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Incorporating homeowners' preferences of heating technologies in the UK TIMES model

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ABSTRACT

Hot water and space heating account for about 80% of total energy consumption in the residential sector in the UK. It is thus crucial to decarbonise residential heating to achieve UK's 2050 greenhouse gas reduction targets. However, the decarbonisation transitions determined by most techno-economic energy system models might be too optimistic or misleading for relying on cost minimisation alone and not considering households' preferences for different heating technologies. This study thus proposes a novel framework to incorporate heterogeneous households' (HHs) preferences into the modelling process of the UK TIMES model. The incorporated preferences for HHs are based on a nationwide survey on homeowners' choices of heating technologies. Preference constraints are then applied to regulate the HHs' choices of heating technologies to reflect the survey results. Consequently, compared to the least-cost transition pathway, the preference-driven pathway adopts heating technologies gradually without abrupt increases of market shares. Heat pumps and electric heaters are deployed much less than in the cost optimal result. Extensive district heating using low-carbon fuels and conservation measures should thus be deployed to provide flexibility for decarbonisation. The proposed framework can also incorporate preferences for other energy consumption technologies and be applied to other linear programming-based energy system models.

1. Introduction

In 2008, the UK Climate Change Act set a legally-binding target to reduce greenhouse gas (GHGs) emissions by 80% below 1990 levels by 2050 [1]. Residential sector accounts for about 24.2% of total GHG emissions in the UK [2]. Specifically, space and water heating contribute to 83% of total residential energy consumptions. It is thus crucial to dramatically decarbonise residential heating with low-carbon heating technologies to achieve the UK GHG reduction target. According to CCC's estimation, around 13% of homes should be heated by heat pumps and heat networks from low-carbon sources, which means at least 2.3 million heat pumps should be deployed by 2030. Nonetheless, CCC has also pointed out the transformation of residential heat sector will require radical behavioural adjustments, which are highly uncertain [3]. Moreover, there is a lack of evidence to show how plausible it is to expect such radical adjustments.

Techno-economic energy system models, such as TIMES models, are often used for constructing energy system transition pathways [4–6]. Such models, however, can sometimes provide misleading outcomes, as they generally only consider technology and cost attributes and determine least-cost transition pathways for satisfying future energy service demands. These models assume all actors or consumers in the energy system to behave economically rationally and have full information for the whole planning horizon [7]. As it's also assumed that the actors are homogenous, small price variations can cause sudden changes of technology portfolios, which is known as “bang-bang” effect (e.g. all consumers preferring a gas boiler and, after a small cost change, all consumers switch to heat pumps), a major problem encountered with techno-economic energy system models such as TIMES [8]. In reality, the behaviour of consumers is not always economically rational due to e.g. lack of information or influential socio-demographic factors [9]. Especially, it has been shown in previous studies that there is a wide range of factors that might influence homeowners' decisions, such as gender, age, income, dwelling type, existing technology, and so on [10–15]. These are elements that can't be captured when relying on a single, cost minimising representative actor. Therefore, in order to be able to capture all the relevant drivers and hurdles of an energy

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system transition, it is important to consider household heterogeneity and corresponding preferences when modelling the transition.

Household behaviour in terms of technology adoption is usually simulated in models by constraining the speed and ceiling of technology diffusion in the optimisation framework (see e.g. Refs. [16] and [17]). These constraints are usually based on aggregate historical trends and experts' judgements. There is thus a danger that the model might only reflect the preconceived notions of the modellers [18]. Due to the ease of implementing such diffusion constraints, however, this approach has been adopted in many techno-economic models. For instance, Kannan and Strachan [19] used a single representative household to represent the residential sector in UK MARKAL while the technology adoption was constrained by historical uptake rates. Although Dodds [20] introduced 36 effective house categories into UK MARKAL to assess decarbonisation strategies for residential heating, the technology growth constraints were still based on historical trends and subjective judgements. Similarly, Energy System Modelling Environment (ESME), an energy optimisation model for the UK, imposes user-defined limits on the annual maximum technology deployment for three dwelling types in the domestic sector [21]. Comparable growth constraints are also found in MESSAGE-III to regulate new investment in technologies [22].

To address this issue, there have been several previous studies focusing on developing new modelling frameworks to incorporate household heterogeneity and household behaviour directly into techno-economic energy models. These studies mainly use hurdle rates or intangible costs to represent households' preferences for new technologies. Moreover, none of the previous studies has explicitly considered district heating and conservation measures along with individual heating technologies for residential heating.

For instance, Smeureanu et al. [9] modelled in the SOCIAL-MARKAL model how an information campaign induced behavioural change and altered lighting demand in the residential sector. On the other hand, Daly et al. [23] and Pye and Daly [24] modelled travel behaviour, modal choice between private cars, buses, and trains, in TIMES models and ESME respectively, using fixed travel time budgets for short- and long-distance trips and allowing investments into infrastructure that decreases travel time (e.g. bus lanes). These studies, however, do not take consumer heterogeneity into account, nor capture any non-cost preferences beyond the time budget.

Other studies have focused more on household heterogeneity in the techno-economic models. For example, Cayla and Maïzi [8] encapsulated households' behaviour into the TIMES-Households models to evaluate diffusions of heating technologies and vehicle stock. Residential and transport sectors were each classified into a number of segments, based on characteristics such as house type and vehicle ownership. Households' investment behaviour was then reflected through discount rates related to households' income level and evaluated based on a nationwide survey [25]. However, consumers' preferences for alternative technologies, beyond the one they currently had, were not explored in the survey. Furthermore, Bunch et al. [26] incorporated behavioural effects from vehicle choice models into a TIMES model to assess the transition to new vehicle types. Consumers were categorised into groups to represent consumer heterogeneities related to adoption barriers (e.g. access to refuelling infrastructure, range anxiety) and related inconvenience costs were estimated for each combination of consumer group and technology. The same methodology was later adopted also by McCollum et al. [27]. As the inconvenience costs are rarely negative, the transition to low-carbon vehicles slowed down when consumers' behaviour was included into the model. In absolute terms, however, the modelled technology transition could still be sudden, as the model continues to make decisions based on cost competitiveness of technologies and merely requires stronger signals than previously before switching to novel technologies.

Nonetheless, not all influential factors on consumers' technology adoption can be easily translated into costs. For example, households' previous heating technology significantly affects their decisions on the next heating technology [14]. The influence of current heating technology can neither be translated into intangible cost nor be easily represented in the previously proposed modelling frameworks, especially, and as suggested in Refs. [14,28,29], heating technology costs might not be as influential as other perceptions and socio-demographic factors and modelling frameworks based on monetary terms alone might therefore no longer be suitable. As a consequence of this, it is critical to develop a more flexible modelling approach to incorporate those influential non-monetary factors to households' preferences and decision making for determining low-carbon transitions of residential heating in the UK.

This study thus aims to develop a new modelling framework that would incorporate those more complex influential factors into a techno-economic energy systems model, UK TIMES (UKTM) [30]. The influential factors to UK homeowners' preferences for heating technologies are first identified through a nationwide survey [31]. The number of representative household types to be included in the model is then reduced through a cluster analysis approach. HHs, formulated based on the characterising influential factors, are then introduced into the model and their decisions are then regulated through constraints reflecting the identified households' preferences. The research procedure is illustrated in Fig. 1.

