Chapter 13
Urban Form, Transportation Energy Consumption, and Environment Impact Integrated Simulation: A Multi-agent Model

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Abstract More energy is being consumed as urbanization spreads. Extensive research has found that a dominant share of urban energy consumption belongs to transportation energy, which has a strong relationship with urban form in the intracity level. However, little attention has been paid to the relationship between urban form, transportation energy consumption, and its environmental impact in the inner-city level. This chapter aims to investigate the impact of urban form, namely, the land-use pattern, distribution of development density, and the number and distribution of job centers on the residential commuting energy consumption (RCEC). We developed a multi-agent model for the urban form, transportation energy consumption, and environmental impact integrated simulation (FEE-MAS). Numerous distinguishable urban forms were generated using the Monte Carlo approach in the hypothetical city. On the one hand, the RCEC for each urban form was calculated using the proposed FEE-MAS; on the other hand, we selected 14 indicators (e.g., Shape Index, Shannon's Diversity Index, and Euclidean Nearest Neighbor Distance) to evaluate each generated urban form using the tool FRAGSTATS, which is loosely coupled with the FEE-MAS model. Afterward, the quantitative relationship between the urban form and RCEC was identified using the calculated 14 indicators and RCEC of all generated urban forms. Several

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M. Kawakami et al. (eds.), *Spatial Planning and Sustainable Development: Approaches for Achieving Sustainable Urban Form in Asian Cities*, Strategies for Sustainability,
DOI 10.1007/978-94-007-5922-0_13,

conclusions were drawn from simulations conducted in the hypothetical city: (1) the RCEC may vary three times for the same space with various urban forms; (2) among the 14 indicators for evaluating urban form, the patch number of job parcels is the most significant variable for the RCEC; (3) the RCECs of all urban forms generated obey a normal distribution; and (4) the shape of an urban form also exerts an influence on the RCEC. In addition, we evaluated several typical urban forms—e.g., compact/sprawl, single center/multicenters, traffic-oriented development, and greenbelt—in terms of the RCEC indicator using our proposed model to quantify those conventional planning theories. We found that not all simulation results obey widely recognized existing theories. The FEE-MAS model can also be used for evaluating plan alternatives in terms of transportation energy consumption and environmental impact in planning practice.

Keywords Land use • Development density • Transportation energy consumption • Environment impact • Multi-agent model (MAS) • Monte Carlo

13.1 Introduction

The global environment is deteriorating with the accelerating consumption of fossil fuel. Human activities related to energy consumption are reported as the dominant driving force of global warming (IPCC 2007). Energy consumption in urban areas comprises 75% of total global consumption and greenhouse gas emissions, 80% of the world total (Shen 2005). With this as the backdrop, the low-carbon society (LCS) has been extensively discussed planetwide. China has been the focus the discussion (Hourcade and Crassous 2008; Remme and Blesl 2008; Shukla et al. 2008) due to the enormous challenges it faces in energy consumption and the corresponding greenhouse gas emissions (Wang and Chen 2008; Zhuang 2008). Mixed land use, compact cities, and smart growth have been recognized as effective tools for solving the urban energy consumption problem, by introducing reasonable spatial organization into urban systems. Fuel for transportation has been proved to have a significant relationship with urban form by many researches, which use the whole city as a sample for intercity comparison. However, not too much attention has been paid to identification of the quantitative relationship between urban form, and transportation energy consumption and environmental impact in the inner city.Conventional land use and integrated transportation models generally have comprehensive structures and a number of modules, requiring large-scale datasets and long-run time (Johnson and McCoy 2006). These models are not suitable for retrieving general rules dominating urban systems, especially the relationship between urban form, and transportation energy consumption and environmental impact. This chapter will thus construct an urban form-transportation energy consumption-environment integrated multi-agent model (FEE-MAS) to identify the quantitative influence of the urban form (e.g., land-use pattern, development density distribution, and the number and distribution of job centers) on transportation energy consumption and environmental impact in the inner-city level. For this analysis and simulation, we derive insightful results based on urban microsamples, such as parcels in the physical space and residents in the social space. In particular, we will focus on the residential commuting energy consumption (RCEC) sector in transportation energy consumption in this chapter as the first stage of the FEE-MAS model.

Three types of factors have been proved to influence the RCEC: urban form (e.g., land-use characteristics), transportation system characteristics (e.g., accessibility, convenience, and service quality), and the socioeconomic attributes of the individual or family (Wang et al. 2008). Urban form, as the important carrier for energy conservation and low-carbon economy, is the basic outcome of spatial plans, and it can guarantee the sustainable development of the urban system from the very beginning of urban development. Many studies have empirically indicated that urban form has strong relationships with energy consumption, especially transportation energy consumption—including passengers and cargo (Owens 1987; Anderson et al. 1996). Generally, the urban form featuring polycentric, high-density, and mixed-use areas corresponds to a lower average transportation energy consumption per capita. For example, Newman and Kenworthy (1989), using many cities as samples, found that the average transportation energy consumption per urban form decreases with population density. Holden and Norland (2005) discovered significant relationships between urban form and household and transportation energy consumption by analyzing eight neighborhoods in the greater Oslo region, which indicates that the compact city policy corresponds with a sustainable urban form. Shim et al. (2006) analyzed the impact of city size, density, and number of centers on transportation energy consumption. Alford and Whiteman (2009) examined the relationships between transportation energy consumption and urban form, as well as the choice of transportation infrastructure, via the evaluation of various urban forms in different subregions of the Melbourne area in Australia.

