Liu et al. Computational Urban Science (2026) 6:42
https://doi.org/10.1007/s43762-026-00277-2

Computational Urban Science

ORIGINAL PAPER

Open Access

Dynamic micro-simulation of domestic electricity consumption: a case of Beijing

Junbe Liu[1], Charlie Wilson[2,3], Ying Zhang[1] and Chengxiang Zhuge[1,4,5,6,7*]

Abstract

Agent-based modelling enables the simulation of household energy consumption at the individual level, considering heterogeneity, interactions and dynamics. However, existing agent-based domestic energy consumption models fail to capture the influence of associated urban subsystems (e.g., population and land use). To fill this gap, we develop an empirically based electricity consumption model and integrate it into an urban microsimulation platform, SelfSim. The resulting SelfSim-Energy model simulates the energy consumption of each household in the context of urban evolution, explicitly representing interlinked energy use and urban dynamics. We apply SelfSim-Energy to Beijing, simulating its urban system evolution from 2021 to 2030, with a focus on domestic energy consumption. We find total electricity consumption increases from 29.1 to 32.3 billion kWh mainly due to population growth. Homeownership declines from 82.1% to 56.8%, leading to a reduction in energy-efficient technology adoption in homes from 78.2% to 69.1% for the example of low-energy lighting. These within-household trends help explain the observed increase in domestic energy consumption. We use scenario analysis to show how changes in population structure, land use development, and socio-economic trends interact to influence domestic energy consumption. This emphasizes the importance of incorporating urban dynamics to better represent and estimate future energy demand in the built environment.

Keywords Energy consumption, Urban micro-simulation, Agent-based modelling, Decision support system, SelfSim

1 Introduction

Domestic electricity consumption is a critical component of global energy use. According to International Energy Agency (2024), the global domestic electricity consumption is continually on the rise in recent history. It can be said to be one of the key drivers behind the surge in overall electricity consumption. In 2022, there was a rise of 13.8% year-on-year in domestic electricity consumption in China, which constitutes a significant part of the overall consumption seen to increase by 3.6% (The Central People's Government, 2023). This increasing electricity demand leads to several issues, such as rising electricity prices, fuel shortages, household energy poverty, and increasing carbon emissions (International Energy Agency, 2022; Rahmati et al., 2024). Therefore, it is necessary to identify the key factors affecting domestic electricity consumption, and further realize energy consumption reduction and sustainable energy development.

Agent-based modeling (ABM) (Macal et al., 2005) is a bottom-up approach that simulates the behaviors and interactions of individual entities to reveal patterns at macro-level. It can be flexibly used in developing energy consumption models in the context of spatial scales

*Correspondence:
Chengxiang Zhuge
chengxiang.zhuge@polyu.edu.hk
[1] Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China
[2] Environmental Change Institute, Oxford University, Oxford, UK
[3] International Institute for Applied Systems Analysis, Laxenburg, Austria
[4] The Hong Kong Polytechnic University Shenzhen Technology and Innovation Research Institute (Futian), Shenzhen, China
[5] Research Institute for Sustainable Urban Development, The Hong Kong Polytechnic University, Hong Kong, China
[6] Smart Cities Research Institute, The Hong Kong Polytechnic University, Hong Kong, China
[7] The Hong Kong Polytechnic University Shenzhen Research Institute, Shenzhen, China

(such as city and national scales). Furthermore, these agent-based energy models can be used to simulate the dynamic evolution of individual energy demand under different scenarios, such as implementation of various energy policies or diffusion of energy-frugal technologies. Although many agent-based energy models have been developed to examine household energy consumption, most of them assumed a fixed urban context and overlooked urban dynamics (such as population and land use dynamics). In fact, many factors that affect energy demand are not fixed but co-evolve with urban dynamics. For instance, economic development can change the employment structures and affect the time people spend at home, and subsequently influence their corresponding domestic energy consumption behaviors. Without considering urban dynamics, these models are difficult to capture the complexity of real-world energy consumption, in particular, the co-evolution of electricity demand with urban development.

To overcome the above limitations with existing agent-based energy models, this study develops an agent-based integrated energy model, SelfSim-Energy, by incorporating a set of empirically-based energy consumption models into an agent-based urban micro-simulation model, SelfSim (Zhuge et al., 2016), so as to simulate energy consumptions of each household in the context of urban evolution. SelfSim-Energy dynamically estimates individual energy consumption and serves as a decision-support system for energy-related planning and policy-making.

2 Literature review

2.1 Domestic energy consumption models

A large number of studies has been aimed at developing domestic electricity consumption models that can accurately predict household energy usage consumption. Broadly, these models can be divided into two main groups: top-down (Yu et al., 2025) and bottom-up models (Swan et al., 2009). Bottom-up models can be further divided into two main types: engineering-based and statistical models.

Top-down models estimating domestic energy consumption are typically developed using aggregated data (such as national income, demographic statistics, and economic indicators), in particular, at the macro-scale (such as regional (Dai et al., 2023) and national (Jannuzzi et al., 1991) scales). For instance, Jannuzzi et al. (1991) focused on the connections among income levels, appliance stock, and electricity consumption in Brazil. The study showed that the electricity consumption would increase faster than income, due to a growing number of household appliances. Bianco et al. (2009) developed a set of linear regression models to predict long-term electricity demand in Italy. Their predictions deviated from the official country projections by −1% to −11%, which indicated that the results provided adequate accuracy over a long-term time horizon. Ardakani et al. (2018) tried to identify the determinants of household energy consumption in Nordic countries, and they found population and the unemployment rate as key influencing factors. Top-down models, although appropriate in depicting the overall trends of consumption at regional or national levels, cannot represent the behavioral patterns of individuals, and are inadequate in providing a precise estimation of the impact of localized energy policies and interventions (Zhang et al., 2012).

In contrast to top-down models, bottom-up approaches analyze domestic electricity consumption from a micro-perspective, usually taking individual households and buildings as modelling units. They encompass a wide range of modeling techniques, generally classified into engineering-based and statistical methods. Engineering-based models simulate energy use by modeling the operation of end-use appliances, and physical characteristics of buildings and their environments. Tools like EnergyPlus (Crawley et al., 2001; Ferrari et al., 2019) are commonly used for this purpose. For example, Shabunko et al. (2018) collected energy profiles and billing data from 400 residential buildings in Brunei Darussalam, based on which they developed three representative models for different building types using EnergyPlus. The models identified key factors (such as ceremonial activities), estimated energy density, and revealed a potential reduction in energy use ranging from 15% to 19.2% depending on building type. Based on the Residential Energy Consumption Survey (RECS), Heiple et al. (2008) developed a high-resolution model with spatial and temporal detail. This model has been found effective in generating detailed energy consumption profiles for buildings in Houston, Texas, and has supported research on urban heat islands and air quality. Although engineering-based approaches offer high-resolution and physically realistic simulations of electricity use, they require extensive input data and calibration (Craig et al., 2014).

In contrast, statistical methods offer a more data-efficient alternative by modelling energy consumption through empirical relationships between household electricity use and explanatory variables such as dwelling type, occupancy, and appliance ownership. These models can be implemented rapidly across diverse settings. For example, Bedir et al. (2013) surveyed 323 Dutch households and applied a multiple regression model. They found that appliance usage duration, dwelling characteristics, and household attributes significantly influenced electricity consumption. Santamouris et al. (2007) investigated how income disparities influence electricity consumption and found that electricity costs per person and per unit area were substantially higher for low-income households, likely due to poor building energy efficiency in this group. Chen et al. (2010) examined summer electricity consumption patterns across seven Chinese cities located in different thermal design zones. Results showed that significant variation in summer energy demand was likely driven by climate and housing characteristics. Statistical methods also enable end-use-specific estimates. Rosenberg (2014) developed a lighting-demand regression model using data from 45 Norwegian households, incorporating daily use, daylight duration, and temperature, for the model estimated lighting as 6–7% of total household consumption, which is consistent with the official data published by Statistics Norway in 2006. Parti et al. (1980) introduced conditional demand analysis (CDA), which models energy use by appliance ownership and usage conditions (such as heating demand modeled solely in winter for households with heaters). However, there is a limitation associated with their core assumption that is treating households as independent entities. This assumption fails to capture the complex interactions that drive real-world behavioral change.

2.2 Agent-based domestic energy consumption models

Taking into consideration the behavioral heterogeneity of individuals and their interactions, Agent-Based Modelling (ABM) is an increasingly employed bottom-up method to simulate domestic energy consumption (Chingcuanco et al., 2012; Du et al., 2025; Tian et al., 2021). However, most of existing models assume a static urban environment, and thus neglect the influence of urban dynamics (such as population and land use dynamics) on domestic energy consumption.

Agent-based energy consumption models that ignore urban dynamics generally focus on appliance ownership and usage patterns. For example, Cao et al. (2017) integrated life-cycle assessment into their model to evaluate the potential of adopting high-efficiency lighting systems in a long-term perspective. Ding et al. (2019) developed a model for student dormitories, and estimated consumption of electricity and water based on students' appliance ownership and time spent indoors. Another group of studies focuses on households' daily activities and how their behavior changes in response to external interventions (such as policies). In cold-climate regions, Song et al. (2020) simulated heating behaviors and quantified potential savings under various policy scenarios. Lee et al. (2014) examined how carbon reduction measures, such as subsidies and carbon taxes, could influence residential behaviors. Two studies conducted by Jensen et al. (2015) and Jensen et al. (2016), further assessed the impact of feedback devices on household decision-making and energy consumption. These devices included both energy-related feedback systems and those providing information about indoor air quality. Alrobaian et al. (2023) proposed an optimization framework to deploy PVs and batteries devices, as well as manage household appliances operational schedule. This framework aimed to maximizing economic and energy effects, and household satisfaction.

Although most ABMs assume a static urban environment, a few models have considered some factors related to urban dynamics. For instance, Tian et al. (2020) explored how change in income would influenced household energy behavior. In their model, household income evolved annually based on a predefined growth rate, which affected the energy consumption level and choice of fuel. In a subsequent study by Tian et al. (2021), income dynamics were further used to simulate households' transitions from coal to electricity. Castesana et al. (2013) considered more comprehensive population dynamics, including birth, death, aging and economic growth. These attributes were linked to residential energy use and carbon emission behaviors, so as to quantify the influence of population dynamics. Palmer et al. (2015) examined how life-stage transitions, including retirement, unemployment, childbirth, relocation, and household downsizing, affect energy behaviors and the adoption of energy-efficient appliances. Focusing on land use, Song et al. (2022) assessed how variations in building height and ambient temperature would influence people's energy behaviors, and captured the interaction between built environment evolution and energy demand.

However, only a few studies have simultaneously incorporated multiple dynamic urban factors into spatially-explicit agent-based energy consumption models. For instance, Chingcuanco et al. (2012) developed an energy consumption model and integrated it into the Integrated Land Use, Transportation, and Environment (ILUTE) model, focusing on heating demand over time. Using a joint logit model, the model dynamically updated fuel and device choices of households, considering evolving socio-demographic and housing attributes. The model was applied to the Greater Toronto–Hamilton Area, to capture long-term patterns in domestic energy behavior from 1986 to 2006. Similarly, Tirumalachetty et al. (2009) developed agent-based frameworks combining land use, transport, and energy modules. The model primarily served as decision-support tools to evaluate energy policy interventions. Wang et al. (2018) introduced an energy consumption model into an open-source and widely recognized urban microsimulation model, UrbanSim (Waddell, 2002), to create an integrated framework. This comprehensive model was subsequently employed to examine the impacts of various land use policies on household energy consumption.