In the following sections, the major findings of the nationwide survey on homeowners' choice of heating technology are first addressed in Section 2. Section 3 briefly describes the application of a cluster analysis approach to reduce the number of representative households. Section 4 addresses the representation of residential heating in the UKTM model and how HHs are integrated into it. The proposed formulation of how preferences are included is explained in Section 5. Section 6 presents the results of the analyses, while section 7 draws out the main conclusions from the study.

2. Homeowners' preferences for heating technology adoption

Numerous studies have been dedicated to investigating factors influencing households' willingness to adopt alternative heating systems in many countries, such as Germany [14,32–37], Sweden [38,39], Norway [13,29,40–42], Finland [15,43], Ireland [10], Greece [11], Italy [12] and Tunisia [44]. According to these studies, influential factors vary considerably among countries and it is thus essential to identify country-specific influential factors for UK homeowners. However, previous UK studies [28,45–49] mostly adopted qualitative analysis and considered a limited range of factors, such as age, income, and house type, while ignoring a wider range of socio-demographic factors, such as education and geographical region of the country.

A nationwide survey in the UK was thus carried out to collect households' stated preferences of heating technologies in response to various technology conditions, such as upfront cost, lifetime, and so on. Along with respondents' choices, their socio-demographic characteristics were also gathered in the survey. The collected survey results were then used to construct a discrete choice model (DCM) to identify most influential factors among the wide range of factors considered in the survey. The survey is briefly described in the Appendix.

The discrete choice model (DCM) can estimate the probability of a specific selection among alternatives under the influence of

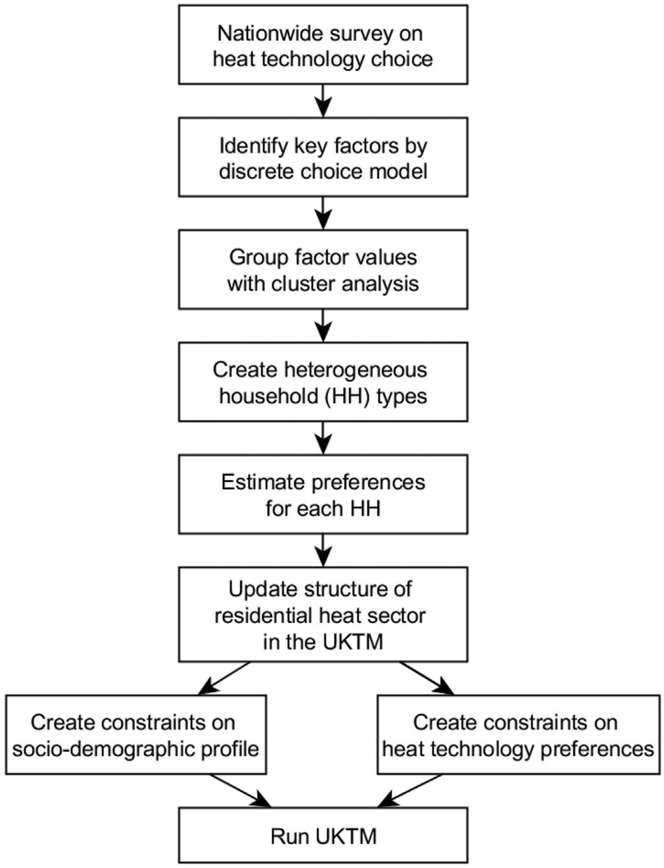


Fig. 1. Research procedure to incorporate homeowners' preferences in the energy system model.

attributes related to the choice [50]. Several studies have used these consumer choice models for residential heating technology choice using various fuel types [12–15, 43,45,46]. Our survey results, which contain both a wide range of socio-demographic factors and technology attributes from the choice experiments, were analysed by the multinomial logit model (MNL) to identify the most influential factors for homeowners' preferences for heating technology adoption.

The statistically significant factors are shown in Table 1. Heaters were categorised into four types: Gas heaters, electric heaters, heat pumps, and solid fuel boilers. Influential factors are found in 5 categories, including existing technology, socio-demography, region, dwelling, and awareness of eco-technology. Each factor might only influence specific technologies and only when that factor is within a specific range. For example, having currently an electric heater increases the likelihood to adopt solid fuel boilers in the future, but lowers the possibility of choosing an electric heater again. On the other hand, households with gas heaters tend to adopt gas heaters again, but the ownership of gas heaters does not increase or decrease their likelihood to choose other types of heaters. Interestingly, costs of heaters were found not to be influential, which is aligned with the suggestions in Refs. [14,28,29].

The most significant factors to almost all heaters identified in the study are existing technology, number of bedrooms, the region of the UK the consumer lives in and the awareness of eco-technologies. To simplify the disaggregation of HHs in the model, only existing technology and number of bedrooms were taken into account to classify households. First, UK region was ignored due to the limited number of sampled homeowners in some regions. Next, although the awareness of eco-technologies also influences homeowners' decisions, the impacts for preferences are relatively minor across various technologies. Finally, even though house type and income are significant for specific heaters, those can be reflected by number of bedrooms. According to the statistics of English Housing Survey (EHS) [51], number of bedrooms is highly correlated to household income and dwelling type; therefore, it is an ideal proxy to represent those household characteristics.

3. Cluster analysis

HHs should be categorised by the identified factors in the previous section. However, every factor contains several levels, such as 5 levels for the number of bedrooms. The total number of HHs can increase exponentially while taking all levels of multiple factors into account simultaneously. Including the full level of detail would significantly increase the computational burden, while providing diminishing returns in terms of representing accurately homeowners' preferences. Therefore, it is essential to aggregate factor levels into fewer number of level groups so that the number of HHs could be reduced considerably, while simultaneously sacrificing as little of the accuracy as possible.

A simple cluster analysis method, k-means, was thus applied to aggregate factors levels into groups with similar adoption preferences. As indicated in Tan et al. [52], cluster analysis refers to algorithms for grouping data objects based only on information found in the data that describes the objects and their relationships. The goal is that the objects within a group be similar to one another and different from the objects in other groups. K-means algorithm [53] is one of the widely used clustering algorithms. To divide data points into K groups, K initial centroids are chosen randomly from the data. K is user-specified parameter which is the desired number of clusters. Each data point is then assigned to the closest centroid and the collection of points belonging to a centroid is a cluster. The centroid of each cluster is then updated based on the points assigned to the cluster. The aforementioned procedure is repeated to update the centroids of clusters until no point changes in each cluster [52]. The objective function of the algorithm can be formulated as follows to minimise the distance between points within the same cluster.

$$\min \sum_{i=1}^{K} \sum_{x \in S_i} \| x - \mu_i \|^2 \tag{1}$$

where μ_i is the mean of points in cluster S_i. In this study, the distance between two HHs is defined as the summation of differences of adoption rates for heating technologies.

The cluster analysis procedure was then applied to aggregate 5 household types by number of bedrooms into clustered groups. The clustered results are shown in Fig. 2. In the original divisions by number of bedrooms, as presented in Fig. 2(a), obvious differences can be found in the adoption rates of heating technologies corresponding to various numbers of bedrooms. However, households with certain numbers of bedrooms are more similar to each other. As shown in Fig. 2(b)~(d), households with 1, 2, and 3 bedrooms have more consistent preferences compared to those with 4 and 5 or more bedrooms.