Urban form, as one of the factors, has significant impact on the traveler's commuting behavior choices and total commuting distance, influenced by the RCEC. The activity-based modeling approach is widely applied using travel diaries as the basic dataset for these researches, in which urban forms at housing and job sites are used as variables for quantitative evaluation. These empirical researches range from the impact of urban form on traveling behavior, mobile traveling behavior, and children's traveling behavior to pedestrian traveling behavior and nonwork traveling behavior (Dieleman et al. 2002; Giuliano and Narayan 2003; Horner 2007; Maat and Timmermans 2009; McMillan 2007; Pan et al. 2009; Schlossberg et al. 2006; Zhang 2005). Moreover, Krizek (2003) also indicated that the traveling behavior of a family could differ from that of their neighborhood.

Multi-agent systems (MAS), as a type of bottom-up approach based on the theory of complex adaptive systems (CAS), can be borrowed to induce the relationship between urban form and the RCEC in the inner-city level. The agent in MAS is the entity with high autonomous ability running in a dynamic physical environment (Zhang et al. 2010). Various researches have been conducted using MAS for simulating residential location choice (Benenson et al. 2001; Brown and Robinson 2006) and commercial facility location choice (Yi et al. 2008). In addition, Kii and Doi (2005) developed an integrated land-use and transportation model based on MAS, incorporating spatial economics to evaluate the compact city policy in terms of quality of life (QOL). Zellner et al. (2008) evaluated the impact of various planning policies on urban form, development density, and air quality in a hypothetical city using a MAS model. Our chapter will also use the MAS approach to develop an explicitly spatial model to evaluate potential total commuting distance, RCEC, and the environmental impact of various types of urban forms to identify their quantitative relationship.

This chapter will investigate the following topics: the varying extent of the RCEC for distinguished urban forms within the same area, the most significant spatial indicator of urban form influencing the RCEC and the weight of each spatial indicator or urban form, the shape of the urban form influencing the RCEC, and the differences between various typical urban forms originating from conventional urban planning theories. Thus, the factors influencing the RCEC, hypothesis of the FEE-MAS model, and simulation procedures will be elaborated in Sect. 13.2. The preliminary results of the model will be introduced in Sect. 13.3. Finally, the concluding remarks and discussion of the FEE-MAS will be presented in Sect. 13.4.

13.2 Approach

13.2.1 Conceptual Model

The residential commuting energy consumption and corresponding environmental impact are the results of various urban activities of residents. The integrated model proposed in this chapter will focus on the RCEC and its environmental impact, as well as their relationship with urban form. Therefore, factors related to the RCEC should be identified from aspects of the socioeconomic attributes of residents, the physical spatial layout of the city, and the characteristics of the urban transportation system (see Fig. 13.1). The RCEC depends on commuting frequency, distance, and mode. Commuting frequency is related to the socioeconomic characteristics of commuters; commuting distance, to land-use characteristics; and commuting mode, to both the socioeconomic characteristics of commuters and land-use characteristics.

13.2.2 Hypothesis of the Model

We propose the following hypotheses for the FEE-MAS model to test planning theories and identify the general rules governing urban systems in a hypothetical city, especially the relationship between the urban form and RCEC:

1. The hypothetical city as a closed system has no transport link with outside regions, and every resident works within the city.
2. Parcels in the city are square and identical in size. The road networks are grids with no subway system.

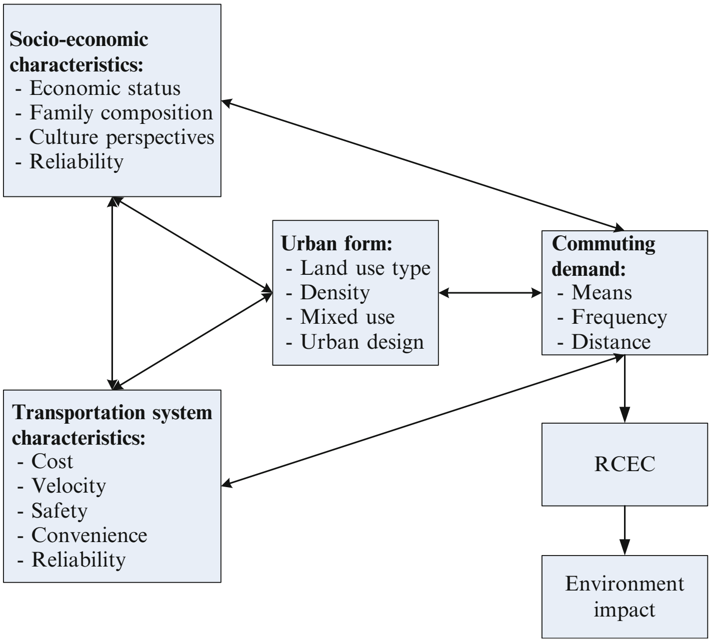


Fig. 13.1 Factors related to the RCEC and environmental impact

3. The hypothetical city is fully developed, and only residential (R) and commercial (C) types of land use are accounted for.
4. A parcel with a floor-area ratio (FAR) of 1 corresponds to one resident living in the parcel.
5. Every resident works and commutes.
6. Only residential commuting energy consumption is counted for residents; household, entertainment, shopping, and other types of energy consumed are excluded.
7. There is no capacity limitation on the job count in each parcel.
8. Residents choose the residing parcel randomly; it is not related to their socio-economic attributes.
9. Three types of commuting modes are considered: car, bus, and biking or walking.
10. The socioeconomic characteristics of the residents remain the same for all generated urban forms and will not vary through simulations.

