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An agent-based model of household energy consumption

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ABSTRACT

How to increase clean energy utilization is a key issue in household energy consumption analysis aimed at alleviating air pollution and improving the health of residents. Clean energy substitution is a complex decision process between related stakeholders, and is affected by a combination of factors such as geographical location and household income. To evaluate the potential of clean energy promotion to contribute to better policy decisions and measures, an agent-based household energy consumption model is established to capture the group habits of different stakeholders and the impact mechanism of critical influential factors. Multi-layered structures including various types of households and energy consumption devices are modeled. The experimental results of several scenario analyses show that increased income, improved technology and subsidies from local governments can influence clean energy substitution in the household in various ways. These findings provide a better understanding of the energy cleaning process and decision-making support for governments.

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1. Introduction

The residential sector has become the second largest energy consumer (behind the industrial sector) in China, accounting for 12.44% of final energy consumption in 2016 (Department of Energy StatisticsNational Bureau of Statistics, 2017). Bulk coal consumption in the residential sector is a key issue for clean energy substitution and environment governance, as it has been identified as one of the major sources of air pollutants (NRDC, 2017). Stringent policies of “replacing coal with electricity” and “replacing coal with gas” have been promoted in the Beijing–Tianjin–Hebei region and surrounding areas in China, while considerable debate has arisen in recent years regarding the challenges in terms of affordability. It is argued that to increase clean energy utilization, a behavior-based analysis is necessary.

Incentive policies in relation to clean energy substitution should consider differences of price affordability or motivation (Liu, 2017; Mi et al., 2016) among residents to evaluate the expected effectiveness. Various factors that affect residents’ energy consumption have been studied including climate, household structure (Jones et al., 2015; Yu et al., 2011), income (Porse et al., 2016; Yun and Steemers, 2011; Zhou and Teng, 2013), and other factors (Ouyang and Hokao, 2009; Tong et al., 2017). These analyses are generally conducted by using statistical approaches or regression analysis (Wei et al., 2017) which have provided a basic understanding of the factors affecting household energy consumption. However, the classical methods are preferred to be defined at the aggregated system level, with limited ability to explore the deep mechanisms involved in disaggregated individual behaviors (Parunak et al., 1998).

An agent-based model is a method focusing on the individual entities (Gustafsson and Sternad, 2010; Macal and North, 2005), and can represent and predict complex group behaviors through the simulation of individual behaviors. The agent-based model is widely used in the social sciences (Linkola et al., 2013), where it is used to model interactions between agents and their environments (Bousquet and Le Page, 2004). In the energy and environmental research fields, many agent-based models have been proposed. Dedurana et al. (2014) proposed an agent-based method to model generalized energy networks, which can be used for power flow calculations for electrical fluids and several additional energy

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carriers. Neshat and Amin-Naseri (2015) proposed a two-sided agent-based framework for sustainable generation expansion planning. MBODJI et al. (2016) used the multi-agent approach to manage a hybrid electrical system by modeling each production and consumption source through an agent to optimize the use of the electrical system in terms of both the energy level and the production cost. Hofer et al. (2018) developed an agent-based model incorporating empirical data about the mobility behavior to calculate the traveled routes and the resulting emissions. FICHERA et al. (2018) built a multi-layer agent-based model to simulate the insertion of renewable-based energy systems into urban territories. Peng et al. (2019) used an agent-based model to study three regions' SO_2 emissions trading processes in China. Zhuge et al. (2019) used an agent-based integrated urban model to investigate the potential expansion and impacts of Electric Vehicle market in Beijing, China at the micro level.

Although there have been numerous achievements in multiple fields, only a few studies have analyzed household behavior, not to mention household energy consumption. Tong et al. (2018) developed an agent-based model to identify the key factors involved in changing behaviors in post-consumer recycling in a residential community in Beijing. Luo et al. (2019) developed an agent-based model of a waste household appliance recovery system. ROBINSON et al. (2015) used an agent-based model to analyze the role of energy service companies in the household market.

This study aims to develop an extendable agent-based model of household energy consumption, which can simulate the consumption of each fuel type at the household level to identify the influence mechanism of different factors in energy consumption.

In this study, the concept of a region is defined and used to store and manage households with the same geographic characteristics. Households located in the same region have similar energy consumption habits, which can be modified based on household income. To simulate household energy consumption, five types of agents are modeled in detail and two dynamic change mechanisms are introduced. The Repast Simphony (Collier, 2003; Repast Suite Documentation, 2019) platform and Java language are used to implement the model. Repast Simphony is written in Java and offers a larger extension than other platforms (Xu et al., 2003), enabling the analysis of more complex functions.

The rest of the paper is organized as follows. In Section 2, the study framework and methods are presented. In Section 3, several experiments are outlined based on various scenarios. In Section 4, the results of the experiments are discussed. In Section 5, a brief conclusion is presented summarizing the results.

2. Framework and methods

2.1. The structure of the agent-based household energy consumption model

The model is composed of five kinds of agents, namely, region, household, operator, device, and fuel. Based on an object-oriented programming approach, each agent is composed of attributes and behaviors which can be presented in the form of member variables and member functions of objects.

2.1.1. Regions

Because of the vast territory, household energy demand differs significantly in various places in China. The region agent is used to represent geographical difference, especially the climate conditions of each region. In line with the building climate demarcation, the regions are divided into 7 types as shown in Fig. 1, including severe cold (SC), severe cold-cold (SCC), cold (C), cold-cold winter hot summer (CHSCW), cold winter hot summer (HSCW), hot summer and warm winter (HSWW), and mild (W) (Huo et al., 2018). Generally, more heating is needed in the north than in the south in China.

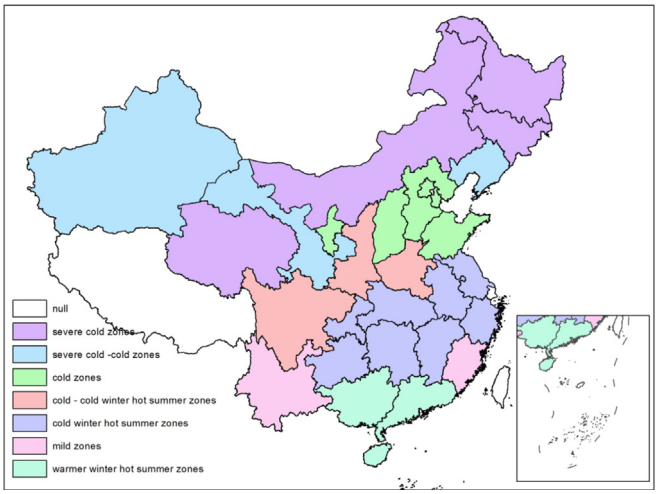


Fig. 1. Regional classification of China based on heating requirements.