2.3 Research gaps and aims

Although there are many studies have developed agent-based models to examine domestic energy consumption, most of them assumed a fixed urban context and overlooked urban dynamics (such as population and land use dynamics). These evolving factors can significantly change home tenure, household composition, appliance adoption, and may finally influence domestic energy consumption (Bardazzi et al., 2020; Cho, 2019; Fu et al., 2014).

To address this gap, this study develops a regression-based electricity consumption model and integrates it into an urban microsimulation framework, SelfSim. This results SelfSim-Energy, which distinguishes itself from many previous integrated Land Use-Transport (LUTI) energy models in the following three aspects. Firstly, it models a diverse set of agent types. SelfSim-Energy not only includes regular agents such as people, but also business occupiers, schools, and facilities. These agents are highly integrated and interdependent, which creates causal feedback loops that ultimately shape domestic energy consumption. Secondly, moving beyond the single-use focus (such as space heating) of many integrated energy models, SelfSim-Energy simulates the dynamics of diverse types of appliances associated with energy consumption. In particular, it explicitly models household decisions to purchase or dispose of these appliances in response to life events. This is helpful to identify which end-use drive energy consumption, and further offer crucial insights for designing energy-saving policies. Third, SelfSim is developed as a GIS-based framework, which enables spatially-explicit simulation. So, SelfSim-Energy can explore how domestic energy demand evolves across the urban environment.

3 Dynamic simulation of domestic energy consumption: SelfSim-Energy

To simulate domestic consumption within the context of urban evolution, we firstly developed a domestic energy consumption model based on empirical findings obtained from a questionnaire survey, and then incorporated it into SelfSim, an agent-based urban micro-simulation framework. The resulting integrated framework is referred to as SelfSim-Energy. Section 3.1 outlines the structure and essential components of the SelfSim version used in this study, and Sect. 3.2 details the construction of the energy consumption model and its integration into SelfSim.

3.1 An urban micro-simulation model: SelfSim

SelfSim is an agent-based urban micro-simulation platform developed by Zhuge et al. (2016) that treats city as a complex adaptive system. It integrates multiple interacting sub-models, including population dynamics, business occupier and school dynamics, real estate, land use, human mobility, and accessibility. These components jointly simulate the co-evolution of demographic, economic, and land use processes within a dynamic urban environment. Each sub-model operates at the level of individual agents and interacts with others through dynamic feedback mechanisms over time. Full details on SelfSim can be found in an accompanying technical report (Liu et al., 2025). SelfSim is a modular framework, allowing users to remove or add new modules according to research purpose. In this study, SelfSim will be extended by integrating an energy consumption module, and those less relevant modules, including social network model (Zhuge et al., 2018c) and transport facility development model, will be removed in order to reduce the demand for disaggregate input data and increase computing time, making SelfSim more feasible and efficient to apply.

Figure 1 provides an overview of the SelfSim version used in this study. The model consists of two modules: initialization and simulation. The initialization module sets up a virtual city for the study area, while the simulation module governs the dynamic evolution of various agents and the environment over time.

(1) Initialization Module

The initialization module is responsible for constructing a synthetic urban environment by generating multiple types of agents and facilities.

- Population: The population is generated at the household level, where each household agent contains one or more person agents. Person agents are assigned with attributes such as age, education, and gender, while household agents include information on household size and income. Typical methods for the population synthesis include Iterative Proportional Fitting (Beckman et al., 1996) and Combinatorial Optimization (Williamson et al., 1998).
- Business occupier and school agents: SelfSim includes school agents and two distinct types of business occupiers, namely firm agents and businessman agents. The model distinguishes these business occupiers by their primary function. Firm agents represent entities that mainly provide production or administrative activities (such as offices and factories) and are assigned attributes such as size and age. Businessman agents represent consumer-facing services that provide shopping and leisure opportunities (such as retail stores, and restaurants), and they are also

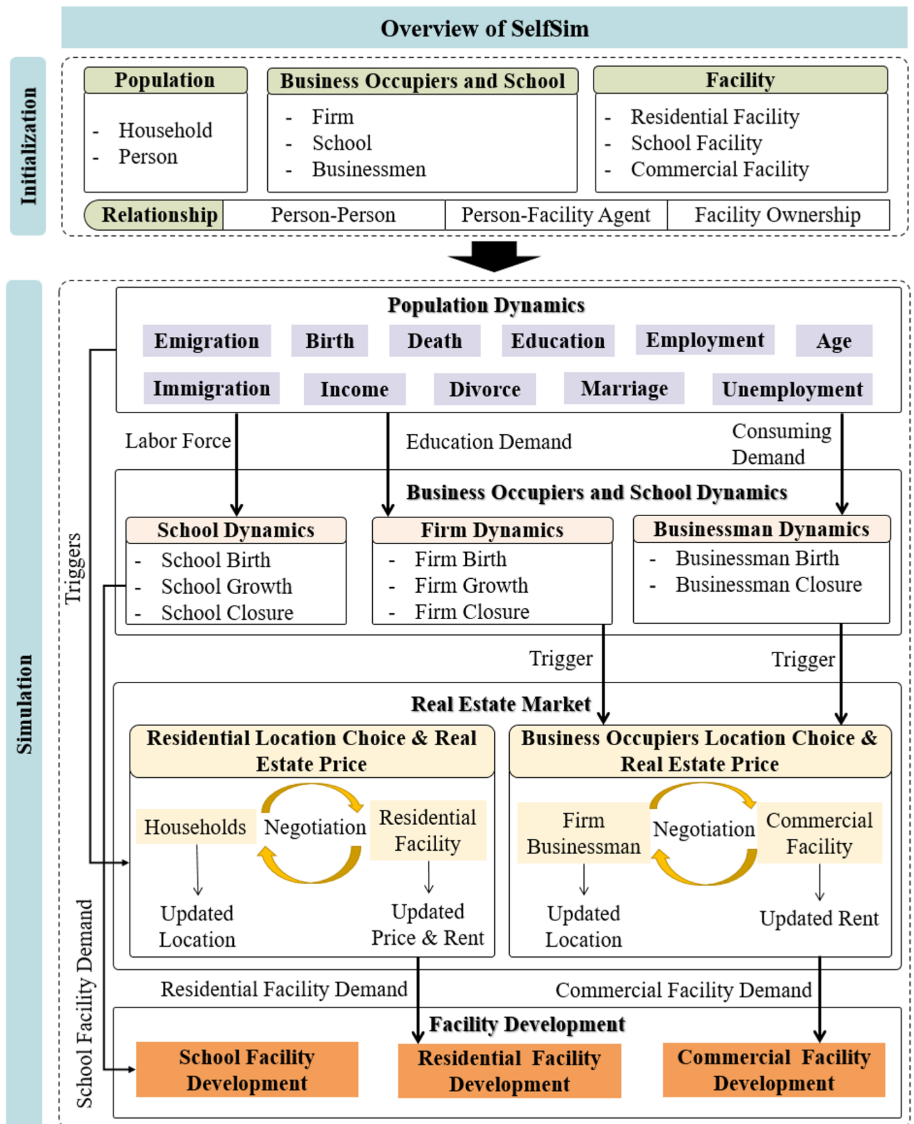


Fig. 1 Framework of SelfSim and the connections between its core models

assigned attributes like size and age. School agents provide educational places for person agents with student status; their key attributes include school type and the number of enrolled students. While functionally distinct, all three types of agents connect to person agents through daily activities and provide workplaces for the employed population. Although these agents do not directly determine domestic energy consumption, they can indirectly influence it by shaping employment structures and residential patterns, which in turn affect household energy demand.

- Facilities: This SelfSim version considers those facilities used for residential, educational, work, and commercial activities. These activity facilities are categorized as residential facilities (housing for population agents), school facilities (used by school agents), and commercial facilities (used by business occupier agents).
- Relationships: This SelfSim version simulates three main types of relationships between agents. The first type concerns relationships among person agents. Within each household, the model represents key familial ties, including parent–child, spousal, and grandparent-grandchild linkages. The second type captures interactions between person agents and facility agents (i.e., firms, businessmen, and schools) through employment, education, and

consumption, reflecting daily activities such as working, studying, shopping, and leisure. The third type concerns facility ownership, which describes how agents are connected to different types of facilities. Household agents are linked to residential facilities either as owners or renters. Business occupier agents, including firms and businessmen, are connected to commercial facilities as renters. For school agents, the model assumes a one-to-one assignment with school facilities.

A procedure of generating such a virtual city can be found in the work by Zhuge et al. (2018b). It should be noted that the algorithms and methods in the virtual city creator may need to be adjusted according to the data availability in the study area. More details on generating a virtual city to initialize SelfSim for this study can be found in Sect. 4.4.

(2) Simulation module

The simulation module captures the dynamic evolution of agents, facilities, and their relationships over time. It simulates decision-making processes of individual agents, interactions among agents, and agent-environment feedbacks. Each simulation run proceeds in discrete annual steps, during which all sub-models are executed sequentially to update the virtual city. As illustrated in Fig. 1, the simulation consists of several sub-models as below (more technical details on each of them can be found in the SelfSim technical report and Appendix 2 in Supplementary Materials):

- Population dynamics model: The population dynamics model simulates the life-cycle transitions of population, capturing a range of demographic processes including birth, death, immigration, emigration, marriage, divorce, aging, education participation, employment status, and income changes. These transitions shape the composition and socio-economic status of the synthetic population over time, and in turn influence various aspects of urban evolution such as labor supply, consumption demand, education demand, and household relocation.
- Business occupier and school dynamics model: This model captures the evolution of firms, businessmen, and schools in response to changes in labor supply, education needs, and consumption demand. It consists of three sub-models: firm dynamics, school dynamics, and businessman dynamics models. Each simulates the birth, growth (such as changes in employee or student numbers), and closure of the respective agents.
- Real estate market model: This model captures how agents choose locations and how their decisions affect real estate price. For households, the model simulates relocation processes associated with demographic events. Two types of triggers are considered: mandatory triggers lead to immediate relocation (e.g., newly formed households), while flexible triggers accumulate over time as household attributes change (e.g., household size), and only induce relocation once a threshold is reached. These households evaluate available residential facilities using a utility-based decision rule and are subsequently assigned to a new residential location through purchase or rental (Zhuge et al., 2018a). For business occupiers, the model captures how new or relocating entities choose commercial facilities (Zhuge et al., 2019). Each year, the prices and rents of residential and commercial facilities are updated through a negotiation process. This process translates the aggregated utility derived from the location choice process into changes of prices and rents.
- Facility development model: This model governs the development of new facilities, including residential, commercial, and school facilities. The development of residential and commercial facilities is driven by predefined annual inputs specifying the number of new facilities and their capacities. In contrast, the construction of school facilities is triggered directly by school births. Once generated, new facilities are allocated to specific locations based on demand-related indicators: residential and commercial facilities are more likely to be located in areas with higher real estate prices or rents, and school facilities tend to be placed in regions with larger student populations.

3.2 Integration of a domestic electricity consumption model into SelfSim: SelfSim-Energy

To simulate the spatiotemporal change of household energy demand, we extend SelfSim by integrating an energy consumption component comprising empirical models for appliance ownership, electricity usage behaviors, and annual electricity, all developed from survey data of Beijing (see Sect. 4.2).