13.2.3 Simulation Procedures

We developed the FEE-MAS model based on ESRI ArcGIS Geoprocessing, using Python. Residential agents and urban parcels are the two types of primary elements of FEE-MAS, whose simulation procedures are illustrated in Fig. 13.2. On the one

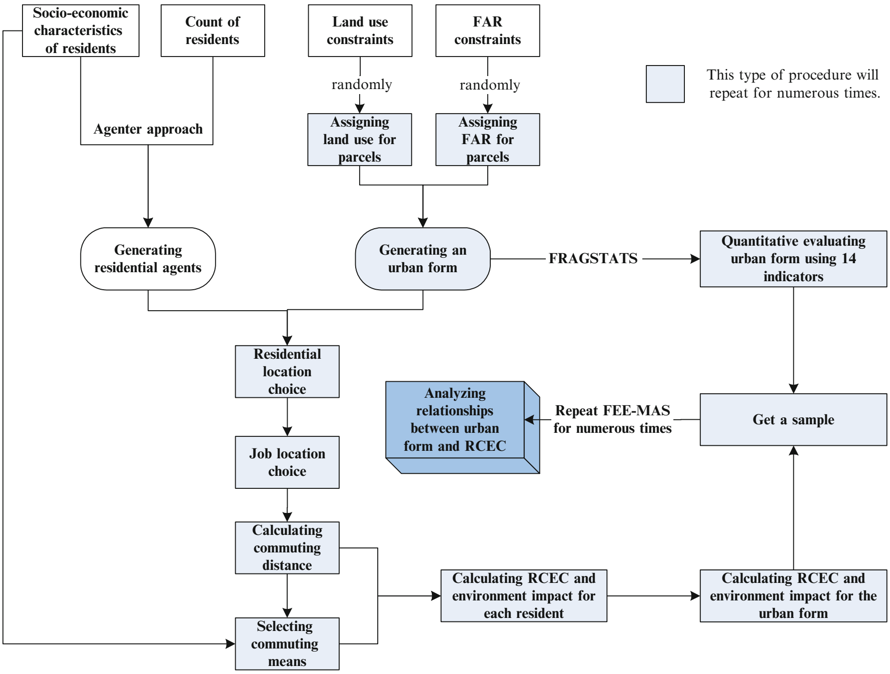


Fig. 13.2 The flow diagram of the FEE-MAS model

hand, each urban form can be generated by setting the land-use pattern and density distribution randomly and measuring them quantitatively using several indicators. On the other hand, residential agents can be generated using the total number of residents and their socioeconomic statistical characteristics. Each residential agent will choose a residential place and a job place in the generated urban form with residential and commercial parcels, then select a commuting mode based on his/her socioeconomic attributes and commuting distance. The RCEC and related environmental impact of each residential agent can thus be calculated, then aggregated in the whole city level by summing all residential agents. At this point, the simulation for an urban form is finished. Finally, we will run the FEE-MAS model for several times to get sufficient samples for analyzing the relationship between the urban form and RCEC.

The detailed simulation procedures are as follows.

13.2.3.1 Generating Residential Agents

Residential agents as the input of FEE-MAS can be generated using the disaggregation approach proposed by Long et al. (2010) from the population census report of Beijing (Beijing Fifth Population Census Office and Beijing Statistical Bureau 2002) and common sense regarding residents' socioeconomic characteristics. Two thousand resident agents were generated for simulations and computing the RCEC in the level of resident. The residential agent can be expressed as A_j, where j is the resident ID. J as 2,000 is the total number of residents. The socioeconomic attributes of residential agents are expressed as A_j^s, where s is the ID of socioeconomic attributes.

13.2.3.2 Generating Urban Forms and Residential Location Choice

The hypothetical urban form is supposed to have a size of 20 parcel × 20 parcel, composed of 400 parcels (see Fig. 13.3). Two thousand residents live in the hypothetical city. In this chapter, the key components of an urban form include the land-use pattern, spatial distribution of density, as well as the number and distribution of commercial parcels. The urban form generation procedure is made up of two steps. First, the land-use pattern is assigned for an urban form F^i (i is the urban form ID). There are two types of land use in the hypothetical city: the residential type (R) and commercial type (C). The number of commercial parcels obeys the uniform distribution of 10–40 for generated urban forms. For instance, if 25 is chosen as the number of commercial parcels for an urban form, 25 parcels will be randomly selected from the 400 parcels and assigned as land-use type "C"; the rest of the parcels are assigned as "R." The land-use type of parcel m in the urban form i is defined as $TP^i{}_m$. In this regard, the land-use pattern is defined for this urban form, with the number and location of commercial parcels defined. Second, a float number randomly selected from 0 to 10, standing for the FAR value $\mathrm{FAR}^i{}_m$, is assigned for each residential parcel m in the urban form i. $\mathrm{FAR}^i{}_m$ is rescaled to meet the sum of FAR values for all residential parcels equal to the count of all residents (2,000), enabling $\mathrm{FAR}^i{}_m$ to represent the resident count of the residential parcel m in the urban form i. The number of urban forms is generated using the Monte Carlo approach for the hypothetical city.

As to the choice of residential location, the 2,000 residents will randomly select a residential parcel, obeying the FAR value of each parcel. For example, three residents randomly selected from the total of 2,000 will reside in a parcel with the FAR as 3. Then, $\sum_{m=1}^{M} AC_m = 2000$, where AC_m is the residential agent count in the parcel m and is equal to its FAR, and M is the parcel count in each urban form (400 in this chapter).

13.2.3.3 Job Location Choice

Two extreme conditions are considered for the process of choosing a job location, without counting residents' socioeconomic characteristics. For the first condition, each resident with full rationality will select the nearest commercial parcel in which to work. For the second condition, each resident will randomly select a commercial