Overall, gas heaters are always the most popular heater to all households, no matter the number of bedrooms. However, the adoption rates for other heater types fluctuate considerably depending on the number of bedrooms. For example, households with 5 or more bedrooms are more likely to choose heat pumps and solid fuel boilers than households with less rooms are. Since the patterns of adoption rates of 1, 2 and 3 bedrooms are similar

Table 1
Influential factors to homeowners' preferences for heating technology adoption.

Category	Influence on adoption	Candidate heating technology			
		Gas heater	Electric heater	Heat pump	Solid fuel boiler
Existing technology	+	Gas heater		Heat pump	Electric heater Solid fuel boiler
	−		Electric heater		
Socio-demography	+	Age	Age (<60)		Age (35–44) Income (>80 k) Income (30 k~80 k)
	−			Income (<15 k)	
Region	+	East Midland North East	London Scotland	East Midland	Scotland York & Humber
Dwelling	+		Detached Semidetached	Number of bedrooms	Number of bedrooms
	−		Flat		
Awareness of eco-technology	+	Insulation		Insulation Heat pump PV	PV Wood pellet boiler
	−	CFL Electric storage heater	Smart meter Heat pump		

+: positive influence as level/value of factor increases; -: negative influence as level/value of factor increases.

according to Fig. 2(a) and (b), those three types of households can be grouped into a single household type without losing much information. As a result, three household types with 1–3, 4, and 5 bedrooms, as illustrated in Fig. 2(c), were adopted to represent households' heterogeneous preferences for heating technologies.

The existing heating technology is also a significant factor in determining the preferences of a household. The existing technologies are in this study aggregated under four types of heating technologies: Gas heaters (GAS), electric heaters (ELC), heat pumps (HP), and solid fuel boilers (SOLID). Since heating technologies have been grouped into 4 types, the cluster analysis was not applied to further reduce the number of types. The adoption rates for each existing heating technologies are shown in Fig. 3. Gas heaters are still the favourite choices for homeowners, no matter

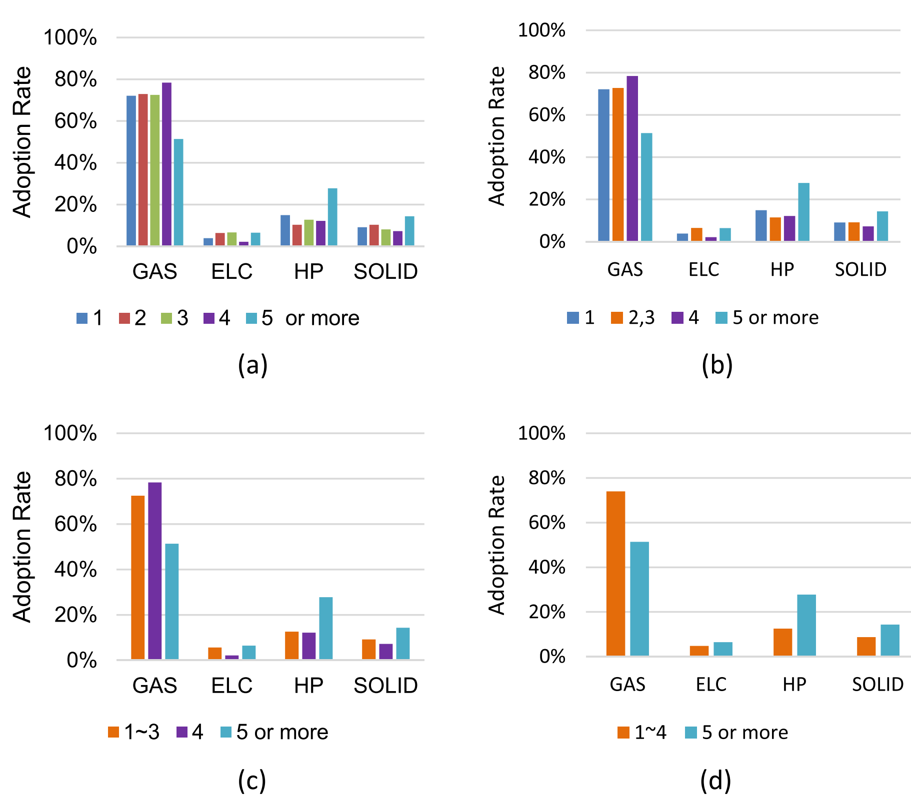


Fig. 2. Adoption rates of heating technologies for (a) non-clustered household types, (b) 4 clustered household types, (c) 3 clustered household types, and (d) 2 clustered household types by bedroom number.

what heating technologies are currently installed. Nonetheless, when a household uses a specific technology, it's much more likely to pick that technology again, compared to households switching to another non-gas technology (or a household switching from another technology to that one). This is especially pronounced with heat pumps, with 40% of the owners choosing a heat pump also for the next heating choice.

Consequently, the adoption rates of heating technologies for three aggregate household types with four existing heater types are shown in Table 2. In the survey samples, there were no households with 4 or 5 bedrooms using heat pumps. Therefore, the adoption rates for those households cannot be estimated from the survey. The preferences of households with 1–3 bedrooms using heat pumps are therefore assumed to also represent the possible preferences for these households. As illustrated in Fig. 2(c), the same existing heater types could have various influences on preferences in different household types. For example, households with solid fuel boilers would have 14.9% and 37.5% of chances of selecting heat pumps for households with 1–3 bedrooms and 5 bedrooms respectively. Therefore, it is essential to take both household type and existing heater type into account when determining the preferences of households.

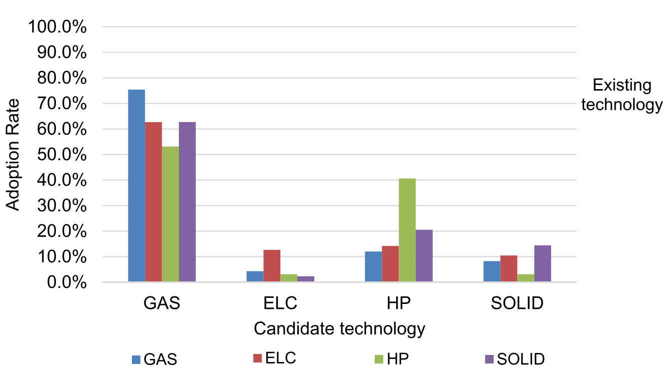


Fig. 3. Adoption rates of heating technologies (x-axis) for households with various existing heating technologies (coloured bars).

Table 2
Adoption rates of heating technologies for three household types with four existing heater types [31].

Household type	Existing heater	Candidate heater			
		GAS	ELC	HP	SOLID
1–3 bedrooms	GAS	75.7%	4.7%	11.5%	8.1%
	ELC	62.7%	14.8%	11.9%	10.6%
	HP	53.1%	3.1%	40.6%	3.1%
	SOLID	65.2%	3.7%	14.9%	16.2%
4 bedrooms	GAS	78.9%	2.2%	11.7%	7.3%
	ELC	75.0%	4.2%	12.5%	8.3%
	HP	*53.1%*[a]	*3.1%*[a]	*40.6%*[a]	*3.1%*[a]
	SOLID	67.7%	0%	24.0%	8.3%
5 bedrooms	GAS	60.2%	6.3%	19.9%	13.6%
	ELC	40.0%	2.5%	45.0%	12.5%
	HP	*53.1%*[a]	*3.1%*[a]	*40.6%*[a]	*3.1%*[a]
	SOLID	47.5%	–	37.5%	15.0%

*GAS: gas heater; ELC: electric heater; HP: heat pump; SOLID: solid fuel boiler.
[a] As there were too few households with 4 or 5 bedrooms in the sample, these values are based on the data for 1–3 bedrooms households.

