Spatial microsimulation modeling for residential energy demand of England in an uncertain future

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(Received 26 November 2013; final version received 25 June 2014)

High quality infrastructure is crucial to economic success and the sustainability of society. Infrastructures for services, such as transport, energy, and water supply, also have long lead times, and therefore require effective long-term planning. In this paper, we report on work undertaken as part of the UK Infrastructure Transitions Research Consortium to construct long-term models of demographic change which can help to inform infrastructure planning for transport, energy, and water as well as IT and waste. A set of demographic microsimulation models (MSM), which are spatially disaggregate to the geography of UK Local Authorities, provides a high level of detail for understanding the drivers of changing patterns of demand. However, although robust forecasting models are required to support projections based on the notion of ‘predict-and-provide,’ the potential for behavioral adaptation is also an important consideration in this context. In this paper, we therefore establish a framework for linkage of a MSM of household composition, with behavior relating to the consumption of energy. We will investigate variations in household energy consumption within and between different household groups. An appropriate range of household types will be defined through the application of decision trees to consumption data from a detailed survey produced by the UK Department of Energy and Climate Change. From this, analysis conclusions will be drawn about the impact of changing demographics at both household and individual level, and about the potential effect of behavioral adjustments for different household groups.

Keywords: spatial modeling; microsimulation; energy consumption; demographic modeling

1. Introduction

National infrastructure (NI, including energy, transport, water, waste, and information communication technology) is a foundation for economic productivity and human well-being. However, the NI of the UK and other advanced economies face serious challenges which include: significant vulnerabilities, capacity limitations, and a number of NI components nearing the end of their useful life (1). The UK Infrastructure Transition Research Consortium (ITRC) has been established, funded by the Engineering and Physical Sciences Research Council, to provide theoretical research, models, and practical decision support tools to enable strategic analysis and planning of NI systems; to respond to future demographic, social, and lifestyle changes; and to build resilience to intensifying impacts of climate change. NI planning requires substantial capital investments over a long time horizon and in consequence, the ITRC forecasts demographic and other kinds of socioeconomic change right up to 2100. The research is divided into five Work Streams (WS) structured as indicated in Figure 1.

In WS1, a generic modeling framework for analysis of long-term change in capacity and demand under uncertainty will be developed and some initial results have been published in the Fast Track Analysis (FTA) report (2). The FTA approach to modeling energy demand is a combination of engineering and behavioral demand modeling, which utilizes a simple econometric approach to evaluate sectoral fuel demand, driven by price, gross domestic product, and population in the underlying transition strategy, and an econometric approach to the effects of population, income, and price. However, there are a number of simplifications for the FTA, especially for the treatment and the separation of demand projections. The FTA report suggests that a more spatially disaggregated treatment would be needed in the later phases of the ITRC. Infrastructure demand exhibits substantial variation, even it is down to the level of the individual person or household. In its current iteration, the research has focused on regional-level demand modeling that, although it effectively captures the broad dynamics of infrastructure utilization nationally, does not recognize the impact that individual household structure will have on infrastructure demand. In this paper, an alternative approach will be introduced to modeling the energy consumption in the residential sector in the medium term associated with demographic development and changing behavior at smaller area level.

In this paper, a framework will be provided for the projection of population change into the medium-term future. The disaggregation of these projections to individual household types will be demonstrated using a demographic microsimulation model (MSM). The energy

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sector will be used to demonstrate the deployment of the MSM as a means to estimate infrastructure demand in response to demographic change.

The energy used in homes is one of the biggest components of the total energy consumption in the UK, which accounts for approximately 26.4% of total energy use in the country by 2011, and represents a major opportunity to cut energy use ([3]).

2. Modeling the energy consumption in the residential sector

Swan and Ugural ([4]) identified modeling technique for residential energy consumption as two distinct approaches, which are top-down approaches and bottom-up approaches. The top-down models aim to determine the effect on energy consumption due to ongoing long-term changes or transitions within the residential sector based on aggregated input data, including macroeconomic indicators, climatic conditions, housing construction/demolition rates, and estimates of appliance ownership in the residential sector ([5–8]). This kind of model is mainly for determining energy supply requirements. They are relatively easy to build and only require aggregated data, which are widely available. Therefore, this top-down strategy is also used in ITRC FTA analysis. However, owing to the relative simplicity and limited information requirement of the top-down models, these models heavily rely on the historical energy consumption, and therefore are unable to model discontinuous advances in technology. Furthermore, the simple structure makes these models lack of representation of end-users which limited the capability of the model in identifying key areas for improvement for the reduction of energy consumption.