32	4	4	9	3	4	9	5	7	**30**	4	2	**46**	7	4	11	6	4	4	8
7	5	5	3	4	**8**	**27**	8	5	8	11	12	**55**	5	5	5	6	5	5	6
6	2	**25**	5	4	**26**	1	5	5	7	4	2	**50**	9	3	2	4	4	5	4
3	6	6	4	5	**32**	6	9	7	4	6	7	6	10	8	6	5	**29**	7	4
43	8	5	10	**66**	4	2	4	7	5	2	**13**	6	3	6	7	5	**20**	4	6
6	5	6	4	4	2	1	5	12	8	**44**	11	10	**48**	3	3	8	4	1	2
5	9	9	6	4	**95**	2	1	6	10	10	9	4	3	5	8	7	5	5	**31**
7	11	5	3	6	4	5	6	7	6	6	7	2	9	0	**34**	4	6	**137**	1
10	4	11	5	5	1	4	5	7	5	2	5	5	6	7	5	2	3	7	**27**
7	7	8	4	4	7	3	13	2	4	3	6	7	9	5	4	10	8	7	6
6	6	5	4	3	**224**	6	6	2	10	7	9	5	7	9	7	6	5	7	3
2	7	11	7	4	6	7	8	10	6	6	4	7	1	6	5	4	7	**132**	1
6	9	7	8	8	3	10	2	5	5	7	8	7	**49**	4	6	9	4	4	2
8	3	5	11	9	5	4	7	4	7	6	2	6	8	0	4	**17**	4	6	**239**
10	3	2	3	8	9	7	3	7	6	6	0	6	2	3	5	4	**42**	6	4
6	6	8	4	9	5	13	12	4	3	5	4	1	8	7	5	4	8	7	4
9	8	5	5	8	4	4	5	4	8	2	**74**	5	2	4	6	0	6	5	4
4	**101**	8	6	10	4	5	4	9	4	2	4	2	9	2	6	8	8	**27**	7
3	7	4	7	7	5	9	5	6	**35**	3	6	5	6	7	5	**8**	2	**17**	6
4	**79**	3	4	4	5	3	6	6	3	2	4	6	**12**	**7**	**19**	8	6	2	7

The commercial parcel

The residential parcel

Fig. 13.3 A generated urban form in the hypothetical city (the number in each residential parcel is the FAR value, and the number in each commercial parcel is the number of working persons)

parcel in which to work, with no rationality and regardless of the commuting distance. For residents with limited rationality between the two extreme conditions, they will select commercial parcels as job places obeying a predefined probability. Therefore, we introduce the variable r as the rational degree of a resident. When r is 1, the resident with full rationality will select the nearest place to work. When r is 0, the resident with no rationality will select a place to work randomly. When r is 0.3, the resident will select the nearest place to work with a probability of 30% and randomly select a place to work with a probability of 70%. All residents are supposed to be identical in terms of r ($r = 1$) as for focusing on the relationship between the urban form and RCEC. It should be noted that attributes (e.g., the scale and quality), in addition to the spatial location of a commercial parcel, are not accounted for in the job location choice procedure of our chapter, although they may have an important impact on people's working choice behavior in reality.

13.2.3.4 Commuting Mode Choice

The choice of commuting mode is not only determined by the socioeconomic characteristics of a resident but also by his/her commuting distance. The latter can be elaborated as $\mathrm{COMM\_TYPE_j} = f(A_j, \mathrm{dist}_j)$, where $\mathrm{COMM\_TYPE_j}$ is the commuting mode of resident j, A_j are the socioeconomic attributes of resident j, dist_j is the commuting distance of resident j, and f is the commuting mode choice function, which is used to determine the resident j's commuting mode based on his/her socioeconomic attributes A_j and commuting distance dist_j. We simplify this process by using a decision tree. Suppose the commuting mode COMM_TYPE is related to the resident's monthly INCOME (unit: CNY) and his/her commuting distance *dist* (unit: km), the decision tree in the form of Python is expressed as follows:

```
if INCOME>= 5000 and dist>= 4:
  COMM_TYPE="Car"
elif dist>= 3:
  COMM_TYPE="Bus"
else:
COMM_TYPE="Biking or Walking"
```

Note: This rule is generated from the household travel surveys of Beijing conducted in 2005.

13.2.3.5 Calculating the RCEC and Environmental Impact for Each Generated Urban Form

The commuting distance can be calculated from the results of residential location choice and job location choice. Regarding the confirmed commuting mode of each resident, the RCEC E_i and environmental impact C_i (e.g., pollutants SO_2 and NO_X, as well as house gas CO_2) can be calculated using indicators for various commuting modes (see Table 13.1). The RCEC and environmental impact on the whole city can be then calculated by summing up all residents. Since this chapter mainly aims to identify the quantitative relationship between the urban form and RCEC, the indicators shown in Table 13.1 are not real values and are only used to illustrate the relative relationship among various commuting modes in terms of the RCEC and environmental impact.

Table 13.1 Transportation energy consumption and environmental impact indicators for various commuting modes

ID	Travel mode	Consumed energy per kilometer per capita	Environment impact per kilometer per capita
1	Car	10	10
2	Bus	2	1
3	Bike or walk	0	0

13.2.3.6 Selecting Indicators for Measuring Urban Forms

We selected 14 indicators developed by McGarigal et al. (2002) for measuring generated urban forms using FRAGSTATS. These indicators, initially developed for evaluating ecological landscape, were borrowed to measure urban forms and are divided into two types (detailed descriptions for these indicators are available at: http://www.umass.edu/landeco/research/fragstats/documents/Metrics/MetricsTOC.htm). The first type is for evaluating the land-use pattern (i.e., the spatial distribution of commercial parcels) and includes seven indicators. The second type is for evaluating the spatial distribution of density (i.e., FAR) and includes the other seven indicators. The calculated indicator is expressed as I_i^k, where k is the ID of the indicator, k is the number of indicators (14 in this chapter), and i is the ID of the generated urban form.

