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The transformation of urban industrial land use: A quantitative method

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Abstract

A large number of cities around the world today owe their land use growth to the rapid development of industrial areas. The spatial structure of industrial distribution in cities shape urban spatial morphology linking with land use, transportation, economic activities, and housing. Meanwhile, growth and expansion of city population and land use reconfigure the spatial structure of industrial distribution. Research into urban industrial spatial distribution and its transformation process may help urban planners and decision makers understand the land use and population dynamics of a city. Genetic algorithms are believed to be one kind of the promising methods to simulate this dynamic process. In this paper, we propose a novel method to simulate urban industrial spatial distribution and its transformation process in Shanghai, China. The results show that along with increasing urban land price over time, industries are going to move outward from the city center. However, the maximum profit of a firm tends to decrease, which could lead industrial factories to move beyond city boundary. The analysis of the current industrial spatial distribution in Shanghai indicates that, when land price in a city rises above a specific threshold, new government policies and other competitive advantages need to be enacted if the city wants to retain industrial firms within the city boundary.

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Keywords: Industrial spatial structure; Spatial analysis; Genetic algorithm; Shanghai

1. Introduction

The expansion of urban land use and transformation of industrial space are two conspicuous phenomena revolving around the development process of cities (Angel et al., 2005). On the one hand, industrial growth and agglomeration are major driving forces of urban land use change and expansion (Walker, 2001). The start-up and concentration of industrial plants lead to the convergence of residential, economic and social activities due to agglomeration effects. Spatial restructuring of industries may also reshape spatial configuration of a city (Clark & Burt, 1980; Viehe, 1981; Walker, 2001). On the other hand, residential population growth, in-migration and expansion of residential space also affect the spatial distribution of industries due to the shifting of land price and local labor market (Hudalah, Viantari, Firman, & Woltjer, 2013; Ning & Yan, 1995). The reconfiguration of urban industrial spatial distribution and urban

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land use expansion are therefore two complementary close-knitting processes determining the spatial trajectory of urban transformation.

It can be argued that appropriate and balanced urban industrial spatial structure is imperative to steady urban growth (Anas, Arnott, & Small, 1998; Fischer & Nijkamp, 2012; Fujita & Thisse, 2013). During the process of rapid urbanization and suburbanization, any ad hoc and unplanned spatial distribution and allocation of industries may bring about undesirable consequences, including high energy consumption and waste, excessive loss of prime agricultural farmland, heavy traffic congestion, and degraded quality of life (Berrigan, Tatalovich, Pickle, Ewing, & Ballard-Barbash, 2014; Brueckner, 2000; Ewing, Meakins, Hamidi, & Nelson, 2014). In China, for example, heavily concentrated manufacturing factories around city center have brought about severe traffic congestion and air pollution, while unordered industrial diffusion has greatly accelerated the removal of prime agricultural land during the past ten years (Chan & Yao, 2008; Tian & Zhu, 2013). Therefore, understanding the relationship between land use change and industrial spatial distribution and their co-transforming processes can help urban planners and decision makers develop a more sustainable and livable city.

Studies on industrial spatial structure can be dated back to the study of industrial structure of American cities in the late 1950s (Alexandersson, 1956) and Alfred Weber's industrial location theory (Weber & Friedrich, 1962). Economic geographers attempt to explain spatial distribution of industrial factories based on land price theory (Alonso, 1964; Isard, 1956; Muth, 1961). For example, Weber pointed out that an industry is usually located where the transportation cost of raw materials and final products is the lowest. Alonso found that manufacturing factories choose to be located close to both market and labor in a city. These pioneering studies lay a basic foundation for the contemporary research on industrial spatial distribution. However, classic location theories say little about the transformation process of industrial structure from a dynamic perspective.

While evolutionary economic geographers have explored evolving spatial structure and distribution of industries using theoretical frameworks based on agglomeration effect, technology innovation, knowledge spillover, and industry life cycle theories (Iammarino & McCann, 2006; Krugman, 1991; Peltoniemi, 2011), most of them only focus on industrial structure alone while neglecting urban spatial process. There is a lack of exploration into how urban land use change is linked with the spatial transformation of industrial activities. Frenken and Boschma (2007) proposed a theoretical framework to investigate industrial dynamics and urban growth, but no specific industrial space is presented or delineated although such understanding of spatial transformation is essential to urban planning and city management. In a practical sense, urban land use change is a continuous transmitting process. Industrial redistribution and residential land use transformation are critical part of urban growth. Reconfiguration of land price space can lead to a redistribution of industrial and residential land use patterns. Likewise, restructuring of industrial and residential land use can alter the spatial structure of land price. This co-transforming process can be better understood through a dynamic simulation perspective.