Figure 2 illustrates how this component integrates into both SelfSim's initialization and simulation stages. During initialization, each household agent is assigned electricity-related attributes—appliance ownership, usage patterns, and annual electricity costs— using random forest predictors and a linear regression estimator. During simulation, the integration follows a sequential updating

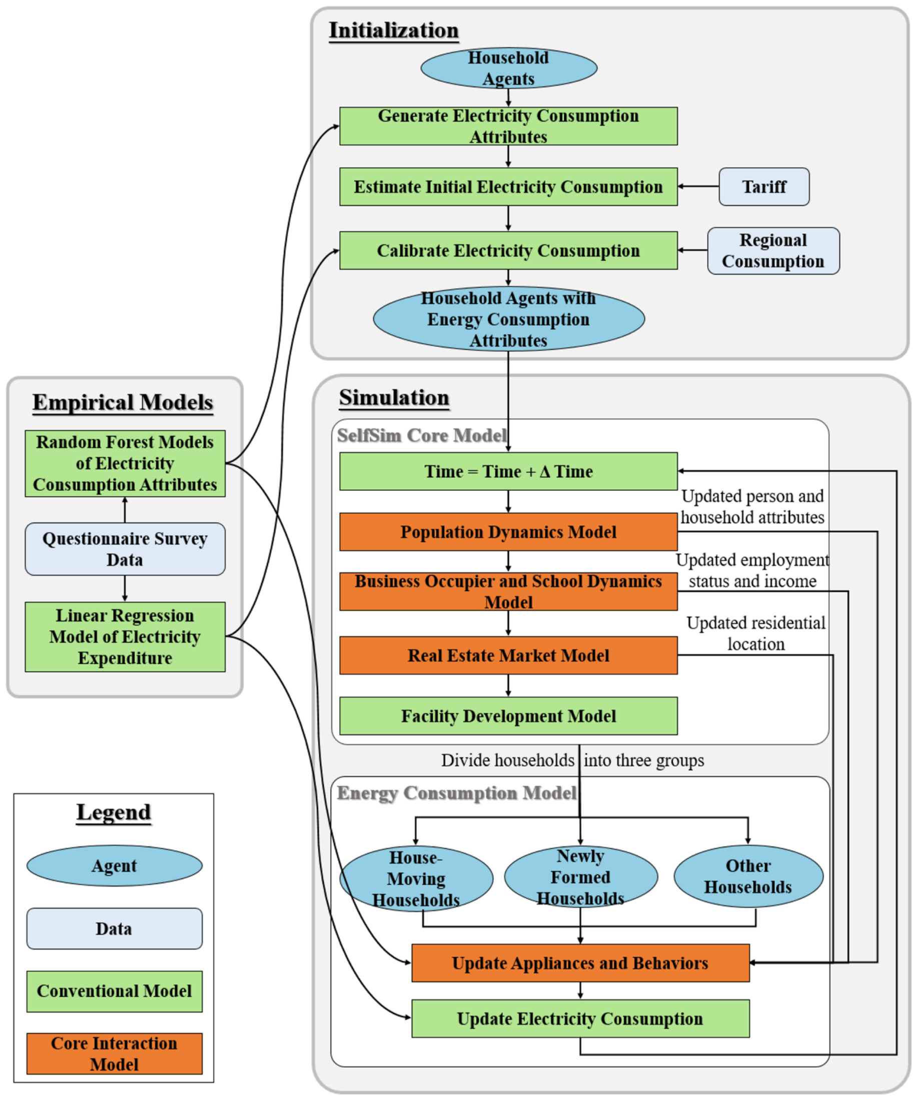


Fig. 2 Integrating an empirically based energy consumption module into SelfSim

process. At each time step, the core SelfSim models first simulate urban dynamics, such as demographic changes and household relocation, to update the attributes of every person and household agents. Once these attributes are updated for the current simulation year, they are further used as inputs to the energy model to update energy-related attributes and estimate annual electricity consumption. The random forest models and the linear regression model remained fixed throughout the simulation, and the evolution of energy consumption is driven by changes in household attributes.

3.2.1 Initialization of electricity consumption attributes

The initialization stage generates household agents with electricity consumption attributes to be used in simulating domestic energy consumption. This procedure includes three steps as follows:

Step 1: Generate energy consumption attributes for household agents. For each household in the synthetic population, a set of random forest models (Breiman, 2001) are applied to predict appliance ownership, electricity usage behaviors, and reported certainty regarding electricity expenditure. These models are trained on household survey data and take socio-demographic variables as input features. Formally, each model aggregates the outputs of multiple decision trees as Eq. (1).

$$\widehat{y} = \text{argmax}_{c \in C} \sum_{t=1}^{T} I[h_t(x)] \tag{1}$$

where, $\widehat{y}$ is the estimated energy consumption attribute and C is the set of possible classes. Each decision tree $h_t(x)$ trained on socio-demographic features x, outputs a class label. The indicator function $I[h_t(x)]$ equals 1 if tree t votes for class c, and 0 otherwise. The class with the highest total number of votes across all trees is selected as the final prediction $\widehat{y}$. In addition, for each appliance owned, a random age is assigned to allow for future simulation of appliance replacement based on predefined lifespans.

Step 2: Estimate initial electricity consumption. We apply the linear regression model in Eq. (2) to the predicted appliance ownership and usage patterns to calculate each household's annual electricity expenditure. The estimated annual electricity fee is then converted into electricity consumption (kWh) based on the local electricity tariff.

$$Y = \beta_0 + \sum_{i=1}^{I} \beta_i X_i \tag{2}$$

where, Y represents the annual electricity fee for each household; β_0 is the constant term; X_i denotes the aggregated energy consumption attributes (such as the intensity of using an air conditioner for cooling), which are used as the independent variables in the model; β_i are the corresponding regression coefficients.

Step 3: Calibrate household consumption based on reported certainty. To refine the accuracy of household-level estimates, we use an optimization algorithm that re-adjusts the initial consumption of each household. The objective function forces the sum of adjusted values within each administrative district to approach the observed total residential consumption sourced from official energy statistics. Adjustments are weighted by each household's survey-reported certainty (such as 0%, 20%, 40%, or 60%), allowing for larger adjustments where uncertainty is higher. The resulting multiplicative adjustment factor for each household is then stored and remains fixed throughout the simulation.

3.2.2 Simulation of household electricity use within urban dynamics

The simulation stage updates each household's electricity consumption dynamically by modeling appliance turnover and behavior changes. After runs the core simulation models (see Sect. 3.1), household attributes such as demographic status, employment, income, and residential location are updated. Based on these updates, the energy consumption model then tracks each household's electricity consumption. To capture response heterogeneity, the model categorizes household agents into three groups: newly formed households (typically resulting from immigration, marriage, or divorce), house-moving households, and other households. Each group follows a specific procedure to update its energy consumption attributes. Finally, the linear regression model (see Eq. (2)) is used to estimate annual electricity consumption of each household. We outline update mechanisms of the three groups of household agents below.

(1) Update Attributes for Newly Formed Households
These households are generated with socio-demographic attributes attached through the demographic events simulated in SelfSim, including immigration, marriage, and divorce in the population dynamics module. Once they are assigned a residential location through the real estate market model, the random forest models will predict appliance ownership and electricity usage behaviors, and the linear regression model will estimate the annual electricity expenditure.

(2) Update Attributes for House-Moving Households
For households with residential relocation during the simulation year, the energy consumption model updates their electricity consumption attributes through a four-step method:

- Step 2.1: Appliance transfer decision. Each household selects which large or white appliances to transfer to its new residence based on appliance category and tenure status before and after moving. We assume that large appliances (such as air conditioner) in rental properties are owned by the residential facility and thus cannot be transferred; renters leaving or entering a rental unit do not move large appliances. For all other cases—namely, large appliances for homeowners and white goods (such as rice cooker) for all households—the decision follows the same rule: the model applies a series of random forest predictors, using household socio-demographics and the new residence's tenure status, to predict continued ownership for each appliance. If continued ownership is predicted, the household transfers the appliance; otherwise, it is left behind.
- Step 2.2: Acquisition of new appliances. This step predicts whether households will purchase additional large appliances or white goods previously not possessed. White goods are modeled as direct purchase choices for all households. Large appliances depend on tenure: homeowners may purchase them outright, while renters only acquire

them when moving into units that already include these appliances.

- Step 2.3: Disposal and replacement of appliances. Each simulation cycle increments each appliance's age by one year. When an appliance reaches its design life, it is removed from the household. Replacement follows two rules. For large appliances in rental units, replacement is automatic as they are supplied by the residential facility. Otherwise, a random forest model predicts whether the household chooses to replace the retired appliance; If so, it purchases a new unit as a replacement.
- Step 2.4: Behavior update. The model will re-predict the household's electricity usage behaviors annually using the random forest models.

(3) Update Attributes for the Other Households

For households that are neither newly generated nor relocating during the simulation year, the update process consists of the following three steps:

- Step 3.1: Disposal and replacement of appliances. This step follows the same logic as described in Step 2.3 of Update Attributes for House-Moving Households, where appliances that reach the end of their lifespan are removed and replacement decisions are made based on tenure and predicted demand.
- Step 3.2: Purchase of additional appliances. The model checks whether the household has experienced triggering events (such as changes in household size). If the number of such triggers exceeds a defined threshold, the model predicts whether to purchase new appliances the household previously did not possess. The decision rules are consistent with those used in Step 2.2: for large appliances in rental properties, they cannot be purchased, as their ownership is fixed once the rental arrangement is established and does not change thereafter; in the other cases, the model applies random forest models to predict whether the household will own (through purchase) the appliance based on its updated attributes.
- Step 3.3: Behavior update. The model re-predicts each household's energy consumption behaviors using random forest models.

4 Applying SelfSim-Energy

4.1 Study area: Beijing

This study uses Beijing, the capital of China as the study area. As one of the most densely populated cities in the country, Beijing had a permanent resident population of approximately 21.89 million in 2020, with an average population density of around 1,312 persons per square kilometer. The city consists of 16 districts in a concentric circle. These 16 districts can be widely divided into three groups: central districts—Dongcheng (DC) and Xicheng (XC); subcentral districts—Chaoyang (CY), Haidian (HD), Shijingshan (SJS), and Fengtai (FT); and outer districts—Mentougou (MTG), Fangshan (FS), Tongzhou (TZ), Shunyi (SY), Changping (CP), Daxing (DX), Huairou (HR), Pinggu (PG), Miyun (MY), and Yanqing (YQ).

Increasing domestic electricity consumption has become a major issue in megacities such as Beijing, where it accounts for a huge proportion of total electricity consumption. Specifically, The total domestic electricity consumption in China grew from 251.6 billion kWh in 2019 to 334.6 billion kWh in 2023, showing a rapid increase of 33% during this period, whereas the average annual domestic electricity consumption per person rose from 1,168 kWh to 1, 531 kWh, which indicates the rising demand of electricity by residential sector (Beijing Municipal Bureau of Statistics, 2024). In response, the Beijing municipal government has implemented a series of policies to reduce electricity consumption. For example, the government encourage residents to save electricity through a tiered electricity pricing scheme, where the electricity price increases as consumption rises (Beijing Municipal Commission of Development & Reform, 2012). In addition, some financial policies are used to encourage residents to adopt energy-saving technologies, such as energy-efficient buildings (such as with high-performance building envelopes) (Beijing Municipal Commission of Housing & Urban–Rural Development, 2023) and energy-efficient appliances (Beijing Municipal Commission of Development & Reform, 2024; Ma et al., 2023).

4.2 Questionnaire survey in Beijing

To calibrate an energy consumption module for SelfSim-Energy, we conducted a questionnaire survey in Beijing. The questionnaire is composed of four parts:

Socio-Demographic Attributes: This part collects both individual- (such as age, income, education) and household-level attributes (such as household income, household size);

Ownership and Usage of Appliances: This part collects data on the ownership and usage behavior of various appliances for cooling, heating, lighting, and water heating, as well as other electrical devices;

Housing Characteristics: This part collects information about the building where respondents live, including its size and the year of construction;

Household Electricity Consumption: This part collects respondents' annual electricity bills and their uncertainty regarding the accuracy of their own bills.

