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Agent-based joint model of residential location choice and real estate price for land use and transport model

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ABSTRACT

Residential location choice (RLC) and real estate price (REP) models are traditional and key components of land use and transport model. In this study, an agent-based joint model of RLC and REP (RLC–REP model) was proposed for SelfSim, an agent-based dynamic evolution of land use and transport model. The RLC–REP model is capable of simulating the negotiation between the active household agents (buyers) and owner agents (sellers) using agent-based modeling. In particular, both utility maximization theory and prospect theory were used to develop a utility function to simulate the location choice behavior of active household agents. The utility function incorporates only two variables: house price and accessibility. The latter variable is calculated using MATSim, an activity-based model. The asking price behavior of owner agents is based on three specific rules. The residential location choices of household agents and house prices can be obtained by negotiation. Finally, genetic algorithm was used to estimate the parameters of the RLC–REP model. The calibrated model was tested in Baoding, a medium-sized city in China, and historical validation was performed to assess its performance. The results suggest that the forecasting ability of the RLC–REP model in terms of real estate price is satisfactory.

1. Introduction

The relationship and interaction between land use and transport have been widely recognized. Land use and transport model, such as UrbanSim (Waddell, 2002), has been applied to comprehensively and systematically investigate the transport- and/or land use-related issues. As the core components of the land use and transport model, residential location choice (RLC) model and real estate price (REP) model have received increasing attention. The RLC model is focused on two topics on whether to move and where to move. The REP model is used to predict the real estate price. To date, the majority of land use and transport models have studied the RLC and REP separately (Habib, 2009; Kryvobokov et al., 2013; Moeckel et al., 2007; Waddell et al., 2003), despite a close relationship and strong interaction between them. Briefly, the residential location choice of buyers can affect the real estate price, and vice versa. Therefore, some attempts have been made for a joint study of these two issues with the so-called joint model of RLC and REP (RLC–REP model) (Ettema, 2011; Filatova et al., 2007, 2009; Magliocca et al., 2011, 2014; Parker & Filatova, 2008; Sweet, 2000). However, the RLC–REP models are limited in two aspects. First, the agent-based modeling has been recognized as a promising approach to study the RLC and REP simultaneously at the microscopic level. However, most of the agent-based RLC–REP models were tested in experiments (Ettema, 2011; Filatova et al., 2007, 2009; Magliocca et al., 2011; Parker & Filatova, 2008) and only few of them were used in real-life scenarios (Habib, 2009; Hurtubia et al., 2012), mainly because of the lack of input data, particularly micro-data. Second, the majority of RLC–REP models did not consider the phenomenon of loss aversion in housing market, which is unrealistic and could introduce bias into the simulation of residential location choice. In order to overcome these limitations, an agent-based RLC–REP model was developed with particular attention to the input data and loss aversion. In particular, the proposed RLC–REP model only incorporates two variables: house price and accessibility. The latter variable decreases the demand for the input data and facilitates easy application of the model. In addition, loss aversion is fully considered with the incorporation of prospect theory into the utility function that is used for the decision-making process of house purchase.

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2. Literature review

2.1. RLC and REP models

The decision-making process of residential location can be divided into the following two stages (Lee & Waddell, 2010): (1) The household will make a decision on whether to move, which is also known as residential mobility (Lee & Waddell, 2010) and (2) the households start searching for houses and then decide where to move (Lee & Waddell, 2010). As these stages are continuous, the questions of whether and where to move can be simultaneously studied using, for example, the nested logit model (Lee & Waddell, 2010) and stated preference approach (Kim et al., 2005).

The studies of REP can be categorized into two aspects: (1) how to predict the price and (2) what factors affect the price. The approaches to predict the REP include spatial regression model (Diao & Ferreira, 2010; Haider & Miller, 2000), hedonic model (Dorantes et al., 2011; Iacono & Levinson, 2011; Martinez & Viegas, 2009), multilevel modeling (Habib & Miller, 2008), and geographically weighted regression model (Du & Mulley, 2006). In addition, several factors have been tested to determine the extent to which they affect the REP. These factors include transport network (such as railway and highway) (Dorantes et al., 2011; Habib & Miller, 2008), accessibility (Du & Mulley, 2006; Habib & Miller, 2008; Iacono & Levinson, 2011; Martinez & Viegas, 2009), the built environment (Diao & Ferreira, 2010), and traffic volumes (Kawamura & Mahajan, 2005).

It has been recognized that the RLC and REP are interrelated and interact with each other. Therefore, several attempts have been made for a joint study of these two factors. The bid-rent model was widely used to determine the residential location and house price simultaneously. In a typical bid-rent model, the buyers bid for houses with the objective of maximizing their individual utilities, and the sellers allocate their houses to the buyers who offer the highest prices (Alonso, 1964; Huang et al., 2014). Traditionally, this model is based on equilibrium and it is assumed that every household searching for houses will be allocated and meanwhile, every house in the market will be allocated to the household. In other words, the number of vacant houses in the market is equivalent to the number of households looking for houses (Hurtubia et al., 2012). For instance, the MUSSA is a representative equilibrium-based model (Martínez & Donoso, 2004). Furthermore, the bid-rent model has been extended with the application of agent-based modeling (Ettema, 2011; Filatova et al., 2007, 2009; Magliocca et al., 2011, 2014; Parker & Filatova, 2008; Sweet, 2000). The extended model is capable of dealing with the disequilibrium housing market, as well as simulating the interactions among heterogeneous agents (Huang et al., 2014; Hurtubia et al., 2012), generally including buyers (households) and sellers (landlords).

In the agent-based RLC–REP models, in general, household agents make their purchase decisions based on the utilities of the houses, which were calculated by utility functions (Ettema, 2011; Filatova et al., 2007, 2009; Magliocca et al., 2011; Parker & Filatova, 2008). However, the majority of these utility functions did not consider the difference between the gain and loss utilities. In particular, according to the prospect theory (Kahneman & Tversky, 1979; Kahneman et al., 1991; Mohamed, 2006; Tversky & Kahneman, 1981), the loss of choosing new house decreases utility more than its increase by an equivalent-sized gain. In order to differentiate the gain utility from loss utility, some RLC–REP models have tried to incorporate the prospect theory into the utility functions (Habib, 2009; Magliocca et al., 2014).

To date, several agent-based RLC–REP models have been proposed; however, most of them were tested in experiments (Ettema, 2011; Filatova et al., 2007, 2009; Magliocca et al., 2011; Parker & Filatova, 2008) and only few of them were used in real-life scenarios (Habib, 2009; Hurtubia et al., 2012). Furthermore, there are also some models that have not even been validated (Parker & Filatova, 2008). In general, the agent-based RLC–REP models have a high demand for the micro-input data, which are not available or accessible in most cases. This is probably the main reason for the limited number of cases studies for agent-based RLC–REP models.

2.2. RLC and REP models in the land use and transport model

RLC and REP models are two essential parts of land use and transport models. Currently, the development of land use and transport models is in micro-simulation stage (Iacono et al., 2008). Therefore, this section focuses on the RLC and REP models that are used in typical micro-simulation land use and transport models, including UrbanSim (Waddell, 2002), ILUTE (Roorda et al., 2008), ILUMASS (Moeckel et al., 2007), and PUMA (Ettema et al., 2007).

2.2.1. UrbanSim

As each module in UrbanSim is treated as a plugin, they can be replaced easily according to users' demand. Therefore, various RLC and REP models are available for UrbanSim. Traditionally, the RLC model in UrbanSim was implemented using mobility model and location choice model, which generally used Monte Carlo and logit models, respectively. The REP model in UrbanSim was generally implemented using the hedonic model (Waddell et al., 2003); however, other approaches, such as alternative geographically weighted regression methodology (Kryvobokov et al., 2013), were also applied.

