Urban Electric Load Forecasting Using Combined Cellular Automata

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Abstract—**With the high-speed economic development in China, the transition of structural function in the urban land system highly effects the development of the urban electric load. Forecasting the urban electric load accurately is the foundation of decision making scientifically for the development and planning of the urban power grid in China. This paper improves the decision method of Transition Matrices of Land Use and Cover Change though integrating Cellular Automation with Markov Model firstly. Then, the combined cellular automation model is used to simulate the urban land function evolvement and forecast the land functions in the future as the start point for electric load forecasting. Considering the changes of urban land functions, electric load density and simultaneity factor, the urban electric load forecasting model is proposed. The model validation is performed by comparing model predictions with the load data and error analysis of different load forecasting methods though case study. The results obtained bear out the accuracy of the adopted methodology for urban load forecasting. Finally, some reasonable suggestions for the improvement of the forecast are given and the future work is raised.**

Keywords—**load forecast, city, cellular automation, load density**

I. Introduction

Forecasting the urban electric load accurately is the primary foundation of the urban power grid planning. The precision directly effects the city planning and social-economical development [1]. Therefore, the urban electric load forecasting must be highly valued with the fast economy growth and the complex changes of land function in China.

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There are many factors influence urban electric load, land functions, urban density, economy development, temperature, etc [2] [3]. For the mid-long term urban electric load forecasting in China with the urban land functions variations, there are larger deviations from the electric load value and its distribution of geography position of the forecasting results with growth rate method, time series method and causality analysis method, etc. While the forecasting results with spatial load forecasting method is better than others because a great deal uncertain data is optimized and land functions are considered. Spatial load forecasting is primarily based on the result of total load forecasting and interrelated factors of planning district to find out the distributive coefficient and determine the load space distribution array [4]-[6]. With the application of geography information system in power system, the historical load data and interrelated decision-making variables are considered to forecast the electric load of urban areas directly [7]. The model of spatial load forecasting based on cellular automation has gradually been used to study the urban development [8]-[12]. The theory is simple and flexible that it can integrate with other methods, such as, simulation of land use evolution based on cellular automata and artificial neural network [13]-[14], niche-based cellular automata for sustainable land use planning [15], cellular automata for simulating complex land use systems combined with neural networks [16], the integration model of system dynamics and cellular automatic [17], land utility planning layout model based on constrained conditions cellular automata [18], cellular automata for simulating land use changes based on support vector machine [19]. At the same time, a new series of analysis models based on cellular automation formed, such as Land Use and Cover Change (LUCC) [20]-[25], Land Use Scenarios Dynamics model (LUSD) [17], *etc*. In previous studies [26], the city power load was forecasted based on the cellular automation model, but the load density

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was not considered.

In this study, the characteristic variance of urban land is considered to improve the transfer matrix decision method based on Markov model. The land use changes are simulated by cellular automata firstly. Then urban electric load forecasting model is proposed based on the changes of land types, urban electric load density and simultaneity factor. At last, a case study is carried on to analysis the validation of the model. In addition, some reasonable proposals are given to improve the precision of urban electric load forecasting in the future.

II. Cellular Automata Theory

Cellular Automata (CA) is a dynamic system in which time and space are discrete [24]. Each cell distributed in the lattice grid has a limited discrete state, abides the same rules, and updates synchronously with certain partial rules. A mass of cells structures the evolution of the dynamic system by simple interaction. CA is structured by a series of rules of model; all the models sufficed for these rules are considered as cellular automata. The position of all the cells in n-dimensional space could be determined by n variables integer matrix [25]. CA is composed by cellular and states, cellular lattice, neighbors, transition rules and time, which is shown in Fig.1.