Meanwhile, the region agent is also modeled as the environment to determine the temporal change and temperature change received by households. The environment is an important concept in an agent-based model. In our model, the temperature of a region changes every hour, and this information is received by households who must decide whether to turn on their air conditioner.

The attributes and behaviors of regions are shown in Table 1.

2.1.2. Households

The household, which is the core agent, represents the home of occupants where the energy consumption occurs in the form of fuel consumed by devices for a certain duration at a certain time (see Fig. 2). A household can only be in one region. Households with similar characteristics have similar energy consumption habits, which can be described in terms of device ownership probability and device operational probability. The device ownership probability is defined as an attribute of household, and the device operational probability is defined based on the use frequency of device as described below.

The attributes and behaviors of households are shown in Table 2.

2.1.3. Operators

Five types of operators are considered in the study, including cooking, heating, water heating, cooling, and electric appliance (Zheng et al., 2017). Electric appliances can be further divided into freezing appliances (fridges and freezers that run continuously), clothes cleaning appliances (washers and dryers that are not switched on every day) and other appliances (devices that are switched on and off every day, e.g., TV). Unlike real-world family members, operators can only operate the devices with which they are associated. The household cannot operate devices directly, only through its associated operators. The attributes and behaviors of operators are shown in Table 3.

2.1.4. Devices and fuel

Devices are direct energy consumers. A device can consume only one type of fuel, thus, devices that consume two or more fuel types in the real world are divided into multi-devices. Further, a device can only be associated with one operator. These devices determine the amount and structure of energy consumption of the

Table 1
Attributes and behaviors of regions.

Name	Description
Attributes	
development level	whether the current region is urban or rural
climate zone	whether the current region is severe cold, severe cold-cold, cold, cold-cold winter hot summer, cold winter hot summer, hot summer and warm winter, or mild
household number	the number of households in the current region. It is designed that the household number in the same climate zone is fixed, but with the process of urbanization, the household number in urban regions will increase while rural regions are opposite.
hour	the hour in the current region (24 h a day)
day	the day in the current region (30 days a month for modeling convenience)
month	the month in the current region (12 months a year)
season	the season in the current region: spring, summer, autumn or winter.
temperature	the temperature by hour in the current region.
household	Whether the household belongs to the current region?
Behaviors	
initial region	determine the basic information of the current region
generate households	generate households that belong to the current region
season change	notify the households in the region when the season changes
temperature change	notify the households when the temperature changes

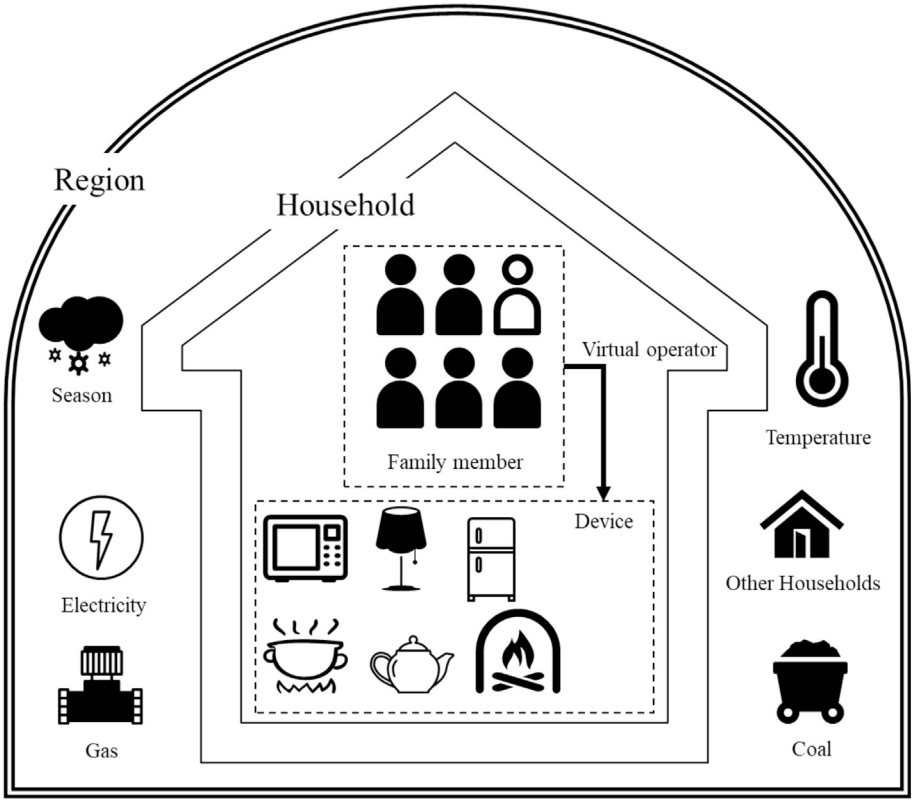


Fig. 2. Household energy consumption.

household. The model contains 35 kinds of devices and 10 kinds of fuels (see Table 4).

The attributes and behaviors of devices are shown in Table 5.

2.2. The modeling procedure

2.2.1. The overall process

The entire process of energy consumption in a region contains generating households, associating operators with households, executing operations, associating device and fuel with operator and subsequently operating device and fuel (Fig. 3). For a household l in region r, if the hourly energy consumption of device D associated with operator o in household is $HE_{r,l,o,D}$, and the duration of operation at the h hour on the d day in the m month is $Dur_{r,l,o,D,m,d,h}$, the annual energy consumption of device D and Operator o will be

$$E_{r,l,o,D} = \sum_{m}\sum_{d}\sum_{h} Dur_{r,l,o,D,m,d,h} * HE_{r,l,o,D} \quad (1)$$

The annual energy consumption of household h will be

Table 2
Attributes and behaviors of households.

Name	Description
Attributes	
income	the annual income
income growth	the annual income growth rate from the base year to the simulated year
operator	whether one operator is belonging to the current household
area	the heating area
device ownership	the probability that a device is owned by the current household
Behaviors	
associate operators	associate available operators
execute operations	traverse the associated operators and execute them in sequence

Table 3
Attributes and behaviors of operators.

Name	Description
Attributes	
active months	the months the operator are executed
active days	the days the operator are executed
active hours	the hours the operator are executed
device operation	the devices which can be executed by the operator
Behaviors	
associate devices	associate executable devices
activate months	determine the active months
activate days	determine the active days
activate hours	determine the active hours
operate devices	traverse the associated devices and operate them in sequence.