4. Heterogeneous households in the UK TIMES model

As discussed in the previous section, the preferences of different household types can differ significantly. Therefore, it is important to represent these diverse preferences in the modelling of heating technology adoption. The proposed framework in this study is implemented to the UKTM model, used by the UK Department of Business, Energy & Industrial Strategy (BEIS) [54] and therefore one of the most influential energy system models in the UK. In the following sections, the UKTM model is first briefly introduced, followed by a more detailed description of how residential heating in considered in UKTM. Finally, the new structure with HH types in the UKTM is explained.

4.1. UK TIMES model

UKTM has been developed by the UCL Energy Institute as the successor to the UK MARKAL model [55]. It is based on the model generator TIMES (The Integrated MARKAL-EFOM System) [7], which is developed and maintained by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency. Besides its academic use, UKTM is the central long-term energy system pathway model used for policy analysis at the CCC and Department for Business, Energy & Industrial Strategy (BEIS) [2,54].

As described in Daly and Fais [30], UKTM is a bottom-up, technology-rich, dynamic, linear programming optimisation model consisting of numerous alternative energy supply/end-use technologies and describing the whole UK energy system. The model is comprised of eight supply-side and demand-side sectors, such as resource, process, electricity, residential sectors. All sectors are calibrated to the base year 2010 to be consistent with the official energy statistics [56], including the existing stock of energy technologies and their characteristics. The temporal variations of energy supply and demand are represented in 16 time-slices (four intra-day times-slices in four seasons). UKTM minimises total welfare costs (under perfect foresight) to meet the exogenously defined energy demands under a range of input assumptions (e.g. technology parameters are drivers of energy demand (GDP and population growth, for example)) and additional constraints (such as maximum technology penetration rates and deployment potentials). The model delivers a cost optimal, system-wide solution for the energy transition over the coming decades [57].

4.2. Residential heating

Due to its important role in residential energy demand, heating is depicted in UKTM in detail, with a range of heating technologies included as alternatives for fulfilling current and future heat demands. Heat can be supplied, for example, by a wide range of boilers, such as conventional gas condensing boilers, wood pellet boilers, air-source or ground-source heat pumps, micro-CHPs, electric storage heaters or other types of electric heaters, or even through district heating networks. The generated heat is then delivered to existing or new houses through pipeline radiator or underfloor heating system. For standalone heaters, no delivery pipeline is required. The ageing existing stock of houses in the UK is, on average, fairly poorly insulated and requires more heating demand than new houses do [58]. Several conservation measures, such as wall insulation, loft insulation, double glazing, and hot water cylinder insulation, are available for the model to reduce heating consumption in the existing houses. As for district heat, it can be supplied by a CHP plant, an electric immersion heater, a boiler station (with various fuel alternatives), a fuel cell, or a central solar heating plant. Fuel switch is also taken into account in the framework, as the model can decide to replace natural gas with biogas for CHPs and boilers, in order to reduce GHG emissions.

Secondary energy carriers, such as electricity and hydrogen, are also considered for heating in the model. While, for example, hydrogen based heating solutions are relatively costly in comparison to conventional technologies today, heat decarbonisation requirements may, under stringent mitigation scenarios, make the technologies competitive, as they allow the decarbonisation to take place in the upstream processing sector. Electric heaters and heat pumps provide similar mitigation alternatives.

4.3. New structure with heterogeneous households

The new schematic of the residential heating sector, reflecting the various household preferences affecting technology choice, can be represented as shown in Fig. 4. HH types, HH1 to HHn, were introduced into the residential heating sector. The heating technologies available to the average household in original structure were duplicated for each household type, so that all HHs can choose any heating technologies available in the market to meet their heating demands.

As the households' preferences are influenced by number of bedrooms, in this study, households were divided into three types, including households with 1–3 bedrooms, 4 bedrooms and 5 and more bedrooms.

Furthermore, to simplify the formulation of the proposed preference model on heating technology adoption, the numerous heating technologies were grouped into four heater types, district heating technologies, and conservation measures. The four heater types include gas heaters (including micro CHP), electric heaters, heat pumps, solid fuel boilers to match with the types considered in the survey on homeowners' preferences. As for the type of electric heaters, central, night storage, and standalone electric heating systems were grouped in the same type.

Finally, the remaining heating technologies not covered by above four types were removed from the set of options available to the model for future years. These heaters include coal heaters, oil heaters and standalone solar water heaters. First, oil and especially coal heaters have a relatively modest market share, are not favoured by homeowners [28] and are expected to be phased out for heat decarbonisation [19]. Second, solar water heaters can only generate about half of year-round water needs, these technologies should be integrated with other heating technologies [28]. Therefore, hybrid systems combining solar water heaters with other heating technologies are considered instead. These hybrid systems are grouped to technology types based on the non-solar technology. For example, the hybrid systems integrating gas heaters and solar water heaters are classified as gas heaters.

With the newly introduced household types and technologies, adoption preferences for each household type can be regulated through a range of newly introduced constraints, as will be explained in the following section.

5. Preference model on heating technology adoption

5.1. Conceptual framework

With newly introduced household types in the model, the preferences of each household type for heating technologies can then be represented correspondingly. In the base year 2010, the mix of heating technologies is calibrated to the historical records in DECC [56] and allocated to the three household types according to the statistics in the EHS [51]. In the model, households choose new heating technologies whenever the heating technologies reach the end of lifetime or heat demands increases and existing capacity is no longer enough to fulfil the demand. Preferences of households, as suggested in Table 2, are applied according to the type of household and the existing heating technology. For example, for households with 1–3 bedrooms, when gas heaters are installed originally, shares of newly installed gas heaters, electric heaters, heat pumps, and solid fuel boilers should be 75.7%, 4.7%, 11.5%, and 8.1% respectively. This new formulation, therefore, takes us from cost optimisation to the other end of the spectrum; costs no longer play a role for the choice of the heating technology and, as the survey suggested, decisions are fully driven by non-monetary factors. Our new formulation can thus be seen to provide, together with the cost optimising variant of the model, a range for how diffusion of technologies in the residential sector might proceed.