Unlike the top-down models, the bottom-up models use disaggregated data as input. These models represent the regional or national energy consumption by modeling and extrapolating the energy consumption of individual end-users, individual households, or groups of household. The common input data include dwelling attributes (i.e. dwelling type, area, size, etc.), climate variables (i.e. temperature, solar radiation, etc.), occupant’s behavior (i.e. indoor temperature, working hours, etc.), and equipment use (i.e. heating time, solar panel, etc.). This highly detailed input information gives the bottom-up models the ability to model the effect of technology options and occupants’ behavior in determining the energy consumption of each individual household by each end-use ([9–11]). As the individual household or group of households were represented, they should be extrapolated to represent the whole housing sector by applying reweighting technique. Like the two sides of a coin, the requirement of highly detailed input information is also the main disadvantage of this type of models. Furthermore, the highly detailed input information also requires a higher computing power for the complex calculation and simulation. However, this computing limitation is no longer critical as the capability of computers increases rapidly ([12]).

Considering the main purpose of this research is to model the residential energy consumption in response to the uncertainty caused by demographic change, behavior adaption, and climate change in the future, the bottom-up strategy was selected due to its high flexibility. Currently, the most comprehensive residential energy model is the Cambridge Housing Model (CHM) developed by Cambridge Architectural Research and has been used to generate Department of Energy and Climate Change (DECC) Housing Energy Fact File (HEFF) and the associated Energy Consumption in the UK ([13]). The CHM utilizes the English Housing Survey (EHS) data as input, to determine energy consumption and associated CO₂ emission by performing the building physics model. There are 16,150 dwellings recorded in the EHS 2009, each of the record are weighted so the sum is equal to 22.3 million which is the total number of dwellings in England in 2009. In this research, a MSM was built to generate a set of synthetic household population for England up to 2100. Then, this synthetic household population is used to reweighting the CHM results, so the detailed residential energy consumption can be calculated by summing up the reweighted CHM results.

3. Methodology

3.1. Modeling framework

In this research, a spatial MSM is built to estimate domestic energy consumption for the whole country and for a long time period (to 2100). The modeling process is made up of three steps as illustrated in Figure 2. First, a series of population projection scenarios were built to
create year-specified aggregated population statistics at local authority level under different scenarios; second, the MSM (called the Population Reconstruction Model, PRM) was used to generate both individual and household microdata; and finally, the detailed energy demand can be calculated based on the characteristics and behavior of each household. The model design therefore follows a 'static ageing' approach, in common with applications, such as SimBritain (14).

3.2. Population projection

The population projections follow, as far as possible, the methodology employed by Ref. (15) in the generation of their national and sub-national projections. In general, the process is as follows:

(1) Initialize the population.

Each projected year is based on trends from the previous five years; so to start the projection, five years worth of data are required. Here, the projection begins from the year 2009, so the years 2004–2008 are required as initial data.

(2) Age the population.

Before starting a new projection, the population must be aged. The Office of National Statistics (ONS) national projections use single-year age groups up to age 89 and then use three groups to represent people aged 90–94, 95–99, and 100+. Therefore, in these latter age groups, only one-fifth of the population will advance to the next group (and none will advance from the final group).

After initial aging, there are no people in the 0–1 age group.

(3) Fertility.

The number of births for a given region is calculated by multiplying the age-specific fertility rates (ASFR) (for all women aged 15–46 inclusive) by the number of women in that age group. Because sub-national fertility data are not available, the total number of births is constrained to sub-national birth projections before being added to the population. The fertility component uses the concept of an ASFR, which is calculated, for each fertile age group (women aged 15–46 inclusive), by dividing the number of births to women of that age group by the number of women in the age group (Equation (1)).

\[
AG_{Year, ASFR} = \frac{AG_{Year, NoB}}{AG_{Year, NoF^{(15–46)}}}
\]  

where \(AG_{Year, NoB}\) represents the total number of births in the year (Year) born by women within age group (AG) for the whole country; \(AG_{Year, NoF^{(15–46)}}\) represents the number of female aged between 15 and 46 within specific age group (AG) in the year (Year).

The national ASFR is available from the ONS national fertility data. To model regional variation, the ONS sub-national projections also calculate a fertility differential by dividing the sum of five years historical sub-national ASFRs with the sum of the national equivalent ASFRs. This differential is used to calculate the current local ASFR. For the projections described here, however, there are no sub-national ASFR data available and so the national ASFR figure is used for all regions.

To limit the errors that will arise from the lack of sub-national ASFR data, once the number of births has been calculated, the ONS sub-national components of change data are used to scale the total number of births so that they match those expected in the sub-national projections. This birth scaling factor is also stored so that a trend can be calculated for later years. The equation can be written as

\[
AG_{Year, ASFR_{LAD}} = \frac{AG_{Year, ASFR}}{\sum AG_{Year, ASFR} \times AG_{Year, NoF^{(15–46)}}}
\]  

where \(AG_{Year, ASFR_{LAD}}\) represents the ASFR for a specific age group (AG) and (LAD) in the specific year (Year); \(AG_{Year, NoF^{(15–46)}}\) represents the total number of births in district (LAD) in the year (Year); \(AG_{Year, NoB}\) is the number of females aged 15–46 within age group (AG) at (LAD) in the year (Year) – these two data-sets can be obtained from ONS sub-national population projections.