- The type for measuring land-use pattern (see red parcels in Fig. 13.7)
  - CLS_CA: Total Area (of commercial parcels)
  - CLS_NP: Number of Patches (A group of adjacent parcels is defined as a patch.)
  - CLS_LPI: Largest Patch Index
  - CLS_ENN_MN: Euclidean Nearest Neighbor Distance
  - Shape indicators
    - CLS_SHAPE_MN: Shape Index
    - CLS_LSI: Landscape Shape Index
    - CLS_PARA_MN: Perimeter-Area Ratio
- The type for measuring FAR (see colored parcels in Fig. 13.6)
  - Diversity indicators
    - LD_SHDI: Shannon's Diversity Index
    - LD_SHEI: Shannon's Evenness Index
  - LD_ENN_MN: Euclidean Nearest Neighbor Distance
  - LD_COHESION: Patch Cohesion Index
  - Contagion-Interspersion
    - LD_CONTAG: Contagion Index
    - LD_DIVISION: Landscape Division Index
    - LD_AI: Aggregation Index

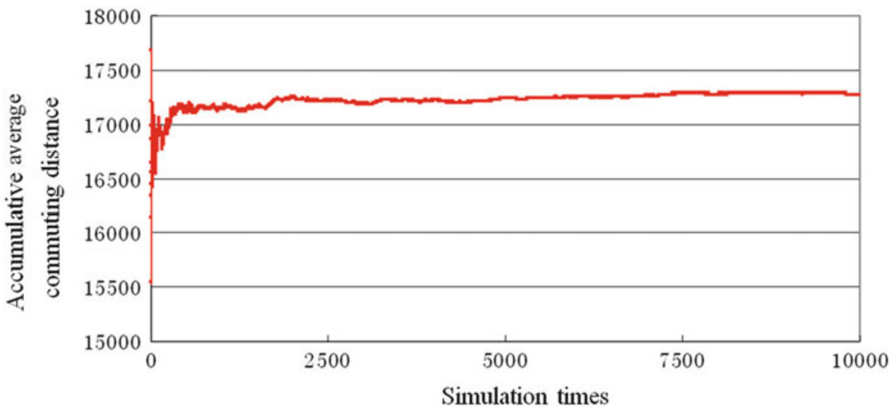


Fig. 13.4 The accumulative average commuting distance for each simulation

13.2.3.7 Identifying the Relationship Between the Urban Form and RCEC

The quantitative relationship between the urban form and RCEC can be identified from the calculated urban form indicators and RCEC. The details are as follows:

1. Conduct correlation analysis among indicators for measuring the urban form to eliminate indicators with high correlation (greater than 0.8 or less than −0.8).
2. Identify the dominant factors influencing the RCEC of the urban form using the global sensitivity analysis approach.
3. Evaluate the influence of the shape of the urban form on the RCEC.
4. Calculate the RCEC for various typical urban forms to test conventional planning theories.

The results of the above tests are shown in Section 3.

13.3 Results

A total of 10,000 parallel simulations, with 10,000 urban forms generated, were conducted using the FEE-MAS model with 112 h consumed. Convergence was reached in terms of the accumulative average commuting distance (see Fig. 13.4), indicating that the 10,000 urban forms generated can represent almost all possible urban forms in the hypothetical city. A big number of simulations were run to guarantee that the identified relationship between the urban form and RCEC is stable and represents the objective characteristics of the urban system.

The descriptive statistical information of 10,000 simulations is shown in Table 13.2, in which *dist* is the total commuting distance, *E* is the total RCEC, and *C* is the total pollutant emission of the whole city.

Table 13.2 The descriptive statistical information for simulation results

Name	Min	Max	Ave	Std. Dev.
dist	9,186	27,848	17,300	2,932
E	64,092	238,378	140,500	27,969
C	62,236	233,844	137,500	27,517
CLS_CA	0.0010	0.0040	0.0025	0.0009
CLS_NP	6	33	19.2	5.6
CLS_LPI	0.2500	3.7500	0.7624	0.3248
CLS_LSI	2.2857	6.0769	4.4267	0.7948
CLS_SHAPE_MN	1.0000	1.2375	1.0423	0.0326
CLS_PARA_MN	34,000	40,000	38,741	877
CLS_ENN_MN	2.1554	6.2072	3.0421	0.5705
LD_ENN_MN	2.3301	5.6048	3.3062	0.3579
LD_CONTAG	24.4728	50.4032	39.2857	4.0672
LD_COHESION	82.6889	96.7945	93.1993	1.4731
LD_DIVISION	0.5431	0.9249	0.6957	0.0553
LD_SHDI	0.7929	1.0989	0.9778	0.0671
LD_SHEI	0.4978	0.7560	0.6090	0.0406
LD_AI	35.8211	54.1918	44.6079	3.0234

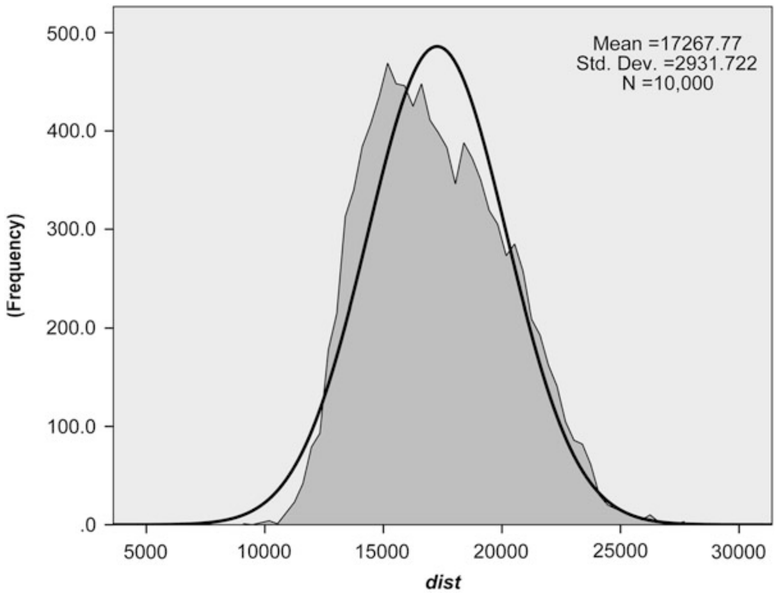


Fig. 13.5 The frequency density distribution of dist compared with the normal distribution