Drawn on biological metaphors to create computer programming systems, evolutionary algorithm is believed to be one of the promising methods to simulate dynamic transformational problems (Manson, 2005). This paper develops a dynamic simulation method for simulating the spatial transformation process of urban industries. A novel model

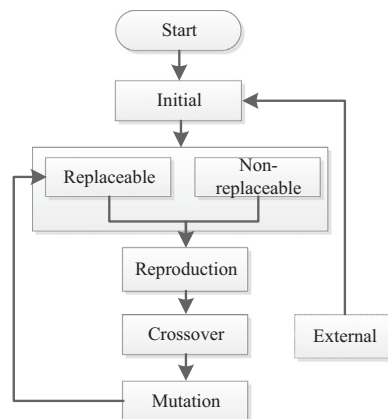


Fig. 1. Framework of GA.

called Location-based Firm Profit (LbFP) model is proposed. Taking Shanghai as a case, this research attempts to demonstrate how urban land use growth may lead to the spatial structural transformation of industries. After this introduction, the paper describes Genetic Algorithm as an important branch of evolutionary algorithms. It then outlines an integrated model used to investigate the spatial interaction among industrial activities in cities. Section 4 presents a theoretical model of urban industrial spatial distribution using a modified Cobb–Douglas production function and the distance decay theory. The study area, data and other simulation parameters will be introduced in Section 5 of this paper. The parameters of core functions are evaluated and the objective function is formalized. Finally, simulation results will be presented and discussed.

2. Genetic algorithms

Genetic algorithm (GA) was first introduced in the 1960s by Holland (1992). It is originated from natural selection and natural genetics in the field of evolutionary biology. A basic GA is usually comprised of three operators: reproduction, crossover, and mutation (Goldberg, 1989) (Fig. 1). In each evolutionary generation, GA selects the best parents according to their characteristics, e.g., their fitness value from a fitness function, in order to ensure that the best offspring could be reproduced in the next generation. Once the parents are selected, GA pairs them randomly and codes them into strings. After that, they will crossover with each other and produce offspring, which, in turn, become potential parents of the next generation. Through this iteration, GA updates parents from generation to generation and their best characteristics are retained and passed over from one generation to next. GA normally uses probabilistic method to generate and mate parents. The method allows information exchange and ensures the best characteristics would survive and become dominating generation after generation. This genetic mechanism is quite similar to natural selection process, in which the best genes and species survive. Because of its good performance among searching algorithms in practical uses, GA has been used widely and validated in many research fields (Michalewicz, Janikow, & Krawczyk, 1992; Mukhopadhyay, Balitanas, Farkhod, Jeon, & Bhattacharyya, 2009).

GA, acting as a closed evolution process, therefore, can be used to solve one or a group of static functions easily. External stressors will be needed to tune it up for the simulating of dynamic systems. To simulate the transformational process of industrial spatial distribution in a city, the initial condition of the searching process of GA needs to change with the elapse of time (Fig. 1), leading to the change of searching results. As such, the optimization searching process evolves over time, which could be used to animate the dynamical process of urban space. The rest of this paper is going to use this method to simulate the transformational process of the spatial industrial distribution of Shanghai, China.

3. Simulating the evolution of urban industrial space

According to the classic location theory, in order to maximize profits, industrial firms tend to choose the optimum locations in a city with minimum costs (Krzyzanowski, 1927). The factors that affect the selection of optimal locations may include land price, transportation cost, urban land use policy, infrastructure, local governance or tax policy (Hayter, 1997; Weber & Friedrich, 1962). In particular, land price and operating cost are considered as the two most stable determinants that influence the site selection of factories in a perfect competitive market city (Alonso, 1964). This research attempts to develop an industrial spatial distribution model by considering the profit maximization of firms under these two factors.

3.1. Industrial profit

The overall profit that a firm produces consists of three parts: output value (*OV*), operating cost (*OC*) and land cost (*LC*), as shown by the following equation (Alonso, 1964):

$$P = OV - OC - LC, \quad (1)$$

where *P* is the total profit, *OV* is the output value, *LC* is the land cost, and *OC* is the operating cost.

Considering industrial production is less influenced by physical environment comparing with agriculture (Hudson, 2014), this study supposes that a city is divided into a number of regular lattices and the possible production efficiency of a firm at each lattice is the same. This uniform arrangement means the output value of each lattice is

homogeneous across the city space. Accordingly, we can estimate the profit that a factory gets at lattice i as:

$$P_i = OV_i - OC_i - LC_i \quad (2)$$

3.2. Land price

Land price in a city is tied closely to where the land is located. Generally, the overall land price in a city decreases from the city center outward (Alonso, 1964; Mills, 1967). Many researches also show that the land price correlates with the size of land parcel (Colwell & Munneke, 1997) and the volume of the construction that will be built on the land parcel. The influence of construction volume is not significant in small cities, but is very important in big cities or where available land for construction is limited. Based on the Cobb–Douglas production function (Douglas, 1976), we can define the price of land, LC_i , at location i in a city as a composite function of *area*, *construction volume* and *distance to city center*:

$$LC_i = \theta A_i R_i / D_i, \quad (3)$$

where θ is the coefficient value, A_i is a function of the land parcel area, R_i is a function of the *Floor Area Ratio (FAR)*, which equals the gross floor area permitted on a site divided by the net land parcel area, and D_i is a function of distance d_i to the city center.