After 2033, when no ONS sub-national projection data are available, a linear regression is used to find the trend in the birth scaling factors and this estimated scaling factor is used to constrain the number of births post 2033.
Mortality.

Mortality is calculated in much the same way as fertility: an age- and gender-specific mortality rate is calculated for each age group and this is multiplied by the number of people in that age group to calculate the number of deaths.

\[
\frac{AG_{Year} \text{ASMR}_{Gender}}{Year} = \frac{AG_{Year} \text{NoD}_{Gender}}{Year} \times \frac{AG_{Year} \text{NoP}_{Gender}}{Year}
\]  

(3)

where \( AG_{Year} \text{ASMR}_{Gender}/Year \) is the national age-specific mortality rate (ASMR) for age group (AG) with gender (Gender) at year (Year); \( AG_{Year} \text{NoD}_{Gender}/Year \) and \( AG_{Year} \text{NoP}_{Gender}/Year \) are the number of deaths and the number of people within age group (AG) with gender (Gender) at year (Year), respectively.

As with fertility, sub-national mortality data are not available, so the number of deaths is constrained to sub-national components of change totals. Mortality works in the same manner as fertility by calculating a local ASMR and an associated mortality differential in order to estimate the current local ASMR. As no sub-national mortality data are available, the projections below simply use the national ASMR for the projected year. Sub-national mortality is also scaled in the same manner as fertility, the exception being that there are separate scaling factors for male and female mortality (Equation (4)).

\[
\frac{AG_{Year} \text{ASMR}_{Gender}/Year_{LAD}}{LAD} = \frac{AG_{Year} \text{ASMR}_{Gender}/Year}{Year} \times \frac{\sum AG_{Year} \text{NoD}_{Gender}/Year_{LAD}}{Year} \times \frac{AG_{Year} \text{NoP}_{Gender}/Year_{LAD}}{Year}
\]  

(4)

where \( AG_{Year} \text{ASMR}_{Gender}/Year_{LAD}/LAD \) refers to the local ASMR for the year (Year); \( AG_{Year} \text{NoD}_{Gender}/Year_{LAD}/LAD \) represents the local (LAD) number of death with gender (Gender) for the year (Year); and \( AG_{Year} \text{NoP}_{Gender}/Year_{LAD}/LAD \) is the local (LAD) population with gender (Gender) within age group (AG) for the year (Year).

(5) Migration.

Migration is the most complicated of the processes in the ONS projections and much of the data required to estimate migration are not available. Hence, migration in the projections below is estimated by calculating the difference in the size of the projected population (by age group) for a given region compared to the expected ONS regional projection. Having constrained the number of births and deaths for each region to ONS sub-national projections, it follows that the residual difference between the projection here and the ONS projection is a result of net migration. This residual is added to the sub-national population for the year being projected. As with the fertility and mortality scaling factors, net migration totals are stored for each age group in each projected year. After 2033 (when there are no sub-national projection data), linear regression is used to find a trend in male and female migration totals, and these trends are used to estimate migration post 2033.

(6) Constraints.

Once the population in each region has been projected by one year, the entire population can be constrained to the national population totals for the given year. Note that, after 2033, this constraining no longer takes place because the ONS have only released a limited number of years of projection data. However, trends in births, deaths, and migration will have been established by 2033 and the projection is able to continue these trends in the absence of constraining national data.

According to the projection results, the population of Great Britain increases from 61 million to 84 million by 2083 and to 89 million by 2100. The results also indicate that the population of Great Britain will become progressively more elderly, which will have a profound impact on the provision of health and social services, such as housing, for which utilization trends to increase with age. Figure 3 shows the change of the age structure between 2010 and 2100. Apart from this baseline estimation, the ONS also produced an envelope of projections from high growth to low growth, which will be discussed in the Section 3.

3.3. Microsimulation

In this research, the PRM (16,17) was used to create synthetic individual and household population data for small geographical area, which uses a combination of two inputs: (1) the Sample of Anonymised Records (SARs) data from census and (2) the small area statistics generated from the population projection model. The PRM is a simple Monte Carlo simulation-based model which produces a synthetic extract from the SAR which is maximally consistent with the known characteristics of a small area. The model creates a complete representation of the national population on an LAD-by-LAD basis. For each household and their component individuals, a wide variety of key socioeconomic and demographic attributes comprising age, gender, marital status, occupation, ethnicity, and health status, as well as housing variables including tenure, household size, and composition will be represented. These individual data enabled us to analyze some more complicated behaviors or household components changes.

The major outputs of the PRM are two data-sets, including a synthetic household and individual population data, respectively. Table 1 summarized the variables available in these two data-sets.

Based on these two data-sets, more household characteristic variables can be derived, including: age of eldest person in the household, age of youngest person in the household, number of children in the household,
Figure 3. Population Pyramid for 2010 (a) and 2100 (b).