2.2.2. ILUTE

In ILUTE, the RLC model was also made up of mobility and location choice models, which used the discrete-time random parameter model and incorporated reference dependence to establish preference orderings for each active household, respectively. For an REP model, a multilevel model that simultaneously considers both temporal and spatial heterogeneities was developed to predict the real estate price (Habib, 2009).

2.2.3. ILUMASS

Also in ILUMASS, the RLC model composed of the residential mobility and location choice. The former was implemented by Monte Carlo simulation and the latter was a function of supply and demand of the housing market and profitability expectations. The REP model in ILUMASS was implemented by an aggregate function (Moeckel et al., 2007).

2.2.4. PUMA

In PUMA, the RLC and REP models were jointly implemented using the multiagent modeling. The unique feature of the model is that households' decisions are based on perceptions of housing market probabilities (Ettema, 2011). However, the RLC–REP model was only tested in an experiment, rather than a real-life scenario.

2.3. Comments on RLC and REP models

On the basis of the literature review, it can be found that, currently, some attempts have been made to study residential mobility, residential location choice, and real estate price simultaneously at the microscopic level using agent-based modeling. In addition, the agent-based RLC–REP models have also been applied to micro-simulation land use and transport models such as PUMA. Therefore, the proposed RLC–REP model will also become agent-based. However, the agent-based RLC–REP models are limited in the following aspects:

First, most of the agent-based RLC–REP models were tested in experiments, rather than real-life scenarios, which is probably because of the lack of input data, particularly the micro- and disaggregate data.

Second, the majority of the RLC–REP models ignored the phenomenon of loss aversion (Kahneman & Tversky, 1979; Kahneman et al., 1991; Mohamed, 2006; Tversky & Kahneman, 1981). However, it was argued that the loss of choosing new house decreases utility more than its increase by an equivalent-sized gain, according to the prospect theory.

In order to overcome these limitations, the proposed agent-based RLC–REP model particularly focused on the model demand for micro-input data and attempts to reduce such demand in two ways: (1) using less variables (factors) to build the model and (2) using aggregate data for calibration when disaggregate data are unavailable. In addition, the proposed RLC–REP model incorporated the prospect theory into utility maximization theory to consider loss aversion to simulate the purchase behavior of buyers, which could make the model much more realistic.

3. Introduction to SelfSim: An agent-based land use and transport model

3.1. Aims of SelfSim

The proposed RLC–REP model works as a core component of SelfSim, an agent-based dynamic evolution land use and transport model. Compared with other agent-based land use and transport models, SelfSim is much more advanced and applicable in the following aspects:

(1) Population synthesis method: Traditionally, iterative proportional fitting (IPF) (Guo & Bhat, 2007) and combinatorial optimization (CO) method (Melhuish et al., 2002) are used to create population for the simulation. However, two limitations exist in traditional approaches. First, the household weights of synthetic population calculated by traditional methods are completely different from the actual ones in most cases. Second, the objective function used in the population synthesis methods did not consider the dispersion of control variables. In order to overcome these limitations, a new heuristic population synthesis method was proposed in SelfSim.

(2) Travel demand model: The four-step method is the traditional approach to forecast the travel demand at macroscopic level. Over the past three decades, the activity-based model has gradually become a promising alternative to the four-step method, and can be used to generate individual travel demand. Among the activity-based models, the MATSim, which is an integrated framework of agent-based model, traffic assignment model, and activity-based model (Horni et al., 2009; Rieser et al., 2007; Zhuge et al., 2014), appears to be the most popular one and has been used in several cities and regions (Bekhor et al., 2010; Meister et al., 2010; Neumann et al., 2012; Zhuge et al., 2014). Therefore, MATSim was used as the travel demand model for SelfSim.

(3) Accessibility model: It was argued that a perfect accessibility model should consider four aspects of land use, transportation, temporal, and individual (Geurs & VAn Wee, 2004). However, most of the accessibility models to date have been limited in the full consideration of these four aspects. In order to overcome this limitation, the proposed accessibility model in SelfSim calculates the accessibility based on the travel behavior of simulation using MATSim.

(4) RLC and REP models. From Section 2, it is clear that the proposed agent-based RLC–REP model make SelfSim more advanced and applicable by incorporating the prospect theory and decreasing the demand for the input data, respectively.

3.2. Framework of SelfSim

The framework of SelfSim is demonstrated in Fig. 1. The SelfSim is composed of initialization and simulation models, which are used to prepare the key inputs for SelfSim and simulate the evolution of land use and transport, respectively. In particular, the initialization models are population development model and initial daily activity schedule model, which are used to generate the virtual population and initial travel demand (daily plans) for agents in the population, respectively. The simulation models make up an iterative loop, which works as follows: First, the demographic development model is used to simulate the changes of individual and household statuses (e.g., marital status) and characteristics (e.g., income) that are associated with the evolution of land use and transport. Second, the activity-based travel demand model, which is based on MATSim, is used to simulate the travel behavior of each agent in the synthetic population, resulting in optimal daily plans and traffic flow status. Third, the micro-simulation-based accessibility model is used to calculate the accessibility using the output of the activity-based travel demand model. Finally, the RLC–REP model is used to simulate the residential location behavior of each household and predict the house price. Meanwhile, the activity location model and transport development model are used to add/remove activity and transport facilities, respectively. However, the activity location model and transport development model have not been developed, and the outputs of these two models will be the input of SelfSim when initialized.

3.3. Relationship between RLC–REP model and other models in SelfSim

The submodels in SelfSim are mutually dependent. For the RLC–REP model, it is connected to several SelfSim components and the data flow is demonstrated in Fig. 2. The main inputs of the RLC–REP model include population, house prices, accessibility, transport infrastructures, and activity facilities. The main outputs of the model are house price and residential locations.

4. RLC–REP model

4.1. Model framework

Fig. 3 demonstrates the framework of the proposed RLC–REP model. The model is composed of the following two modules:

Step 1: Select active household agents: Affordability and inducement (e.g., marriage) are used to screen the households, and those passing the screening will become active household agents and enter the house market to search for their houses.

Step 2: Negotiation between active household agents and owner agents: Negotiation mainly includes the following two events: (1) Active household agents temporarily choose houses and (2) owner agents update prices. The negotiation will not stop until at least one of the criteria is met.

4.2. Select active household agents

In this study, the active household agent particularly refers to the household agent who is more likely to purchase a house, but the decision of buying depends on the negotiation with owner agents in the housing market. For the active household agents, the following assumptions are made: (1) All active household agents are assumed to have their own houses and the renters who do not have a house are not considered in the model. A similar assumption is commonly used in most of the micro-simulation land use and transport models (Ettema, 2011; Habib, 2009). (2) The active household agents cannot be immigrants. For the immigrants, the residential locations are randomly allocated in SelfSim.