Empirical studies show that the land price is not a linear function of distance to the city center. It is a decreasing concave function of distance (Colwell & Munneke, 1997; Kau & Sirmans, 1979). Hence, the distance influence on the price of land can be written as:

$$p_{D_i} = \theta_1 e^{\mu d_i} \quad (4)$$

where D_i indicates the influence of distance on land price, θ_1 is the land price of city center, d_i is the distance to the city center, and μ is the rate at which the land price changes with the increasing/decreasing distance.

It is also found that the price of land appears as a concave function of parcel size (Brownstone & De Vany, 1991). The bigger the land size which developers ask for, the more discount they can get from land sellers. The influence of land size on the price of land can be defined as:

$$p_{A_i} = \theta_2 e^{\varepsilon(a_i - 1)}, \quad (5)$$

where A_i indicates the influence of sold land size on land price, θ_2 is the land price of city center, ε is the area elasticity of the land price, and a_i is the land size at location i in the city.

Observations show that the price of land can be a linear relationship with *FAR* (Gao, Asami, & Katsumata, 2006), so the influence of *FAR* can be defined as:

$$p_{R_i} = m + n * FAR_i, \quad (6)$$

where R_i indicates the influence of Floor Area Ratio on land price, FAR_i is the floor area ratio at location i , m is a constant, and n is coefficient value.

The land price of location, therefore, can be wrote as:

$$LC_i = \theta * FAR_i * e^{\varepsilon(a_i - 1)} * e^{\mu d_i}$$

The function above shows that θ is the initial per unit land price of the city center where $d_i = 0$, $a_i = 1$, and $FAR_i = 1$.

3.3. Firm production operating cost

The operating cost of a firm in a city includes several components, such as labor cost, transportation cost, and energy consumption cost. Most of these production cost factors are isotropic and hence homogeneous across a city space where a unified and competitive local labor market operates with an exception for transportation cost. The transportation cost may include production transportation cost of a firm and daily transportations of its employee. Theoretically, the better transportation accessibility a location is, the lower the transportation cost is, and as a result the lower operating cost a firm has to bear. We propose the influence of transportation cost on the operating cost of a

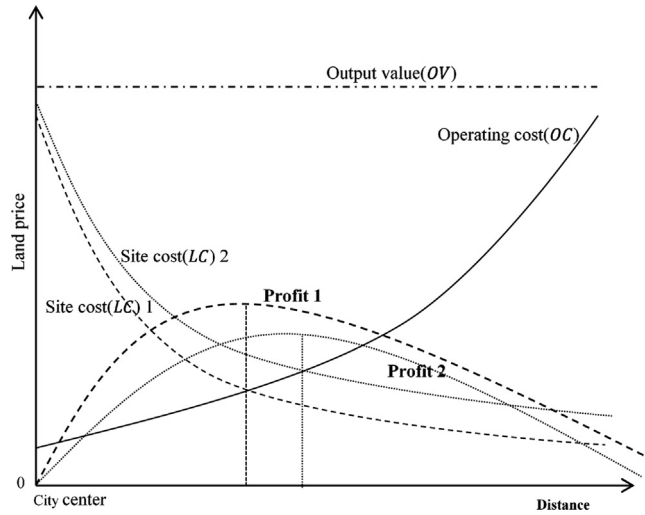


Fig. 2. Costs, revenue and profits of the firm according to location.

firm as follows:

$$OC_i = OC/T_i, \tag{7}$$

where OC is the universal operating cost of industry (a constant value across the city) and T_i is the transportation accessibility of a firm.

Road density is one of the important indicators for transportation accessibility. In general, the higher the road density is, the more accessible of the firm location is. We define the influence of distance on the transportation accessibility of a firm at location i in a city as follow:

$$T_i = \omega e^{\rho d_i}, \tag{8}$$

where ρ is the coefficient, d_i is the distance to the city center, and ω is the road density of the city center area.

3.4. Location-based Firm Profit (LbFP) model

Taking all above factors into consideration, this research proposes a novel Location-based Firm Profit (LbFP) model to simulate the dynamics of industrial spatial distribution in a city. The model reflects the spatial distribution of industrial firms in a city, especially metropolitan ones, where effects of urban land price are often paramount.

$$P_i = OV - \frac{OC}{\omega e^{\rho d_i}} - \theta * FAR_i * e^{\epsilon(a_i - 1)} * e^{\mu d_i}, \tag{9}$$

In order to visualize the structure of the model clearly, the three main factors are plotted in Fig. 2. The horizontal axis represents the distance originated from city center and the vertical axis is the average land price at the city center. The figure shows that, with the increasing distance from the city center in a city, the site cost (site cost 1 curve) decreases, but the operating cost increases quickly. Supposing the net output and per unit sale price among firms is constant across city space, the overall profit of a firm (profit 1 curve) reaches the highest point at certain distance and then declines with the increasing distance from the city center. The industrial firms in a city, ideally, will choose to cluster around the maximum profit distance from the city center.