The total commuting distance for each urban form (*dist*) is the core variable in the simulation results. From the frequency distribution of *dist*, the variation of total commuting distance *dist* varies by urban form, ranging from 9,186 to 27,848 among all generated urban forms. Fig. 13.5 shows the probability density distribution of

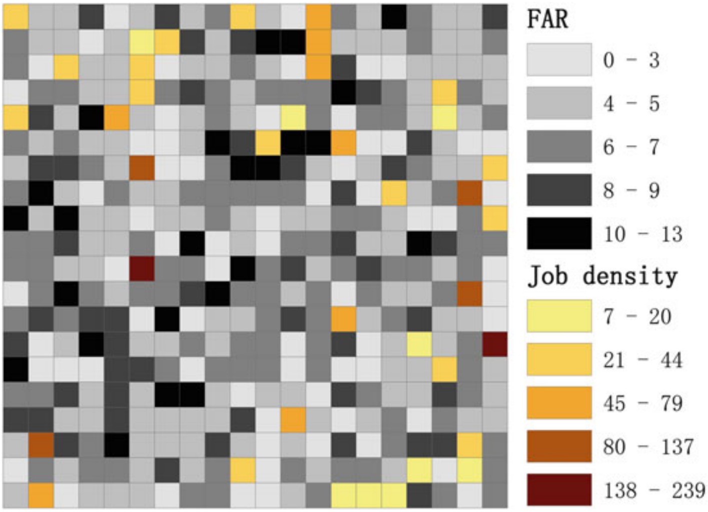


Fig. 13.6 FAR distributions for an exemplified urban form with the results of job location choice

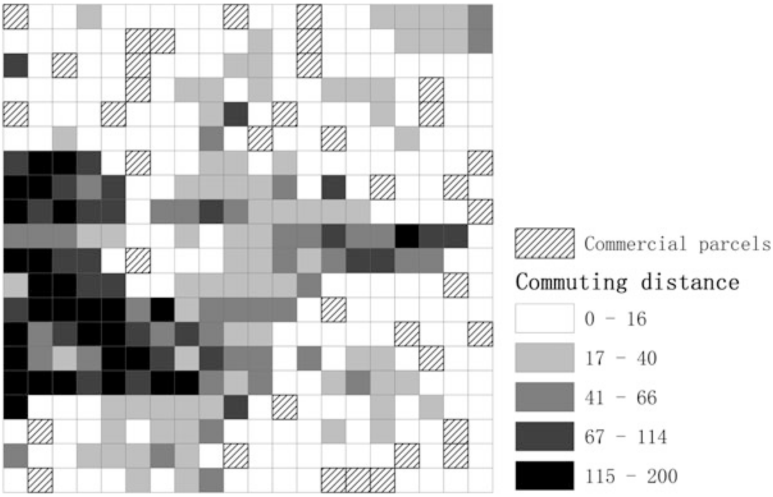


Fig. 13.7 The commuting distance map for an exemplified urban form

dist, which is very similar with the normal distribution curve shown in the figure, with the average value of 17,267.77 and standard deviation of 2,931.722.

To illustrate the general information regarding the 10,000 simulations, Fig. 13.6 shows one generated urban form with the results of job location choice and Fig. 13.7, the spatial distribution of commercial parcels and commuting distance for each residential parcel.

13.4 Correlation Analysis of Indicators for Evaluating the Urban Form

Correlation analysis is conducted on all indicators to measure urban form. Variables with a correlation value of greater than 0.8 or less than −0.8 are eliminated from further analysis, including CLS_CA, CLS_LSI, CLS_ENN_MN, LD_SHEI, LD_AI, LD_CONTAG, and LD_COHESION.

13.4.1 Global Sensitivity Analysis

The relationship between spatial indicators and commuting distance can be identified using the global sensitivity analysis (GSA) approach. In contrast to the local sensitivity analysis (LSA) approach that changes one factor at a time (OAT) to see the effect of factor variation on the output, the GSA can detect the parameters' sensitivity by adjusting all parameters' values in the whole parameters' value space. That is to say, we can see the "tree" via LSA and the "forest" via GSA. The indicators that remained after the correlation analysis are inputted into the GSA process. We adopted the linear regression approach as one type of widely used GSA approach, in which ln (*dist*) is regarded as the dependent variable, and spatial variables are the independent variables. The regression results are illustrated in Table 13.3; spatial variable LD_SHDI is not significant and is eliminated from the linear regression. The regression results show that each variable is significant at the 0.001 level, and the coefficient of the variable CLS_NP is negative and least among all variables, indicating that the number of job centers has the greatest influence on the total commuting distance of the whole city. The more job centers there are, the less the commuting distance. The mean shape index CLS_SHAPE_MN is negative, denoting that the urban form with more complex commercial parcel distribution and irregular shape will result in less commuting distance. The reason may lie in the principle that the job location choice of residents in this chapter is the nearest commercial parcel and a resident will be more likely to find a commercial parcel to work in the more irregular the commercial parcel distribution is.