Furthermore, district heating or conservation measures can also be applied for heat provision or reduction in households. For district heating networks, strong policy support from the government is required to construct the infrastructure, e.g. the installation of heat pipelines to already built-up areas, to enable the consumer to choose the technology. In other words, individual homeowners cannot simply choose to switch to district heating, if there is no heating network in place. It is, therefore, assumed that policy

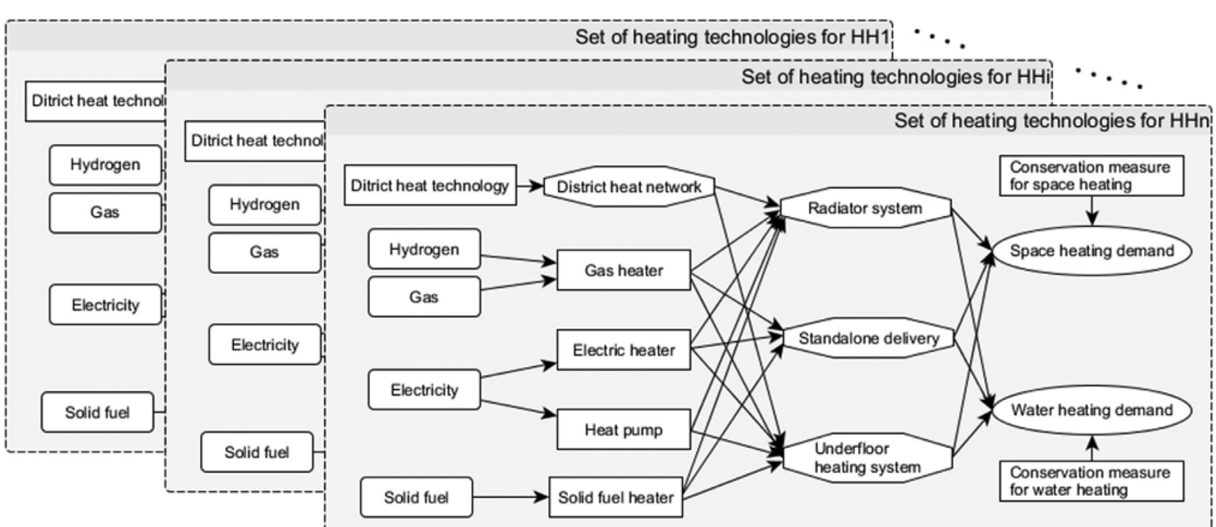


Fig. 4. Simplified representation of the new residential heating sector with duplicated sets of heating technology for each household type in UKTM.

makers have higher influence on the development of technology and the adoption of district heating is determined by the model based on the cost competitiveness compared to other heating technologies, subject to conservative assumptions concerning its maximum market share. As the focus of our study is on the choice of heating technologies, the adoption of conservation measures is also determined by the model based on the cost competitiveness alone.

From the technical modelling perspective, the most challenging part of the decision procedure in the proposed model is to determine the preferences based on the previously adopted heater types for each household type throughout the model horizon. An approach has thus been developed to trace the lost heat provision of the decommissioned heating technologies of each heater type for each household type at each time-step. The lost heat provision is then replaced by heat from new heating technologies, which are selected according to the corresponding preferences. More details will be given in the following section.

5.2. Preference model

To implement the conceptual framework in the UKTM, the new preference model will regulate the adoption behaviour of individual household types. In the model description below, the existing system equations, related to e.g. energy supply, transformation, delivery, consumption etc., in the UKTM are omitted. The definitions of variables used in the following equations are listed in Table 3. Four heater types are taken into account, gas heaters (GAS), electric heaters (ELC), heat pumps (HP), and solid fuel boilers (SOLID).

$$\text{Minimize} \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{k=1}^{K} c_{i,k,t} \times nc_{i,k,t} + \textit{other existing system costs} \tag{2}$$

Subject to

$$\sum_{k=1}^{K} h_{i,k,t} + dh_{i,t} + csv_{i,t} = r_i \times THD_t \qquad i = 1,\ldots,N \tag{3}$$

$$\sum_{k=1}^{K} nh_{i,j,k,t} + ndh_{i,j,t} + ncsv_{i,j,t} \geq vh_{i,j,t-1} - vh_{i,j,t} \tag{4}$$

$$nh_{i,j,k,t} = PF_{i,j,k,t}\sum_{k=1}^{K} nh_{i,j,k,t} \quad i = 1,\ldots,N; j,k = GAS, ELC, HP, SOLID \tag{5}$$

$$CAPACT_k \times nc_{i,k,t} = \sum_{j=1}^{K} nh_{i,j,k,t} \tag{6}$$

$$dh_{i,t} \leq DH_{i,t} \qquad i = 1,\ldots,N \tag{7}$$

$$csv_{i,t} \leq CSV_{i,t} \qquad i = 1,\ldots,N \tag{8}$$

$$DH_{i,t} \geq DH_{i,t-1} \qquad i = 1,\ldots,N \tag{9}$$

$$CSV_{i,t} \geq CSV_{i,t-1} \qquad i = 1,\ldots,N \tag{10}$$

other existing sysetm constraints

Equation (2) is the objective function which determines optimal combinations of technologies across the energy system, including heating technologies in the residential sector, with minimal total system cost and while satisfying all the constraints. Equation (3) ensures the total heat provided by heating technologies in each household type can fulfil the corresponding heat demand of that household type. The ratios (r_i) of heat demands for individual household types to the total residential heat demand (THD_t) are estimated according to the demographic profile of the household types in the UK and the corresponding average floor areas of each household type based on EHS. The heat demands of each household type are expected to increase since the total residential heat

Table 3
Definitions of variables in the preference model.

Variable	Definition
i	Household type
j	The previously adopted heater type
k	The newly adopted heater type
t	Modelling year
K	Total number of heater types
N	Total number of household types
T	Total number of modelling years
THD_t	Total heat demand in the residential sector in year t
r_i	The ratio of heat demand of household type i to the total residential heat demand
$c_{i,k,t}$	The net present cost of the heater type k installed in year t per unit of capacity
$nc_{i,k,t}$	New capacity additions of heater type k in household type i in year t
$h_{i,k,t}$	Heat provided by heater type k to household i in year t
$dh_{i,t}$	Heat provided by district heating network to household type i in year t
$csv_{i,t}$	Conserved heat demand of household type i in year t
$DH_{i,t}$	The maximum potential of district heating for household type i in year t
$CSV_{i,t}$	The maximum potential of conservation measures for household type i in year t
$vh_{i,j,t}$	Heat provision of the vintage heater type j to household i in year t
$nh_{i,j,k,t}$	Heat provided by newly installed heater type k in year t in household i which had heater type j in year t-1
$ndh_{i,j,t}$	New provision of heat from district heating network in year t to household type i which had heater type j in year t-1
$ncsv_{i,j,t}$	New conservation of heat in year t in household type i which had heater type j in year t-1
$PF_{i,j,k,t}$	Household type i's preference ratio of adopting heater type k in year t while heater type j is installed previously
$CAPACT_k$	Coefficient to convert capacity to heat provision for heater type k

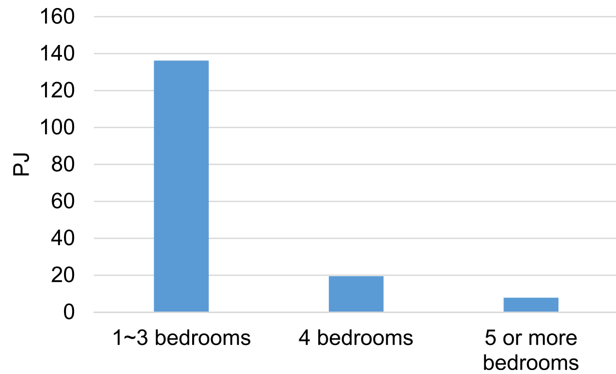


Fig. 5. Maximum potentials of district heating for each household type in urban area by 2050.

