Business case for electric heat pumps under different day-ahead price scenarios

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***Abstract*—This paper aims to present a probabilistic assessment, via a two-stage stochastic optimization, of the potential benefits from cost optimizing the interaction of thermal and electrical systems of an aggregation of buildings, through the use of domestic electric heat pumps. As more and more intermittent generation is integrated into the grid, while capacity margins are shrinking, not only might prices drop on average but they could also become much more volatile than at present. Potential future day-ahead price scenarios are therefore analyzed in this paper, by using specific price evolution stochastic models developed to take into account different levels of average prices and volatility. Results suggest that lower average values of day-ahead prices combined with very high volatility can lead to noticeable economic benefits from managing EHP aggregation to exploit potential arbitrage opportunities.**

***Index Terms*-- Business cases, electric heat pumps, markets, stochastic price models, uncertainty.**

I. NOMENCLATURE

s	scenario index, from 1 to N_s
i	settlement period index, from 0 to N_i
p_s	scenario probability
λ_i	day-ahead price, £/kWh
$\mu_{s,i}^{-}$	negative imbalance price, £/kWh
$\mu_{s,i}^{+}$	positive imbalance price, £/kWh
$\chi_{s,i}^{-}$	physical import price, £/kWh
D_i	day-ahead purchase, kWh
$I_{s,i}^{-}$	negative imbalance volume, kWh
$I_{s,i}^{+}$	positive imbalance volume, kWh
$E_{s,i}^{-}$	physical import volume, kWh
y_t	price data at time t
A_p	auto-regressive parameter with order p
M_q	moving-average parameter with order q
ε_t	white noise process
c	constant term

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II. INTRODUCTION

Concerns of climate change, energy security and affordability are increasingly encouraging interest in improving efficiency of energy systems. One method for achieving this is to optimize the interaction between thermal and electrical systems. In particular, electric heat pumps (EHP) can improve operational flexibility (for both system and network purposes [1]) by exploiting the storage potential of different building fabrics and thermal energy stores [2]. Such flexibility can create attractive business cases for EHP owners and relevant aggregators as this provides them with incentives to adjust consumption for system balancing. The financial benefits of such business cases have been studied in previous works, such as in [3] for EHP, [4] for air-conditioning (AC) units, [5] for heating, ventilation and AC (HVAC) and electric vehicles, [6] for various appliances, [7] for demand response (DR) in general, and [8] for EHP and combined heat and power units. However in these works only current market prices have been considered. Yet, the impact of higher wind variability and tighter capacity margins may change future market prices, causing greater volatility [9], [10], possibly associated to overall lower average prices [11]. As a result, this paper systematically investigates the effect of likely future changes in electricity prices on DR business cases based on exploiting the flexibility available in aggregating EHP.

III. PHYSICAL HEATING SYSTEM MODEL

A. *Stochastic optimisation model overview*

The basis of the employed stochastic optimization model is a physical heating system model (displayed in Fig. 1) incorporating the heating unit, thermal energy store (TES), building, and domestic hot water (DHW) demand. As described in detail in the previous work [3], the building and its TES are modeled as a pair of lumped systems, each characterized by a pair of thermal resistance and capacitance values. The heating unit is characterized by its coefficient of performance (COP) and operating limits. The DHW demand is set according to a user-defined profile.

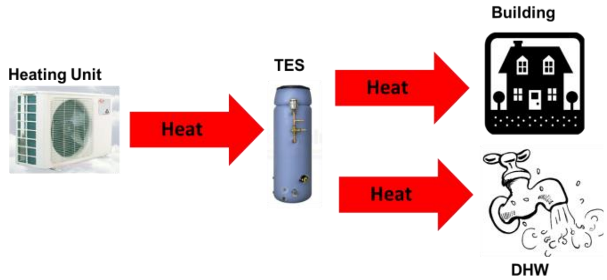

Fig. 1. The heating system model

The building's space heating demand is a function of the building's characteristics, the outdoor temperature and the indoor set temperature. The problem considered in this work is that of a retailer-aggregator who is responsible for providing thermal comfort to required standards, as well as non-heating electricity and DHW, to a number of dwellings connected to the wider grid through a common grid connection point, thus forming a micro-grid. The retailer-aggregator is assumed to be balancing-responsible, as well as being responsible for paying third party charges (i.e., grid fees). In other words, the retailer-aggregator first buys electricity on the wholesale day-ahead (DA) market and then must settle any imbalances between contracted and used electricity according to the imbalance settlement process (ISP). However, although DA prices are known at the DA stage, imbalance prices are not; these are only known after delivery. As a result, the model needs to consider uncertainty in imbalance prices. Furthermore, a number of parameters are unknown at the DA stage. These unknown parameters include the heat demand determinants (outdoor temperature, DHW demand and dwelling active occupancy), as well as the non-heating electricity profiles. All this makes the problem stochastic, where the objective is to minimize the expected total costs of a retailer-aggregator subject to uncertainty.