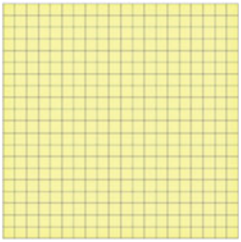
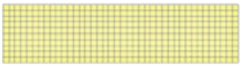
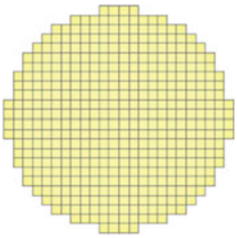
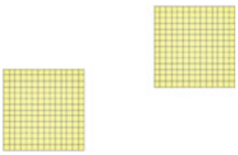
Table 13.3 Global sensitivity analysis for simulation results

Variable	Standardized coefficient	*t*	Sig.
Constance		198.017	.000
CLS_NP	−.771	−121.363	.000
CLS_SHAPE_MN	−.114	−19.246	.000
CLS_PARA_MN	.076	14.449	.000
LD_ENN_MN	.040	7.359	.000
CLS_LPI	−.030	−4.451	.000
LD_DIVISION	−.026	−3.975	.000

13.5 Identifying the Relationship Between the Shape of the Urban Form and RCEC

The previous results are based on square urban forms with 400 parcels. To test the influence of the shape of the urban form on total commuting distance, we select four types of shapes, as shown in Table 13.4—square, rectangle, circle, and poly-clusters. For each shape, we generated 5,000 different urban forms based on the approach elaborated in Sect. 13.2.3.2, using the FEE-MAS model. The total commuting distance for each urban form with various shapes is calculated as shown in Table 13.4, in which the average value of *dist* denotes the influence of the shape of the urban form on total commuting distance. According to the computation results, the circle has the least commuting distance and the square, the greatest.

Table 13.4 Simulation results of commuting distance for urban forms with various shapes

Shape	Shape	Min	Max	Ave	Std. Dev.
Square		9,186	27,848	17,300	2,932
Rectangle		6,943	33,187	16,801	4,904
Circle		7,419	25,750	13,460	2,906
Poly-clusters		6,583	47,535	14,948	4,910

Note: The parcel in each urban form may differ from the others due to different map scales

The multi-cluster has a shorter commuting distance than the mono-cluster. The three conclusions above are all in accord with conventional planning theories. However, the rectangle has a shorter commuting distance than the square, which is not the same as the conventional planning theory. This may be because the resident with full rationality in our model will choose the nearest commercial parcel to work in. The results may vary in the random selection of the work place, which will be explored in future research.

13.5.1 Evaluating Typical Urban Forms

For evaluating conventional planning theories, such as greenbelts, transit-oriented development (TOD), poly-centers, and the compact city, we generated six typical urban forms (see Fig. 13.8), taking the number of job centers and the distribution of development density into account. The shape of each urban form is the same as the urban form generated in Sect. 13.2.3.2 "Generating Urban Forms and Residential Location Choice," with 400 parcels and 2,000 residents. These typical urban forms are generated according to conventional planning theories rather than the approach in Sect. 13.2.3.2. For the sprawl pattern with low-density developments, the FAR of each residential parcel is 5 and the built-up area is the size of 400 parcels. For the compact pattern with high-density developments, the FAR of each residential parcel is 20 and the built-up area is the size of 100 parcels. In the urban form based on TOD, the FAR decays as the distance to the city center increases. As for the urban form with a greenbelt, parcels within the belt remain undeveloped.

We calculated the total commuting distance for each typical urban form (see results in Table 13.5):

- The total commuting distance of the urban form with a sprawl pattern (e.g., A and E) is double that of a compact pattern (e.g., B and F). This could be due to their differences in total urban built-up area, regardless the mono-center or poly-center urban form.
- In contrast to the mono-center and TOD urban form with the same shape (C), the urban form with mono-center and sprawling pattern has greater commuting distance.
- For mono-center cities, the introduction of a greenbelt (D) will increase the development density of the city with the same built-up amount and slightly increase the total commuting distance compared with the sprawl pattern (A).
- The urban form with poly-centers and compact pattern (F) has the least commuting distance because reducing the size of an urban developed area also reduces the general distance between the working place and living place.
- The urban form with poly-centers (E) has the biggest total commuting distance, which is similar to the urban form with a mono-center and greenbelt (D).