Table 4
Devices and fuels included in the model and the associated operators.

Operator	Device (Fuel)	
Cooking	pipeline gas cooker (pipeline gas)	electric kettle (electricity)
	pipeline coal gas cooker (pipeline coal gas)	oil stove (oil)
	bottled gas cooker (bottled gas)	biogas stove (biogas)
	electric cooker (electricity)	solar stove (solar)
	microwave oven (electricity)	firewood stove (firewood)
	oven (electricity)	rice cooker (electricity)
	coal stove (coal)	pressure cooker (electricity)
Heating	Centralized heating (thermal power)	coal heating boiler (coal)
	firewood heating stove (firewood)	firewood bed (firewood)
	coal heating stove (coal)	air conditioning (electricity)
	electric heating stove (electricity)	gas heating stove (pipeline gas)
	firewood heating boiler (firewood)	
Water Heating	solar water heater (solar)	electric water heater (electricity)
	pipeline gas water heater (pipeline gas)	bottled gas water heater (bottled gas)
Cooling	air conditioning (electricity)	
Appliance	Television (electricity)	Light (electricity)
	computer (electricity)	
Freezing	fridge (electricity)	freezer (electricity)
Clothes cleaning	washer (electricity)	dryer (electricity)

Table 5
The attributes and behaviors of devices.

Name	Description
Attributes	
fuel	the fuel type consumed by the current device
active months	the months the device is used
active days	the days the device is used
active hours	the hours the device is used.
active durations	the durations the device is used in an active hour
hourly power	the hourly energy consumption of the device, calculated according to “China Household Energy Consumption Report 2016”
Behaviors	
activate months	determine the active months
activate days	determine the active days
activate hours	determine the active hours
activate duration	determine the active durations in active hours
consume fuel	fuel is consumed by device

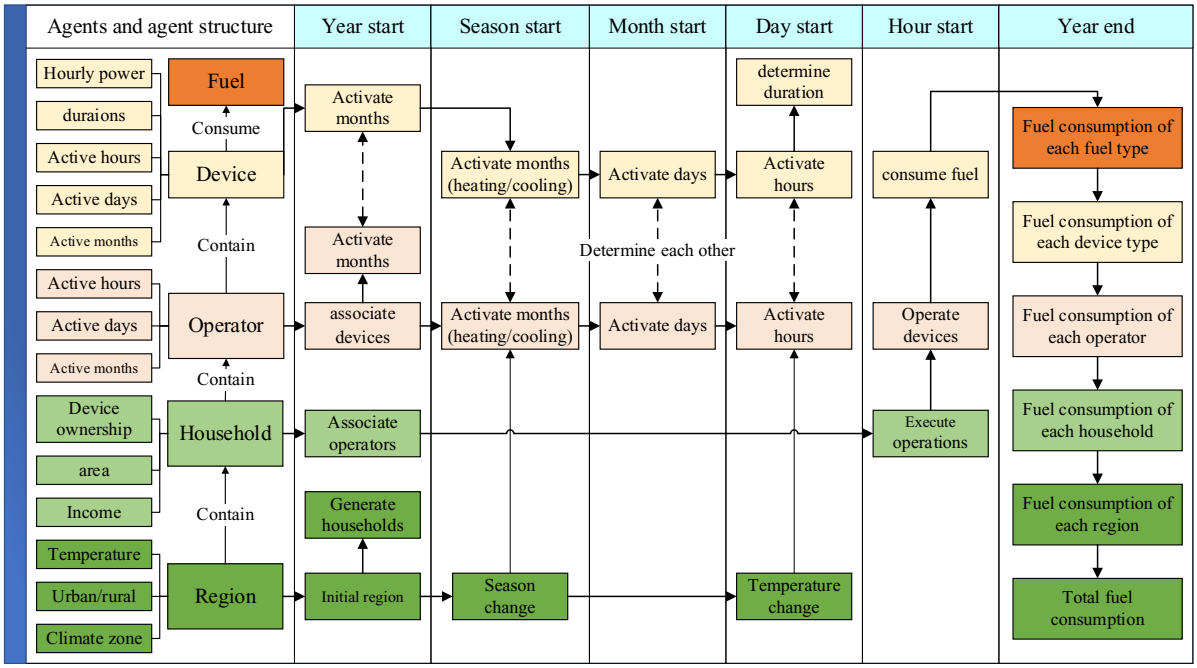


Fig. 3. The structure and process of the agent-based household energy consumption model.

$$E_{r,l} = \sum_{o}\sum_{D}\sum_{m}\sum_{d}\sum_{h} Dur_{r,l,o,D,m,d,h} * HE_{r,l,o,D} \quad (2)$$

Therefore, the annual energy consumption of region r will be

$$E_r = \sum_{l}\sum_{o}\sum_{D}\sum_{m}\sum_{d}\sum_{h} Dur_{o,D,m,d,h,l,r} * HE_{o,D,l,r} \quad (3)$$

The annual energy consumption of region r in the real world can be estimated as

$$E_{r,w} = \gamma * E_r \quad (4)$$

The γ is the ratio between the number of households in the real world and the number of households in the region.

The device operation rules are described by the probability distributions based on the surveyed samples. The activation strategies for the months, days, and hours of the various operators are shown in Table 6. For some operators, the active months, days, and hours will be set as a constant. For example, cooking appliances will be operated each month. While for other operators, the probability distributions are used to activate months, days, and hours are obtained from surveyed sample. Few devices are operated based on environmental information. For example, whether the air conditioner will be turned on depends on the temperature in the environment.

2.3. The behavior change mechanism

The change of household energy consumption habit can be described in terms of behavior changes of various modeled agents. To simulate the clean energy substitution, one income-driven mechanism and one device-replacement mechanism are proposed in the study.

2.3.1. Income-driven mechanism

Income is an important factor affecting residents' energy consumption behavior. Whether the increase of residents' income will increase the proportion of clean energy consumption is a question worthy of simulation. An income-driven mechanism is modeled here based on the conditional probability of device ownership at a given income level. It is assumed that the device ownership is related to the income level of household. With the changing of income distribution of households, the device ownership of household and corresponding device operation and fuel consumption will be changed.

The income level is divided into $IL_i, i = 1, 2, \ldots I$. For a household in $Region_r, r = 1, 2, \ldots, R$, the number of households is assumed to be H_r, and The probability that the income level of IL_i in $Region_r$ is $P(IL_i) = H_{i,r}/H_r$, and the probability that the household with income level IL_i owned device D is $P(D, IL_i) = H_{i,r,D}/H_r$. The probability that a device D is owned by a household at a given income level IL_i is

Table 6
Activation strategies for various operators.