Table 1. The variables in the PRM results.

| Variable | Definition                          | Variable | Definition                          |
|----------|-------------------------------------|----------|-------------------------------------|
| id       | Individual ID                       | id       | Household ID                        |
| household| Household ID                        | region   | ID of LAD                           |
| region   | ID of LAD                           | size     | Number of people in the household   |
| year     | Modeling Year                       | type     | Dwelling type of household          |
| age      | Age of individual                   | year     | Modeling year                       |
| gender   | Gender of individual                | marital status | Marital status of individual       |
| marital status | Marital status of individual | hrp | Household Represent Person          |
| health   | Health status of the individual     | social class | Social class (five classes) of the individual |

Table 2 shows, based on the number of people and whether including retired person.

Figure 4 illustrates the variation of the six categories of households during 2010 and 2100 in these four LADs. According to the simulation results, the increasing of retired household (Class 1 and 2) is much greater in rural area than in urban area; while in the urban area, smaller household (Class 1, 3, and 4) has a significant increase. These simulation results will help us to understand the population trend in a more flexible way. Thanks to the flexibility of the approach to modeling individuals, which is adopted here; a more detailed classification process will be applied to group households according to their energy consumption (Figure 5).

Table 2. Six types of household in the four LADs.

| Retired household | Non-retired Household |
|-------------------|-----------------------|
| 1 person          | 2 or more persons     |
| 2                  | Without children      |
| 3                  | 1 adults with children |
| 4                  | 2 adults with children |
| 5                  | 3 or more adults with children |
| 6                  |                       |
3.4. Deriving the energy consumption statistic

The energy consumption statistic is derived from EHS data and CHM. EHS is a continuous national survey commissioned by the Department for Communities and Local Government (18), which comprised two elements including a household interview survey and a physical survey of dwellings, covering approximately 17,000 sample households in 2009–2010. The CHM is a domestic energy model for Great Britain, which was used to generate estimates of energy use for DECC HEFF and the associated Energy Consumption in the UK (13). In CHM 2009 data-set, 16,150 weighted cases were selected from EHS and performed building physics calculations to determine energy consumption by use and by fuel type.
In this study, the Chi-Squared Automatic Interaction Detector (CHAID) analysis was applied to assess the relationship between household characteristics and the household energy consumption. The CHAID decision tree is able to create a manageable set of clusters detailing the energy consumption for each type of household. The clusters are organized as nodes on a hierarchical tree, each variable breakdown, representing an additional characteristic of the cluster, to an additional branch. Each branch segment produced in the decision tree is mutually exclusive and represents a set of conditional probabilities. In practice, the ‘Total Fuel Costs’ was used as dependent variable, and other 10 household variables as independent variables. Eight of these 10 variables were selected for the decision tree model, and 41 classes of households (terminal nodes) were generated according to the analysis results. Table 3 below summarizes the results of the CHAID analysis. The definition of each class can be seen from Table 4.

According to the CHM results, the energy consumption profile can be obtained as the Figure 6. As Figure 6 shows, the average energy consumption varies among the different types of households. For instance, a detached house occupied by more than four people (Class 24) is almost four times as a single student-occupied flat (Class 26) household.

3.5. Reweighting the EHS cases and calculating the energy consumption

Once the decision tree has been established by CHAID, we can use it to reweight the housing survey cases according to the microsimulation results. The decision tree was firstly applied to the synthetic household population generated by the model to classify the household record into 41 different classes, and then the number of the cases in each class can be counted by region and by year. Figure 7 shows the number of each class for England by 2010 and 2100.

As Figure 7 indicates, the number of single occupied flat (Class 26 for working or unemployed household and 25 for economic inactive households) has the highest increase during the next 90 years, while the single occupied households with other dwelling types also increased dramatically; for instance, the number of terraced house (Class 40 and 41) grows from 1.6 million to 5.5 million, semi-detached house (Class 30 and 31) from 1.7 million to 5.7 million, and detached house (Class 53 and 54) from 0.9 million to 3.2 million. Another trend that we can find from the modeling results is that along with the population aging, the number of retired household grows faster than the other households in the same conditions; for instance, the number of two-personed semi-detached house with retired people (Class 34) grows much faster than the same type of household without retired person (Class 33 and 32).

4. Estimating residence energy consumption in an uncertain future

4.1. Energy Consumption under baseline model

Having reweighted the EHS cases, the total household energy consumption can be calculated based on the energy consumption profile for each class of households. According to the modeling results, the total residence energy consumption grows from 544 TWh in 2010 to 965 TWh in 2100. The bar chart below shows the comparison of the total household energy consumption in England by fuel type and by end-user, respectively. From the fuel type perspective, the dominant energy source is gas as it taken as 72% of the residence energy market. The second highest consumed type of energy in households is electricity, which counts for 19% of the total energy consumption. From the end-user perspective, most of the energy consumed in the households

| Dependent variable | CHAID |
|--------------------|-------|
| Number of persons in the household, dwelling type, number of retired people, Ethnicity of HRP, Working status of HRP, Number of dependent children in household, Age of HRP, Age of oldest person in household, Age of youngest person in household, and Region |
| None |
| 3 |
| 100 |
| 50 |
| Dwelling type, number of persons in the household, Working status of HRP, age of HRP, age of oldest person in household, age of youngest person in household, and region |
| 61 |
| 41 |
| 3 |