However, this pattern of spatial clustering of firms in a city will change over time when the overall land price (site cost 2 curve and in Fig. 2) increases because of growing competition for urban land of a city. This means that the firm profit curve in Fig. 2 (profit 2 curve) will have the same shape but the maximum profit point will move outward from the city center. Given the increasing land price, the maximum profit that a firm can generate is going to decrease if the output value unchanged. The above theoretical model will be employed to simulate the transformation process of industrial space in Shanghai, China.

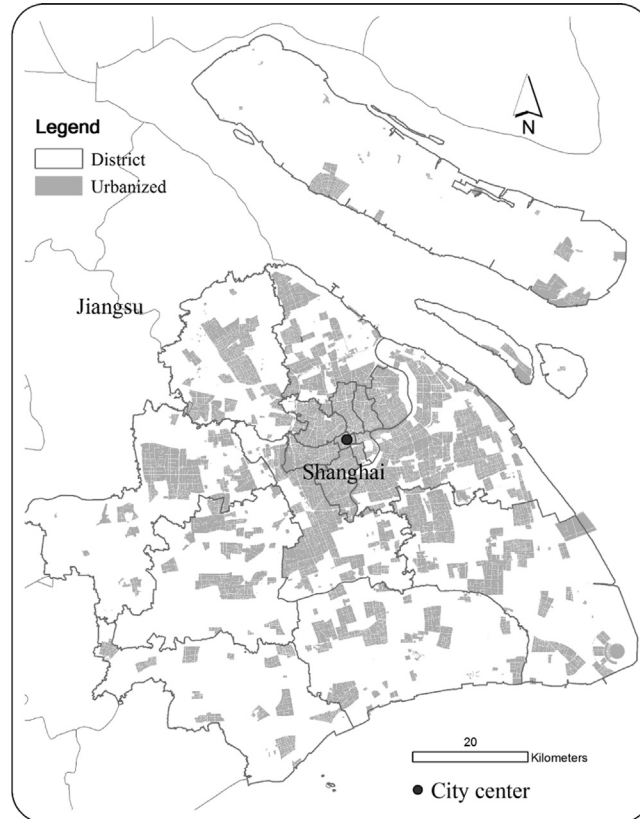


Fig. 3. The map of Shanghai, China.

4. Study area and data

Shanghai is located at the tip of the Yangtze River Delta. The city of Shanghai covers a land area of 6396 km² and is the largest city in China by population according to 2010 census. Since 1978 when economic reforms were initiated, Shanghai has experienced a rapid pace of growth and development, and has been one of the fastest developing cities around the world for the last three decades. The urbanized land area of Shanghai in 2010 was almost three times as much as that in 1987. Its urban landscape, especially the spatial distribution of manufacturing firms has changed greatly. Fig. 3 shows the city of Shanghai and its built-up areas up to 2013 based on the data from Shanghai Urban Planning and Land Resources Administration Bureau. The research into the evolution of industrial space can shed light on the mechanisms of urban and industrial evolution in Shanghai. Such knowledge is important for urban planning and city management. One of the major goals of this study is to calibrate the theoretical land price model, LbFP, outlined in the previous section using real data on Shanghai.

Before 1978, there was no land market under the planned socialist economy in China. The commodification of land started in the later 1980s and was accelerated after 1998 when privatization and commodification of housing were announced by the state council. In 2001, the municipal government of Shanghai launched land auction policy in order to make the land transaction activities public and transparent and also to make the land price to reflect fully the value of land. Since then, land developers can bid for the lands that are permitted to circulate in land market. This has made the price of urban land less influenced by non-market factors, such as governmental allocation. Hence, we can reasonably assume that the data on the land transactions reflect the real value of the land in Shanghai.

This research collected 250 traded land parcels between 2011 and 2013 from the website of Shanghai Municipal Planning and Land Resources Administration (<http://www.shgtj.gov.cn/>). The data is formatted by the serial number of the sold land parcel, and its address, area, price, and FAR. According to the addresses provided by their transaction announcements, the research located all the 250 land parcels on the digital map of Shanghai and

Table 1
Model estimation.