Virtual operator	Months activation	Days activation	Hours activation	Duration activation
Cooking	12 months	Stochastic	Stochastic	Stochastic
Heating	Winter	30 days	24 h (Centralized Heating)/Stochastic	One hour
Cooling	Stochastic	Stochastic	Base on temperature	Stochastic
Water Heating	12 months	Stochastic	Stochastic	Stochastic
Freezing	Stochastic	30 days	Stochastic	Stochastic
Clothes cleaning	12 months	Stochastic	Stochastic	Stochastic
Other Appliances	12 months	30 days	Stochastic	Stochastic

$$P(D|IL_i) = P(D, IL_i) \Big/ P(IL_i) = \frac{H_{i,r,D}}{H_r} \Big/ \frac{H_{i,r}}{H_r} \quad (5)$$

It is assumed that $H_{i,r,D}/H_r$ is approximately equal to $H_{i,D}/H$ here due to insufficient sample size.

2.3.2. The device-replacement mechanism

Besides income, technology development and government subsidies can also affect residents' device ownership decisions. To further explore the influence mechanism of these factors, a device-replacement mechanism is designed, and the replacement of coal-powered devices by electricity-powered devices is modeled in detail.

For a given household, the energy provided by coal in the base year is E_b kgce, and the price of coal is C_c yuan/kgce, while the price of electricity is C_e yuan/kgce. The simulations are carried out for the base year Y_b and the scenario year Y_s. Annual income in the base year is I_b *yuan*, and the annual growth rate of income is R_b. The percentage of the increased income that a household is willing to pay for device replacement is α, while the subsidy paid by the government is S *yuan*.

If the coal-powered device is replaced by an electricity-powered device, the energy originally provided by coal will now be provided by electricity. The cost of household is given by

$$Cost_{c,e} = E_b * C_e \quad (6)$$

The potential budget of the household is given by

$$Budget_{c,e} = E_b * C_c + I_b * \left((1 + R_b)^{(Y_s - Y_b)} - 1\right) * \alpha + S \quad (7)$$

k is the period from base year to simulated year. For a household with a smaller $Cost_{c,e}/Budget_{c,e}$ ratio, the expense will be relatively more bearable, and thus the willingness to replace the device will be greater.

The probability that a household will replace a coal-powered device with an electricity-powered device is defined as follows:

$$P_{c,e} = \begin{cases} 1 - \beta * Cost_{c,e} \Big/ Budget_{c,e} & Cost_{c,e} \Big/ Budget_{c,e} < \dfrac{1}{\beta} \\ 0 & Cost_{c,e} \Big/ Budget_{c,e} \geq \dfrac{1}{\beta} \end{cases} \quad (8)$$

If the $Cost_{c,e}/Budget_{c,e}$ is in the range of $[0, 1/\beta)$, the value of $P_{c,e}$ will be in the range $[1, 0)$, and thus β defines the threshold $Cost_{c,e}/Budget_{c,e}$ ratio beyond which a device will be replaced. Only if the value of $Budget_{c,e}$ is greater than $\beta * Cost_{c,e}$ is, it is possible to replace the device.

3. Verification

3.1. Static verification

The energy consumption in the base year (2014) is simulated in the static verification. The energy consumption habit of the household is set in terms of the device ownership probability and device operation probabilities obtained from the sample provided by CRECS 2014 (China Residential Energy Consumption Survey, 2014). The basic parameters setting are shown in Table 7.

As shown in Fig. 4, the annual energy consumption distribution by household in the simulation results is well consistent with that of the sample. Most households' annual energy consumption is below 1000 kgce.

The proportions of household energy consumption (coal, pipeline coal gas, bottled natural gas, pipeline natural gas, heat, and electricity) are also compared with the statistical data. Because of the characteristics of the agent-based model, the simulation results in different experiments (see Fig. 5, exp. n means the nth experiment) are not constant but remained within a certain range in each case. The average result of all experiments (see Fig. 5, exp. avg) is also well consistent with that of statistical data. For heat, electricity, coal, bottled natural gas, and pipeline natural gas, the deviations between the average simulated result and the statistical data are −1%, −1%, 2%, 3%, and −3%, respectively.

3.2. Dynamic verification

The energy consumption in the period of 2009–2016 are simulated in the dynamic verification. In the simulated year, the income of the household is changed based on the statistical data. The energy consumption habit of the household is updated following the income-driven mechanisms. The average consumptions in the simulated year are converted to relative values, by taking 1.0 as consumption in the base year.

The simulation results for coal, pipeline natural gas, heat, and electricity fit well to the historical data (see Fig. 6). There has been consistent growth in the consumption of pipeline natural gas, heat and electricity from 2009 to 2016, while a tendency of increasing first and then declining in the coal consumption. The simulation results replicate these trends very well.

4. Scenario analysis

4.1. Scenario settings

To forecast the consumption trends of household energy consumption and further explore the effects of specific factors, we designed seven scenarios. The scenario 1 is designed to conduct energy consumption simulation under the income-driven mechanism. The scenarios 2–7 are designed to conduct energy consumption simulation under the device-replacement mechanism. Among them, scenarios 2–4 are focusing on the single factor, scenarios 5 and 6 are focusing on the two combined factors simulation, and the scenario 7 is focusing on the comprehensive simulation of all three factors. The basic parameters setting can be found in Table 7, while other scenario related parameters are defined in Table 8. The average annual income growth rate for urban and rural regions are set as 5% per year and 9% per year, respectively, based on the average increase rate of China Statistical Yearbook 2014–2017.

The subsidy is a policy measures for replacing coal with electricity in the Beijing-Tianjin-Hebei and surrounding areas. According to the NRDC (2017), the current subsidies are varied from 600 yuan to 2400 yuan per household. Therefore, five level of subsidies (S) (600, 1000, 1500, 2000, 2400 yuan) are tested here. Technology improvement in the electricity heating is simulated in the form of a reduction in the price of electricity (C_e). In the long term, the wide promotion of air source heat pump is anticipated, therefore, a continuous decrease of electricity price from 5 yuan/kgce to 2 yuan/kgce is assumed, and various values of C_e are set.

4.2. Simulation results

4.2.1. Income driven mechanism

The results (see Fig. 7) show that, the consumption of coal and firewood are expected to continue to decline from the peak reached in 2011. The consumption of solar power will continue to grow while the consumption of biogas will continue to decline. The consumption of coal will maintain a steady downward trend to approximately 80% of the 2014 consumption level by 2025.