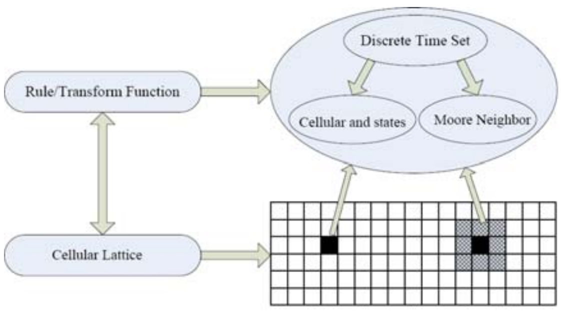

Fig.1. Construction of CA

- Cellular and states. Cell is the prime part of CA, which distributes in discrete one-dimension, two-dimension or multi-dimension lattices of Euclidean Space. Cell's state could be binary form as {0, l}, or integer discrete set.
- Cellular Lattice. The set which distributed by cellular lattice contains three elements, such as geometry partitions, boundary condition and configuration.
- Moore Neighbor. The neighbor type of two-dimension CA shown as Fig.1 corresponds to the grid, which is much suitable that electric load cell. The black cell is the center cell, and the gray one is the neighbor.
- Transition rules and time. It is the core of CA, which expresses the logical relationship of the process simulated, determines the process and result of the dynamic evolution of CA. The transfer function *f* of cells is presented in (1).

$$S_i(t+1) = f(S_i(t), S_N(t)) \tag{1}$$

where $S_i(t)$ is the state of the cell *i* at time *t*, and $S_N(t)$ is the combination state of neighbor cells at time *t*. *f is* the local mapping or local rule of CA.

III. Electric Load Forecasting Model of Cities

A. General Model of LUCC

LUCC is the mutual conversion between different land functions in a certain region. The model is shown as:

$$\Delta L = \Delta L_1 + \Delta L_2 + \cdots + \Delta L_i \tag{2}$$

where ΔL is the total change value of land functions, and ΔL_i is the change value of type *i* in certain period.

There are many influencing factors of land function changes. The changes could be established as (3).

$$\Delta L_i = F(x_1, x_2, \cdots, x_j) \tag{3}$$

where $x_1, x_2, \cdots, x_j$ are the main influencing factors of land function changes.

Supposing that the factors in (3) are independent mutually, (3) could be decomposed into (4).

$$F(x_1, x_2, \cdots, x_j) = f(x_1) + f(x_2) + \cdots + f(x_j) \tag{4}$$

where $f(x_j)$ is only the function of x_j.

The land use change is simulated by determining the transformation matrix.

B. Transformation Model of Land Types

The dynamic evolution of land types has the characteristic of the Markov Model in certain situation. There are mutual transformations of different land types in certain region, which is hard to describe by function accurately. Make a block of land type as a cell, supposing that there are eight neighbors of each cell, *i.e.* Moore Neighbor.

Define that there are *N* cells and *M* states in the system model. Each state stands for one land type, indicated by *k*, *l*. *k*, *l*=$1, \cdots, M$.

If the land type of cell *i* is *k* at time *t*, define that $N_i^k(t) = 1$. If the land type of cell *i* is not *k* at time *t*, define that $N_i^k(t) = 0$.

The sum of land types of *N* cells is computed by (5) and (6).

$$N^k(t) = \sum_{i=1}^{N} N_i^k(t) \tag{5}$$

where $N^k(t)$ is the amount of cells of type *k* at time *t*.

$$N(t) = \sum_{k=1}^{M} N^k(t) = \sum_{k=1}^{M} \sum_{i=1}^{N} N_i^k(t) \tag{6}$$

where $N(t)$ is the amount of cells of all types at time *t*.

The amount of the cells is invariable in certain period if the area studied is determinate. So $N(t)=N$, $t=1,\cdots,\tau$. τ is the time period studied, which is the interval between two time phases.

The density of certain land type *k* is computed by (7).

$$\rho^k(t)=\frac{N^k(t)}{N} \tag{7}$$

All states of the cells correspond to grids one-to-one. There is just one land type corresponding to each cell at any time. If the type *k* of cell *i* at time *t* is changed to type *l* at time *t*+1, define that $\Delta N_i^{kl}=1$, otherwise $\Delta N_i^{kl}=0$.