The questionnaire survey was conducted from October 19th to November 2nd, 2021 in Beijing, with 389 valid samples obtained. Figure 3 compares the spatial patterns of samples with population, indicating that their patterns are similar and thus the samples should be spatially representative.

4.3 Empirically-based models for domestic energy consumption

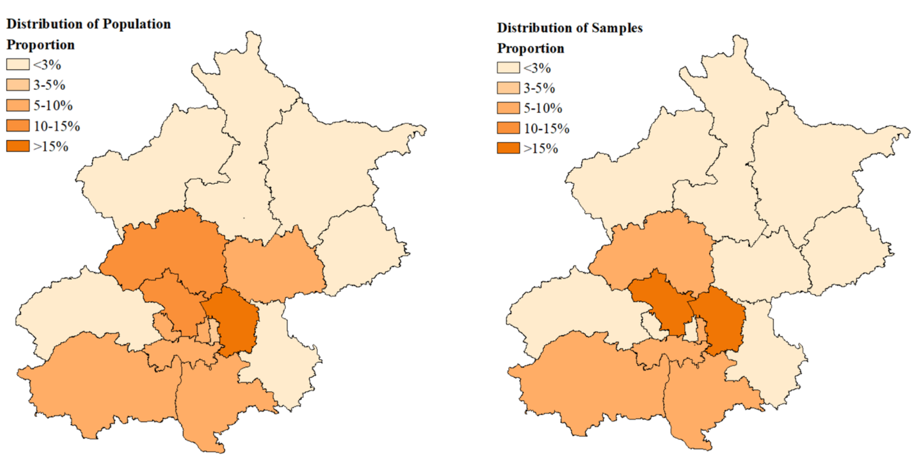
4.3.1 A linear regression model of annual electricity expenditure

We conducted a linear regression analysis of the survey data to identify factors that influence domestic electricity consumption. The variables collected from the questionnaire were divided into four groups: socio-demographic attributes, dwelling attributes, heating and cooling systems, and other variables. Using a stepwise procedure, we developed linear regression models for each group to identify the significant variables. Subsequently, the significant variables from each category were integrated as independent variables to develop the final linear regression model. To enhance the robustness of the model, we only used samples that indicated being "very certain" or "certain" about their annual electricity bill ($N=196$).

We included the statistically significant variables identified in the four separate models above as explanatory variables, and then developed an integrated model for annual electricity consumption. As presented in Table 1, the model demonstrated that both the intensity of air conditioners used for cooling (*Int_cool*, defined as a composite of ownership, duration of use, and temperature settings) and cooking devices (*Int_cook*, defined as a composite of cooking frequency and appliance ownership) were significant positive variables, indicating higher usage intensity leads to higher consumption. It is worth noting that *Int_cool* also absorbs part of the variation in electricity consumption attributable to dwelling characteristics, such as dwelling size (measured by number of bedrooms; Pearson's $r=0.31$, $p<0.01$). Although the adoption of LED lighting was not found to be statistically significant in this model ($p=0.217$), it was retained in the model for its importance in policy design. The model explained 12.4% of the variance in domestic electricity consumption. The explanatory power of the linear regression model is relatively low, because of the highly heterogeneous household energy consumption and unobserved factors. However, we retained this linear specification rather than adopting complex machine learning models to preserve the transparency of the agents' behavioral rules, which is crucial for tracing causal mechanisms in our scenario analysis. In addition, the whole SelfSim-Energy model was calibrated and validated using the observed energy consumption data at both city- and district-levels, ensuring that the model could represent

Table 1 An annual electricity consumption regression model in Beijing ($R^2=0.124$)

Variable	Coef.	p
Int_cool	0.210	0.001
Int_cook	69.962	0.001
LED	−288.008	0.217
Constant	2,188.867	



(a) Distribution of Population *(b) Distribution of Samples*

Fig. 3 Spatial distribution of actual population and survey samples the real-world to some extent. More details on the model development can be found in Appendix 1.2 of the Supplementary Information.

4.3.2 Random forest models of electricity consumption attributes

Based on the results in Table 1, we developed a set of random forest classification models to estimate household electricity consumption attributes, including ownership of ten types of appliances and six electricity usage behaviors.

The modeling process was carried out in two stages. First, ownerships of appliances were predicted using household socio-demographic attributes (i.e., household income and residential facility ownership) as model variables. These ownership predictions were then used, alongside the original socio-demographic variables, as inputs in a second set of models to predict electricity usage behaviors. The complete list of predicted energy attributes is provided in Table A1 in supplementary materials.

The models achieved an average classification accuracy of 0.72 and an average F1-score of 0.71, which were considered adequate for predictions in the SelfSim-Energy simulation. Household income and household size consistently emerged as the most influential predictors. Detailed prediction results for all variables are reported in Appendix Table A8 in Supplementary Materials.

4.4 Initialization, calibration and validation of SelfSim-energy

4.4.1 Initialization and calibration of the core SelfSim model

A virtual Beijing for the year 2018 was constructed using macro-level constraints (such as city-level distribution of socio-demographic attributes) and other micro-datasets (such as real estate micro data), as detailed in Table A9 in supplementary materials. To reduce computational complexity, this virtual urban system was downscaled at a 1:1000 ratio, meaning each agent in the model represents 1,000 real-world individuals. This scaling reflects a trade-off between computational efficiency and the level of detail in representing individual behavior. Given that the objective of this study is to examine how urban dynamics influence spatially aggregated patterns (e.g., at the district level), this level of downscaling is considered suitable for the intended analysis.

A synthetic population was generated using the Iterative Proportional Updating (IPU) algorithm, which requires both micro-level seed data and macro-level constraints. For the macro-level constraints, we used the official demographic statistics for Beijing in 2018 (Beijing Municipal Bureau of Statistics, 2019). For the micro-level seed data, we utilized the personal and household attribute sections from three of our own questionnaire surveys (conducted in 2020, 2021, and 2023), pooling them to create a larger and more diverse sample. The IPU algorithm then integrated these two data sources, resulting in a synthetic population containing 21,297 person and 9,323 household agents.

For business and school entities, a direct 1:1,000 downscaling of the entity count was not appropriate. This is because many entities (such as universities) are limited in number. Consequently, a 1:1,000 reduction would result in an insufficient number of agents to achieve a meaningful spatial representation. To balance model representativeness with computational feasibility, we first set up a reasonable range (i.e., 500–1,000) for the number of agents in each category, so as to make the facility system scaled down appropriately. We then applied the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm (Schubert et al., 2017) to Point of Interest (POI) data obtained from Gaode Map, tuning its parameters to generate agent counts that fell within this desired range. The DBSCAN-based facility aggregation is conducted at the district-level, preserving the relative spatial distribution of facilities across districts. This process resulted in the final counts of 1,000 firm agents, 960 businessman agents, and 522 school agents. It is important to note that although the agent counts were determined by the clustering process and thus were not based on the 1:1,000 ratio, their collective functional capacity (such as the total jobs provided by firms) was scaled to this ratio, by assigning socioeconomic attributes based on 2018 macro-statistics.

The spatial locations for residential and commercial facilities were likewise sourced from POI data. A gravity model (Anderson, 2011) was employed to determine the real estate price for each facility, using an interpolated price surface as a key input. This price surface was generated based on micro-data obtained from HomeLink (one of China's largest real estate brokerage platforms), and constrained by the 2018 district-level average real estate prices and rents.

We calibrated the SelfSim model by running simulations for 2019–2020 and tuning key parameters to minimize discrepancies between simulated and observed metrics, namely district-level population distribution and citywide average real estate prices and rents. The calibration was generally satisfactory: for district-level population distribution, the mean absolute errors (MAE) were 11.48% and 16.51% in 2019 and 2020, respectively. For average residential facility price and rent, the errors were 6.68% and −5.4% in 2019, and 9.4% and −3.5% in 2020.

4.4.2 Initialization and calibration of the energy consumption module

Using the calibrated 2020 virtual Beijing model, we initialized each household's energy attributes following Sect. 3.2.1. First, random forest models (see Sect. 4.3.2), trained with the Beijing survey data, predict each household's appliance ownership, usage behaviors, and self-reported annual electricity bill certainty based on their synthetic socio-demographic attributes. To facilitate the simulation of future appliance replacement, each appliance was assigned with an initial age, randomly drawn from a uniform distribution within its expected lifespan (see Table A10 in Supplementary Materials). Next, we applied the linear regression model (see Eq. (2)) to compute each household's annual electricity expenditure, which we converted to consumption (kWh) based on the local residential tariff rates. Finally, the initial household electricity consumption estimates for the year 2020 were calibrated using the method detailed in Sect. 3.2.1. In this application, each household's potential consumption adjustment was constrained by its predicted level of certainty, with allowed maximum adjustment ranges of 0%, 20%, 40%, or 60%. The optimization process aimed to align the aggregated consumption for each of the 16 districts in Beijing with the observed totals reported by Beijing Municipal Bureau of Statistics (2021). The results of this calibration show an acceptable level of accuracy when compared with observed data for the year 2020. As shown in Fig. 4, at the city-wide level, the total generated electricity consumption was 28.65 billion kWh, compared to an observed value of 27.69 billion kWh, with an absolute percentage error (APE) of 3.5%. At the district level, the mean absolute percentage error (MAPE) was 13.93%.

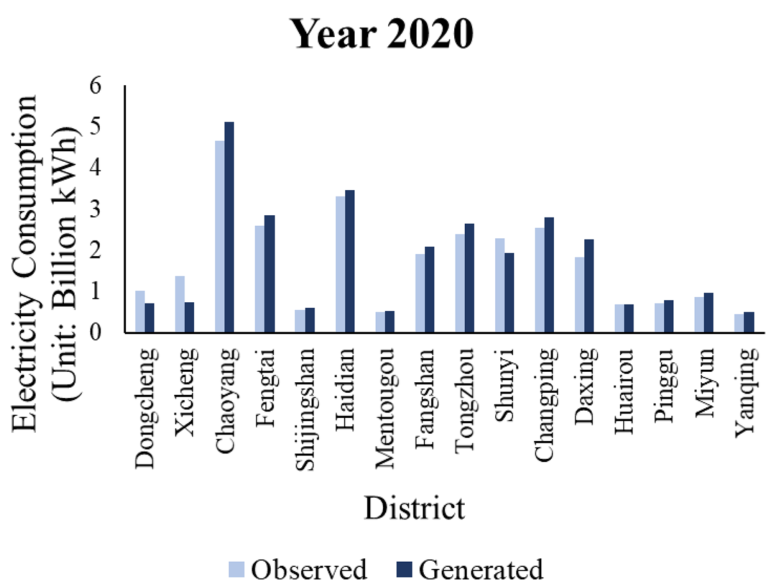


Fig. 4 A comparison between observed and generated electricity consumptions in 2020