Table 7
The parameter settings for the verification.

Parameters	Static verification	Dynamic verification	
H_s	3600	3600	total number of households in the model
Y_b	2014	2014	The base year in which the sample is surveyed
I_b	calculated by author[1]	calculated by author[1]	The annual income of households in the base year
Y_s	2014	2009–2016	The simulated year
HP_r	Survey data 2014[2]	Survey data 2009-2016[2]	The number of households in region r
TP_r	survey data 2014[3]	survey data 2009-2016[3]	The temperature in region r
$R_{b,ub}$	0	survey data 2009-2016[4]	the annual income growth rate for urban regions
$R_{b,rr}$	0	survey data 2009-2016[4]	the annual income growth rate for rural regions
PB_{eq}	calculated by author[5]	calculated by author[6]	The device ownership probabilities
Repetition	20 times	20 times per year	The repeated times for each experiment
Description	1 set randomly according to the sample provided by CRECS 2014 (China Residential Energy Consumption Survey) 2 calculated based on the Population at Year-end by Region from Almanac of China's Population 3 set randomly based on the Monthly Maximum and Minimum Temperature from China Meteorological Yearbook 4 calculated according to the "Per Capita Disposable Income of Households by Region" from China Statistical Yearbook [5] set randomly according to the regional distribution provided by CRECS 2014 6 modified according to income-driven behavior change mechanism based on PB_{eq} in the base year		

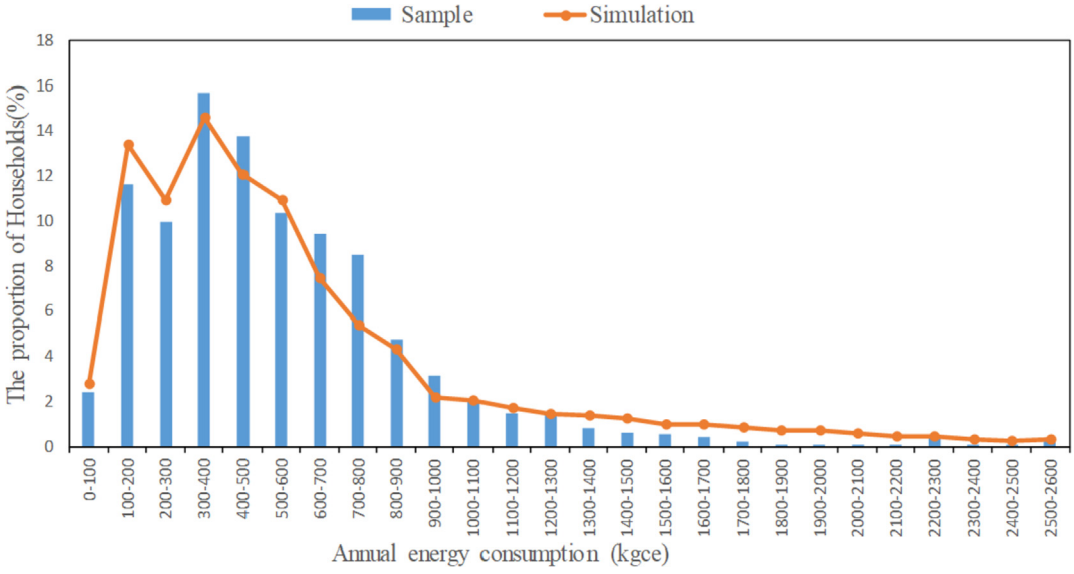


Fig. 4. Annual energy consumption distribution by household.

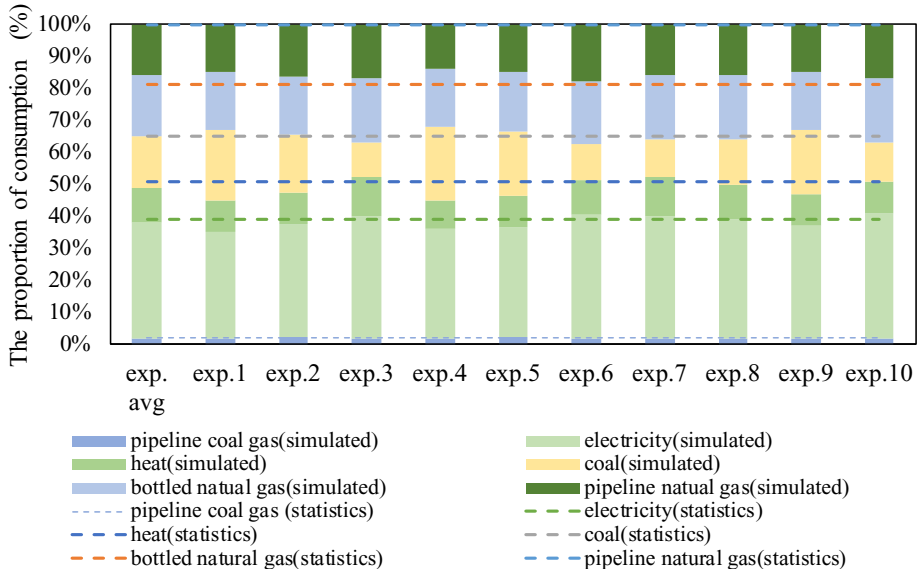


Fig. 5. Energy consumption in the base year.