To the whole cell space, the amount of land type *k* change to land type *l* could be computed by (8).

$$\Delta N^{kl}=\sum_{i=1}^{N}\Delta N_i^{kl} \tag{8}$$

The variable quantity of certain land type *k* from time *t* to time *t*+1 is determined by (9).

$$\Delta N^k = N^k(t+1)-N^k(t) \tag{9}$$

The total amount of land type *l* is the sum of the changes from other land types to land type *l* at time *t*+1 is shown as (10).

$$\begin{aligned} N^l(t+1) &= \sum_{k=1}^{M}\Delta N^{kl} \\ &= \sum_{k=1}^{M}\frac{\Delta N^{kl}}{N^k(t)}\times N^k(t)=\sum_{k=1}^{M}p_{kl}N^k(t) \end{aligned} \tag{10}$$

where $p_{kl}=\dfrac{\Delta N^{kl}}{N^k(t)}$ is the probability of the land type *k* change to land type *l* at time *t*. Then the transform matrix P can be got.

The probabilities of an arbitrary land type *k* or *l* at time *t* or *t*+1 are computed by (11) and (12) respectively.

$$\pi^k(t)=\frac{N^k(t)}{N} \tag{11}$$

$$\pi^l(t+1)=\frac{N^l(t+1)}{N} \tag{12}$$

where $\pi^k(t)$ is the probabilities of land type *k* at time *t*, and $\pi^l(t+1)$ is the probabilities of land type *l* at time *t*+1. $N^k(t)$ is the cell amount of land type *k* at time *t*, $N^l(t+1)$ is the cell amount of land type *l* at time *t*+1, and *N* is the total cells amount.

Then the transform matrix $\Pi(t+1)$ and $\Pi(t)$ satisfy the relation shown as (13).

$$\Pi(t+1)=\Pi(t)P \tag{13}$$

Namely,

$$S(n)=S(n-1)P=S(0)P^n \tag{14}$$

where *S*(*n*) is the state probability vector of land type at time *n* in the future, and *S*(0) is the state probability vector of land type at the beginning, short for initial state probability vector.

The land use system can be divided into a series of mutual evolution states based on land type. *S*(0) can be got from the percentage of each state in the system at the initial time.

Transform probability can be got by annual average change rate of certain land type at certain interval, namely the annual average percentage of each land type original. p_{kl} can be computed by (15) appreciatively.

$$p_{kl}=\frac{U_{kl}/n}{U_{k0}}\times 100\% \tag{15}$$

where U_{kl} is the amount of the land type *k* change to type *l* at the research time, *n* is the time interval, and U_{k0} is the amount of land type *k* at the initial time.

C. Urban Electric Load Forecasting Model

Based on the forecast result of land type change, the urban electric load demand can be forecasted by (16).

$$L(t)=\delta(t)\sum_{k=1}^{M}S_k(t)\times\phi_k(t) \tag{16}$$

where $L(t)$ is the electric load of city at time *t*, $S_k(t)$ is the square of land type *k* at time *t*, $\phi_k(t)$ is the load density of land type *k* at time *t*, and $\delta(t)$ is the load simultaneous rate at time *t*.

$\delta(t)$ relates to the power consumption characteristics and customer numbers of each kind of loads, etc. It can be forecasted based on the load structure and load characteristic in the future.

The load densities of various function lands in different period are different. With the development of national economy and the improvement of living standard, the load density of commercial area and residential area increase largely. The load densities are normally forecasted using Analogue Method, Growth Rate Method, Sigmoid Curve Forecasting Methods, etc. They are all based on the historic data analysis and comparative research of similar region in the world. Sigmoid Curve is fitted based on the historic load density data. It can reflect the feature of the change of $\phi_k(t)$ that increase gradually, then increase rapidly, and then increase slowly to stable state, or saturation point. So $\phi_k(t)$ can be determined by (17).

$$\phi_k(t)=\frac{1}{c_k+a_k e^{b_k t}} \tag{17}$$

where a_k,b_k,c_k are the coefficients of load density curve of land type *k* at time *t*, $a_k>0, b_k<0, c_k>0$.

IV. THE CASE STUDY

One city in China is selected for case study based on the urban electric load forecasting model. Its urban load in 2000 is tested based on the model by historical data of land type, square, load density, and load simultaneous rate, to show its validity. Then the urban load in the future is forecasted.