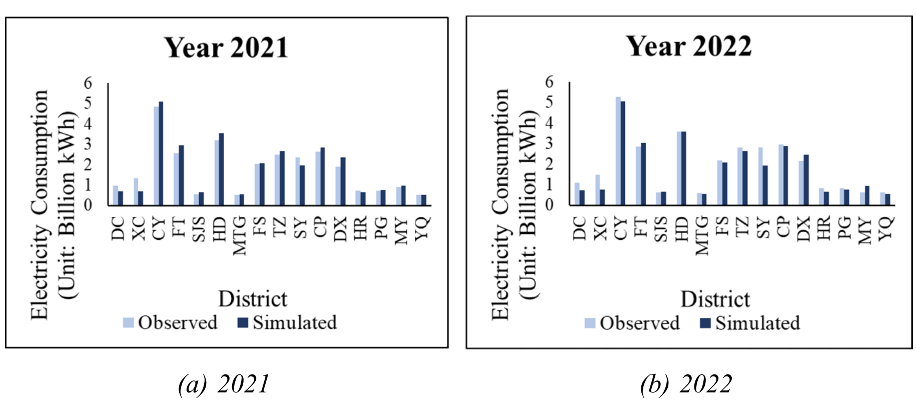


Fig. 5 A comparison between observed and simulated electricity consumptions in 2021 and 2022

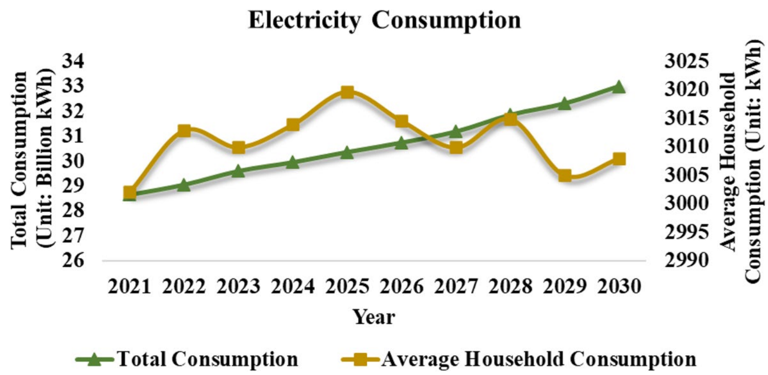


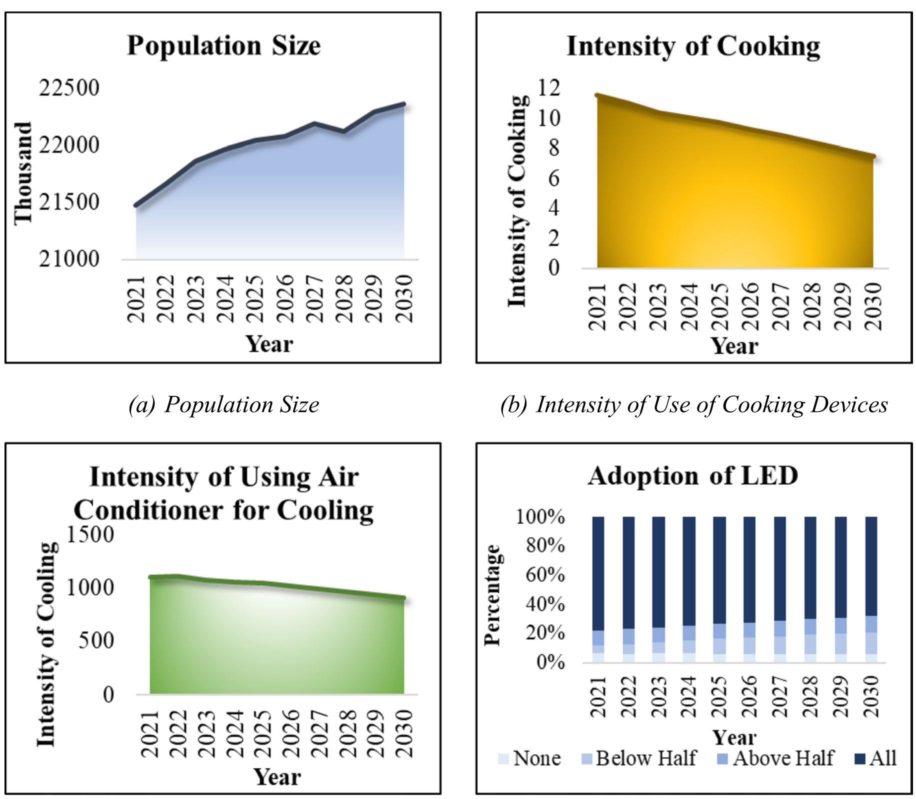
Fig. 6 Annual total and average household electricity consumption

4.4.3 Validation of domestic electricity consumption

The model was further validated by comparing the simulated domestic electricity consumption in 2021 and 2022 against the observed values (see Fig. 5a and b). In 2021, the APE was 2.1% and the MAPE across districts was 12.53%. For 2022, the APE and MAPE were 6.49% and 16.16%, respectively.

4.4.4 SelfSim-Energy results from the reference scenario (RefSc)

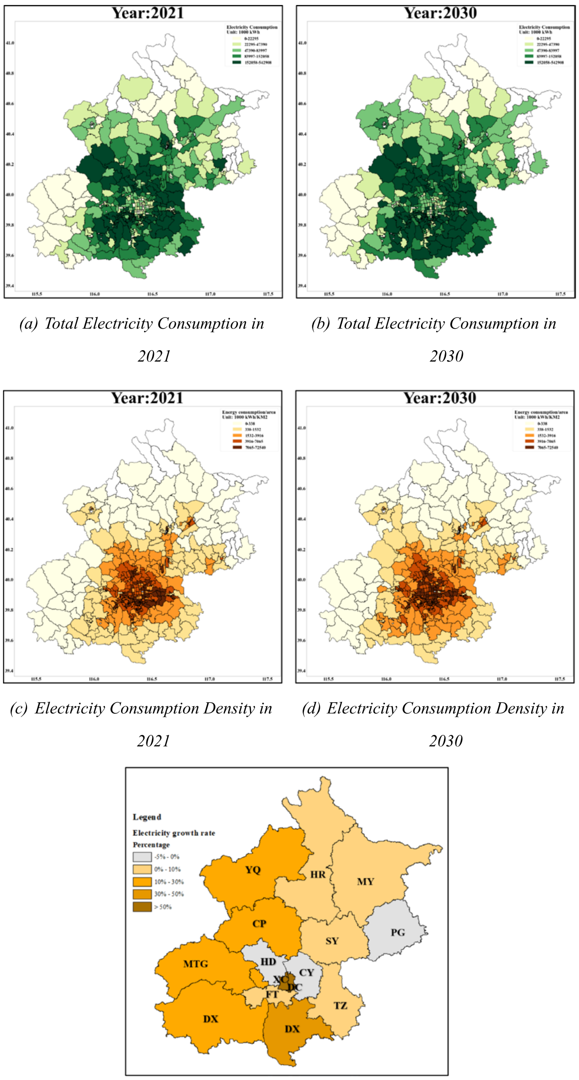
We used the calibrated SelfSim model to simulate Beijing's urban evolution from 2021 to 2030, assuming that the system would evolve over time as assuming path-dependent evolution of the system. The simulation generated detailed outputs on population dynamics and real



(a) Population Size *(b) Intensity of Use of Cooking Devices*

(c) Intensity of Air Conditioners Use for Cooling *(d) Adoption of LED*

Fig. 7 Changes in population size, intensity of use of cooking devices, intensity of air conditioners use for cooling, and LED percentage from 2021 to 2030



(a) Total Electricity Consumption in 2021 *(b) Total Electricity Consumption in 2030*

(c) Electricity Consumption Density in 2021 *(d) Electricity Consumption Density in 2030*

(e) Electricity Consumption Growth Rate

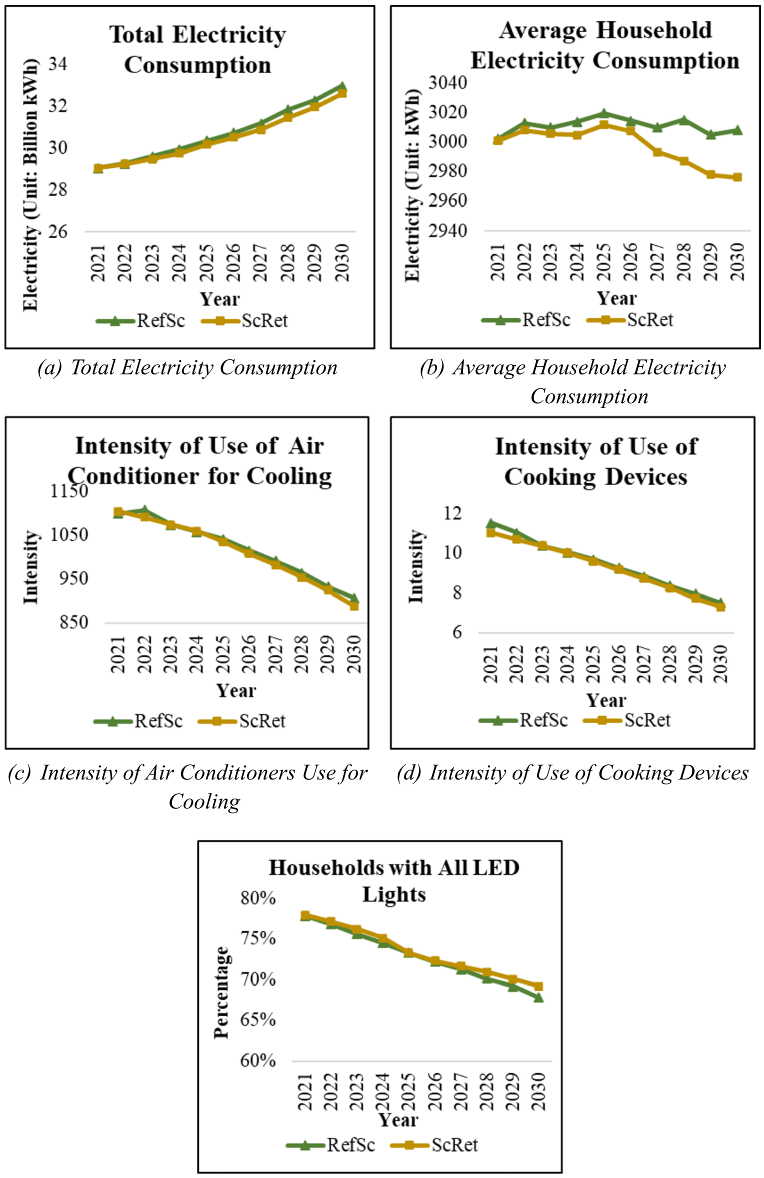
Fig. 8 Spatial distribution of electricity consumptions in 2021 and 2030

estate prices (see Appendix 3.2 in Supplementary Materials for more details).

Figure 6 presents the total and average household electricity consumptions over this period. While the total consumption rose from 29.06 to 32.31 billion kWh, average household consumption remained stable, increasing only marginally by 0.2% (from 3002 to 3008 kWh). This indicates that the growth in total consumption is driven primarily by the increase in the simulated population size, as shown by Fig. 7a.