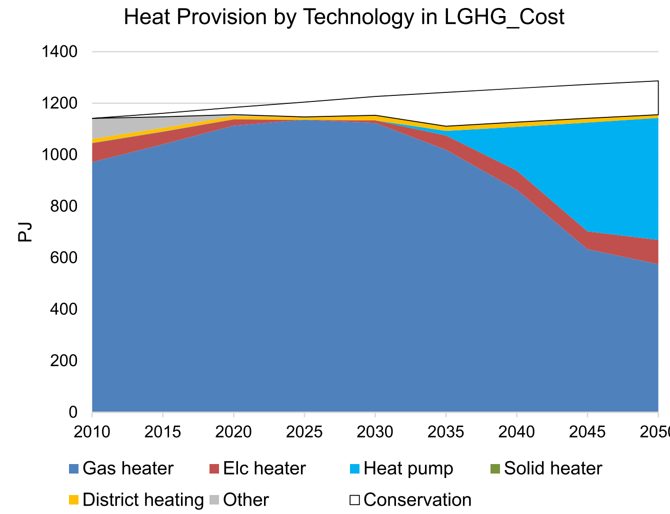


Fig. 6. Heating technology mix for the case without preference-related constraints.

demand continues increasing for the higher population and housing stock in the future.

Equation (4) ensures the lost heat provision of vintage heaters of a specific heater type in each household type can be replaced by the heat provision from new heating technologies, including individual heating technologies, district heating network ($ndh_{i,j,t}$), and conservation measures ($ncsv_{i,j,t}$). This equation is essential to enable the model to trace the required heat demands for each household type with a specific existing heater type in year *t-1*. With the traced heat demands, preferences for heating technologies can then be applied to regulate choices of each household type. The right hand side of the equation evaluates the lost heat provision of a heater type by comparing the difference in heat provisions of vintage heaters of heater type *j* between year $t-1$ and year *t*. According to the left hand side of the equation, the household type *i* can then choose heaters *k*, district heating, and conservation measures to fill the lost heat provision.

Furthermore, the adoption rates of individual heater types for each household type are regulated by Equation (5). The share ($PF_{i,j,k,t}$) of new heat provision from heater type *k* of the total new heat provision for the household type *i* with existing heater type *j* is matched with the corresponding adoption rate in Table 2. The adoption rate can also vary over time to reflect changes in preferences for new heating technologies. This equation also regulates the technology adoption for the new heat demands for new households. Since those households do not have existing technologies, the constraints then only reflect the influences of number of bedrooms on preferences. Finally, Equation (6) is the capacity constraint for the new heating technologies.

Since the preference constraints only apply to heater types, it means individual heating technologies grouped under a given heater type can still compete with each other based on their energy efficiency and costs (e.g. gas heaters and micro-CHPs).

Equation (4) suggests that households can choose district heating and conservation measures to fulfil heat demands if those technologies are more cost-effective. However, not every household is suitable for these as district heating is only feasible in urban areas and conservation measures are much more effective in ageing housing stock. Equations (7) and (8) are then imposed to limit the maximum potentials of district heating and conservation measures in each household type. We follow Element Energy [59], which estimated the maximal potential of district heating in the UK by 2050 to be about 136 PJ. Since district heating is much more likely to be economically feasible in urban areas [59], the potential for each household type was estimated based on the share of the household type in urban area according to EHS. The estimated potentials for three household types are illustrated in Fig. 5. On the other hand, the total potential of conservation measures by 2050 was adopted from DECC's study for evaluating the impact of Green Deal, an energy efficiency policy for domestic buildings, which is about 154 PJ [60]. The potential is redistributed among three household types according to the proportions of heat demand in each household type.

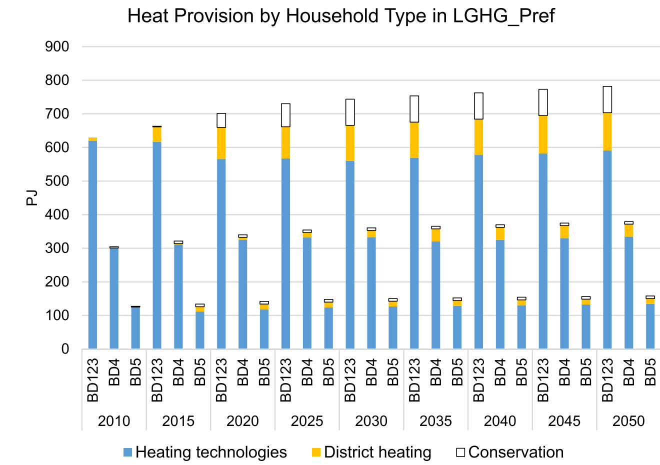
Finally, equations (9) and (10) ensure the installed district heat network and conservation measures should be functional after being introduced into the system. In other words, there will be no redundant heating facilities in the system. As a result, households cannot just switch back to individual heating technologies for heat provision while there are district heat network and conservation measures in place.

6. Results and discussions

Two scenarios were applied to investigate the impacts of preferences for heating technologies. The definitions of these scenarios are listed in Table 4. The GHG targets are the same for both scenarios, including the legally binding 2050 target to reduce GHG emissions by 80% on the levels of 1990 and the five carbon budgets [61]. Our first scenario (LGHG_Cost) functions as the reference case

Table 4
Definitions of scenarios for various preference settings.

Scenario	GHG emission targets	Preference settings
LGHG_Cost	1^{st} to 5th UK Carbon Budget and 80% reduction on 1990 level by 2050 (constraining cumulative emissions from 2030 to 2050)	Without preference related constraints
LGHG_Pref	1^{st} to 5th UK Carbon Budget and 80% reduction on 1990 level by 2050 (constraining cumulative emissions from 2030 to 2050)	With preference related constraints



* BD123: households with 1~3 bedrooms; BD4: households with 4 bedrooms; BD5: households with 5 or more bedrooms.

Fig. 7. Types of heating measures for each household type for the case with preference constraints.

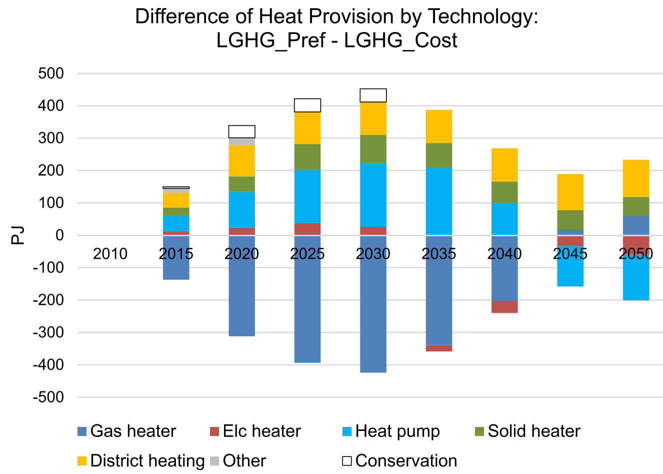


Fig. 9. Differences of heating technology mix between cases with and without preference-related constraints.

and does not take into account the new preference formulation. On the other hand, LGHG_Pref further incorporated preference related constraints, allowing us to assess what the impact of these constraints may be for the residential sector and energy system as a whole. Preference constraints were applied to all households, including those renting houses. Our aim is to compare and contrast the two scenarios, one relying purely on cost driven decisions and the other purely on non-cost elements, in order to understand the magnitude of the uncertainty created by consideration of behaviour on the cost effective system transition.