The objective function, given in equation (1), states that for each scenario s, with probability p_s of occurring, the DA energy costs, imbalance (negative and positive) costs and the physical import costs are determined and summed over each settlement period i. The import costs include all costs related to electricity consumption: transmission costs, distribution costs, balancing services costs, environmental and social obligations (ESO) and value-added-tax (VAT). Note that the retailer operating costs are not included, as these costs are not directly attributable to consumption, and thus do not produce relevant price signals.

$$\text{Min}\left\{\sum_{s=1}^{N_s}\sum_{i=1}^{N_i}\left(p_s\left(\lambda_i D_i + \mu_{s,i}^- I_{s,i}^- - \mu_{s,i}^+ I_{s,i}^+ + \chi_{s,i}^- E_{s,i}^-\right)\right)\right\} \tag{1}$$

As described in [3] and [8], to model the effect of the uncertain parameters on the decision-making process, a two-stage stochastic optimization approach is required [12]. In the first stage, the retailer-aggregator decides how much electricity to buy in the DA market, while the second stage corresponds to the settlement periods in which the electricity is delivered. The EHP and the TES set points, the building temperature and the imbalance purchases are all determined in the second stage. To estimate the cost of energy for a whole year, the model is run for seven representative days (summer weekday & weekend, spring/autumn weekday & weekend, winter weekday & weekend, and a "peak" day). The representative days are selected by using a version of the scenario reduction technique described in [3], to find the most representative DA price profile for each season.

B. *Consumer price components*

A development compared to the model presented in [3] is in the treatment of the retail prices. Whereas previously, all non-energy costs (i.e., grid fees, taxes, environmental and social obligations) were added to the electricity import price at a flat rate, each price component is now itemized. This enables time varying grid fees, as well as energy market prices to be considered, making the analysis more realistic. This treatment of prices in fact allows measuring the impact of the optimization on different price components, which will be of particular interest to the parties in receipt of revenues related to those prices.

IV. PRICE MODELLING

Future price scenarios are modeled using a custom price process employing an auto-regressive moving average ARMA(p,q) model with seasonal lags and orders p, q [13]. This model, written in equation (2), is composed of an auto-regressive parameter A_p with order p, a moving average parameter M_q with order q, a constant c and an error term ε_t. This error term is modelled as a set of random variables (white noise process), which are assumed to be independent and identically distributed samples drawn from a Pareto distribution with mean α and standard deviation σ. The model hence creates a new random price process at each simulation.

$$A_p y_t = c + M_q \varepsilon_t \tag{2}$$

Prices are fitted on a non-linear model to daily prices recorded in the Elexon portal of market index prices in the United Kingdom (UK) from January 2009 to May 2014 [14]. The price series is modeled as a sum of two components, a deterministic non-linear function that explains the seasonal or expected prices for a given hour in a given year, and a stochastic component that explains deviations of actual prices from average prices.

The deterministic component is modeled with a sum of sine functions to model the observed daily peaks and troughs in the data. The difference between actual values and modeled ones are considered residuals and present strong seasonal correlation since above (below) average prices usually follow above (below) average prices. In order to remove any serial correlation, a regression is performed on the stochastic price component using a matrix of significant lags determined by the autocorrelation and partial autocorrelation functions of the residuals. This creates an auto-regressive model with seasonal lags whereby the serial correlation in the residuals is removed, allowing the residuals to be modeled as independent random draws from a suitable distribution. By plotting the cumulative distribution function of the price data, a Pareto distribution provides the best fit since the price data presents very fat tails at each end of the distribution, caused by sudden price spikes.

The price model can then be simulated to create a new stochastic price process using the actual mean price, the sinusoidal model (deterministic), the regression parameters, the autocorrelation lags and the residual probability distribution (stochastic). Each simulation creates a new stochastic price process with the same mean and volatility as the actual price data but with different values. To simulate a new price process with a different mean value, the mean price is altered. On the other hand, to create a new price process with a different level of volatility, the statistical parameter of the distribution, its standard deviation, is altered accordingly.