To further investigate the stable pattern of the average household electricity consumption, we analyzed the changes in those influencing factors which are used as model variables for the household energy consumption estimation. As shown in Fig. 7b, the usage intensity of cooking devices (*Int_cook*) decreased by 34.92%, mainly driven by the reduced ownership of cooking appliances, which dropped from an average of 4.8 per household in 2021 to 3.27 in 2030. This decline is consistent with the observed reductions in household size (–10%), the average number of underage household members (–39%), and the homeownership (–30.78%), all of which are positively associated with cooking appliance ownership. It should also be noted that in the current version of Self-Sim, dwelling size is assumed to be proportional to the number of residents, meaning that household size essentially determines dwelling size. Therefore, a more detailed analysis of dwelling size was not conducted at this stage. Similarly, Fig. 7c shows that the intensity of air conditioners used for cooling (*Int_cool*) declined by 17.55%. Although household income increased, leading to a slight rise in the average number of units per household from 0.80 to 0.87, both the duration of air conditioner used for cooling (*Dur_cool*) and the temperature of air conditioners set for cooling (*Temp_cool*) decreased. Given that household size exerts a positive influence on number of hours of using air conditioner for cooling on weekdays (*Cool_weekday*, a behavior related to *Dur_cool*), and temperatures of air conditioners for cooling which was set during the day and night (*Cool_day_temp* and *Cool_night_temp*, two behaviors related to *Temp_cool*), its reduction also contributed to the decline in cooling intensity. While the reductions in cooking and cooling demand would generally reduce energy demand, Fig. 7d shows a decline in LED adoption which increases energy demand and so partially offsets these effects. Our survey results indicated that households owning a residential facility were more likely to adopt LED lighting. However, the declining homeownership, from 82.11% in 2021 to 56.84% in 2030, may explain the lower LED adoption, and further contributed to the slight changes in average household electricity consumption.

Figure 8 compares the spatial distributions of electricity consumptions in 2021 and 2030. In 2030, electricity use was concentrated in central and sub-central districts, largely mirroring population distribution. From the perspective of growth rates, most districts exhibit an upward trend in electricity consumption, primarily driven by population growth. This increase is particularly pronounced in the two core districts (Dongcheng (DC) and Xicheng (XC)), where electricity demand has risen significantly by 109% and 149%, respectively. Likely, new commercial and residential developments were focused in these core zones, reinforcing this pattern. These findings underscore that the spatial distribution of electricity consumption is closely intertwined with land use dynamics.



(a) Total Electricity Consumption

(b) Average Household Electricity Consumption

(c) Intensity of Air Conditioners Use for Cooling

(d) Intensity of Use of Cooking Devices

(e) Households with All LED Lights

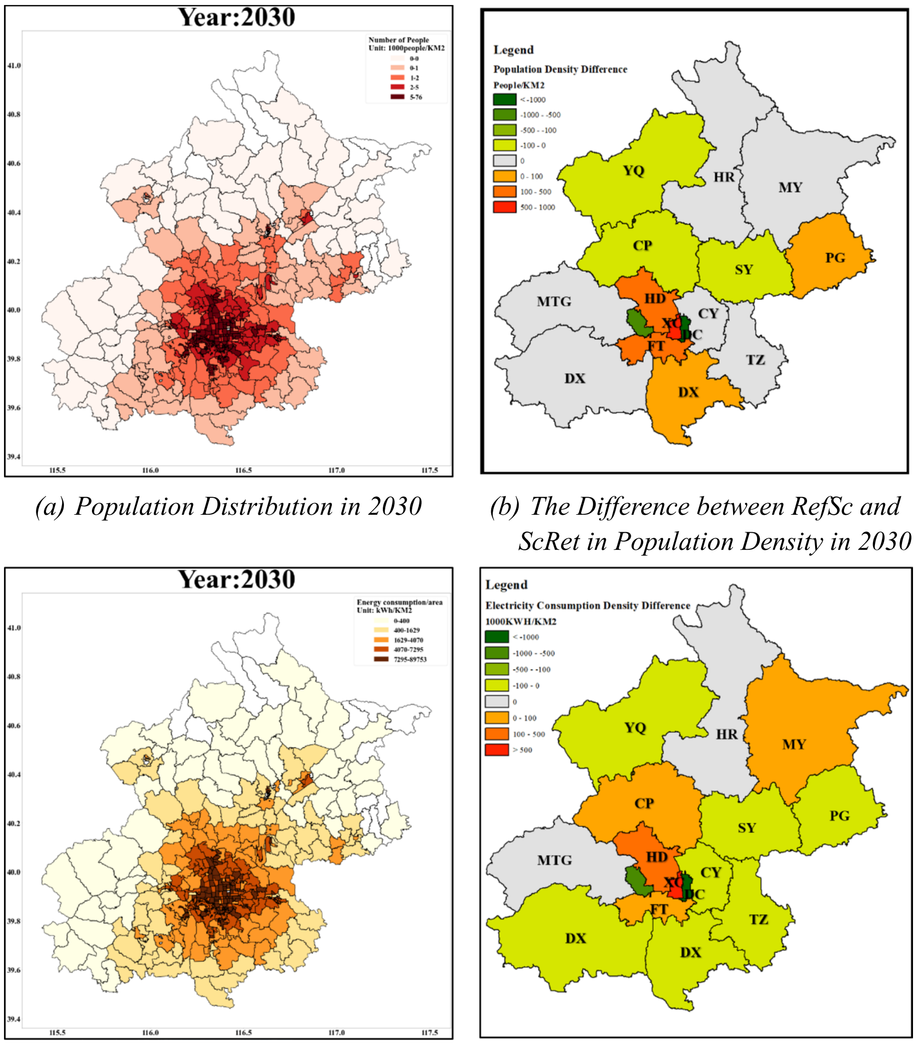
Fig. 9 Influence of delaying retirement on domestic electricity consumption

4.5 What-if scenarios

4.5.1 Scenario RetireDelay (ScRet): Impact of delaying retirement age

Population dynamics could influence household energy consumption, as appliance ownership and electricity usage behavior may be linked to socio-demographic attributes. Therefore, we set up a "what-if" scenario, RetireDelay (ScRet), to explore the influence of the policy of delaying retirement age on domestic energy consumption, with considering aging population has become a common issue to many cities. Specifically, in the scenario, we changed the retirement age to 65 years for all person agents; while in reality, it should be 60 for men and 55 for women (the same as setting of Reference Scenario (RefSc)). Delaying retirement directly affects person agents' employment status, resulting in a smaller proportion of retirees within households and the higher household income.

Following the implementation of the delayed retirement policy, in 2030, the working population increased from 14.461 million in RefSc to 15.760 million in ScRet, with a growth rate of 9.0%. Correspondingly, the retired population declined by 35.90%, and household income increased by 7.31%. However, the homeownership fell



(a) *Population Distribution in 2030*

(b) *The Difference between RefSc and ScRet in Population Density in 2030*

(c) *Electricity Consumption Density in 2030*

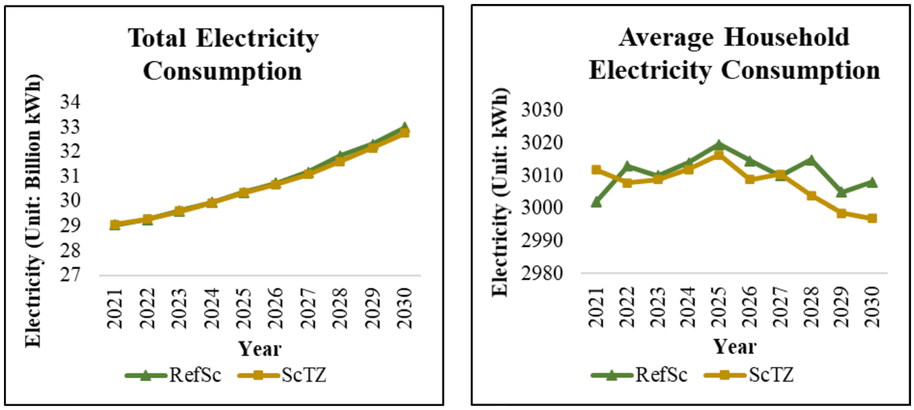
(d) *The Difference between RefSc and ScRet in Electricity Consumption Density in 2030*

Fig. 10 Spatial differences between ScRet and RefSc in population and energy consumption densities in 2030

by 2.55%. This was possibly because the larger working population increased the demand for residential facility in central, employment-dense districts. Due to the high housing prices in these areas, more households were pushed into the rental market, lowering the overall homeownership rate.

Figure 9 compares ScRet and RefSc in terms of aggregate and household-level electricity consumption in 2030. Under ScRet, the total residential and average electricity consumptions slightly decreased by 1.2% and 1.1% respectively. These declines were possibly driven by changes in energy consumption behaviors: the intensity of use of air conditioners for cooling decreased by 2.1%, and the intensity of cooking appliance use fell by 2.8%. These reductions might be attributed to the shorter time spent at home as the working population increases. In addition, although the homeownership decreased, the adoption rate of LED lighting technologies slightly rised from 68 to 69%, possibly because higher household income might have made households more willing to invest in energy-efficient appliances (Schleich, 2019).

In spatial terms, the delayed retirement policy also affects population distribution (through the residential location choice and real estate price model in SelfSim) and further associated electricity consumption



(a) Total Electricity Consumption *(b) Average Household Electricity Consumption*

Fig. 11 Influence of concentrating new facility development in Tongzhou (TZ) on domestic electricity consumption

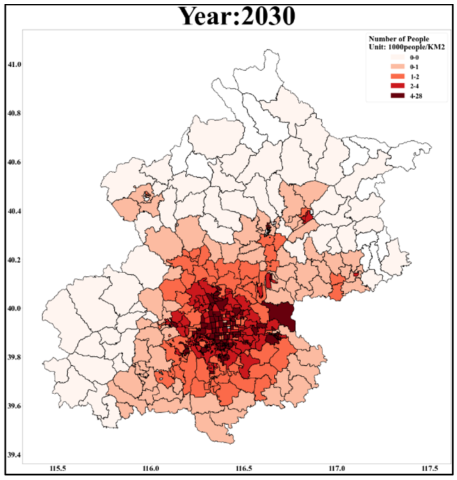
patterns. Figure 10 illustrates the spatial differences in 2030 between RefSc and ScRet. As shown in Fig. 10a and b, in ScRet, more population allocated in Haidian (HD), Xicheng (XC), Fengtai (FT) districts which offer more employment opportunities. This is because households evaluate the accessibility of residential facilities based on the commuting distance to the workplaces of household members in SelfSim. With more person agents remaining in the workforce under ScRet, residential facilities located closer to employment centers become more attractive due to higher accessibility scores. Consequently, electricity consumption densities in Xicheng, Haidian, Fengtai districts show a significant increase in ScRet (see Fig. 10c and d).

4.5.2 Scenario Tongzhou (ScTZ): Investigating the influence of the development of a new urban sub-center

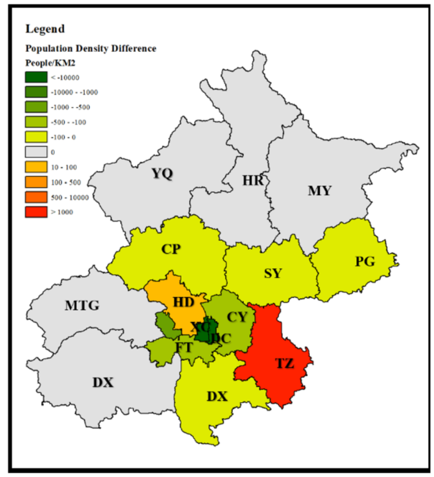
Apart from population dynamics, land use change could also be another factor which can greatly influence domestic energy consumption. As shown in RefSc (see Sect. 4.4.4), the development of new facilities may significantly influence the spatial pattern of domestic electricity consumption pattern. To further examine this effect, we designed a "what-if" scenario, Scenario Tongzhou (ScTZ), which explores the impact of concentrating new facility development in Beijing's sub-center, Tongzhou (TZ) district. Unlike RefSc, where new facilities are distributed citywide based on agents' demand, ScTZ assumes all new residential and commercial facilities are allocated exclusively to Tongzhou (TZ) during the simulation period.