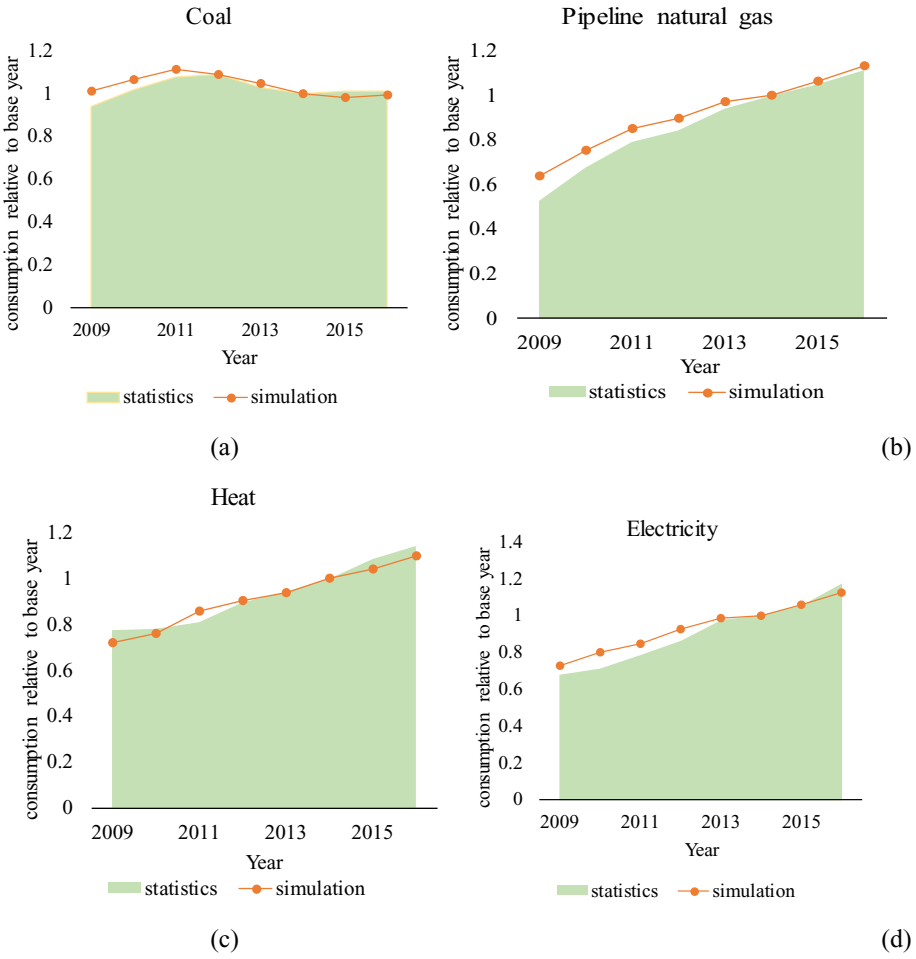


Fig. 6. The comparison between the simulation and statistical yearbook data.

Table 8
Parameter settings for different scenarios.

Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Mechanism	Income-driven	Device-replacement					
Influence factor	Income growth	Income growth	Subsidies	Technology improvement	Income growth and Subsidies	income growth and technology improvement	Comprehensive
$R_{b,ub}$	$1.05^{Y_s-y_b}-1$	$1.05^{Y_s-y_b}-1$	0	0	$1.05^{Y_s-y_b}-1$	$1.05^{Y_s-y_b}-1$	$1.05^{Y_s-y_b}-1$
$R_{b,rr}$	$1.09^{Y_s-y_b}-1$	$1.09^{Y_s-y_b}-1$	0	0	$1.09^{Y_s-y_b}-1$	$1.09^{Y_s-y_b}-1$	$1.09^{Y_s-y_b}-1$
α		0.05	0.05	0.05	0.05	0.05	0.05
S	0	0	600/1000/1500/2000/2400	0	600/1000/1500/2000/2400	0	1000
C_c	1.0	1.0	1.0	1.0	1.0	1.0	1.0
C_e	5.0	5.0	5.0	5.0/4.7/4.4/4.1/3.8/3.5/3.2/2.9/2.6/2.3/2.0	5.0	4.7/4.1/3.5/2.9	4.7/4.1/3.5/2.9
β	1.0	1.0	1.0	1,0.25,0.2	1.0	1.0	1.0
Repetition	20	20	20	20	20	20	20

This may be an indication that, as living standards improve, residents will spontaneously move toward clean energy consumption, but the clean energy that is not convenient to use (such as household biogas) may still be unpopular.

4.2.2. Device-replacement mechanism: single factor

In the scenarios that analyze the effect of single factor, the effect of income growth, subsidies and technology improvement are simulated.

Only considering the effect of income growth (see Fig. 8 a), the total coal consumption in 2025 will be 80% of that in the base year. Only considering the effect of subsidies (see Fig. 8 b), coal consumption will be 70% of that in the base year, when the subsidies are 2400 yuan. The income growth and subsidies have both nonlinear impact on the device replacement. Generally, more income and subsidies will bring about more reduction in coal

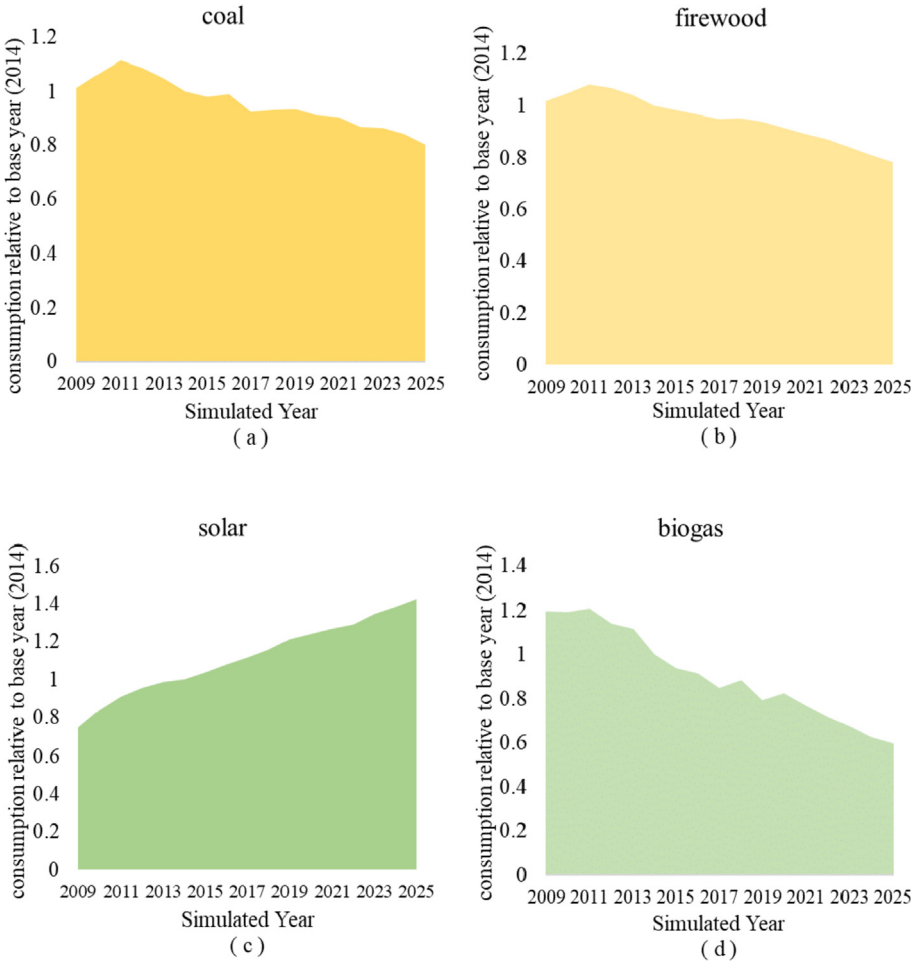


Fig. 7. Simulation of future energy consumption.