V. Case Studies

To exemplify the effect of the variation on mean DA price levels and DA price volatility, an aggregation of fifty flats, insulated to a high standard, is defined. The parameters which describe the aggregation, as well as the relevant environmental and demand parameters, and the price components, are described below.

A. Resource parameters

The thermal resistance and capacitance values for the flats defined in this case study were taken from detailed modeling of UK building stock undertaken using the DesignBuilder software [15], [16]. Each flat was assigned a 145 liter TES, with resistance and capacitance values derived from [17]. The TES minimum and maximum temperatures were set at 40°C and 55°C. EHP COP values vary according to the outside temperature, as described in [3]. The maximum power of each EHP is set to be able to maintain a set temperature of 21°C at an external temperature of -4°C, whilst supplying the maximum possible DHW demand.

B. Environmental parameters

The relevant environmental parameters, like the outdoor temperature and solar insolation (relevant for solar heating effects), are uncertain at the DA stage. Using the scenario reduction algorithm described in [3], three scenarios of environmental profiles are defined for each season/test each with their associated probability of occurrence. These are combined with the imbalance price profiles (see Section V.D) to form, in total, nine scenarios for each season/test.

C. Demand parameters

As previously described, the space heating demand is determined by dwelling active occupancy, set temperature, as well as the building parameters. The set temperature varies by dwelling and is set according to a pseudo-random process following the distribution of set temperatures described in [18]. For each dwelling the number of occupants is set following a pseudo-random process based on [19]. This informs the synthesis of pseudo-random active occupancy, DHW and non-heating electricity demand profiles, which are generated as described in [2]. Each dwelling is assigned a different set of profiles for each scenario representing the uncertainty of these profiles at the DA stage.

D. Price components

The original series of DA and imbalance prices are taken from the UK context, from 01/01/2009 to 12/05/2014 [14]. Note that the UK has separate positive and negative imbalance prices, so that DA trading is always preferred rather than being exposed to the ISP. For each test (described in TABLE I), the series of historical DA prices are subject to the price model, mean price levels and volatility levels. The imbalance price record is then set by applying the difference between the original DA and imbalance price series to the new DA price series. For each season the scenario reduction algorithm is run to find the most representative daily price profile to represent the season. The scenario reduction algorithm is run again as part of the scenario formulation process to produce three imbalance price scenarios, with associated probabilities, for each season/test. These, together with the environmental parameter profiles, form the required nine scenarios.

As well as DA and imbalance prices, several other price components are relevant to the dwellings situated on the distribution network in the UK. These are fees related to distribution use of system (DUoS) (for maintenance and operation of distribution networks), transmission network use of system (TNUoS) (for maintenance and operation of transmission networks), balancing services use of system (BSUoS) (for provision of system balancing services), ESO (for government environmental and social programs) and VAT (a general consumption tax). For this case study, the various price components were set based on half-hourly metered domestic dwellings situated in the North-West of England. DUoS fees were taken from [20], whilst TNUoS fees (charged on the average consumption in the highest three settlement periods [21]) were taken from [22]. Similarly to imbalance prices, BSUoS fees [23] are not known a priori and hence scenarios for these fees are determined along with the imbalance prices. ESO and VAT is set according to rates relevant to domestic consumers [24]. Naturally, the price components vary across seasons. As an example of the price evolution through the day, Fig. 2 shows the expected price profile for a winter weekday for Test 1 (see TABLE I). Fig. 2 shows that ESO and VAT rates are constant, whilst DUoS rates vary significantly throughout the day. DA prices, expected imbalance prices[1] and BSUoS fees also vary, peaking in the early evening, when system load is the highest. There is no TNUoS fee shown here as TNUoS fees are only considered when a TRIAD (one of the three highest demand periods in the year) occurs, on the expected fifteen peak days of the year that define the peak season.