Fig. 4 demonstrates the procedure of selecting active household agents. It includes the following steps: (1) Identification of the contributing factors that may make households search new residential locations; (2) counting the number of contributing factors for each household agent; (3) ranking the household agents based on the number of contributing factors; and (4) checking the affordability of each

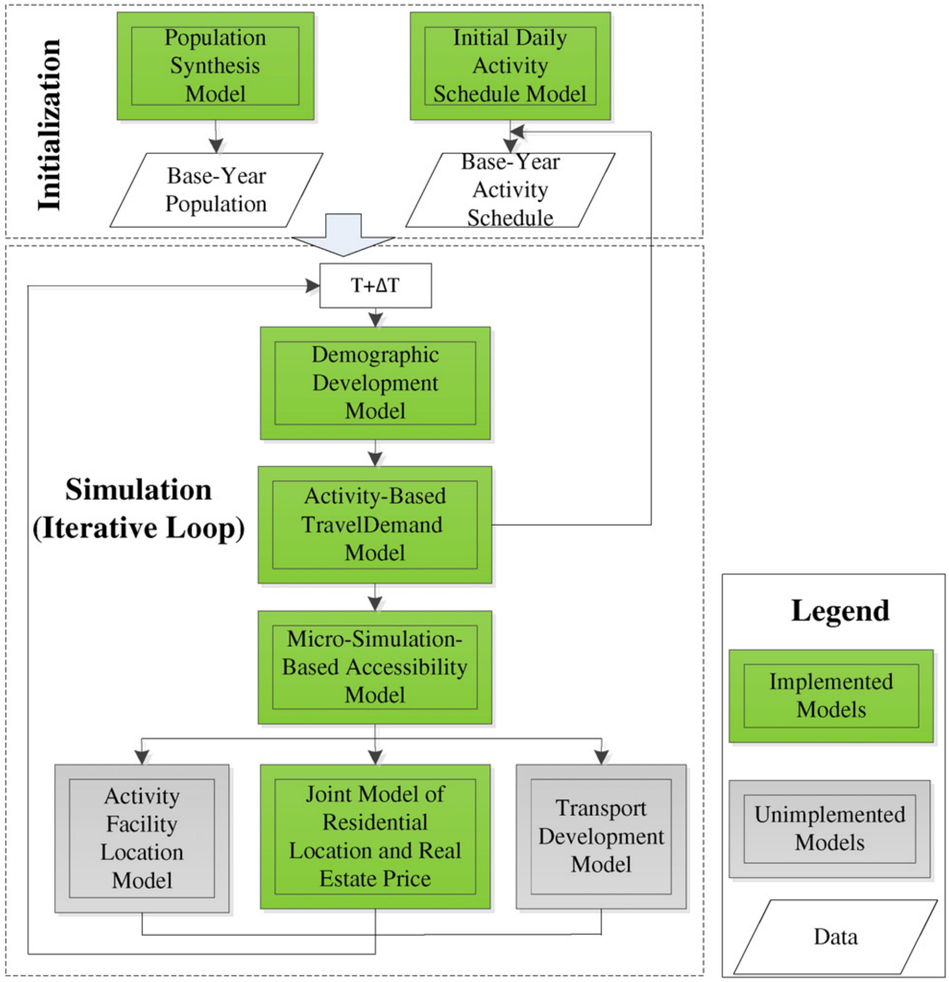

Fig. 1. Framework of SelfSim.

household agent sequentially according to the ranking. In particular, the household agent who has more contributing factors is on the top of the checklist, and thus will be checked first. After being checked, the household agent who affords to buy a house will become the active household agent and will be added to the set of active household agents. Otherwise, the household agent will be removed from the checklist. The affordability check continues until the number of active household agents reaches the specific maximum value. The maximum value can be set based on users' experience or relevant survey data.

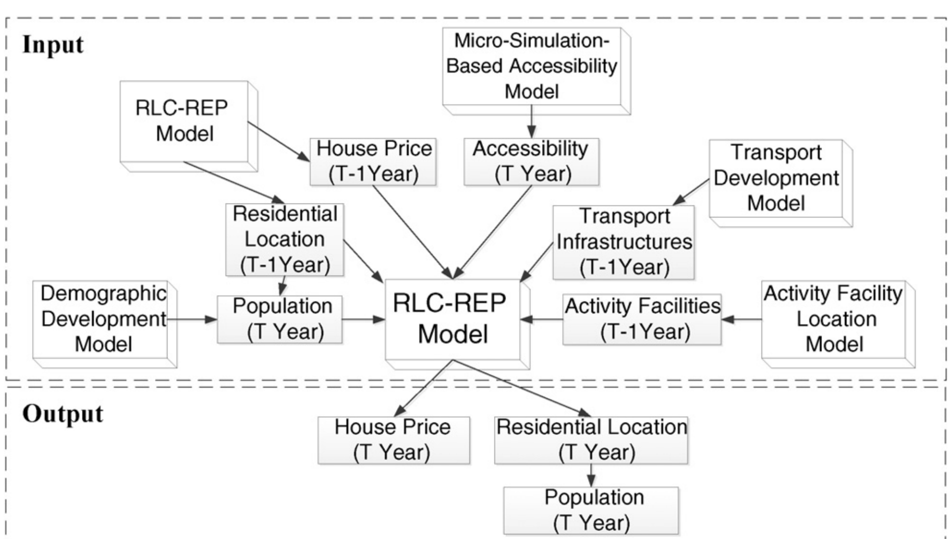

Fig. 2. Data Flow of RLC–REP model.

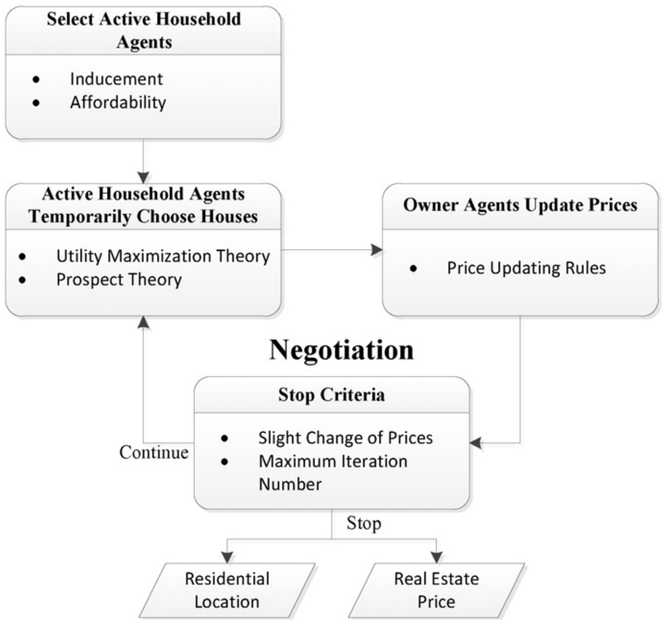

Fig. 3. Framework of the RLC–REP model.

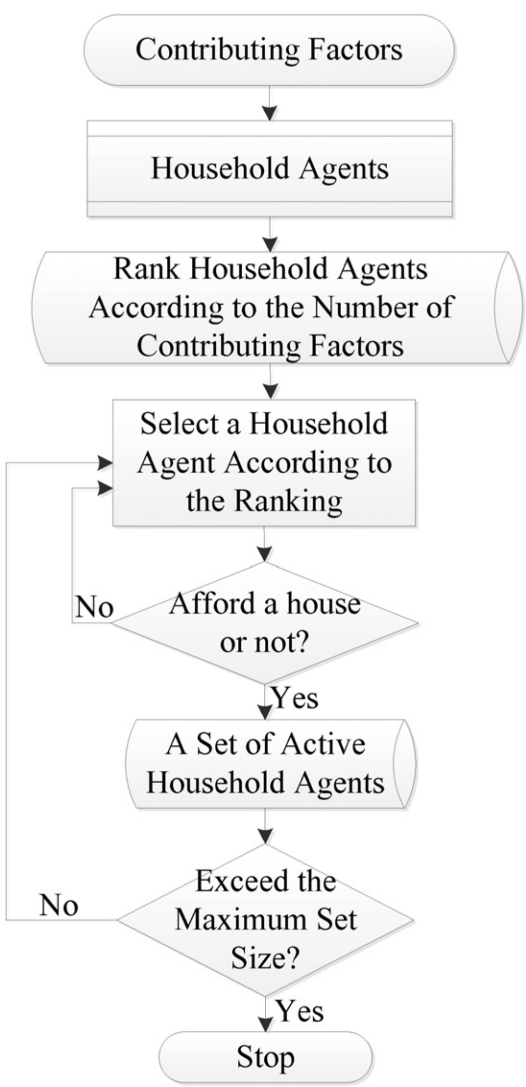

Fig. 4. Procedure of selecting active household agents.