Table 3 Summary of the CHAID analysis.
### Table 4. Definition of each type of household.

| Class ID | Dwelling type | Household size | Age of HRP | Age of youngest person | Age of oldest person | Working status of HRP | Region |
|----------|---------------|----------------|------------|------------------------|---------------------|---------------------|--------|
| 25       | Flat          | 1              |            |                        |                     | Working/unemployed   |        |
| 26       | Flat          | 1              |            |                        |                     | Inactive/student     |        |
| 27       | Flat          | 2              | ≤34        |                        |                     |                     |        |
| 28       | Flat          | 2              | 35−64      |                        |                     |                     |        |
| 29       | Flat          | 2              | >64        |                        |                     |                     |        |
| 7        | Flat          | 3              |            |                        |                     |                     |        |
| 8        | Flat          | 4              |            |                        |                     |                     |        |
| 9        | Flat          | 5+             |            |                        |                     |                     |        |
| 30       | Semi detached | 1              | ≤54        |                        |                     |                     |        |
| 31       | Semi detached | 1              | >54        |                        |                     |                     |        |
| 32       | Semi detached | 2              | ≤49        |                        |                     |                     |        |
| 33       | Semi detached | 2              | 50−74      |                        |                     |                     |        |
| 34       | Semi detached | 2              | >74        |                        |                     |                     |        |
| 35       | Semi detached | 3              | ≤34        |                        |                     |                     |        |
| 36       | Semi detached | 3              | 35−54      |                        |                     |                     |        |
| 37       | Semi detached | 3              | >54        |                        |                     |                     |        |
| 38       | Semi detached | 4              | ≤34        |                        |                     |                     |        |
| 39       | Semi detached | 4              | >35        |                        |                     |                     |        |
| 40       | Semi detached | 5+             |            |                        |                     |                     |        |
| 41       | Semi detached | 1              | ≤59        |                        |                     |                     |        |
| 42       | Semi detached | 1              | >59        |                        |                     |                     |        |
| 43       | Terrace       | 2              | ≤44        |                        |                     |                     |        |
| 44       | Terrace       | 2              | 45−54      |                        |                     |                     |        |
| 45       | Terrace       | 2              | >54        |                        |                     |                     |        |
| 46       | Terrace       | 3              | ≤34        |                        |                     |                     |        |
| 47       | Terrace       | 3              | 34−49      |                        |                     |                     |        |
| 48       | Terrace       | 3              | >49        |                        |                     |                     |        |
| 49       | Terrace       | 4              |            |                        |                     | South West, South East, East of England |        |
| 50       | Terrace       | 4              |            |                        |                     | London, West Midlands, North East |        |
| 51       | Terrace       | 5+             | ≤14        |                        |                     | East Midlands, North West, Yorkshire, and Humber |        |
| 52       | Terrace       | 5+             | >14        |                        |                     |                     |        |
| 53       | Detached      | 1              |            |                        |                     | Working                |        |
| 54       | Detached      | 1              |            |                        |                     | Inactive/student/unemployed |        |
| 55       | Detached      | 2              |            |                        |                     | Working/unemployed    |        |
| 56       | Detached      | 2              |            |                        |                     | Inactive/student      |        |
| 57       | Detached      | 3              | ≤9         |                        |                     |                     |        |
| 58       | Detached      | 3              | >9         |                        |                     |                     |        |
| 59       | Detached      | 4              | ≤49        |                        |                     |                     |        |
| 60       | Detached      | 4              | >49        |                        |                     |                     |        |
| 24       | Detached      | 5              |            |                        |                     |                     |        |
Figure 6. Energy profile of each type of household.

Figure 7. Change of number of different type of household between 2010 and 2100.

Figure 8. Residential energy consumption in England in 2010 and 2100 by fuel type (baseline scenario).

Figure 9. Residential energy consumption in England in 2010 and 2100 by end-use (baseline scenario).
(approx. 70%) is used for space heating. This phenomenon indicates a considerable opportunity to reduce energy consumption by introducing better insulated houses or higher efficiency heating equipment (Figures 8 and 9).

Figure 10 shows the increasing in energy consumption at LAD level by different types of energy. The maps in Figure 10 indicate that the highest growth in energy consumption occurs in South East of England and across the trans-Pennine corridor in the north, following the trend of population growth in those regions.

4.2. Uncertainty caused by demographic development

4.2.1. Demographic development scenarios

In order to understand the impact of social-economic policies on demographic development, three scenario domains which have been set up represents prosperity (rich or poor), sustainability (environmental or consumptionist) and isolation (conservative or liberal) as Table 5 illustrated. Each has a ‘high’ or a ‘low’ dimension and the model drivers (fertility, mortality and migration) change accordingly. For example, low mortality would be expected under a high prosperity scenario, with the opposite occurring with low prosperity. It is necessary to estimate the extent to which each scenario dimension will influence the model drivers. (both in scale and direction).