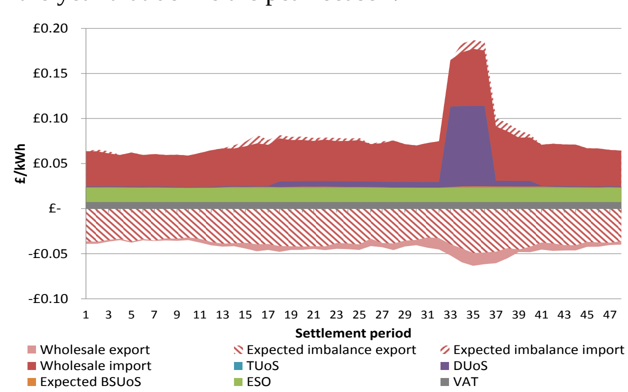

Fig. 2. Winter weekday price components

[1] The negative imbalance prices is shown as additional to the DA import price, and the DA export price as additional to the positive imbalance price

VI. RESULTS

A. DA prices

The following studies are run to assess the effect of changing mean and price volatility in DA prices on the benefits of a retailer-aggregator optimizing the operation of domestic EHP. Changes to mean price levels and price volatility are detailed in TABLE I. These price scenarios were chosen as representative of the general trends in UK wholesale prices, forecasted by the UK regulator, Ofgem [11]. As described in Section IV, a new stochastic DA price process is simulated based on actual price data, with its mean and volatility altered accordingly. A comparison of the actual price on a day (21st January 2009) with the simulated prices for Test 4 and Test 7 is shown in Fig. 3, where the solid line represents the actual price data, while the other two lines represent simulated prices with a 5% and 10% decrease in mean value. The prices, although shifted downwards, differ from the actual data since a new process is generated at each simulation.

TABLE I: TEST DEFINITIONS

Test	% change to mean prices	% change to price volatility
1	0	0
2	0	50
3	0	100
4	-5	0
5	-5	50
6	-5	100
7	-10	0
8	-10	50
9	-10	100

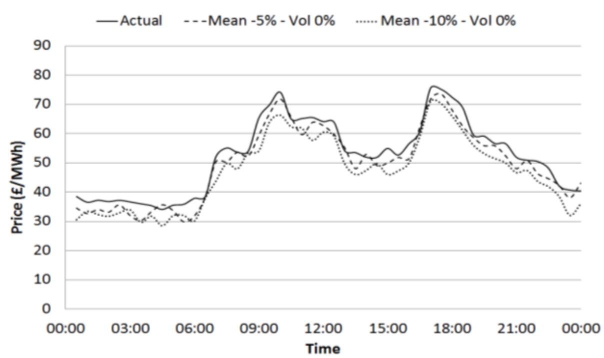

Fig. 3. Actual vs. Simulated Prices for 21st January 2009 with different mean values

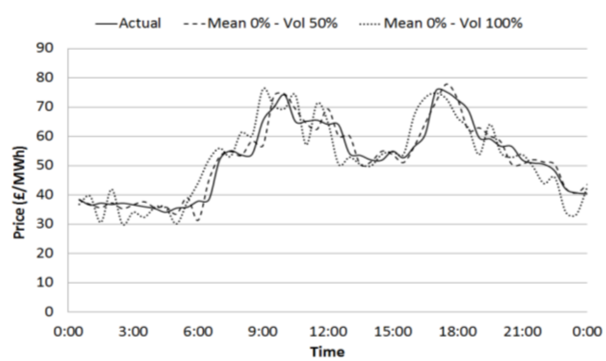

Fig. 4. Actual vs. Simulated Prices for 21st January 2009 with different levels of volatility

In Fig. 4, the solid line represents the actual price data, while the other two represent simulated prices with a 50% and 100% increase in volatility, corresponding to Test 2 and Test 3 respectively. As the price model generates one day of prices, corresponding to the 48 settlement periods, the simulation is repeated for each day.

B. Costs

Changes to mean price levels and price volatility will be of particular interest to two groups. Those who may wish to optimize their portfolio of EHP resources, and want to quantify potential benefits; and, those retailer-aggregators (or similar parties) who are already responsible for flexible EHP resources and want to understand how changing DA price may affect their business. Fig. 5 shows the effect of moving from a simple load following policy (where heating units are simply operated when there is an active occupant in the dwelling) to a cost optimization, as described in Section III.