4.2.1. Contributing factors

There are several contributing factors affecting the purchase behavior of active household agents, which differ for each case and theoretically need to be identified by relevant survey. However, such survey data are not always available in most of the cases and it is also uneconomical to carry out such survey for just studying RLC and/or REP. Therefore, the contributing factors are determined by reviewing the relevant studies.

Mulder and Hooimeijer (1999) indicated that the rate of residential mobility has a close relationship with life cycle stage, size and tenure of the current dwelling, and events in other domains of the life course (Dieleman, 2001). In addition, on the basis of the analysis of the rate of residential mobility in Beijing over the period 1980–2001, Li (2004) argued that age, marital status, job, education, tenure, and membership of the Chinese Communist Party are closely related to the rate of residential mobility. According to this report, age, marital status, employment status, education, and house size are the recommended contributing factors. However, the final implementation of the contributing factors needs to be based on the availability of the relevant data.

4.2.2. Affordability

Affordability to buy a new house is a condition to check a household agent if he/she can become an active household agent. As a common indicator to check the affordability, the house price to income ratio (*HPI*) is used in this model (Lau & Li, 2006), which can be calculated as

$$HPI_q = \frac{HP}{12 \cdot I_q}, \tag{1}$$

where *HP* is the average house price in a city and I_q represents the monthly income of the *q*th household agent. In addition, it is important to note that both *HP* and I_q vary over time, because *HP* can either increase or decrease through the negotiation between household agents and owner agents. In this case, I_q also changes over time, which is simulated by the demographic development model in SelfSim.

In general, the *HPI* ranges from 4 to 6, but it differs between regions. In this study, it is assumed that the *q*th household agent can become an active household agent only if $HPI_q \geq HPI_{standar}$, where $HPI_{standar}$ is the standard house price to income ratio.

4.3. Negotiation between active household agents and owner agents

4.3.1. Active household agents temporarily choose houses

The negotiation between active household agents and owner agents is viewed as an iterative process composed of two modules. As one of the module, each active household agent temporarily chooses a house as his/her first choice. Fig. 5 demonstrates how active household agents make their decision in the housing market. They decide on choosing new houses based on a utility function, which incorporates accessibility and house price as the variables. The utility function is proposed with

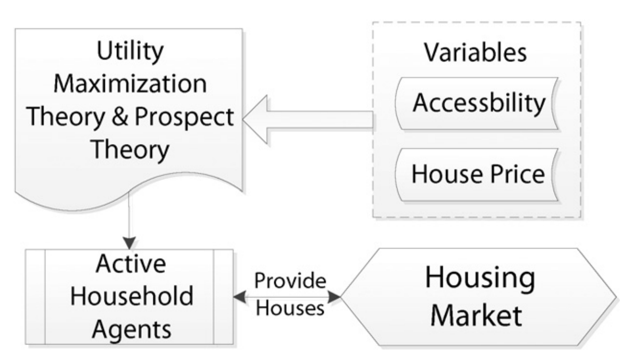

Fig. 5. Decision-making process of active household agents.

the application of both utility maximization theory and prospect theory. In addition, it is assumed that the houses currently owned by the active household agents will be put into the housing market for bidding. However, the agents will not sell their houses until they have new ones to move. Details on modeling of active household agents' decision-making process are as follows:

4.3.1.1. Variables used for modeling decision-making process. There are various factors affecting the residential location choice behavior of the active household agents. These include house size, number of rooms, house quality, accessibility, and house price. In the proposed RLC–REP model, only two factors, accessibility and house price, were adopted as the variables. The reasons are as follows: First, house price is one of the key factors influencing the house purchase behavior; furthermore, it can be found that accessibility appears to be a factor more commonly used in a few studies on residential location choices (Chen et al., 2008; Srour et al., 2002; Stegman, 1969; Waddell, 1996); Second, it is important to consider whether the relevant data are generally accessible during modeling, particularly agent-based modeling, as it requires disaggregate input data that are often not easy to access. In this case, it seems much more difficult to access the disaggregate data associated with other factors such as house size, number of rooms, and house quality. This is because (1) such data are recorded by, for example, relevant government agencies and cannot be accessed by the public and (2) they are difficult to be acquired through survey, mainly because of privacy issues.

4.3.1.2. Utility function: Application of utility maximization theory. The utility maximization theory is a traditional approach for modeling the residential location choice behavior (Eluru et al., 2010; Pinjari et al., 2011). The utility of ith house chosen by qth active household agent can be expressed as

$$U_{q/i} = \beta_A \cdot A_{q/i} + \beta_P \cdot P_{q/i} + \varepsilon_{q/i}, \tag{2}$$

where $U_{q/i}$ denotes the utility of choosing ith house for the qth active household agent; $A_{q/i}$ and $P_{q/i}$ denote the observed values of house accessibility and price, respectively; β_A and β_P respectively denote the parameters of house accessibility and price to be estimated; and $\varepsilon_{q/i}$ denotes an idiosyncratic error term assumed to follow Gumbel distribution.

4.3.1.3. Utility function: Application of prospect theory. The active household agents may lose or gain utility in terms of both accessibility and house price when they move to new houses. For instance, household agents probably choose houses with high prices to improve accessibility, in which case, they lose the utility of price but gain the utility of accessibility. In addition, it is argued that loss aversion exists in housing market, that is, the utility of loss is higher than that of gain, in which case, the values of loss and gain are the same (Habib, 2009; Magliocca et al., 2014). Therefore, incorporating loss aversion into RLC–REP model can make the model more realistic in terms of simulating decision-making processes of active household agents. For example, it is assumed that an active household agent currently lives in a house which is worth 1 million RMB, and there are two candidate houses worth 1.2 and 0.8 million RMB, respectively. It can be easily found that the agent will lose 0.2 million RMB if he/she chooses the former, but will gain 0.2 million RMB on choosing the latter. However, the utility of loss will be much higher than that of the gain if loss aversion is applied.

In order to quantify the loss or gain, the reference point has to be defined. In this case, the present house can be viewed as the reference point, as the loss and gain can be easily calculated by comparing the present house and potential (new) house. The reference function can be expressed as (Habib, 2009; Hardie et al., 1993; Tversky & Kahneman, 1991)

$$R(x_j) = \begin{cases} U_i(x_j) - U_r(x_j) & U_i(x_j) \geq U_r(x_j) \\ \lambda_j \left[U_i(x_j) - U_r(x_j) \right] & U_i(x_j) < U_r(x_j) \end{cases}, \tag{3}$$

where x_j denotes the jth variable; two variables are involved, accessibility and house price; $U_i(x_j)$ and $U_r(x_j)$ denote the potential and present utilities, respectively; and λ_j denotes the parameter for loss aversion.

Substituting Eq. (3) into Eq. (2), we obtain

$$\begin{aligned} U_{q/i} = {} & \beta_A \cdot \left[\delta_A \cdot AGain_{q/i} + (1-\delta_A) \cdot \lambda_A \cdot ALoss_{q/i} \right] \\ & + \beta_p \cdot \left[\delta_P \cdot PGain_{q/i} + (1-\delta_P) \cdot \lambda_p \cdot PLoss_{q/i} \right] + \varepsilon_{q/i}, \end{aligned} \tag{4}$$

where $AGain_{q/i}$ and $ALoss_{q/i}$ respectively denote the gain and loss of choosing ith house in terms of accessibility; $PGain_{q/i}$ and $PLoss_{q/i}$ respectively denote the gain and loss of choosing ith house in terms of house price; $\delta_t (t = A,P)$ can be either 0 or 1. If qth active household agent gains utility in terms of variable t when choosing ith house, then δ_t will be set to 1, otherwise, it will become 0.

4.3.1.4. Active household agents temporarily choose houses. It is assumed that χ percentage of active household agents with higher utilities will finally purchase houses. That is, the active household agents will be ranked according to the utilities of the potential houses, and the first χ percentage of active household agents will be selected as the buyers who will be temporarily allocated with houses. The rest are assumed to despair house purchase. Such allocation is carried out in each negotiation (iteration).