	Model	Estimated function	Model Sig.
Land area vs. price	$p_{A_i} = \theta_2 e^{\varepsilon(a_i - 1)}$,	$p_i = 583.773e^{-(2.053E-6)(a_i - 1)}$	0.074
Land price vs. FAR	$p_{R_i} = m + n * FAR_i$	$p_i = -29914.595 + 20191.179 * FAR_i$	0.000
Land price vs. distance	$p_{D_i} = \theta_1 e^{\mu d_i}$	$p_i = 56098.395e^{-0.120d_i}$	0.000
Overall regression of land price and distance	$p_i = \theta * FAR_i * e^{\varepsilon * \lg(a_i)} * e^{\mu d_i}$	$p_i = 96331.086 * FAR_i * e^{-0.315 * \lg(a_i)} * e^{-0.087d_i}$	
Land size vs. distance	$a_i = m + n * d_i$	$a_i = 32829.411 + 552.861 * d_i$	0.034
FAR vs. distance	$FAR_i = \theta e^{\mu d_i}$	$FAR_i = 3.104e^{-0.021d_i}$	0.000
Road density vs. distance	$T_i = \omega e^{\rho d_i}$	$T_i = 7.524 * e^{-0.027 * d_i}$	0.000

measured their distances from the city center using ArcGIS (this research uses the original point of Shanghai Local Coordinate System as the city center point).

To estimate the effect of the land parcel size on the price of land, the area and price data of 100 sold land parcels were collected on the Qingpu Industry Park. The industry park was planned in the middle of 1990s. It is located around 35 km west of the city center and covers 16.1 km². Since the park is far away from the city center and the majority of the land parcels were sold only for industrial use, it can be reasonably assumed that the land price of this area is less influenced by the distance to the city center and urban land use policies. The comparison of the land price and land parcel size in this area can reflect the direct influence of land size on the land price of the city.

The plots of those data and preliminary regression analysis show several important facts: 1) the land price follows a decreasing concave trend as land plot size increases; 2) the size of traded land plot has a linear relationship with the distance away from the city center; 3) the FAR has a linear relationship with the land price; 4) the FAR has a negative exponential relationship with the increasing distance away from the city center. Based on these empirical observations, several regression analyses were conducted to obtain the estimated function of land price with the parameter d_i (Table 1). Among them, $\lg(a_i)$ was used for the overall regression when we found the ε value of land area vs. price is too small ($-2.053E6$). The regression results show that almost all the models are statistically significant at a 95% confidence level. The land area vs. price model is significant at a 90% confidence level.

To investigate the relationship between the road density and the distance to city center, we use the current road network of Shanghai and divide it into 12 rings with a width of 5 km each. The result shows that the road density decreases exponentially from the city center outward (Table 1).

Based on the regressions above, the overall industrial spatial distribution model could be defined as the basic object function with parameter d_i :

$$P_i = OV - \frac{OC}{7.524 * e^{-0.027 * d_i}} - 96331.086 * FAR_i * e^{-0.315 * \lg(a_i)} * e^{-0.087d_i}, \quad (10)$$

$$a_i = 32829.411 + 552.861 * d_i, \quad (11)$$

$$FAR_i = 3.104e^{-0.021d_i}, \quad (12)$$

where d_i is the distance from location i to the city center, OV is the universal output value of the factories across the city, and OC is the universal initial operating cost. Both OV and OC are constants.

The calculation results above show that the FAR around the city center of Shanghai is 3.104 ($d_i = 0$), the minimum land size is 32,829.412 m² ($d_i = 0$), and the corresponding sale price is 72,085.996 CNY/m². This means the owner of a firm needs to pay at least 23,223.581 CNY/m² if he wants to build a one floor factory around the city center of Shanghai.

5. Simulation and discussion

From the previous section we can see that the distance parameter d acts as the only independent variable of the LbFP model after all the real data implementation. The dependent variable P will change with the variation of distance and it will come to the maximum point when d equals to the optimal value with predefined constant values of OV and OC . The research question is then to search for the optimal value d , which can be solved by using GA.

Table 2
Parameters for the micro-GA calculation.

Parameter	Value
Max external generations	300
Max internal generations	2000
Crossover probability	0.8
Initial internal population	10
Initial external population	10
Selection operator	Tournament
Crossover operator	Single point
Encoding method	Binary
Mutation operator	0.0001

Therefore, the fitness function of the simulation process of GA could be defined as:

$$F = \text{fitness}(d_i) = OV - \frac{OC}{7.524 * e^{-0.027 * d_i}} - Ini * FAR_i * e^{-0.315 * \lg(a_i)} * e^{-0.087 d_i} \quad (13)$$

$$a_i = 32829.411 + 552.861 * d_i \quad (14)$$

$$FAR_i = 3.104 e^{-0.021 d_i} \quad (15)$$

The main purpose of this model is to find the optimum location of an industrial firm disregard its production capacity and efficiency. The output value and non-transportation operating cost for any firm can be given any constant numbers. Nevertheless, if the pre-set output value is too small and the operating cost is too big, the simulating result of profit will be negative which means the firm is losing money and can be bankruptcy any time. This will deviate the purpose of simulating the restructuring of urban industrial land use. Therefore, in the simulation of industrial spatial distribution of Shanghai, we suppose that the constant initial production value (*OV*) of a firm at any location is 10,000 CNY and the initial operating cost (*OC*) is 1000 CNY according to preliminary simulation run results. *Ini* is the initial land price of the city center of Shanghai with corresponding *FAR* and *a* values. The regression result shows the value of *Ini* is 96,331.086 CNY/m² during the period 2011 to 2013. To simulate the transformation of industry distribution of Shanghai, this research set *Ini* value at time 0 as 100 CNY and this number will increase by 100 after each iteration considering the minimum incremental change on land price market of the city. The algorithm was programmed using software Matlab according to the following simulation procedure and the simulation parameters are summarized in [Table 2](#).