It is clear that significant benefits can be gained from moving to a cost optimization under all tests, where a minimum saving of £66 is realized under the Test 1 scenario, where both mean and volatility are the same as today. However, as volatility increases, so do the benefits. Test 2 and Test 3 see a 3% and 5% respective increase over Test 1. Similar results can be seen for all tests, where Test 9 shows the highest benefit of £72 and represents an 8% increase over Test 1. A slight increase in benefits is realized from a reduction in the mean price but this only represents a 2% increase for a 10% decrease in mean value. The most substantial benefits arise from avoiding TNUoS charges and the periods of high DUoS charges. Further benefits come from shifting electricity consumption away from periods of high DA prices. Nonetheless, the cost of negative imbalances can be larger when optimizing than under load following, even though the overall energy cost is lower. This is due to the optimization relying more on the ISP for additional electricity since, as can be seen in Fig. 2, the difference between the wholesale export price and the expected imbalance export price (i.e., between the DA price and the system sell price) is equal to or greater than the difference between the expected imbalance import price and the wholesale import price (i.e., between the DA price and the system buy price). This suggests that it is better to be in a short position in the DA market and rely on paying negative imbalance prices rather than being long and paying the positive imbalance prices.

Additionally, the expected benefit from the optimization generally increases as price volatility increases, given the greater benefits from intelligently shifting demand. There is, however, no significant change when the mean price level changes, since the changes in the mean affect both the load following and the optimized cases equally. The variability in the results also comes from the fact that each simulation generates a new stochastic price process, resulting in slightly different results every time. The parties who already optimize EHP resources will be more interested in the effect of price changes on the optimization compared with current prices (Test 1: mean 0%, volatility 0%). Fig. 6 shows that expected savings generally increase as the DA price mean drops.

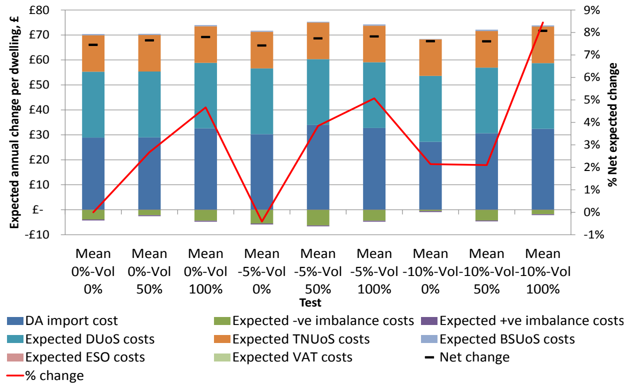

Fig. 5. Expected annual benefits from optimizing EHP operation compared with load following for each test case

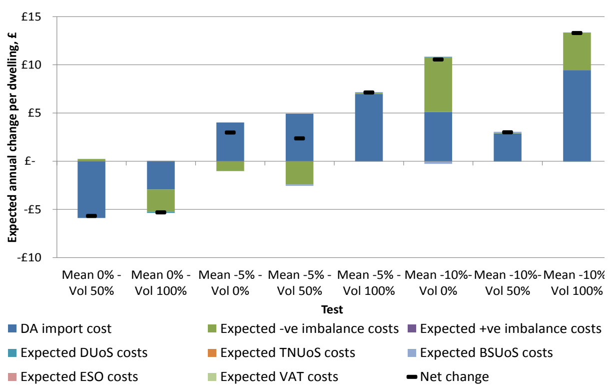

Fig. 6. Effect of future market prices on expected annual savings compared to current prices (Test 1)

On the other hand, there is no clear trend related to changes in volatility, perhaps since the results exhibit some variability, as discussed in Section IV. Indeed, from current results it is not possible to draw conclusions on the effect of changing volatility on costs.

VII. Conclusion

This paper investigates the effect of likely future changes in day-ahead electricity prices, including different average prices and prices with higher volatility, on business cases for electric heat pump (EHP) owners and aggregators. A novel price simulation model is presented in order to simulate future stochastic price scenarios reflecting different market conditions anticipated by the electricity regulator in the United Kingdom (UK). These include prices with lower mean values and higher volatility. Simulated prices are used in a two-stage stochastic programming model to optimize the day-ahead electricity purchase strategy of a retailer-aggregator using EHP to supply thermal energy and minimize energy costs subject to multiple uncertainties, including imbalance prices, outdoor temperature, building occupancy, domestic hot water and non-heating electricity demand. The paper presents an increase in savings, realized from optimizing the aggregation of EHP to take advantage of market price arbitrage, where the largest savings occur under high volatile market prices, as there is a greater benefit from shifting demand to periods of low prices. Although the results show that greater savings can arise from lower average prices, they are not firmly correlated with changes in volatility, due to the nature of the price model. A larger number of tests would therefore need to be run in order to draw firmer conclusions.

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