Table 5 summarizes these relationships with 0 implying no relationship (the dimension has no influence over the model driver) and $+/−1$ indicating a strong positive or negative influence. For example, in the ‘rich’ scenario, life expectancy is expected to be strongly and positively influenced by prosperity, and hence has a value of 1.0. On the other hand, fertility is unlikely to be influenced.

![Figure 10. Change of energy consumption between 2010 and 2100.](image-url)
by national environmental sustainability policies (the sustainability scenarios) so has values of 0.

The high prosperity scenario assumes an increased population growth under each projection driver (fertility, mortality, and migration). This is a common finding in demographic research (19) and is supported by the recent DEMIFER report:

If policies are successful in achieving sustainable growth, the levels of fertility, life expectancy and migration will increase. (20)

The inverse of the high prosperity scenario, the ‘poor’ scenario, assumes that there will be low population growth as a result of both fertilities, mortality and migration.

If environmental challenges have not been met and economic growth has fallen, the levels of fertility, life expectancy and migration will be low. (20)

In a scenario that is highly environmentally sustainable, it is hypothesized that highly sustainable lifestyles lead to greater life expectancy and lower migration (21).

In the two high growth scenarios (GSE and EME) medical advances will be higher. (20)

It is also assumed that fertility will not be affected as governments attempt to manage the growing population by not introducing family-friendly policies.

The low sustainability scenario is the inverse of high sustainability, leading to lower life expectancy and increased migration as international prosperity differences lead to increased movement of people.

The high isolation scenario assumes that countries become more individualistic. It is hypothesized that the reduction in migration will lead to family-friendly policies that encourage fertility in order to maintain the population size (20). It is also hypothesized that the expected lack of prosperity associated with greater isolationism will prevent the life expectancy benefits that would otherwise be expected to occur.

With a low isolation outlook, migration will increase and the family-friendly initiatives that drive population growth in the conservative scenario will not be necessary.

### 4.2.2. Projection components for each scenario

As there are three scenarios, each with a high and a low dimension, there are a total of $2^3 = 8$ different scenario combinations. By summing the values in Table 6, it is possible to identify the behavior of each model component under the eight scenario combinations, hereafter referred to as the component strength. This is illustrated graphically by Figure 11.

To apply the direction and strength of each driver in the projection model, each strength must be converted into a rate multiplier. For example, in the ONS ‘high’ scenario, it is assumed that the principal fertility rate of 1.84 increases to 2.04 (22) – this is an increase of 10%, so the rate multiplier would be 1.1. The equivalent strength value for fertility under the ONS high scenario is +0.5, so the fertility rate multipliers in all the remaining scenarios can be scaled linearly relative to a strength of +0.5 equalling a rate multiplier of 1.1. For example, scenario ‘a’ – which assumes high prosperity, sustainability, and isolation – has a fertility strength of $0.25 + 0 + 0.5 = + 0.75$, which represents a 10% increase, and half as much again. Hence, a total 15% increase in fertility compared to the baseline, and thus a multiplier of 1.15.

The migration component behaves in a similar manner. In the high scenario, it is assumed that migration increases from 180,000 to 240,000 (22) – an increase of 33%. As with fertility, the multipliers for other strength values can also be scaled linearly. For example, migration in scenario ‘h’ – low prosperity, sustainability, and isolation – has a strength value of $-0.5 + 1.0 + 1.0 = + 1.5$ which leads to an increase of $1+(1.5/0.5)\times 0.33 = 1.99$.

The situation with respect to mortality, however, is slightly different as a life expectancy improvement, which operates to reduce mortality. In the high scenario, this improvement increases from 1% to 2% (22) so the mortality rate actually decreases by 1% in the high scenario, and increases by 1% (to 0%) in the low scenario.

In general, the rate multiplier for all drivers can be calculated as:

$$1 + \left(\frac{s}{0.5}\right) \times \text{pct}$$

(5)
where $s$ is the strength of the component and $pct$ is the relevant ONS percentage change (e.g. 10% for fertility, −1% for mortality, and 33% for migration). Using this approach for the three model drivers (fertility, mortality, and migration), it is possible to calculate consistent rate multipliers using the ONS high, medium, and low conversions as a framework. This is illustrated in Table 6. The values for the fertility, mortality, and migration multipliers are implemented directly in the projection simulation.

Figure 12 illustrates the change in total population up to 2100 under the different scenario conditions. Scenarios a–d all assume high prosperity and, as a result, generally predict higher population growth that under the ONS base projection. Scenarios b and d, in particular, show considerably higher population growth, which is driven by migration as they are both non-isolationist scenarios. Conversely, scenarios e–h, which are all low prosperity scenarios, exhibit lower population growth than the ONS baseline scenario.