Simulating procedure:

```

begin
%% external
  initialize ini, max-external-generation
  for ini = 1 to max-external-generation
    update initial population
    %% micro-GA (internal)
    initialize max-population, max-inter-generation, p-mutation, p-crossover
    for 1 to max-inter-generation
      reproduction (replaceable-parents; nonreplaceable-parents)
%% 'roulette wheel' to select parents, parents have higher fitness value have more chance to produce
next      generation.
Coding
%% code parents(value) into binary strings
      crossover
%% exchange parts of parent strings to generate new generation strings
      mutation
%% some part of parent strings can mutate during crossover
      'tournament elitism' to produce nonreplaceable-parents

```

end
 end
 results report
 end

During the simulation, the model recorded the optimization distance of an industrial factory to be located from the city center and the corresponding land price. The vertical axis of Fig. 4 represents the increasing land price (CNY/m²) at the city center over time and the horizontal axis is the optimum distance of a firm away from city center. The simulation results show that the distance of maximum profit location for a firm increases very quickly outward from the city center before the land price value of the city center reaches 5000 CNY/m². But, the distance effects of land price change decrease when the land price at the city center is higher than 5000 CNY/m². This result means industrial companies will move outward very quickly in response to the early rise of land price when land market is initially introduced in Shanghai. Such outward push effect becomes smaller over time when the land price is above 5000 CNY/m². This can be one of the shocking points in urban land use when land suddenly becomes highly valuable. The results also show that at the time when the land price of

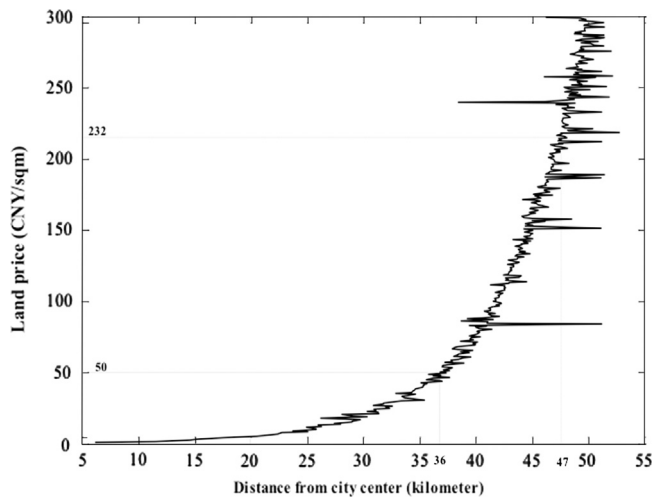


Fig. 4. Changing optimum location of industrial firms under different price scenarios.

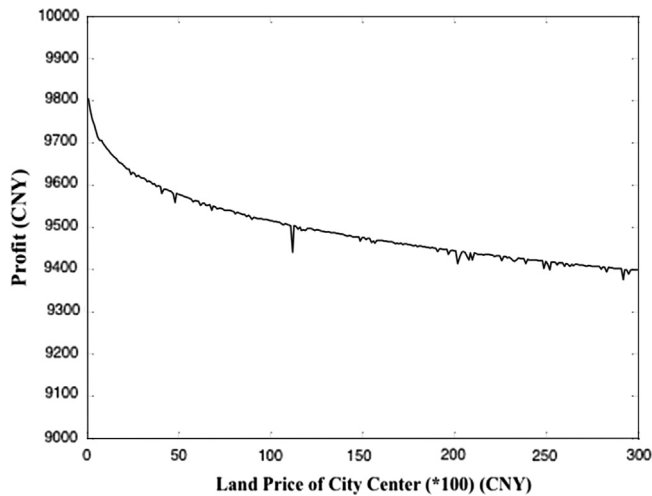


Fig. 5. The maximum profit location vs. city center land price in Shanghai.