The land use situation of the city is shown in “TABLE. I”. The land function types contain ten kinds, such as Residential land(R), commercial land (C), Industrial land (M), Warehouse land (W), External traffic land (T), Road square land(S), Municipal facilities land (U), Green land (G), Special land (D), Unutilized land (E).

TBALE I.
SITUATION OF LAND FUNCTION TYPE OF THE CITY

Land Type	1980		1990		2000	
	Square (km^2)	Percent (%)	Square (km^2)	Percent (%)	Square (km^2)	Percent (%)
R	254.36	21.05	273.1	22.6	299.4	24.77
C	101.23	8.38	119.9	9.92	131.0	10.84
M	246.85	20.43	268.6	22.2	283.7	23.48
W	20.89	1.73	25.13	2.08	30.87	2.55
T	41.37	3.42	48.72	4.03	54.03	4.47
S	110.68	9.16	121.5	10.1	130.6	10.81
U	9.92	0.82	12.43	1.03	15.55	1.29
G	112.9	9.34	125.6	10.4	132.0	10.92
D	6.98	0.58	8.76	0.72	10.38	0.86
E	303.22	25.09	204.6	16.9	121	10.01
Total	1208.4	1	1208.4	1	1208.4	1

The land function change during 1980-2000 is shown in Fig. 2.

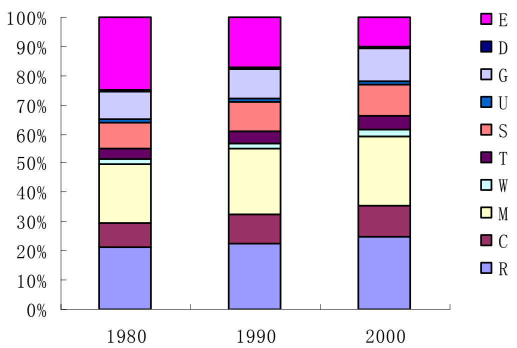

Fig.2. Land function changes from 1980 to 2000

From TABLE I and Fig.2, it can be seen clearly that the dynamic change situation in three periods contains unutilized land’s decreasing continuously, residential land and other land’s increasing continuously, and mutual changing in each land type.

A. Definition of Cells

Define that the cell size is 100cm×100cm. Then the coverage data of various periods are shown in TABLE II.

TBALE II.
AMOUNT OF THE LAND USE CELLS

Land Type	1980	1990	2000
R	25436	27312	29936
C	10123	11987	13099
M	24685	26862	28369
W	2089	2513	3087
T	4137	4872	5403
S	11068	12151	13057
U	992	1243	1555
G	11290	12563	13196
D	698	876	1038
E	30322	20461	12100
Total	120840	120840	120840

B. Simulation of Urban Land State Transitions

Taking 1990 as the basis year, the initial state matrix S(1990) can be got from TABLE I.

$$S(1990)=[0.2260\ \ 0.0992\ \ 0.2223\ \ 0.0208\ \ 0.0403\ \ 0.1006\ \ 0.0103\ \ 0.1040\ \ 0.0072\ \ 0.1693]^T$$

The land use transform proportion from 1980 to 1990 is shown in TABLE III. The transform probability matrix of each land type in the 1990’s can be calculated based on land use transform matrix and the situation of the transformation annual average resulted from (15), namely initial state transform probability matrix *P*, which is shown in TABLE IV.

TBALE III.
LAND USE TRANSFORM PROPORTION FROM 1980 TO 1990

		1990									
		R	C	M	W	T	S	U	G	D	E
	R	0.996	0.001	0.001	0.001	0.000	0.000	0.001	0.000	0.000	0.000
	C	0.009	0.974	0.005	0.002	0.000	0.002	0.002	0.000	0.000	0.006
	M	0.002	0.006	0.988	0.001	0.000	0.000	0.000	0.001	0.000	0.001
	W	0.000	0.013	0.049	0.925	0.000	0.000	0.000	0.000	0.000	0.013
1980	T	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000
	S	0.000	0.002	0.000	0.000	0.002	0.997	0.000	0.000	0.000	0.000
	U	0.000	0.000	0.000	0.040	0.000	0.000	0.789	0.098	0.073	0.000
	G	0.000	0.004	0.000	0.000	0.000	0.000	0.000	0.996	0.000	0.000
	D	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
	E	0.060	0.061	0.076	0.016	0.024	0.036	0.014	0.039	0.003	0.671