The heat provision by technology for the case LGHG_Cost is illustrated in Fig. 6. Since there was no preference applied in the model, the model optimised the whole energy system to achieve the predefined GHG emission targets with minimum system costs. In the early stage of the modelling period, gas heaters are still the favourite technologies while GHG emissions can be reduced with lower costs in other sectors. With the stricter GHG emission targets after 2030, share of gas for heating starts to decline and more and more of the gas heaters are efficient micro-CHPs. Approaching 2050, low-carbon electricity is used more and more, to further decarbonise the sector by rapidly increasing the share of heat pumps during the last 10 years of the model horizon. Conservation

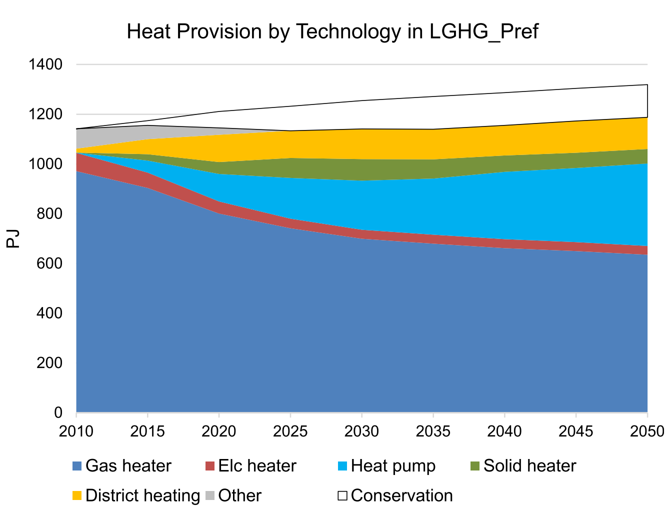


Fig. 8. Heating technology mix for the case with preference-related constraints.

measures are cost-effective and are therefore introduced into the system from early on and up to the maximum potential by 2035. It is also noteworthy that the heat provision from district heating is limited, about 12.6 PJ by 2050.

The heat provisions by household type and by technology for case LGHG_Pref are shown in Fig. 7 and Fig. 8 respectively. The influences of the preferences on heating technology choices are revealed by the differences of heat provision, system costs, GHG emissions, and carbon prices between the cases of LGHG_Pref and LGHG_Cost, as shown in Figs. 9–11.

As illustrated in Fig. 7, individual household types attain heat from various mixes of heating technologies for their continually increasing heat demands. While individual heating technologies remain the major heat supply sources, district heating also provides considerable heat to each household type, especially for households with 1–3 bedrooms. Due to the cost-effectiveness, conservation measures reach the maximum potentials by 2020 for 5 bedrooms and by 2035 for 1–3 bedrooms and 4 bedrooms. Moreover, district heating plays a more crucial role in LGHG_Pref than it does in LGHG_Cost. By 2050, heat provisions from district heating reach more than 60% of the maximum potential for 1–3 bedrooms and 4 bedrooms, which are about 106 PJ and 12 PJ respectively, and the maximum potential for 5 bedrooms, which is about 7.8 PJ.

As shown in Fig. 8, the transition of heating technologies is much smoother than that in the previous case. For example, unlike in LGHG_Cost, heat pumps are introduced from very beginning of the modelling period, following the preferences of certain percentage of gas using households that would consider to adopting heat pumps. On the other hand, the share of heat provision from electric heaters is limited throughout the modelling period. This is due to the relative low preference rates for electric heaters, ranging from 2.2% to 14.8%. Even current users of electric heaters living in households with 1–3 bedrooms are much more likely to move to another technology, especially gas heaters. Finally, the share of gas heaters declines over time. In the base year, almost all the heat provision is from gas heaters. The decommission of gas heaters opens the chance to introduce other heater types into the system and while gas heaters are still the most common choice for the new heater, they are not as common a choice as they are in the current stock. Moreover, the increasing share of district heating and conservation measures reduces the full volume of heat provision for which gas heaters compete over.

Fig. 8 also shows that heat provision from district heating is much larger than that in the previous case, starting from the

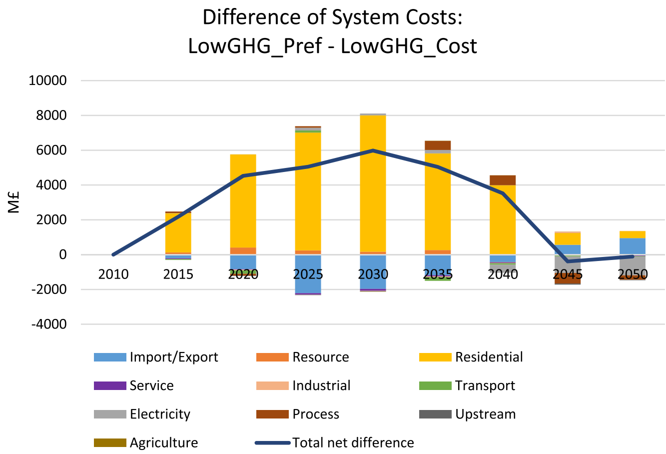


Fig. 10. Differences of annual undiscounted energy system costs between cases with and without preference-related constraints.

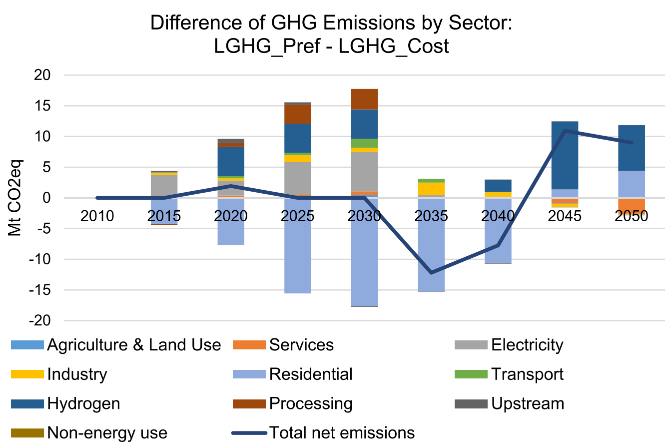


Fig. 11. Differences of GHG emissions by sector between cases with and without preference-related constraints.

beginning of the modelling horizon. In LGHG_Pref, preferences drive households to adopt heat pumps, even when the cost is much higher than that of competing technologies. To reduce the total costs, the model introduces more district heating and conservation measures than it does in LGHG_Cost. From the perspective of the system wide planner (i.e. government), it's more cost effective to provide district heating for the consumers than to allow them to choose more costly individual heating systems. The fuel used for district heating also changes over time, as the tightening GHG emissions targets requires further reductions from all sectors. To reduce GHG emissions from district heating, fuels are switched sequentially from natural gas, hydrogen, and electricity to solid fuel, latter being more expensive but with zero GHG emission (bioenergy is assumed to be carbon neutral). At first, gas boilers are adopted for district heating, then gradually replaced by hydrogen-fuelled boilers. As approaching 2050, electric heaters gradually dominate; finally, solid fuel boilers are also deployed to generate heat for district heating.

