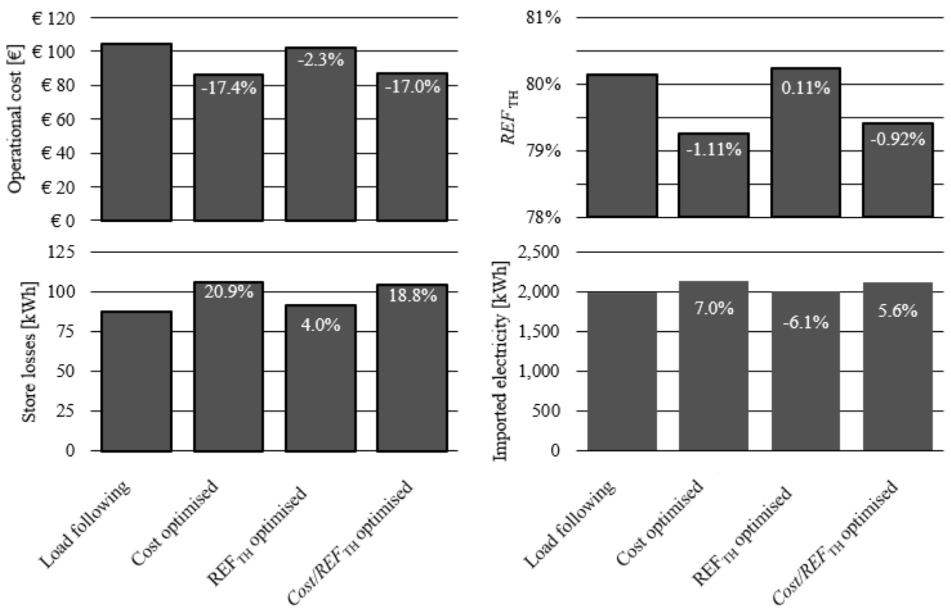

Figure 5. Optimisation results comparing *Cost*, REF_{TH}, storage losses, and electricity imports

The preferential use of low electricity rates facilitates implicit demand flexibility which benefits the grid operator. The optimised schedule avoids expensive peak demands by shifting heat pump operation. The share of wind generated electricity, converted by the heat pump, was increased by 4.4%. The reason for this is an unusual moderate negative relationship between REF_{EL} and *SMP* in January 2015. A stronger negative relationship, as displayed in fig. 1 for January 2017, is expected to yield a larger increase in utilised electricity from wind generation. The transmission system operator Eirgrid estimated, that installed renewable generation capacity in Ireland will have to increase by 28-42% until 2020 to achieve the 40% renewable electricity target [18] which will further increase REF_{TH}.

The modelled optimisation strategies generally perform according to the expected outcomes. The cost optimisation delivers significant savings at the cost of slightly sacrificing REF_{TH}, increasing storage losses and increased electricity consumption. The optimisation for maximum REF_{TH} on the other hand does not yield a significant improvement. This is due to the fact, that the low-cost periods favoured by the cost optimisation algorithm coincide with large shares of electricity generation on the national grid. Hence, optimisation for low cost also optimises for high REF_{TH}.

The performance results of the different control strategies are based on actual finalised and measured data. However, the performance of an actual real-life controller is affected by the uncertainty of the weather forecast, heat demand prediction and electricity cost prediction. Retrospective analysis of weather forecast and electricity SMP suggest root mean square errors of 1.96 degrees and 17.8%, respectively, with a tendency to underestimate ambient air temperature and to overestimate *SMP*. As a result, such a controller would perform better than the original optimisation suggests. But, it is also very likely that the opposite could occur. It is therefore crucial to develop methods to reduce uncertainty. The same can be stated for the heat demand profile, that is known for the purpose of this study but must be predicted for a real controller employing machine learning techniques that consider historical performance but also react to changing circumstantial changes of weather and occupant behaviour.

Finally, GA optimisation performed satisfactorily. However, it is impossible to note the accuracy of the acquired optimal results. Multiple optimisation runs could be conducted to estimate the spread of potential optimal results. Furthermore, more experimentation may be required to identify the best parameters and further decrease optimisation time. The migration of model and optimisation routine from tabulated spreadsheets to a more efficient platform such as Python also promises better computational performance.

Conclusions

Heat pumps will be a key technology in the decarbonisation of the heating sector and the large-scale implementation of renewable sources into an integrated energy system. The GA modelling approach was successfully demonstrated with an opportunity of improved system integration of control, component design (*i. e.* size of TES) and cost optimisation while delivering heat with a *REF* that exceeds 79%. Operational cost reductions of more than 17% compared to a load following reference system were identified. This is achieved using a locally optimised heat pump and TES system using GA to schedule the heat pump according to local weather predictions, predicted load and day-ahead SMP.

It is shown that TES can be used to decouple space heating demands and supply heat efficiently, while not jeopardising timely supply of heating loads. However, more electricity is required, lowering the heat pump seasonal performance factor and potentially increasing associated CO_2 emissions depending on the *REF* of consumed electricity. This study used known weather conditions, heat demand profiles and electricity prices. Future research will involve temperature forecasts and day-ahead electricity prices from existing web services and a self-learning heat demand predictor module. Further savings are expected for longer optimisation horizons with appropriate storage capacity. Storage losses are significantly increased due to long storage periods at high temperatures and should be minimised by appropriate insulation levels. Cost optimised operation not only achieves the expected lowest operational cost but also achieves a REF_{TH} that is almost identical to the REF_{TH} optimised value. Hence, future research may focus on cost optimisation, experimental validation, incorporation of predictive elements and retrospective evaluation of prediction uncertainty.

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Nomenclature

δ – binary heat pump variable

Subscripts

EL – electricity
TH – thermal

Acronyms

ANN – artificial neural network
COP – coefficient of performance
DLAF – distribution loss adjustment factor
ETS – emissions trading system
GA – genetic algorithm
MLFN – multiple-layer feed forward net
REF – renewable energy fraction, [%]
SMP – system marginal price, [€]
TES – thermal energy storage
THRES – thermal hybrid renewable energy system

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