Overall, ScTZ had almost the same total electricity consumption and average household electricity consumption as RefSc, suggesting that exclusively allocating new buildings to Tongzhou (TZ) would have little influence on energy consumption patterns at the macro level (see Fig. 11).

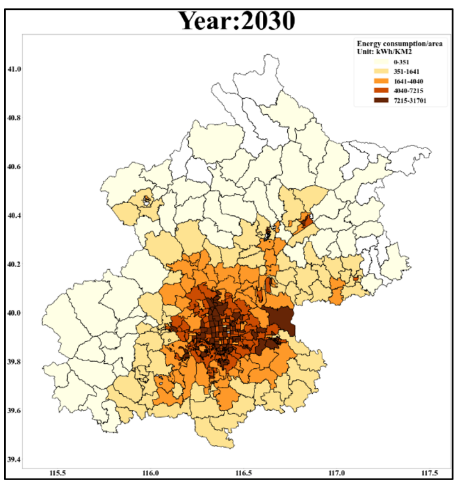
However, spatial outcomes revealed notable differences. As shown in Fig. 12a and b, by 2030, the population density in Tongzhou's (TZ's) central area became comparable to that of Beijing's core urban districts. While nearby districts (such as Dongcheng (DC) and Xicheng (XC)) experienced a noticeable reduction in population density. This spatial redistribution was primarily driven by two mechanisms within the real estate model (including residential location choice and real estate price model as well as firm/businessman location choice and commercial facility rent model). The concentration of newly developed residential facilities directly increased the likelihood that household agents would relocate to Tongzhou (TZ). In addition, the growing number of commercial facilities raised the probability that firm and businessman agents are located there. This results in a higher concentration of employment opportunities, which improves the accessibility of Tongzhou (TZ) and further encourages households to settle here. This spatial redistribution directly influenced electricity consumption patterns. As shown in Fig. 12c and d, domestic electricity consumption in Tongzhou (TZ) increased by 66% relative to RefSc, while Dongcheng (DC) and Xicheng (XC) saw decreases of 54% and 46%, respectively. These results suggested that prioritizing building development in Tongzhou (TZ) could effectively change population patterns, therefore easing electricity demand in overcrowded central districts.



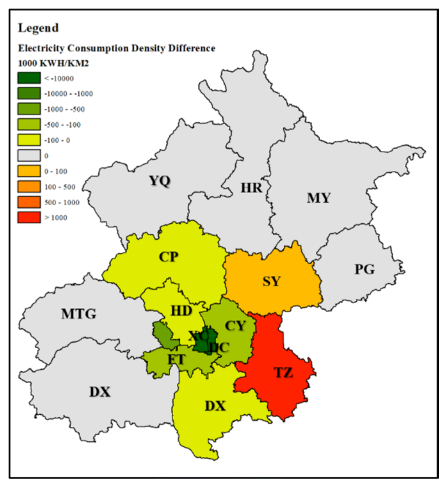
(a) Population Distribution in 2030



(b) The Difference between RefSc and ScTZ in Population Density in 2030



(c) Density of Electricity Consumption in 2030



(d) The Difference between RefSc and ScTZ in Density of Electricity Consumption in 2030

Fig. 12 Spatial differences between ScTZ and RefSc in population and energy consumption densities in 2030

5 Conclusions

This study developed SelfSim-Energy, a framework combining the urban dynamic models of SelfSim with a regression-based energy consumption model. SelfSim-Energy can simulate domestic electricity consumption within the context of urban evolution, capturing interactions between energy, population, and land use.

We applied SelfSim-Energy to Beijing, simulating the evolution of the urban system from 2021 to 2030 from a micro-perspective. We then developed two "what-if" scenarios—delaying retirement age, and concentrating facility development in Tongzhou—to demonstrate how urban dynamics would influence domestic energy consumption. Our results showed that domestic electricity consumption is closely related to other urban systems, highlighting the importance of considering urban dynamics when developing energy consumption models. In the reference scenario, total electricity consumption steadily increased, primarily driven by population growth and declining LED adoption rates (associated with a decrease in homeownership). Delaying retirement age slightly reduced overall electricity use while shifting demand towards districts offering more job opportunities, such as Xicheng and Haidian. Concentrating development in Tongzhou effectively redistributed energy demand by moving the population out of the central districts. This scenario demonstrated the potential of land use planning to balance spatial energy demand.

Our study points to important policy insights. Firstly, decreasing homeownership is associated with the lower adoption rate of energy-efficient appliances such as LED lighting. This is consistent with the principal agent problem (International Energy Agency, 2007) which describes how the interests of owners (landlords) and tenants are misaligned. Landlords are unwilling to bear upfront investment costs in energy efficiency that yield energy cost savings for tenants, while tenants have limited incentives to invest in properties they do not own. These "split incentives" need tackling through policy instruments such as targeted subsidies or incentive schemes for both landlords and tenants to promote the uptake of energy-efficient appliances (Wilson et al., 2015). Secondly, aging population and the policy of delaying retirement age alters the spatial pattern of electricity demand. The spatial distribution of the working population should be taken into consideration in urban and energy infrastructure planning. Thirdly, guiding new urban development to sub-centers can effectively help alleviate pressure on electricity systems in central districts.

SelfSim-Energy currently relies on a regression model of annual household electricity usage, and cannot capture intraday appliance usage patterns. Thus, this model is limited in modeling time-varying demand and peak hourly load that directly place significant stress on grid infrastructure. Despite this limitation, annual electricity consumption remains a useful indicator for infrastructure planning, as it reflects the long-term trend and spatial distribution of energy demand. These patterns help identify areas that are more likely to face electricity pressure in the future and can be used to assess how policies influence residential energy demand over time. To address the limitation, we will develop an activity-based model that could estimate electricity consumption based on appliance usage activities in future. This activity-based model would enable a more realistic simulation of residential load profile, and could explore how changes in out-home activity (such as change in workplace and shopping frequency) would influence domestic energy consumption. Another limitation is that the model treats the physical characteristics of the environment in a simplified way. In particular, it does not capture how buildings evolve over time or how they may interact with households (e.g., through changes in energy efficiency or retrofit decisions). Accounting for these processes would help better represent long-term changes in residential energy demand, and will be considered in future model development.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1007/s43762-026-00277-2.

Supplementary Material 1.

Acknowledgements
We thank the Shenzhen Park of Hetao Shenzhen-Hong Kong Science and Technology Innovation Cooperation Zone and this research has been supported by the "Theories for Spatiotemporal Intelligence and Reliable Data Analysis" (Project ID: HZQSWS-KCCYB-2024058), the MTR Research Funding Scheme (Grant No.: PTU-25012), the European Research Council (ERC) for the iDODDLE project (grant #101003083), the Shenzhen Municipal Science and Technology Innovation Commission (Grant No.: JCYJ20230807140401003), and the Research Grants from the Smart Cities Research Institute (Grant No.: CDAR and CDB9), the Department of Land Surveying and Geo-Informatics (Grant No.: WZ44, TD2P, TD0C and ZZVJ) and Research Institute for Sustainable Urban Development (Grant No.: BBWR) at the Hong Kong Polytechnic University.

Authors' contributions
Junbei Liu: Methodology, Software, Validation, Formal analysis, Visualization, Writing – original draft. Charlie Wilson: Methodology, Validation, Writing – review & editing. Ying Zhang: Software, Validation, Writing – review & editing. Chengxiang Zhuge: Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition.

Data availability
The data that has been used is confidential.

Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Received: 13 February 2026 Revised: 24 April 2026 Accepted: 8 June 2026
Published online: 22 June 2026

References
Alrobaian, A. A., & Alsagri, A. S. (2023). Multi-agent-based energy management for a fully electrified residential consumption. *Energy, 282*, Article 128852. https://doi.org/10.1016/j.energy.2023.128852
Anderson, J. E. (2011). The gravity model. *Annual Review of Economics, 3*(1), 133–160. https://doi.org/10.1146/annurev-economics-111809-125114
Ardakani, S. R., Hossein, S. M., & Aslani, A. (2018). Statistical approaches to forecasting domestic energy consumption and assessing determinants: The case of Nordic countries. *Strategic Planning for Energy and the Environment, 38*(1), 26–71. https://doi.org/10.1080/10485236.2018.12016689
Bardazzi, R., & Pazienza, M. G. (2020). When I was your age: Generational effects on long-run residential energy consumption in Italy. *Energy Research & Social Science, 70*, Article 101611. https://doi.org/10.1016/j.erss.2020.101611
Beckman, R. J., Baggerly, K. A., & McKay, M. D. (1996). Creating synthetic baseline populations. *Transportation Research Part A: Policy and Practice, 30*(6), 415–429. https://doi.org/10.1016/0965-8564(96)00004-3
Bedir, M., Hasselaar, E., & Itard, L. (2013). Determinants of electricity consumption in Dutch dwellings. *Energy and Buildings, 58*, 194–207. https://doi.org/10.1016/j.enbuild.2012.10.016
Beijing Municipal Bureau of Statistics. (2019). *Beijing Statistical Yearbook 2019*. https://nj.tjj.beijing.gov.cn/nj/main/2019-tjnj/zk/e/indexch.htm
Beijing Municipal Bureau of Statistics. (2021). *Beijing Regional Statistical Yearbook 2021*. https://nj.tjj.beijing.gov.cn/nj/qxnj/2021/zk/e/indexce.htm
Beijing Municipal Bureau of Statistics. (2024). *Beijing Statistical Bulletin on National Economic and Social Development for 2023*. Retrieved on 12th

August 2024 from https://tjj.beijing.gov.cn/zxfbu/202403/t20240319_3594001.html

Beijing Municipal Commission of Development and Reform. (2012). *Notice from the Beijing Municipal Commission of Development and Reform on the Implementation of a Tiered Electricity Pricing System for Residential Electricity Consumption in Beijing*. Retrieved on 14th August 2024 from https://fgw.beijing.gov.cn/fgwzwgk/2024zcwj/bwqtwj/201912/t20191226_3725245.htm

Beijing Municipal Commission of Development and Reform. (2024). *Beijing's Enhanced Energy Conservation Implementation Plan (2024 Edition)*. https://www.beijing.gov.cn/zhengce/zhengcefagui/202402/t20240202_3554355.html

Beijing Municipal Commission of Housing and Urban-Rural Development. (2023). *Beijing Regulations on the Management of Financial Incentives for Green Building Development*. Retrieved on 14th August 2024 from https://www.beijing.gov.cn/zhengce/zhengcefagui/201905/t20190522_60428.html

Bianco, V., Manca, O., & Nardini, S. (2009). Electricity consumption forecasting in Italy using linear regression models. *Energy, 34*(9), 1413–1421. https://doi.org/10.1016/j.energy.2009.06.034

Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32.