4.3.2. Owner agents update price

As the other module of the negotiation between active household agents and owner agents, the latter update their house prices depending on the attraction of the houses that are related to the temporary purchase choices of the active household agents. In particular, the attraction of an owner agent is defined as a function of the number of active household agents who temporarily chose houses in the charge of the owner agent (Eq. (5)). It is important to note that the owner agent refers to a representative of households on a road node who would like to sell his/her houses, and the agent is responsible for negotiating with active household agents on behalf of the households. Consequently, the prices of the houses from the same road node are the same. The reason for the aggregation of households on a road node is that the SelfSim views that all activity facilities, such as houses and shopping malls, are centered on each road node. In particular, each activity facility is allocated to the closest road node and the facilities are assumed to be located on the road nodes. The aforementioned function is expressed as:

$$A_i = \frac{N_i}{T_i}, \tag{5}$$

where A_i denotes the attraction of ith owner agent; N_i denotes the number of active household agents temporarily choosing houses in the charge of the ith owner agent as their first choices; and T_i denotes the number of houses that the ith owner agent would like to sell.

For an owner agent, the rules of updating the house price are defined as follows:

Case 1. $A_i \in [Q_{\min}, Q_{\max}]$..

If the attraction of ith owner agent falls into a particular section with the upper bound $Q_{\max}$ and lower bound $Q_{\min}$, the owner agent will not update the house price, resulting in the price staying at P_i.

Case 2. $A_i \in (Q_{\max}, +\infty)$.

If the attraction of ith owner agent exceeds the upper bound $Q_{\max}$, then a further check on whether the updated price $P_i + \Delta P_i$ exceeds the maximum house price of the ith owner agent (P_i^{Max}) is necessary, where ΔP_i denotes the variation of house price for one update, which needs to be predefined. P_i^{Max} can be calculated as follows:

$$P_i^{Max} = (1 + \eta_{Max}) \cdot P_i, \tag{6}$$

where η_{Max} denotes the maximum increase rate of house price and should be >0.

If $P_i + \Delta P_i \leq P_i^{Max}$, then the house price of the ith owner agent will be updated to $P_i + \Delta P_i$, otherwise, it will stay at P_i.

Case 3. $A_i \in [0, Q_{\min})$.

Similarly, if the attraction of ith owner agent is below the lower bound $Q_{\min}$, then a further check on whether the updated price $P_i - \Delta P_i$ is higher than the minimum house price of the ith owner agent (P_i^{Min}) is necessary. P_i^{Min} can be calculated as follows:

$$P_i^{Min} = (1 - \eta_{Min}) \cdot P_i, \tag{7}$$

where η_{Max} denotes the maximum decrease rate of the house price, and $0 \leq \eta_{Min} < 1$.

If $P_i - \Delta P_i \leq P_i^{Min}$, then the house price of the ith owner agent will be updated to $P_i - \Delta P_i$, otherwise, it will stay at P_i.

4.3.3. Stop criteria

The negation between active household agents and owner agents will not stop until one of the following stop criteria is met:

(1) Slight change of house price: If the house price changes slightly over a specific number of negotiations, then further negotiation is useless and should not be continued. In particular, if the change rate of house prices is lower than a certain rate ($\theta_{\max}$) over the past l negations, then their changes are viewed as slight, and further negotiation is not required. This slight change in house price is defined as

$$(\theta_t < \theta_{\max}) \& (\theta_{t+1} < \theta_{\max}) \& \ldots \& (\theta_{t+l} < \theta_{\max}), \tag{8}$$

where θ_t denotes the change rate of house prices at tth iteration, which can be calculated as

$$\theta_t = K_t / Z_{total}, \tag{9}$$

where K_t denotes the number of houses that change their price at the tth iteration, compared with the house prices at $(t-1)$th iteration and Z_{total} denotes the total number of houses involved.

(2) Maximum iteration number ($R_{\max}$): It has been defined that the negotiation will stop once the maximum number of iterations $R_{\max}$ is reached. This definition is commonly used in a number of iterative algorithms, which may not be able to converge.

5. Micro-simulation-based accessibility model

In SelfSim, the micro-simulation-based accessibility model calculates accessibility based on simulating the travel behavior of agents using MATSim, a state-of-the-art activity-based model (Horni et al., 2009; Rieser et al., 2007; Zhuge et al., 2014). The MATSim is mainly composed of three modules: execution, scoring, and replanning. These modules form an iterative loop, aiming at optimizing the daily plans of agents and obtaining realistic traffic flow data. The execution module is used to execute the daily plans of agents, from which the traffic flow can be obtained. The scoring module can score the daily plans using a utility function based on the performance of agents in the execution module. The replanning module is used to adapt the daily plans according to their scores. The quantification of accessibility is based on the scores of daily plans. Currently, in SelfSim, only the RLC–REP model needs accessibility. In particular, accessibility of both potential and present houses needs to be quantified for the activity household agents when they decide on the purchase of houses. The following methods are used to calculate them:

5.1. Quantifying accessibility of the present house

The accessibility of the present house of an activity household agent is defined as the average score of daily plans of all household members, which can be calculated as

$$A_{Present} = \frac{\sum_{i=1}^{m} U_i}{m}, \tag{10}$$

where $A_{Present}$ denotes the accessibility of the present house; m denotes the number of household members; and U_i denotes the score of the daily plan of the household member i and can be calculated as

$$U_i = U_{Act,i} + U_{Travel,i}, \tag{11}$$

where $U_{Act,i}$ denotes the total score of performing activities and $U_{Travel,i}$ denotes the total travel utility of household member i. More details on the calculation of these two parameters can be found in the studies of MATSim (Horni et al., 2009; Rieser et al., 2007; Zhuge et al., 2014).

5.2. Quantifying accessibility of a potential house

The accessibility of a potential house is defined as the average accessibility of all household agents living on the road node where the potential house is located. It is worth noting that each road node in SelfSim is viewed as a base where activity facilities are located. It can be defined as:

$$A_{Potential} = \frac{\sum_{j=1}^{N} U_{H,j}}{N}, \tag{12}$$

where $A_{Potential}$ denotes the accessibility of a potential house; $U_{H,j}$ denotes the accessibility of the household agent j living in his/her house (Eq. (10)) and N denotes the number of household agents living on the road node where the potential house is located.

6. Model calibration

6.1. Classification of parameters in the model

The RLC–REP model involves various parameters, which are categorized into two groups as follows:

(1) Parameters to be estimated

Parameters in this group are estimated using observed data through model calibration. They are

- β_A and β_p: The parameters of house accessibility and price, respectively. Both of them are used for the utility function of a house.
- λ_A and λ_p: The parameters of house accessibility and price, respectively. Both of them are used for loss aversion in prospect theory.
- $Q_{\max}$ and $Q_{\min}$: The upper and lower bounds of the attraction of an owner agent. If the attraction falls into the section with the lower and upper bounds, the owner agent will not update the house prices.
- χ: It is used to limit the number of active household agents entering housing market.

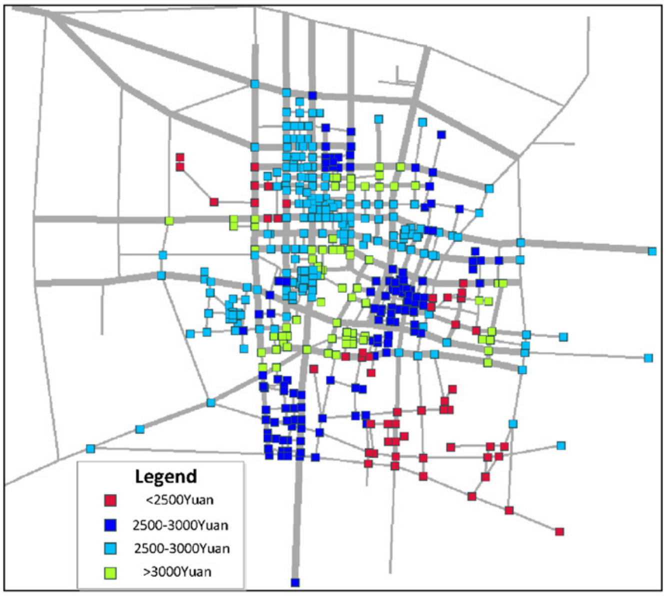

Fig. 6. Spatial distribution of house prices of Baoding in 2007 (Yuan/m^2).