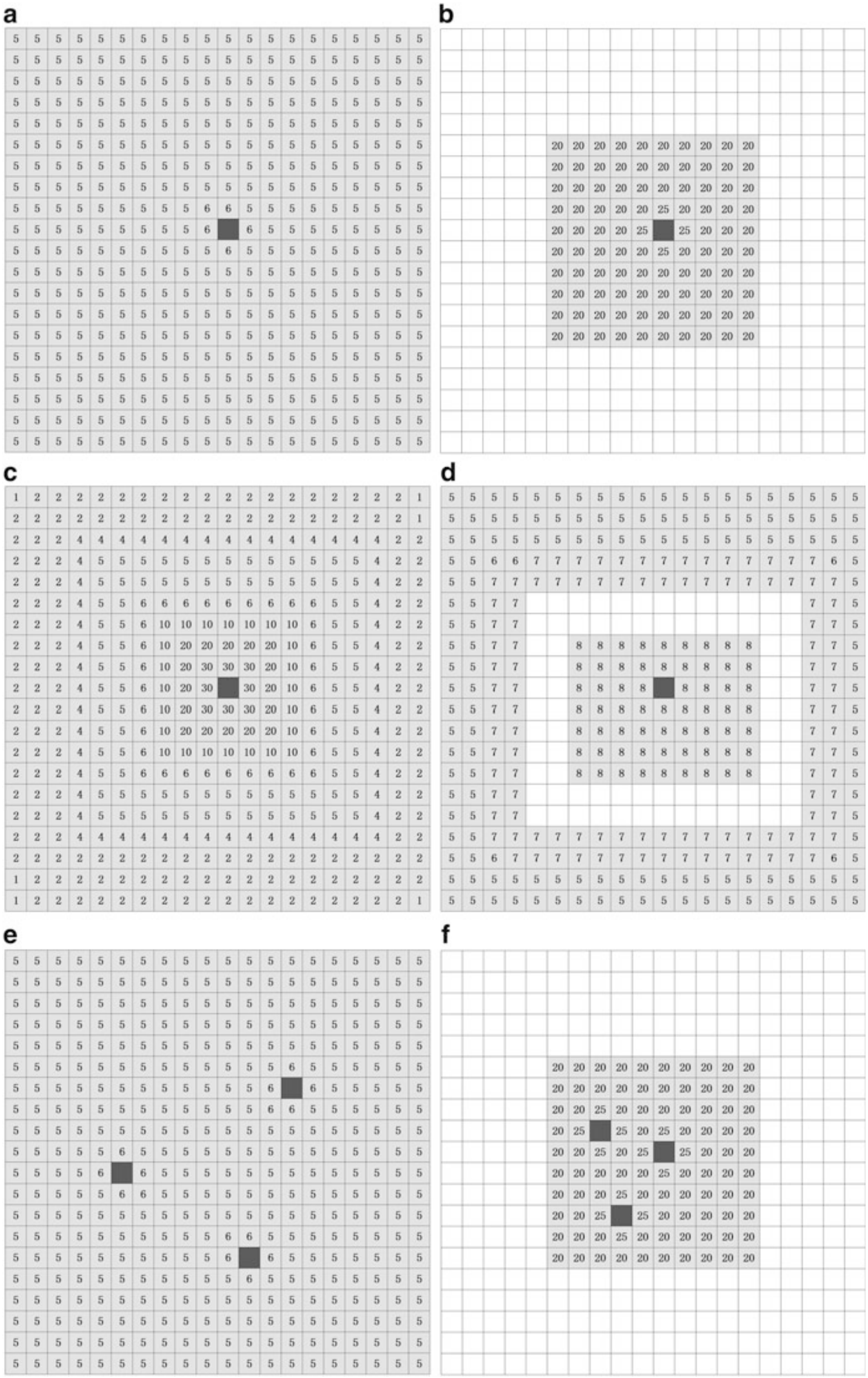


Fig. 13.8 Six typical urban forms in the hypothetical city. Note: Parcels in dark grey are commercial; in light grey, residential; and in white, undeveloped. The figure in each parcel is its FAR. We only use one commercial parcel to illustrate the spatial layout of job centers rather than the real size of job centers

Table 13.5 Simulations results for six typical urban forms

Typical urban form	Total distance	Energy consumed	Environment impact	Order of total distance
A Mono-center and sprawl	20,006	171,792	168,391	3
B Mono-center and compact	10,020	78,528	76,344	5
C Mono-center and TOD	14,092	113,456	110,673	4
D Mono-center and greenbelt	20,026	170,228	166,674	2
E Poly-centers and sprawl	22,264	191,168	187,429	1
F Poly-center and compact	8,860	64,648	62,879	6

13.6 Conclusions and Discussion

This chapter aims to investigate the impact of urban form—the land-use pattern, development density distribution, as well as number and distribution of job centers—on the residential commuting energy consumption (RCEC). We developed a multi-agent model named FEE-MAS based on complex adaptive system theories for the urban form, residential transportation energy consumption, and environmental impact integrated simulation, with residents and parcels as the basic units in the simulations. Numerous distinguished urban forms are generated in the hypothetical city using the Monte Carlo approach. On the one hand, the RCEC for each urban form is calculated using the proposed FEE-MAS, which integrates the residential location choice, job location choice, and commuting mode choice for residents. On the other hand, we selected 14 indicators (e.g., Shape Index, Shannon's Diversity Index, and Euclidean Nearest Neighbor Distance) to evaluate each generated urban form using FRAGSTATS, which is loosely coupled with the FEE-MAS model. Then, the quantitative relationship between the urban form and RCEC is identified based on the 14 indicators calculated and RCEC of each urban form.

Several conclusions are drawn from simulations conducted in the hypothetical city: (1) The RCEC may vary three times for the same space with different urban forms. (2) Among the 14 indicators selected for measuring urban form, the patch number of job parcels is the most significant variable influencing the potential RCEC of the urban form. (3) The RCECs of all urban forms generated obey a normal distribution. (4) The shape of the urban form also exerts an influence on the RCEC. In addition, we evaluated several typical urban forms (e.g., compact/sprawl, single center/poly-centers, traffic-oriented development (TOD), and greenbelt) in terms of the RCEC indicator using our proposed model to quantify the conventional urban planning theories. The FEE-MAS model can also be applied for evaluating urban spatial alternatives in terms of energy consumption and environmental impact.

Most existing land-use and transportation integrated models (LUTMs), such as UrbanSim (Waddell 2002) and Tranus (Putman 1975), can facilitate the calculation of total commuting distance for real cities. Our developed FEE-MAS model can be regarded as a lightweight LUTM, with which commuting distance for various cities can be calculated. The FEE-MAS model is developed to identify the principal rules governing dynamic urban systems, rather than perform empirical applications for real cities of LUTMs. The FEE-MAS model features the identification of the dynamic relationship between urban form and commuting distance in a manner of inner-city analysis, which is not possible for intercity researches.

The spatial-explicit FEE-MAS model can meanwhile be applied for evaluating planning alternatives in real cities in terms of commuting distance, energy consumption, and environmental impact, thus providing a low-carbon alternative to planners and decision makers. This process can guarantee low-carbon city development in the planning stage by embedding it in the comprehensive planning alternative evaluation procedure.

In addition to applying the model to the practical city, we will be conducting further research. (1) The energy consumption of households, entertainment, and industrial sectors will be taken into account besides the residential commuting energy consumption that was analyzed by the current FEE-MAS model. (2) The relationship between the socioeconomic attributes of residents and their rationality will be considered in the form of $r = g(A_j)$, where A_j is the resident j's socioeconomic attribute set and g is the function for calculating the rationality of a resident using his/her socioeconomic attributes. The socioeconomic attributes of the residents will then be introduced into the residential location choice process of the model. (3) The capacity of jobs in commercial parcels will be incorporated in the job location choice process to simulate a more practical result. (4) The transportation network is expected to be included in the model to replace the current Manhattan distance in this chapter for a more precise calculation of residential commuting energy consumption.

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