Cao, J., Choi, C. H., & Zhao, F. (2017). Agent-based modeling of the adoption of high-efficiency lighting in the residential sector. *Sustainable Energy Technologies and Assessments, 19*, 70–78. https://doi.org/10.1016/j.seta.2016.12.003

Castesana, P., & Puliafito, S. (2013). Development of an agent-based model and its application to the estimation of global carbon emissions. *Low Carbon Economy, 4*(4), 24–34. https://doi.org/10.4236/lce.2013.44A003

Chen, S., Yoshino, H., & Li, N. (2010). Statistical analyses on summer energy consumption characteristics of residential buildings in some cities of China. *Energy and Buildings, 42*(1), 136–146. https://doi.org/10.1016/j.enbuild.2009.07.003

Chingcuanco, F., & Miller, E. J. (2012). A microsimulation model of urban energy use: Modelling residential space heating demand in ILUTE. *Computers, Environment and Urban Systems, 36*(2), 186–194. https://doi.org/10.1016/j.compenvurbsys.2011.11.005

Cho, J. (2019). Does moving home affect energy use? Exploring the microdynamics of residential energy consumption in the United States. *Energy Research & Social Science, 54*, 85–95. https://doi.org/10.1016/j.erss.2019.04.003

Craig, T., Polhill, J. G., Dent, I., Galan-Diaz, C., & Heslop, S. (2014). The North East Scotland energy monitoring project: Exploring relationships between household occupants and energy usage. *Energy and Buildings, 75*, 493–503. https://doi.org/10.1016/j.enbuild.2014.02.038

Crawley, D. B., Lawrie, L. K., Winkelmann, F. C., Buhl, W. F., Huang, Y. J., Pedersen, C. O., Strand, R. K., Liesen, R. J., Fisher, D. E., & Witte, M. J. (2001). EnergyPlus: Creating a new-generation building energy simulation program. *Energy and Buildings, 33*(4), 319–331. https://doi.org/10.1016/S0378-7788(00)00114-6

Dai, T.-Y., Radhakrishnan, P., Nweye, K., Estrada, R., Niyogi, D., & Nagy, Z. (2023). Analyzing the impact of COVID-19 on the electricity demand in Austin, TX using an ensemble-model based counterfactual and 400,000 smart meters. *Computational Urban Science, 3*(1), 20. https://doi.org/10.1007/s43762-023-00095-w

Ding, Z., Hu, T., Li, M., Xu, X., & Zou, P. X. W. (2019). Agent-based model for simulating building energy management in student residences. *Energy and Buildings, 198*, 11–27. https://doi.org/10.1016/j.enbuild.2019.05.053

Du, H., Han, Q., de Vries, B., & Sun, J. (2025). Renewable energy adoption in urban residential communities in China: An agent-based model for assessing intervention impact. *Computers, Environment and Urban Systems, 121*, Article 102323. https://doi.org/10.1016/j.compenvurbsys.2025.102323

Ferrari, S., Zagarella, F., Caputo, P., & Bonomolo, M. (2019). Assessment of tools for urban energy planning. *Energy, 176*, 544–551. https://doi.org/10.1016/j.energy.2019.04.054

Fu, C., Wang, W., & Tang, J. (2014). Exploring the sensitivity of residential energy consumption in China: Implications from a micro-demographic analysis. *Energy Research & Social Science, 2*, 1–11. https://doi.org/10.1016/j.erss.2014.04.010

Heiple, S., & Sailor, D. J. (2008). Using building energy simulation and geospatial modeling techniques to determine high resolution building sector energy consumption profiles. *Energy and Buildings, 40*(8), 1426–1436. https://doi.org/10.1016/j.enbuild.2008.01.005

International Energy Agency. (2007). *Mind the Gap: Quantifying Principal Agent Problems in Energy Efficiency*. Retrieved on 21st April 2026 from https://www.iea.org/reports/mind-the-gap

International Energy Agency. (2022). *Surging electricity demand is putting power systems under strain around the world*. Retrieved on 19th June 2024 from https://www.iea.org/news/surging-electricity-demand-is-putting-power-systems-under-strain-around-the-world

International Energy Agency. (2024). *Electricity Market Report 2023*. https://www.iea.org/reports/electricity-market-report-2023

Jannuzzi, G. D. M., & Schipper, L. (1991). The structure of electricity demand in the Brazilian household sector. *Energy Policy, 19*(9), 879–891. https://doi.org/10.1016/0301-4215(91)90013-E

Jensen, T., Holtz, G., Baedeker, C., & Chappin, Émile. J. L. (2016). Energy-efficiency impacts of an air-quality feedback device in residential buildings: An agent-based modeling assessment. *Energy and Buildings, 116*, 151–163. https://doi.org/10.1016/j.enbuild.2015.11.067

Jensen, T., Holtz, G., & Chappin, É. J. L. (2015). Agent-based assessment framework for behavior-changing feedback devices: Spreading of devices and heating behavior. *Technological Forecasting and Social Change, 98*, 105–119. https://doi.org/10.1016/j.techfore.2015.06.006

Lee, T., Yao, R., & Coker, P. (2014). An analysis of UK policies for domestic energy reduction using an agent based tool. *Energy Policy, 66*, 267–279. https://doi.org/10.1016/j.enpol.2013.11.004

Liu, Junbei, Bu, Yilan, Zhou, Songzi, Zhang, Ying, Huang, Xingjun, Tang, Justin Hayse Chiwing, & Zhuge, Chengxiang. (2025). *SelfSim: An agent-based integrated framework for simulating the impacts of sustainable technologies, infrastructures and policies in smart cities*.Research Gate. https://doi.org/10.13140/RG.2.2.20784.01284

Ma, M., Tang, X., Shi, C., Wang, M., Li, X., Luo, P., & Zhang, B. (2023). Roadmap towards clean and low-carbon heating to 2060: The case of northern urban region in China. *Energy, 284*, Article 129181. https://doi.org/10.1016/j.energy.2023.129181

Macal, Charles M, & North, Michael J. (2005). *Tutorial on agent-based modeling and simulation*. Paper presented at the Proceedings of the Winter Simulation Conference, 2005. https://doi.org/10.1109/WSC.2005.1574234

Palmer, J., Sorda, G., & Madlener, R. (2015). Modeling the diffusion of residential photovoltaic systems in Italy: An agent-based simulation. *Technological Forecasting and Social Change, 99*, 106–131. https://doi.org/10.1016/j.techfore.2015.06.011

Parti, M., & Parti, C. (1980). The total and appliance-specific conditional demand for electricity in the household sector. *The Bell Journal of Economics*. https://doi.org/10.2307/3003415

Rahmati, B., Rabiei-Dastjerdi, H., Bibri, S. E., Aghajani, M. A., & Kazemi, M. (2024). Reducing urban energy consumption and carbon emissions: A novel GIS-based model for sustainable spatial accessibility to local services and resources. *Computational Urban Science, 4*(1), 37. https://doi.org/10.1007/s43762-024-00139-9

Rosenberg, E. (2014). Calculation method for electricity end-use for residential lighting. *Energy, 66*, 295–304. https://doi.org/10.1016/j.energy.2013.12.049

Santamouris, M., Kapsis, K., Korres, D., Livada, I., Pavlou, C., & Assimakopoulos, M. N. (2007). On the relation between the energy and social characteristics of the residential sector. *Energy and Buildings, 39*(8), 893–905. https://doi.org/10.1016/j.enbuild.2006.11.001

Schleich, J. (2019). Energy efficient technology adoption in low-income households in the European Union-What is the evidence? *Energy Policy, 125*, 196–206. https://doi.org/10.1016/j.enpol.2018.10.061

Schubert, E., Sander, J., Ester, M., Kriegel, H. P., & Xu, X. (2017). DBSCAN revisited, revisited: Why and how you should (still) use DBSCAN. *ACM Transactions on Database Systems (TODS), 42*(3), 1–21. https://doi.org/10.1145/3068335

Shabunko, V., Lim, C. M., & Mathew, S. (2018). EnergyPlus models for the benchmarking of residential buildings in Brunei Darussalam. *Energy and Buildings, 169*, 507–516. https://doi.org/10.1016/j.enbuild.2016.03.039

Song, S.-Y., & Leng, H. (2020). Modeling the household electricity usage behavior and energy-saving management in severely cold regions. *Energies, 13*(21), 5581. https://doi.org/10.3390/en13215581

Song, S., Leng, H., & Guo, R. (2022). Multi-agent-based model for the urban macro-level impact factors of building energy consumption on different types of land. *Land, 11*(11), Article 1986. https://doi.org/10.3390/land11111986

Swan, L. G., & Ugursal, V. I. (2009). Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable & Sustainable Energy Reviews, 13*(8), 1819–1835. https://doi.org/10.1016/j.rser.2008.09.033

The Central People's Government. (2023). *Total electricity consumption increased by 3.6% year-on-year in 2022*. Retrieved on 19th June 2024 from https://www.gov.cn/xinwen/2023-01/18/content_5737694.htm

Tian, S., & Chang, S. (2020). An agent-based model of household energy consumption. *Journal of Cleaner Production, 242*, Article 118378. https://doi.org/10.1016/j.jclepro.2019.118378

Tian, S., Lu, Y., Ge, X., & Zheng, Y. (2021). An agent-based modeling approach combined with deep learning method in simulating household energy consumption. *Journal of Building Engineering, 43*, Article 103210. https://doi.org/10.1016/j.jobe.2021.103210

Tirumalachetty, Sumala, Kockelman, K, Kumar, Saurabh, & Forecaster, Travel Demand. (2009). *Micro-simulation models of urban regions: anticipating greenhouse gas emissions from transport and housing in Austin, Texas*. Paper presented at the 88th Annual Meeting of the Transportation Research Board, washington DC. https://www.researchgate.net/publication/228667311

Waddell, P. (2002). UrbanSim: Modeling urban development for land use, transportation, and environmental planning. *Journal of the American Planning Association, 68*(3), 297–314. https://doi.org/10.1080/01944360208976274

Wang, D., & Yuan, C. (2018). Modeling and forecasting household energy consumption and related CO2 emissions integrating UrbanSim and transportation models: An Atlanta BeltLine case study. *Transportation Planning and Technology, 41*(4), 448–462. https://doi.org/10.1080/03081060.2018.1453917

Williamson, P., Birkin, M., & Rees, P. H. (1998). The estimation of population microdata by using data from small area statistics and samples of anonymised records. *Environment and Planning A, 30*(5), 785–816. https://doi.org/10.1068/a300785

Wilson, C., Crane, L., & Chryssochoidis, G. (2015). Why do homeowners renovate energy efficiently? Contrasting perspectives and implications for policy. *Energy Research & Social Science, 7*, 12–22. https://doi.org/10.1016/j.erss.2015.03.002

Yu, P., Zhang, L., Zhang, C., & Yu, P. (2025). Urban residential energy consumption under extreme temperatures in China: Asymmetric patterns, heterogeneous drivers, and adaptive zoning strategies. *Sustainable Cities and Society*. https://doi.org/10.1016/j.scs.2025.106976

Zhang, T., Siebers, P.-O., & Aickelin, U. (2012). A three-dimensional model of residential energy consumer archetypes for local energy policy design in the UK. *Energy Policy, 47*, 102–110. https://doi.org/10.1016/j.enpol.2012.04.027

Zhuge, C., & Shao, C. (2018). Agent-based modelling of purchasing, renting and investing behaviour in dynamic housing markets. *Journal of Computational Science, 27*, 130–146. https://doi.org/10.1016/j.jocs.2018.05.007

Zhuge, C., & Shao, C. (2019). Agent-based modelling of office market for a land use and transport model. *Transportmetrica b: Transport Dynamics*. https://doi.org/10.1080/21680566.2019.1589599

Zhuge, C., Shao, C., Gao, J., Dong, C., & Zhang, H. (2016). Agent-based joint model of residential location choice and real estate price for land use and transport model. *Computers, Environment and Urban Systems, 57*, 93–105. https://doi.org/10.1016/j.compenvurbsys.2016.02.001

Zhuge, C., Shao, C., Wang, S., & Hu, Y. (2018a). An agent- and GIS-based virtual city creator: A case study of Beijing, China. *Journal of Transport and Land Use, 11*(1), 1231–1256.

Zhuge, C., Shao, C., & Wei, B. (2018b). An agent-based spatial urban social network generator: A case study of Beijing, China. *Journal of Computational Science, 29*, 46–58. https://doi.org/10.1016/j.jocs.2018.09.005

Publisher's Note