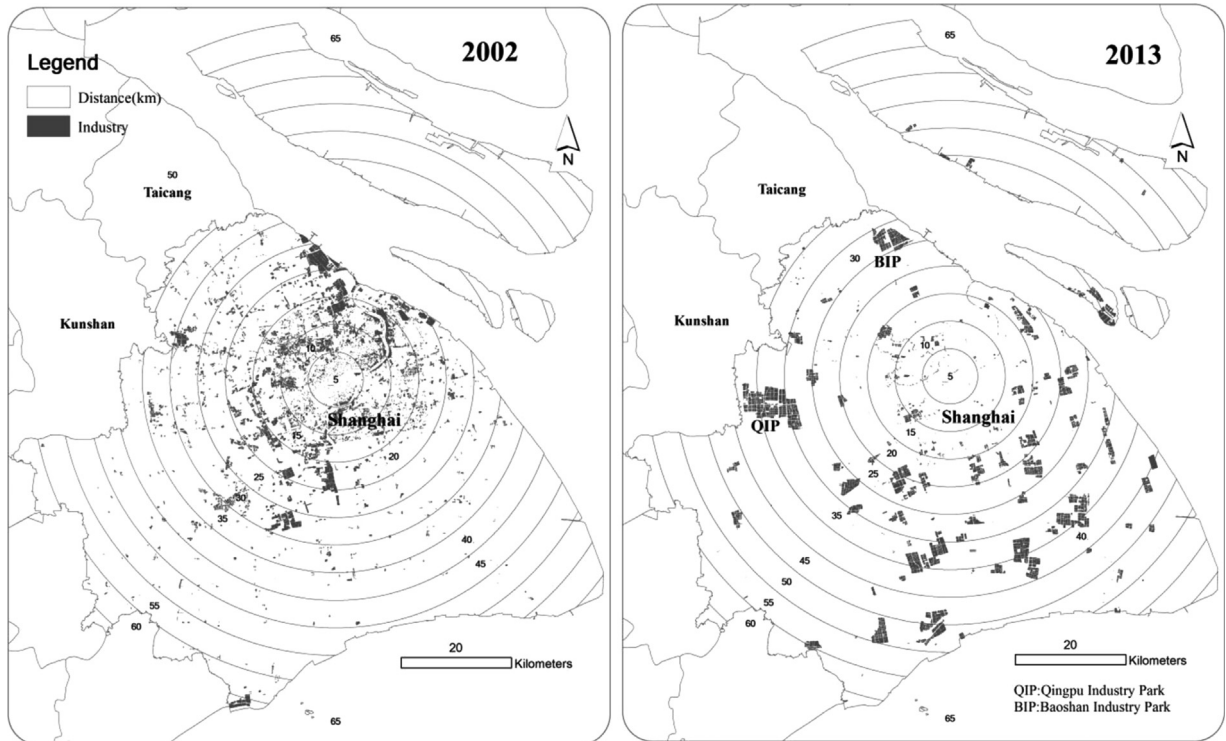


Fig. 6. Spatial distribution of industrial firms in Shanghai (year 2002 and 2013).

city center is 23,223.581 CNY/m², as it is the case during the period of 2011–2013, the best profit location for industries is somewhere between 40 and 50 km away from Shanghai's city center.

Fig. 5 presents the changing maximum profits assuming different land price level at the city. The horizontal axis of the figure represents the land price increment at the city center and the vertical axis is correspondingly the maximized profit with the varying optimum distance of firm location from city center. The figure shows that the maximum firm profit decreases steadily because of the growing operating costs resulted from increasing transportation costs, even though industrial firms move adaptively to the best location due to increasing land price of the city center. From a long-term view, if the land price at the city center climbs up to a point which makes the profit lower than what is expected by the firm owners, these firms will probably move to other provinces due to the fact of decreasing profit.

Considering it is hard to trace one or several firms' location–relocation activities lead by the evolutionary processes of urban land use change historically, this research will valid the simulated results through the comparison of actual change of industrial land use directly. To facilitate the visualization of industrial land use distribution, we first divides Shanghai into concentric areal rings with a width of 5 km each and overlays the concentric rings with the industrial land use maps in 2002 and 2013 (Fig. 6: left). Prior to 2000, industrial land use in Shanghai was not the result of land market transaction but rather the planned land allocation. Therefore, the 2002 industrial land use does not reflect the transaction price of land. The 2002 map shows that the distribution of industrial firms was mainly located inside of the 25 km circle around the city center, which accounted for 80% of the total industrial land use in Shanghai. Since 2000, several reform policies and regulations have been launched in an effort to speed up the market transaction of land use. As a result, the average land price of the city center has soared quickly from 6000 CNY/m² in 2000 to 16,000 CNY/m² in 2013. Because of rising land price, a large number of manufacturing firms have been forced to move out the central city area outward from their previous locations to suburban regions. The 2013 land use map (Fig. 6: right) shows that the distribution of industrial firms were mainly located more than 15 km out of the city center and most of them resided between 30 km and 40 km from the city center, accounting for 54% industrial land use of the city.