(2) Parameters to be particularly set

These parameters can be set to particular values based on the users' experience or requirements. They are

- ϕ_{size}: The number of the active household agents.
- $HPI_{standar}$: The standard house price to income ratio for the study area.
- η_{Max} and η_{Min}: The maximum increasing and decreasing ratios of house price, respectively. They are used for restricting the change of house price in a specific range.
- l and $\theta_{\max}$: Associated with one of the stop criteria of the slight change of house price.
- $R_{\max}$: Maximum iteration number, which is one of the stop criteria.

6.2. Genetic algorithm-based parameter estimation

Genetic algorithm (GA), which has been widely applied for calibration (Katare et al., 2004; Park & Froment, 1998; Yao & Sethares, 1994), was used to estimate the parameters of the RLC–REP model, including β_A, β_p, λ_A, λ_p, $Q_{\max}$, $Q_{\min}$, and χ. The GA is mainly composed of encoding, population initialization, fitness function, selection, crossover, mutation, and stop criteria, which are described as follows (Li et al., 2014):

6.2.1. Step 0: Encoding

Of the three typical encoding methods (binary coding, gray coding, and real number encoding), real number encoding was adopted. As

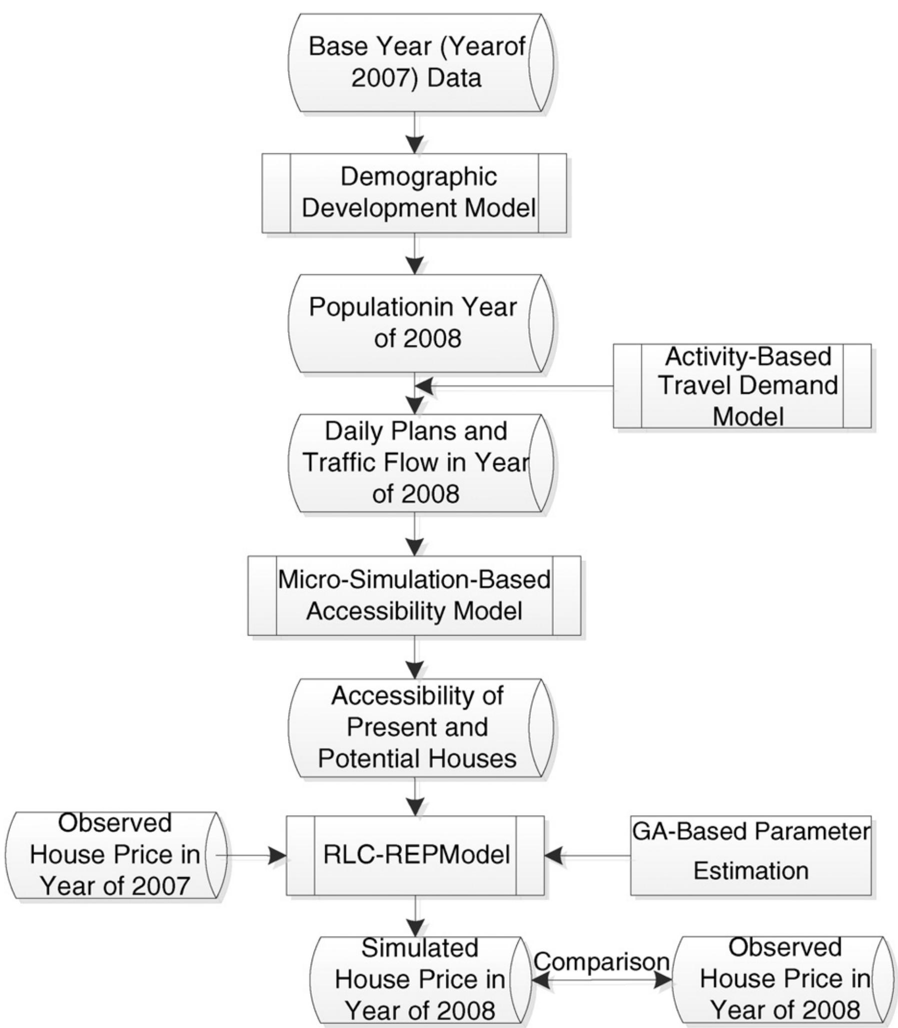

Fig. 7. Procedure of calibrating the RLC–REP Model.

a result, β_A, β_p, λ_A, λ_p, $Q_{\max}$, and χ can be encoded and placed onto the chromosome sequentially. In addition, the upper and lower bounds of these parameters are defined as follows: $\beta_A \in [-50, 50]$, $\beta_p \in [-100, 100]$, $\lambda_A \in [-10, 10]$, $\lambda_p \in [-10, 10]$, $Q_{\max} \in [1.1, 3.0]$, $Q_{\min} \in [0.1, 1.0]$, and $\chi \in [0.1, 1]$, where β_A and β_p can be decimals; λ_A and λ_p must be integers; $Q_{\max}$, $Q_{\max}$, and χ must be the integral multiples of 0.1.

6.2.2. Step 1: Population initialization

Population initialization is used to randomly generate a specific number of chromosomes. The number in this study is set to 50.

6.2.3. Step 2: Fitness function

The fitness function is used to evaluate each chromosome in the population. According to this function, it can be found that the GA is aimed at searching for an optimal solution, which can minimize the gap between the observed and simulated house prices. It can be expressed as follows:

$$\min\ f = \frac{\sum_{i=0}^{I} \frac{|P_{i,simulated} - P_{i,observed}|}{P_{i,observed}}}{I}, \tag{13}$$

where $P_{i,simulated}$ and $P_{i,observed}$ denote the simulated and observed house prices of ith owner agent, respectively, and I denotes the number of owner agents.

6.2.4. Step 3: Selection

In general, the chromosome with high fitness value is more likely to be selected as a member for the next generation. This selection mechanism can be expressed as:

$$w_k = S_k \Big/ \sum_{j=1}^{K} S_j \quad k = 1, 2, \cdots, K, \tag{14}$$

where w_k denotes the probability of kth chromosome to be selected; S_k and S_j denote the fitness values of kth and jth chromosome, respectively; and K is the population size, which is set to 50 in this case.

6.2.5. Step 4: Crossover and mutation

The crossover probability (p_c) and mutation probability (p_m) are used to determine the number of chromosomes performing crossover and mutation, respectively. In this case, $p_c = 0.1$ and $p_m = 0.1$.

6.2.6. Step 5: Stop criteria

The two stop criteria commonly used in GA are as follows: (1) The maximum iteration number and (2) slight change of the average fitness value. In this case, the maximum iteration number is set to 50. A change is observed to be slight change when the variation of average fitness value is <0.1% for over five consecutive iterations.

7. Case study

7.1. Scenario description

Baoding, a medium-sized city in China, is used as a case study. The agent-based RLC–REP model runs as a component of SelfSim to simulate the coevolution of land use and transport in Baoding from 2007 to 2013. The performance of this model is examined in the context of land use and transport evolution. In the base year of 2007, the population size of Baoding was 1,060,783. However, only 20% of the total population, which approximated 59,970 households, is simulated in the scenario to accelerate the simulation, as running MATSim for the whole population could be very time consuming.