Figure 13 shows the growth of population at regional level between 2010 and 2100 under eight different scenarios. According to the projection results, the following trends can be summarized:

1. Generally, the population of southeast of Great Britain is growing faster than the northwest in all of the eight scenarios (Figure 16).

![Figure 11: The scenario cube depicting the eight different scenario configurations.](image-url)

![Figure 12: Population projection for UK under different scenarios.](image-url)

Table 6 Numerical values for the model components under different scenarios, combinations.

| Scenario | Prosperity | Sustainability | Isolation | Fertility strength | Mortality strength | Migration strength | Fertility multiplier | Mortality multiplier | Migration multiplier |
|----------|------------|----------------|-----------|-------------------|-------------------|-------------------|---------------------|---------------------|---------------------|
| a        | H          | H              | H         | 0.75              | 1.25              | −1.5              | 1.15                | 0.975               | 0.01                |
| b        | H          | H              | L         | −0.25             | 1.75              | 0.5               | 0.95                | 0.965               | 1.33                |
| c        | H          | L              | H         | 0.75              | 0.25              | 0.5               | 1.15                | 0.995               | 1.33                |
| d        | H          | L              | L         | −0.25             | 0.75              | 2.5               | 0.95                | 0.985               | 2.65                |
| e        | L          | H              | H         | 0.25              | −0.75             | −2.5              | 1.05                | 1.015               | 0.00                |
| f        | L          | H              | L         | −0.75             | −0.25             | −0.5              | 0.85                | 1.005               | 0.67                |
| g        | L          | L              | H         | 0.25              | −1.75             | −0.5              | 1.05                | 1.035               | 0.67                |
| h        | L          | L              | L         | −0.75             | −1.25             | 1.5               | 0.85                | 1.025               | 1.99                |
| ONS high | +0.50      | +0.50          | +0.5      | 1.10              | 0.90              | 0.90              | 1.00                | 1.00                | 1.00                |
| ONS baseline | 0.00      | 0.00           | 0.00      | 1.00              | 1.00              | 1.00              | 1.00                | 1.00                | 1.00                |
| ONS low  | −0.50      | −0.50          | −0.50     | 0.90              | 1.010             | 0.67              | 1.00                | 1.00                | 1.00                |

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The higher prosperity scenarios (Scenario a, b, c, d) will lead to a higher population growth (compare to e, f, g, h), due to the lower mortality rates associated with these scenarios.

Migration policy has a considerable impact on the regional population trend, especially for London. The more conservative policies (Scenario a, c, e, g) will lead to a relative higher population growth in London than the surrounding GORs, while for those more liberal policies (Scenario b, d, f, h), the population growths in London are lower than the surrounding areas (i.e. South East, East of England, etc.).

The higher population growth can be found in the North West than the surrounding areas (i.e. Yorkshire, Humber, and North East) under Scenario g and h which involve higher liberal and more consumptionist policies.

Due to the linear relationship between the population density and proportion of urban area, the growth of urban area appears in the similar trend as population growth.

Figure 14 shows the variation of household from 2010 to 2100 under these eight scenarios and baseline scenario. According to the modeling results, the trend for household is not exactly matching the trend of population. For example, the scenario with the highest increase in household is scenario b, while with highest increase in population is scenario d.

4.2.3. Estimating energy consumption associated with different scenarios

It is very unlikely that any of the eight scenarios will be reliable for 90 years. The purpose of these projections is...
to set up boundaries from eight directions, so the future population can be expected as some value between these projection results. In this paper, we will take scenario d and g, which are scenarios with highest and lowest population growth, respectively, as examples to illustrate the residence energy demand associated with the upper and lower population boundaries. According to the modeling results, the residential energy consumption will achieve 1975 TWh, which is about two times as baseline model (965 TWh), while the total energy demand in 2100 under scenario g is much lower than the baseline scenario as only 615 TWh of energy demand for the whole England. Figure 15 shows the comparison of residence energy consumption in 2010 (denoted as 2010), 2100 under baseline scenario (denoted as 2100) and 2100 under scenario d and g (denoted as 2100d and 2100g) by GORs. As Figure 15 shows, the impact of socioeconomic policies varies from region to region. Taking scenario d as an example, even though the energy consumption is higher than the baseline scenario in all of the GORs, the differences are greater in the south than the north of England. The biggest difference appears in the South West where the energy consumption will achieve 278 TWh, which is 148% higher than the value under baseline scenario. Whereas in the North West, the energy consumption value under scenario d is only 77% higher than the value under baseline scenario. London is an exceptional case as it is already an over populated urban area. So, the pressure on population growth is easily to spread into the surrounding areas such as South East, East of England, and South West. That partly explained the reason why the energy consumption increases more rapidly in these three regions than in London. The modeling results of scenario g show a similar pattern as the policy impact south of England greater than the north England (even though in a different way, as the energy consumption in south England dropped more than the north).