TBALE IV.
LAND USE TRANSFORM PROBABILITY DURING 1980-1990

	R	C	M	W	T	S	U	G	D	E
R	0.9996	0.0001	0.0001	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000
C	0.0009	0.9973	0.0005	0.0002	0.0000	0.0002	0.0003	0.0000	0.0000	0.0007
M	0.0002	0.0006	0.9988	0.0001	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001
W	0.0000	0.0013	0.0050	0.9922	0.0000	0.0000	0.0000	0.0000	0.0000	0.0017
T	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
S	0.0000	0.0002	0.0000	0.0000	0.0002	0.9997	0.0000	0.0000	0.0000	0.0000
U	0.0000	0.0000	0.0000	0.0046	0.0000	0.0000	0.9766	0.0109	0.0081	0.0000
G	0.0000	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.9996	0.0000	0.0000
D	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
E	0.0071	0.0073	0.0090	0.0019	0.0028	0.0043	0.0018	0.0046	0.0003	0.9608

When n=10, the transform probability matrix from 1990 to 2000 is shown in TABLE V.

TBALE V.
LAND USE TRANSFORM PROBABILITY DURING 1980-1990

	R	C	M	W	T	S	U	G	D	E
R	0.9921	0.0024	0.0021	0.0014	0.0000	0.0000	0.0011	0.0002	0.0001	0.0006
C	0.0190	0.9488	0.0102	0.0032	0.0003	0.0041	0.0043	0.0010	0.0004	0.0096
M	0.0048	0.0127	0.9761	0.0022	0.0001	0.0001	0.0001	0.0020	0.0000	0.0021
W	0.0021	0.0257	0.0945	0.8556	0.0007	0.0011	0.0004	0.0012	0.0001	0.0215
T	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
S	0.0000	0.0034	0.0000	0.0000	0.0034	0.9932	0.0000	0.0000	0.0000	0.0000
U	0.0001	0.0017	0.0037	0.0691	0.0000	0.0000	0.6231	0.1746	0.1299	0.0010
G	0.0001	0.0075	0.0000	0.0000	0.0000	0.0000	0.0000	0.9924	0.0000	0.0000
D	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
E	0.1009	0.1014	0.1269	0.0260	0.0395	0.0607	0.0204	0.0672	0.0069	0.4504

According to the characters of Markov model and the definition of the conditional probability, the transform probability matrix P^n of any year after 1990 can be got by (14) with the help of MATLAB software. Then, the square percentage of each land use type can be calculated in 2000.

S (2000) = S (1990) × P_{ij}^{10}

=[0.2368 0.1095 0.2342 0.0229 0.0445 0.1066 0.0108 0.1115 0.0086 0.1148]^{T}

Supposing that the total square of the city is invariable, get the square can be got based on the percentage of land type, which is shown in TABLE VI.

TBALE VI.
SQUARE OF EACH LAND TYPE IN 2000

Land Type	R	C	M	W	T	S	U	G	D	E
Percentage (%)	23.7	11.0	23.4	2.3	4.5	10.7	1.1	11.2	0.9	11.5
Square (km^2)	286.1	132.3	283.0	27.7	53.8	128.8	13.1	134.8	10.4	138.7

C. Urban Electric Load Forecasting

Firstly, the electric load of the city in 2000 is forecasted based on different methods to test the effectiveness of the combined CA model. Then the load of the city in the future is forecasted.

The electric load can be computed based on the load density data in TABLE VII and the land use situation in TABLE VI, which is shown in TABLE VIII.