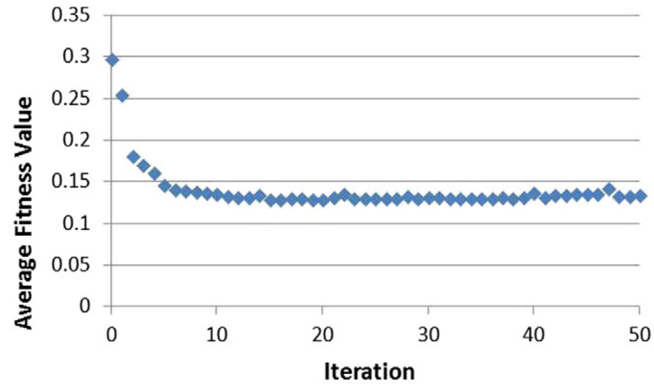

Fig. 8. Convergence process of GA-based parameter estimation.

The data used for calibration and validation of the RLC–REP model are the prices of 42 residential communities from 2007 to 2013. In particular, the 2007 data are used for calibration and those from 2008 to 2013 are used for validation. The 42 residential communities, which are composed of a number of residential buildings and flats, are representative samples, as these communities are nearly spatially uniform. Because the activity facilities in SelfSim, such as dwellings, shop, and school, are modeled based on the node of road network, that is, all activity facilities center on the node, the house prices at a node is assumed to be the same. In addition, the house price of each node, which is predominated by an owner agent, is set using the 42 residential communities. In particular, each node selects the residential community that is spatially closest to it and sets the house price of the node as the price of the residential community. Fig. 6 demonstrates the road network and house prices of Baoding in 2007. The house prices of each node are generated using the prices of 42 residential communities.

7.2. Calibration of RLC–REP model

7.2.1. Procedure of model calibration

Fig. 7 demonstrates the procedure of calibrating the RLC–REP model. First, the base year data, such as the synthetic population, daily plans, transport network, and activity facilities, are inputted into the demographic development model, which is used to simulate the change of individual and household status and characteristics related to the evolution of land use and transport, and the 2008 population is outputted. Then, the activity-based travel demand model is used to update the travel demand, obtaining new daily plans of agents and traffic flow in 2008. Afterward, the accessibility of the present and potential houses, which is calculated using the micro-simulation-based accessibility model, together with the observed house prices in 2007, is used as the input for the RLC–REP model. The output of the RLC–REP model is the simulated house prices in 2008, which are compared against the observed prices in 2008. The GA-based calibration is aimed at optimizing

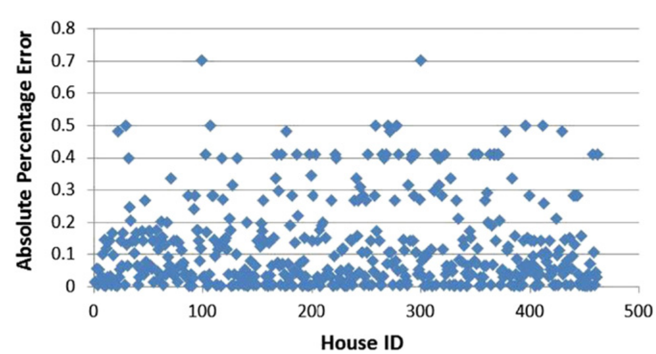

Fig. 9. Distribution of the APEs of house prices at each road node.

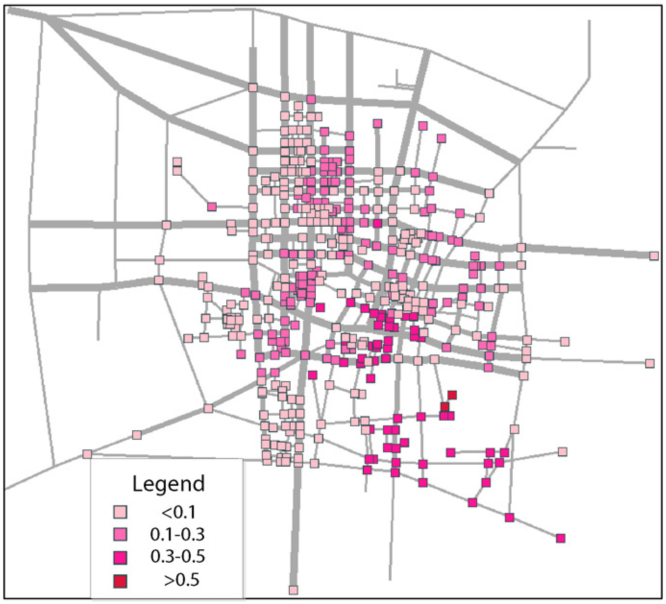

Fig. 10. Spatial distribution of the APEs of house prices at each road node.

the minimization of the gap between the simulated and observed house prices. Furthermore, in addition to the parameters to be estimated, the following parameters are to be particularly set: $\phi_{size} = 0.1$, $HPI_{standar} = 4$, $\eta_{Max} = \eta_{Min} = 0.8$, $l = 6$, $\theta_{\max} = 0.01$, and $R_{\max} = 30$.

7.2.2. Results of model calibration

Fig. 8 shows the convergence process of GA-based parameter estimation. It can be observed that the average fitness value decreases from 0.30 to 0.13 and does not decrease further. In the final generation, the fitness value of the best chromosome is 0.1 and the corresponding parameters are estimated as follows: $\beta_A = 24.6$, $\beta_p = -13.3$, $\lambda_A = 7$, $\lambda_p = 10$, $Q_{\max} = 2.6$, $Q_{\min} = 0.3$, and $\chi = 0.1$.

Absolute percentage error (APE) and mean absolute percentage error (MAPE) are used to assess the performance of GA-based calibration. These are shown by the following expressions:

$$\text{APE} = \frac{|P_{i,simulated} - P_{i,observed}|}{P_{i,observed}} \tag{15}$$

$$\text{MAPE} = \frac{\sum_{i=0}^{I} \frac{|P_{i,simulated} - P_{i,observed}|}{P_{i,observed}}}{I}. \tag{16}$$

Figs. 9 and 10 show the distribution and spatial distribution of the APEs of house prices at each road node, respectively. It can be observed from Fig. 9 that most of the APEs fall into the section from 0 to 0.2.