According to the simulation results, the majority of industrial factories should reside 40–50 km away from the city center when the land price of the city center reaches to 23,223.581 CNY/m². Comparing Fig. 6 with Fig. 3, we can see that the main directions for spatial industrial expansion are in the west and the north of the city and the city

boundary in these two directions are about 40 km from the city center of Shanghai. This means that the firms in these areas would have to move further to cross the city boundary if they want to have better profit margins. Such cross border industrial development is actually quite evident in the regions neighboring Shanghai, such as Kunshan, Taicang and Suzhou. Take Kunshan as an example. It was a rural county before 1990 but has since grown up to a city of more than one million people during the last three decades. The total industrial output value of Kunshan in 2003 was only 106.7 billion CNY, but rose to 700.1 billion CNY in 2010 (according to Kunshan Statistical Bureau 2011: <http://www.kstj.gov.cn>), expanding almost seven times since 2003.

From the 2013 industrial land use map (Fig. 6: right) we can see that the west and north directions are associated with two main industrial parks of the city: Qingpu Industrial Park (QIP) and Baoshan Industrial Park (BIP). The map shows that these two industrial parks were pushed to the locations very close to the border of neighboring Jiangsu province, but still are located inside the city's boundary. According to the simulation results, the factories at these areas should move further away from the city center if they want to make better profits. In practice, the municipal government of Shanghai introduced a set of policy measures and incentives to mitigate the effects of escalating land price in order to keep industrial firms inside of the city boundary by providing better infrastructures and giving tax reduction. Compare with the boundary limit of available land use in the west and north directions, we can see there are more industrial parks in the south and east directions and a lot of them locate further away from city center than those in the west and north directions. Some of these industrial parks are located even further than 50 km away from city center. This means that industrial firms would move further outward from city center given the current land price level if there were no boundary and other geographic limiting conditions.

6. Conclusion

Urban development and evolution are closely associated with growth and distribution of industrial firms. The spatial restructuring of industrial space shapes significantly city structure and its spatial configuration. In the meantime, the continuous expansion of city size also alters the spatial distribution of industrial location. The research into the transformation of industrial spatial distribution provides insights into the mechanisms of urban growth and industrial land use dynamics and help to derive valuable information for urban planning and city management.

This paper develops a dynamic industrial spatial distribution model based on evolutionary theory and Genetic Algorithms and applies it to simulating the industrial transformation process in Shanghai, China. The results show that given the increasing land price over time, industrial firms move gradually from the areas close to the city center to distant suburban areas. Given the continuous increase of land price in the city center in the near future, the location of industrial firms may move further out in the area close to municipal boundary because of administrative system in China. While the relocation of industrial firms is to maintain high profit, the maximum profit a firm could produce is, however, decreasing over time because of increasing land value in the city. The analysis of the current industrial land use of Shanghai demonstrates that the developed model delineates well the dynamical process of industrial spatial distribution and reveals clearly the land price is a significant mechanism in reconfiguring industrial space in Shanghai, China.

With the successful simulation of industrial spatial evolution in Shanghai, China, this research shows that it is possible to build a computer simulation model to delineate the dynamical evolutionary urban land use process through appropriate modeling methods. Different from main stream industrial spatial redistribution researches, which delineate the deconcentration or suburbanization process of manufacturing industry among mega cities qualitatively (Henley, 1994; Hudalah et al., 2013; Viehe, 1981; Walker, 2001), this research simulates the dynamic industrial deconcentration quantitatively. Moreover, the use of recent land auction and historical industrial land use data helps to validate the simulation results. The findings of spatial industrial diffusion process in the study area are in general consistent with the empirical observations in literature (Marton & Wu, 2006; Ning & Yan, 1995; Wu, 2008). The results of this study can greatly help urban managers and planners to understand the city better.

There are still several things need further exploration and research. First, this model was built up based on classic urban geography theories which presume isotropic urban surroundings. The land price of a city conforms a concentric circle declining tendency according to the LbFP model. There is no delineation about natural, human, political environmental discrepancies among different directions and sub-districts.

Second, the model takes land price as one of the core factors which determine the location and relocation of industrial firms. There are many other factors which may influence land use decision making by an industrial firm. For example, a firm will not move from its current location easily considering its path dependency, and firms will

also put local government policies and other preferences into their consideration when they choose location for their future production activities.

Third, the simulation model developed in this research is a one dimension computer simulation model. One of the main simulation results is the optimum distance of an industrial firm location from city center under the given land price. It is possible to build a Cellular Automata (CA) based or agent based model to simulate the dynamical processes of industrial spatial distribution in two dimensional geographic space in future.

Even though the case study of Shanghai shows that there is great potential to apply the built up LbFP model to other cities, there are several challenges needed to be considered. First, as a metropolitan city, the land price of Shanghai took a key role in determining land use, especially industrial land use. This can not be compared with a medium or small city where there are no obvious land price various among difference location. Second, market, instead of policy and other factors, dominated the decocentration process of industrial land use in Shanghai. In hence, it is hard to apply the model to a city where government policy, planning strategy, and other factors dominate land use type and direction.

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