5. Modeling residence energy consumption associated with climate/behavior/technology change

The CHM has provided a modeling framework for each household sample in EHS based on its physical
condition and climate variables. The MSM used here allows the EHS cases to be reweighted towards emerging population profiles. We can also investigate the impact of climate or evolution of property on energy consumption in the next 90 years.

Since global warming has been acknowledged as an overwhelming trend in the foreseeable future, in this paper, this assumption will be accepted as the basic scenario. In practice, we use the temperature projections generated from UK Climate Projection (UKCP09) project. The UKCP09 is designed to provide projections of a number of atmospheric variables including temperature, perception and humidity, etc., with detailed spatial and temporal averaging (23).

According to UKCP09, all areas of the UK warm during the next 90 years, and more so in summer than in winter. In general, the mean temperatures changes in summer are greatest in parts of southern England (up to 4.2 °C) and least in the Scottish islands (over 2.5 °C) by the 2080s (2070 to 2099) compared to the a 1961–1990 baseline; and in winter, the mean temperatures will increase by 3.1 °C in southern England and 1.8 °C in northern Scotland.

In practice, we adjusted the average temperature variable in the climate module of the CHM based on the UKCP09 results to estimate the energy consumption in 2100. Figure 16 shows the comparison of the energy consumption in 2010 (denoted as 2010), 2100 (denoted as 2100), and 2100 with climate change (denoted as 2100c) by fuel type based on population projection under baseline scenario. It suggested that the global warming did reduce the residence energy demand, especially for gas as the increasing temperature reduced the energy usage in house and water heating, and gas is the main energy type used in heating. It should be also be noted that none of the property in EHS samples are equipped with house cooling system (i.e. air conditioning) because it is not so necessary in 2009. However, when the temperature is continuing to grow, the demand for air conditions might be increased accordingly which may consume extra energy in the summer.

Many studies have demonstrated that behavior of household has also a significant impact on energy consumption/carbon emission, and a number of behavior-based models have been built since late 1970s (6,24–26). In 2009, Dietz divided 17 behaviors into five categories in their research, which includes: home weatherization and upgrades of heating and cooling equipment, more efficient vehicles and non-heating and cooling home equipment, equipment maintenance, equipment adjustments, and daily use behaviors, and find out these actions can immediately achieve about 20% reduction in carbon emission/energy consumption.

Similarly, in this paper, we will test the impact of the behavior/technology change based on existing technology even though the more energy efficient technique are very likely to be developed during the next
90 years. The behavior changes involved in this paper include:

1. Insulated cylinder with all of the applicable domestic hot water (DHW) system;
2. Increasing the share of solar-powered DHW system by 30%;
3. Higher efficiency of main heating system;
4. Converting all the single glazed window to double glazed; and
5. Increasing the share of low energy lighting to 100%.

Figure 17 shows the modeling results based on these actions (denoted as 2100es) based on the 2100 baseline population. Compared to original estimation, these actions can save about 15% of total energy mainly in space and water heating.

6. Conclusions and discussion

In this paper, we have demonstrated a microsimulation-based energy consumption model for a mid-long-term planning purpose, which is able to estimate the energy consumption in the residential sector by considering demographic development, climate change, and behavior changes simultaneously at a reasonable spatial (LAD level) and temporal (year) resolution. A spatial MSM was built to represent each individual household by tenant’s attributes (i.e. household size, age group, etc.), appliance ownership (i.e. water tank, etc.), and property physical conditions (i.e. insulation). Then, the energy consumption for each household is calculated based on these variables, exterior climate condition, and the tenants’ behavior.

According to the simulation results, the population growth is the key driver of residential energy consumption, while climate and behavior change have significant impact on it. The spatially disaggregated model offers a better understanding of the spatial distribution of the energy demand, thus provides a better evidence for the infrastructure planning in the future. One of the main drawbacks of the model is that it simplifies the migration representation, and therefore cannot model the migration dynamically. As a support model for infrastructure planning purpose, this model cannot take the impact of infrastructure development on demographic change into account. This problem will be studied in the Work Stream 3 under the ITRC framework.

This climate model does not take the number of days with extreme weather into account. In fact, according to UKCP09, one of the most considerable consequences of global warming is an increase in both the number of cold days in the winter and the hot days in the summer, which means the actual energy consumption might be higher than we modeled.

Like most of the bottom-up approaches, the model that we presented in this paper does not take economic impact and capacity constraint into account as the top-down models, as the ITRC FTA model does. All of the energy consumption estimations under different scenarios are based on existing technologies and associated behavior patterns of the residents. We noticed that the economic conditions, technology advance, and associated behavior changes would dramatically impact the behavior of the residents and reshape the energy consumption profile for the residential sector. However, those issues are not the main concerns of this paper. We have demonstrated that the model itself is able to represent the change of technology and behavior in the Section 5; however, more critical scenario settings are needed in future study.

Acknowledgments

The research reported in this paper was part of the UK Infrastructure Transitions Research Consortium (ITRC) funded by the Engineering and Physical Sciences Research Council under program grant EP/I01344X/1.

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