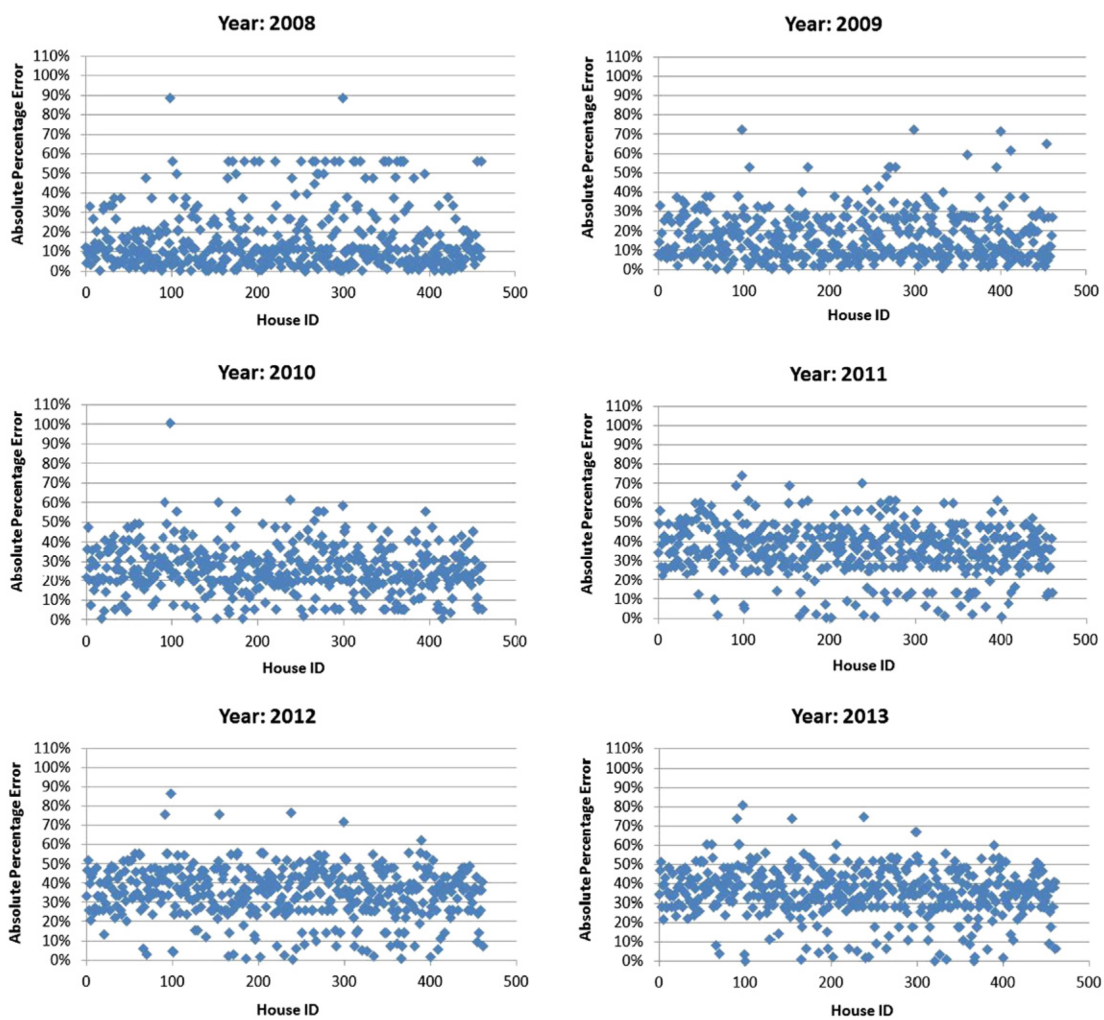

Fig. 11. Distribution of APEs of house price at each road node from 2008 to 2013.

Fig. 12. Spatial Distribution of APEs of house price at each road node from 2008 to 2013.

Furthermore, according to Fig. 10, most of the APEs are distributed spatially uniform, apart from those in the southeast of the city, which are significantly higher than the rest. The possible reason is the existence of some special factors affecting the house price in the southeast of the city, which has not been considered in the RLC–REP Model. Overall, the value of MAPE is 0.126, which indicates that the proposed RLC–REP model performs better than similar agent-based RLC–REP models in forecasting the house price (Habib, 2009; Hurtubia et al., 2012). More details on the comparison can be found in Section 7.3.

7.3. Application of RLC–REP model

The calibrated RLC–REP model was used to simulate the residential location choices of agents in the population and forecast the house prices from 2007 to 2013, in the context of land use and transport evolution that was simulated using SelfSim. The performance of the RLC–REP model was assessed through the comparison between the simulated and observed house prices from 2008 to 2013 using the indices of APE and MAPE.

Overall, the MAPEs from 2008 to 2013 are 15.7%, 17.0%, 25.8%, 35.9%, 35.0%, and 35.6%, respectively. Fig. 11 demonstrates the distribution of APEs of house prices at each road node from 2008 to 2013. It can be observed from the figure that the RLC–REP model performs well in the first three years and relatively worse after the third year; however, the performance becomes relatively stable in the last three years. Fig. 12 demonstrates the spatial distribution of APEs of house prices at each road node from 2008 to 2013. It can be found that the APEs are spatially random in the first three years. However, in the following three years, the APEs in the north of Baoding became significantly higher than others. The possible reasons of the forecasting errors are summarized as follows. First, as the proposed RLC–REP model runs in the context of land use and transport evolution using SelfSim, the errors of other submodels of SelfSim could be introduced into the error of the RLC–REP model, which could make the error larger than actual. Second, it can be found that the relatively larger errors are found in the north of Baoding, which might be due to some special polices on house prices and/or residential choice locations that have not been considered in the RLC–REP model.

In order to further assess the performance of the proposed RLC–REP model, a comparison between the model and two similar agent-based RLC–REP models that were proposed by Hurtubia et al. (2012) and Habib (2009), respectively, was performed. For easy description, these three RLC–REP models are named as “RLC–REP model,” “RLC–REP–Ricardo model,” and “RLC–REP–Habib model,” respectively.

First, it should be noted that the RLC–REP model adopts only two variables (accessibility and house price) to characterize the house, which is much less than 10 variables in RLC–REP–Ricardo model (Hurtubia et al., 2012) and 19 variables in RLC–REP–Habib model (Habib, 2009).

Second, historical validation of the RLC–REP model compared the simulated and observed house prices at 463 road nodes, while the RLC–REP–Ricardo model compared these parameters by communes and the total number of communes was 151 (Hurtubia et al., 2012), and the RLC–REP–Habib model compared only the simulated and observed average price of all houses (Habib, 2009). It can be found that the proposed RLC–REP model was validated from a more micro-perspective.

Third, because these three models were applied to simulate different periods, only the base year model performances are compared as follows: (1) The base year MAPE of the proposed RLC–REP model is 0.7%, while that of the RLC–REP–Habib model is 9.41% (Habib, 2009). (2) For the RLC–REP model, 43% of the simulated house prices exhibits a difference <10% from observed ones and 80% exhibits a difference <25%, whereas in the RLC–REP–Ricardo model, these proportions are 42% and 86%, respectively (Hurtubia et al., 2012).

Overall, on the basis of the aforementioned comparisons, it can be found that the proposed RLC–REP model uses less number of variables to characterize the houses and is historically validated from a more micro-perspective, but provides satisfactory simulation results compared with two similar models.

8. Conclusions

An agent-based RLC–REP model was proposed to simulate the residential location choice behavior of household agents, pricing behavior of house owner agents, and negotiation between these two types of agents. This model serves as key component of agent-based land use and transport model, SelfSim, which is aimed at becoming an advanced micro-simulation land use and transport model easy to be applied to real cases. In order to be consistent with the aim of SelfSim, the RLC–REP model pays particular attention to the innovation and applicability when modeling. In particular, in terms of innovation, the RLC–REP model incorporates the prospect theory into the utility maximization theory to simulate the decision-making behavior of buyers in housing market. Consequently, the phenomenon of loss aversion can be seriously considered. For easy application, the RLC–REP model adopts only two variables, accessibility and house price, which decreases the demand for micro-data, which are generally difficult to be accessed. It is also worth noting that the calculation of accessibility is based on MATSim, a state-of-the-art activity-based model. In addition, a GA-based calibration method was proposed to estimate the parameters in the RLC–REP model. The calibrated model was applied to Baoding, a Chinese medium-sized city, in the context of land use and transport evolution, which was simulated using SelfSim. The results suggest that the RLC–REP model performs well in terms of real estate price forecasting.

Although the RLC–REP model can be an advance on the studies of RLC and/or REP, more research needs to be done. First, for a new proposed RLC–REP model, it is important to carry out both historical validation and uncertainty analysis. However, uncertainty analysis on the model has not been conducted yet. In order to overcome this limitation, the global sensitivity analysis can be used to fully test the parameters. Second, the results of the historical validation show that the model errors are not spatially uniform. This problem can be addressed by adjusting the proposed model when used in real cases. For example, some particular policies on real estate price need to be inputted to the model. Third, as the performance of the RLC–REP model was assessed in the context of land use and transport evolution using SelfSim, errors from other SelfSim components could also affect the performance. Therefore, it is important to calculate the errors of the RLC–REP model and SelfSim components separately to accurately assess the performance of the proposed model.

Acknowledgments

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