The differences between these two cases are further revealed in Fig. 9. The positive values indicate the heat provisions of corresponding technologies are higher in the case of LGHG_Pref. Before 2040, in LGHG_Pref, there is much more heat from electric heaters, heat pumps, solid fuel boilers, and district heating, to replace heat from gas heaters in LGHG_Cost. As noted, in LGHG_Pref conservation measures are also adopted much earlier and, as LGHG_Cost, reach maximum potential by 2035. The pattern changes abruptly from 2045, when in LGHG_Cost heat provision from heat pumps is rapidly expanded to cut off GHG emissions dramatically. As a result, in LGHG_Cost 141.56 PJ more heat is provided by heat pumps in 2050.

As mentioned in previous sections, LGHG_Cost uses more gas heaters in the early stage and switches to heat pumps and electric heaters approaching 2050. Therefore, LGHG_Cost consumes much more natural gas in the beginning but requires more electricity in the last 10 years than LGHG_Pref does. LGHG_Pref, on the other hand, consumes more electricity before 2040 and uses more natural gas after 2045. This is because of the higher deployment of heat pumps and electric heaters before 2040 and the higher adoption of gas heaters after 2045. The preference constraints also lead to higher adoption of solid fuel boilers, so that the consumption of biofuels is higher in LGHG_Pref over the modelling period. In addition, LGHG_Pref also consumes more solar from 2040. This means there are more hybrid heating systems with solar water heaters are adopted. Finally, more hydrogen is also used for district heating in LGHG_Pref (mixed with natural gas). In terms of total net fuel consumption, the LGHG_Pref requires less fuels before 2040 for there are more energy efficient heaters in place, such as heat pumps. After 2045, however, LGHG_Pref consumes more fuels as heat pumps in LGHG_Cost increase sharply.

Furthermore, as indicated in Fig. 10, the total system costs are higher over almost all the modelling periods in LGHG_Pref. The higher costs are due to the investments in more expensive heating technologies, such as heat pumps, solid fuel boilers and district heating, before 2040. In contrast, since 2045, LGHG_Cost adopts more heat pumps which leads to the higher costs in the electricity sector. At the same time, LGHG_Pref spends more on natural gas as gas heaters are deployed more widely. Although the total net costs by 2050 are similar between these two cases, the accumulative system cost difference is up to 129.2 billion GBP for the whole modelling period (over 3 billion annually, in net present value).

Finally, the differences of GHG emissions by sector between these two cases are shown in Fig. 11. As presented by the total net emissions, the GHG emissions are basically the same before 2030 for the fixed targets of the 1st to 5th Carbon Budgets. However, as LGHG_Pref consumes more electricity for heat provision, the GHG emissions are higher in electricity sector than that in LGHG_Cost. Furthermore, the low emissions from heating allows the model to choose fossil fuels for hydrogen production to reduce total system costs – and therefore move emissions from end use to the conversion sector. After 2035, the imposed constraint of fixed cumulative GHG emissions gave the model some flexibility to reduce total system costs by deciding on the timing of the GHG reductions. Therefore, LGHG_Cost chose cheaper but more carbon intensive technologies, such as gas heaters, to reduce system costs at first. Then, more expensive low-carbon heating technologies are chosen later when the cost of technologies fall further. As a result, LGHG_Cost has higher GHG emissions between 2035 and 2040, but emit less GHGs after 2045. Lastly, the higher emissions in LGHG_Pref from 2045 are for the higher consumption of hydrogen. More hydrogen, produced from natural gas and coal, is consumed in both the residential and service sectors.

7. Conclusions

Long-term energy planning models, such as TIMES model, are usually applied to develop least cost decarbonisation pathways for the energy system, including the residential heating sector. However, the cost optimising, linear programming framework of these models assumes economically rational, homogeneous actors, is sensitive to cost assumptions of technologies and can suddenly switch fully to alternative technologies. To overcome these weaknesses, and to offer a counterfactual to purely cost driven approach, a novel framework has been developed to incorporate heterogeneous homeowners' preferences for heating technologies into the UKTM model. This allows us to simulate the diffusion of technologies based on empirical data, instead of relying on somewhat subjective growth constraints [17].

The nationwide survey identified existing technologies, age, income, region, dwelling characteristics, and knowledge of eco-technology as the six most influential factors for determining homeowners' preferences for heating systems. Among those factors, existing technologies and number of bedrooms are the most persistent and representative ones and therefore chosen to be taken into account when modelling the penetration of heating technologies in the UK energy system. Cost was found not to have a statistically significant impact on homeowners' choices.

As shown in our study, without considering preferences of the heterogeneous households, the energy system model adopts as many gas heaters as possible during the coming decades, with a dramatic increase in the share of heat pumps towards the end of the time horizon. Such a rapid transition, however, is driven by the cost optimisation approach and does not appear plausible in light of the households' preferences that were surveyed. Since the survey indicates that households are heterogeneous and adoptions of heating technologies for households are influenced by the technologies these households currently have, abrupt changes in the technology mix are unlikely to happen over a short period.

By incorporating households' preferences into the updated model, the penetration of heating technologies shows a more gradual and smoother development than those in the standard model. This shows how the residential sector might be gradually decarbonised as consumers move from one technology regime to another, as described by the observed preferences. However, solely relying on households' preferences for individual heating technologies does, in our scenario, imply costs that are high enough to trigger investments in district heating and conservation to reduce the need for house specific heating technologies. The introduction of district heating provides the system higher flexibility for heat decarbonisation. For instance, even if the penetration of low-carbon heaters, such as heat pumps, would not proceed as rapidly as hoped, district heat network can further decarbonise residential heating by switching to low- or zero-emissions fuels, such as biofuels or hydrogen produced with CCS. The government should thus strengthen supporting policies to introduce district heating in urban areas in larger scale as early as possible. Also, conservation measures are highly cost-effective and not in conflict with other heating measures. The maximum potential of these measures was thus always exploited before 2050 in both study cases. To reduce total costs for residential heating, these no-regret measures should also be widely installed in ageing housing stock to reduce heat demand.

The proposed preference model has successfully incorporated households' preferences into the energy systems model. However, in the survey, only four heater types were considered for their fuels and installation requirements. For future works, a more detailed survey on homeowners' preferences for heating technologies is essential for distinguishing homeowners' attitudes toward extra candidate heating technologies, such as micro-CHPs. In addition, the influential factors were based on the stated preferences from the survey. To further verify those factors, experiments on revealed preferences should be carried out in the future. Furthermore, when more samples are available, other influential factors, such as region, might become representative enough to be applied in the same framework to investigate the influences to provide more comprehensive insights. Finally, preferences might vary over time after more low-carbon heating technologies are introduced. Temporal variations of preferences can also be applied in the proposed framework to explore the sensitivities of energy systems to temporally varying preferences.

This study is the first of its kind to explicitly incorporate influential factors to homeowners' preferences for heating technologies in a linear programming framework, the UK TIMES model. Unlike previous studies, this study not only considers household heterogeneity but also successfully incorporates an endogenously changing temporal preference element into the modelling process. Moreover, the framework can also be applied to households' preferences for other end-use energy technologies whenever the cost is not crucial to preferences, and is also suitable for other linear programming-based energy models, not only limited to TIMES model.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.energy.2018.01.150.

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