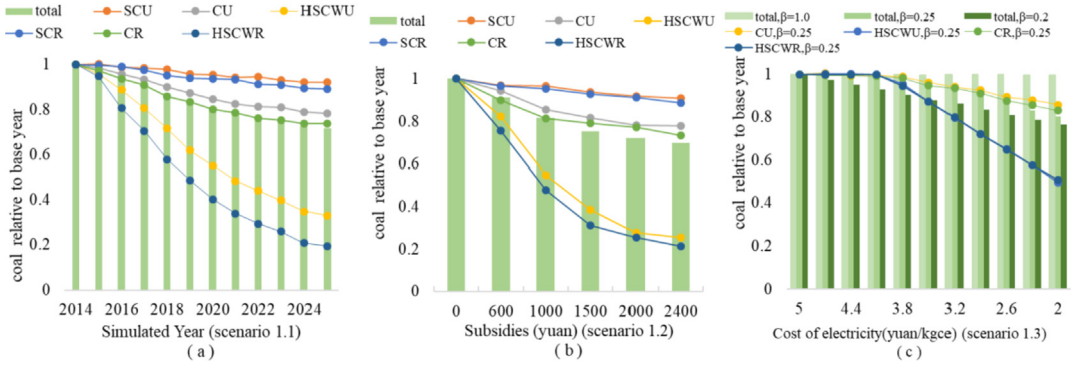


Fig. 8. Simulation results for scenarios 1.1, 1.2, and 1.3 (SCU means severe cold urban, CU means urban cold urban, HSCWU means cold winter hot summer urban, SCR means severe cold rural, CR means cold rural, HSCWR means cold winter hot summer rural).

consumption.

The effect of technology improvement (see Fig. 8 c) is obviously different from income growth and subsidies. The decrease of coal consumption will highly depend on the value of β. As the value of β becomes larger, more reduction in the cost of electricity are needed before technology improvement take effect. When the value of β is 1.0, coal consumption seems no decrease during the experiment.

In addition, the reduction in coal consumption varies in different regions (see Fig. 8). It seems that the climate zone and the urbanization of the region (urban or rural) result in different levels of sensitivity in relation to income growth, technology improvement, and subsidies. The average reduction in coal consumption in various regions is shown Fig. 9. In terms of urbanization, the reduction in coal consumption will be greater in rural than urban. In terms of climate zone, the remarkable decrease of coal consumption in mild regions (W) and cold winter hot summer regions (HSCW) can be observed.

These results may be helpful in promoting rational

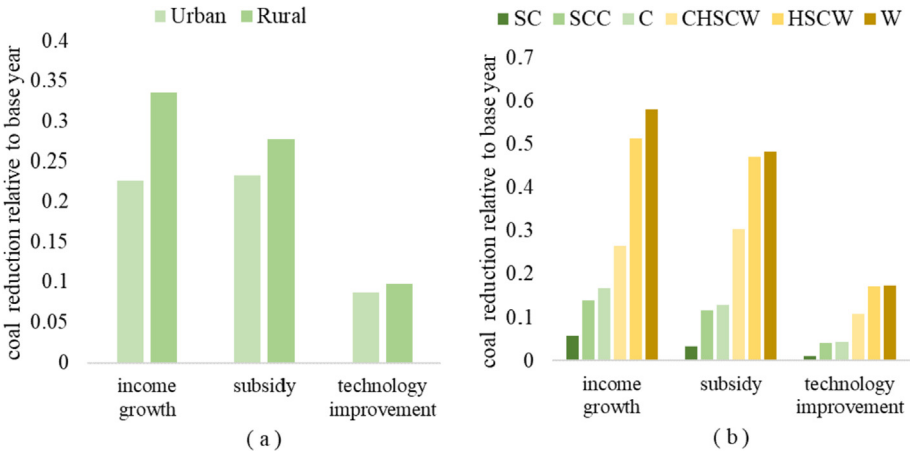


Fig. 9. Average reductions in coal consumption in various regions.

environmental governance or clean energy policies that deliver greater returns on investment. The most cost-effective measures can be developed considering the region diversification.

4.2.3. Device-replacement mechanism: multi factors

In multi factor scenarios, multi factors from the device-replacement mechanism are modified simultaneously based on the base year to simulate the combined influence of different factors on the replacement of coal-powered device.

The simulation results for scenarios 2.1 (see Fig. 10 a, sub. X means that the added subsidies are X yuan) show that subsidies will enhance the device replacement effect brought about by income growth. However, the same subsidies do not always mean the same enhancement. A diminishing marginal benefit can be observed. As income grows, the reductions in coal consumption enhanced by subsidies relative to that without subsidies become less and less (see Fig. 10 b, avg. means the average reductions for different subsidies), and the reductions enhanced by more subsidies (such as sub. 2000) relative to less subsidies (such as sub. 600) become less and less, too (see Fig. 10 c).

The simulation results for scenarios 2.2 (see Fig. 11 a, tech. Y means the cost of electricity is Y yuan /kgce) show that technology improvement will enhance the device replacement effect brought about by income growth. When β is 1.0, technology improvement cannot reduce the coal consumption itself (scenario 1.3) but can enhance the reduction brought about by income growth. As income grows, the reductions in coal consumption enhanced by technology improvement will decrease slowly after a rapidly rising (see Fig. 11 b, avg. means the average reductions for different technology improvement), and the reductions enhanced by higher improvement (such as tech.2.9) relative to lower improvement (such as tech.4.7) have similar trend (see Fig. 11 c).

In real world, income growth, subsidies, technology improvement often occur simultaneously. The simulation results for scenarios 3 show that the reduction in coal consumption enhanced by subsidies can be further enhanced by technology improvement (see Fig. 12 a). As income grows, the reductions in coal consumption further enhanced by technology improvement relative to that enhanced by subsidies only will decrease slowly (see Fig. 12 b, avg. means the average reductions for different technology improvement and subsidies), and the reductions enhanced by technology improvement and subsidies simultaneously are always more than that enhanced by subsidies only, even if the technology is improved only a little (see Fig. 12 c).

5. Discussion and conclusion

This study establishes an extendable agent-based model to explore the rules of household energy consumption. The results illustrate the huge potential of agent-based modeling in household energy consumption simulations.

Five types of agent are designed. Among them, the region is served as both agent and environment, the household classification plays a vital role, and the operator, devices and fuels are depicted in detail. The design of device operation is the key to successfully simulating household energy consumption. The device ownership probability and device operation probability are created to conduct the simulation. Two behavior change mechanisms are designed,

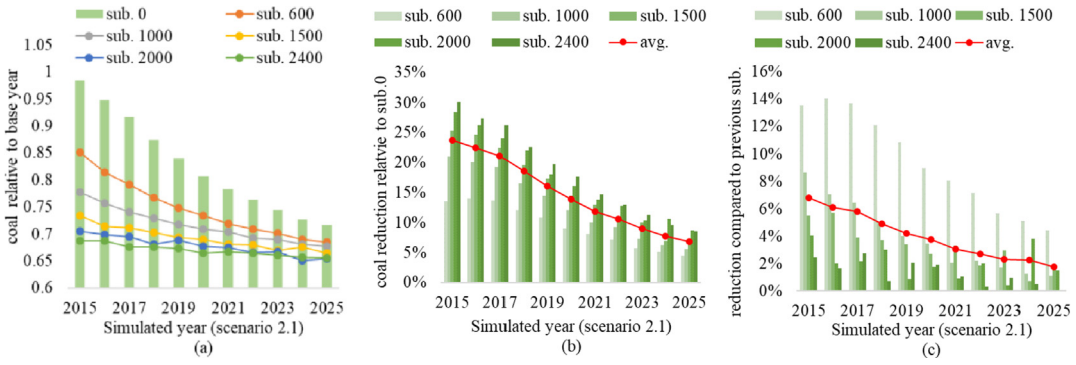


Fig. 10. Simulation results for scenarios 2.1.

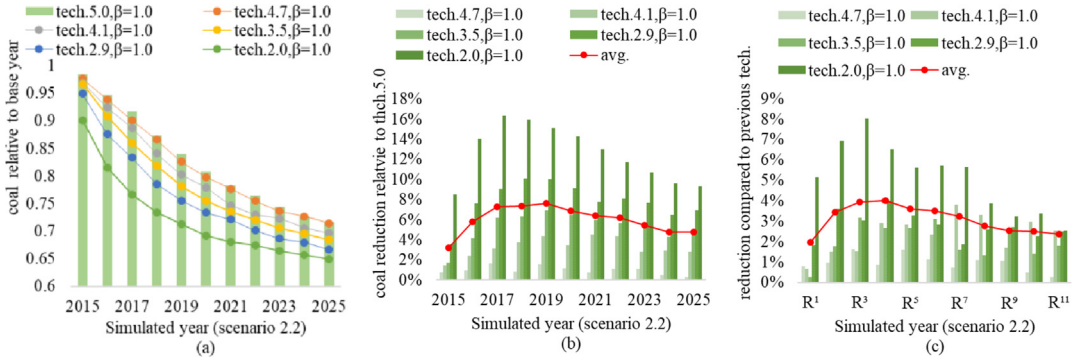


Fig. 11. Simulation results for scenarios 2.2.

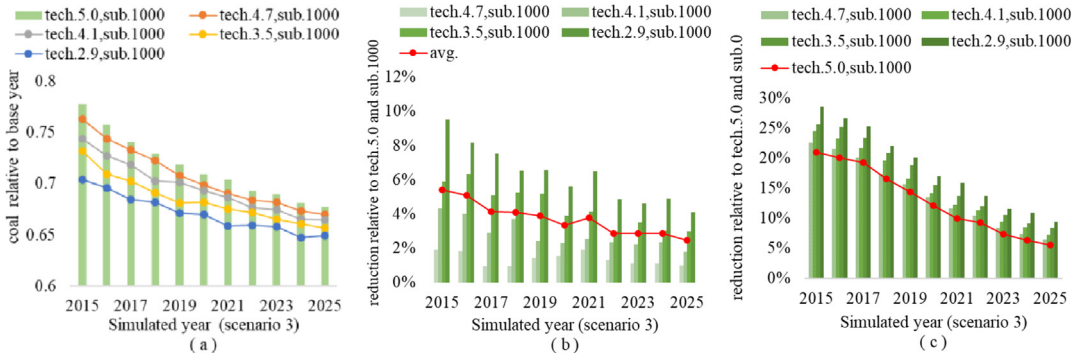


Fig. 12. Simulation results for scenario 3.

including income-driven mechanism and device-replacement mechanism. The model is verified in static way and dynamic way. The simulated results are well consistent with the statistical data.

Under the income-driven mechanism, the results show that if the rates of income growth can be maintained, the use of firewood and coal will continue to decline, while the use of solar power will increase. This may mean that improved living standards will promote the use of clean energy.

Under the device replacement mechanism, the results show that different factors impact energy consumption in different ways. The cost gap between clean and non-clean energy determines the willingness of households to replace their consumption of non-clean energy. With increasing income and the addition of subsidies, bearable spending to replace non-clean energy will increase, and with the decline in the cost of clean energy, the additional expenses incurred in replacing non-clean energy will decrease, and thus more and more households will choose to replace their non-clean energy use.

The reductions in coal consumption brought about by income growth and subsidies will be less and less as more and more devices have been replaced. However, the reduction brought about by technology improvement seems to be linearly in certain range. A diminishing marginal benefit can be observed in the effect of income growth and subsidies. As more and more devices have been replaced, more and more additional expenses will be needed to replace left devices, then the effects of income growth and subsidies will be smaller and smaller. Technology improvement can decrease the additional expenses proportionally, so the effect of technology improvement is linear.

The reductions brought about by income growth can be enhanced by subsidies and technology improvement. As income grows, the enhancement brought about by subsidies will be less and less, and the enhancement brought about by technology improvement will decrease slowly after rapidly rising. It is worth noting that technology improvement cannot reduce the coal consumption itself but can enhance the reduction brought about by income growth, when β is 1.0. Besides, the reduction in coal consumption enhanced by subsidies can be further enhanced by technology improvement even if the technology is improved only a little.

These findings may help us to adopt targeted measures in relation to various consumer groups in the process of promoting clean energy to obtain better returns on investment. In summary, when subsidies are considered to promote the device replacement, maybe we can find the best time that can maximize the effect of the input subsidies or avoid investing in ineffective subsidies by analyzing the current situation. However, technology improvement seems always to be useful and can generate continuous benefits.

In sum, the agent-based model can be widely used in the household energy consumption analysis. More influence factors (e.g., number of family members, the ages of family members age structure, and education level of family members) and behavior change mechanisms (e.g., interaction between households) can be designed further.

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