TBALE VII.
INDEX OF THE LAND LOAD DENSITY UNIT: kW/hm^2

Land Type	R	C	M	W	T	S	U	G	D	E
2010	500	1000	500	40	30	30	250	15	250	0

TBALE VIII.
ELECTRIC LOAD FORECASTING OF THE CITY IN 2000 UNIT: MW

Land Type	R	C	M	W	T	S	U	G	D	Total
Load	100.14	92.61	99.04	0.83	1.21	2.90	2.62	1.68	2.08	303.11

The load simultaneous rate is selected as 0.85 after the historic data analysis. When the load density is considered, the load forecasted is changed to 258.83MW, while actual load is 261.52MW in 2000. The relative deviation rate is -1.03%, whose error is much smaller proves that this method is close to the actual value, and it has a certain practicability.

Comparing with the methods of regression analysis, growth rate, unit consumption, and spatial load forecasting only, the method of combined CA has its advantages. The forecast error comparing is shown in TABLE IX.

TBALE IX.
LOAD FORECASTING AND ERROR ANALYSIS

Method	Power Load in 2000 (MW)	Error (%)
Regression analysis	243.12	-5.89%
Growth rate	285.46	9.15
Unit consumption	272.1	4.04
Spatial Load Forecasting	250.4	-4.25
Combined CA model	258.83	-1.03

From TABLE IX, it can be seen that the result of the method of combined CA is closest to the actual value compared to other methods. Commonly, the result of Growth Rate is higher and higher with the times goes long than other methods because of its growth as power index. While the method of combined CA takes the characteristic variance of the urban land into account, its result is feasible.

The load density in 2010 is forecasted based on the historic data and the data of similar region around the world. The power load in 2010 can be forecasted by (15) and (16), which is shown in TABLE X.

TBALE X.
ELECTRIC LOAD FORECASTING OF THE CITY IN 2010

Land Type	Percentage of different land type	Square (km^2)	Load (MW)
R	24.43%	295.25	147.71
C	11.63%	140.56	140.59
M	24.20%	292.37	146.2
W	2.40%	29.036	1.17
T	4.74%	57.3	1.72
S	11.06%	133.66	4.02
U	1.06%	12.773	3.21
G	11.69%	141.31	2.12
D	0.98%	11.856	2.98
R	7.83%	94.611	0
Total	100%	1208.4	449.72

The load simultaneous rate in 2010 is forecasted as 0.86, and then the load in 2010 will be 386.76MW.

The evolvements of land functions, the load density, the load simultaneous rate etc. are considered in the method of combined CA. It can be seen from the result of error comparing analysis that the method is much closer to the reality.

V. CONCLUSIONS

As rapid social and economic development of cities in China, cities' grid plan and construction should be improved quickly and scientifically and the load forecast is the key point. To improve the accuracy of urban electric load forecasting, the combined Cellular Automata forecast model is raised. In this study, the situation of the urban land change is analyzed and forecasted with the Markov Model with the Land Use and Cover Change based on CA. Then the urban electric load forecasting model is set up based on the land function transformation, load density evolvement and the load simultaneous rate. The traditional load forecast model is changed to forecast the change of urban land types firstly and combined Markov Model, CA, and other factors together which gives a new approach of consideration. It is proved more practically and scientifically based on case study.

It is a new concept to forecast the urban electric load with spatial load forecasting based on combined CA. Some correlated parameters and rules need to be optimized and perfected. The load density of most of cities in China has not yet reaches the saturation load in a short time. But it also needs to be further studied in the future.

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REFERENCE

[1] Wang Cheng-shan, Wang San-yi, and Xie Yin-hua, The Complexity and New Technology Application of Urban Power Distribution System Planning, Zhejiang Electric Power, vol.1, pp.1-5, 2004.

[2] Isabelle Larivi`ere U, and Ga¨etan Lafrance, Modeling the electricity consumption of cities: effect of urban density, Energy Economics, No.21, pp.53-66, 1999.

[3] M. Beccali, M. Cellura, V. Lo Brano, and A. Marvuglia, Forecasting daily urban electric load profiles using artificial neural networks, Energy Conversion and Management, vol.45, pp.2879–2900, 2004.

[4] Wu Pei, Ding Ming, and Chen Min-jiang, Spatial Load Forecasting Based On Fuzzy Reasoning and Multi-objective Programming, Power System Technology, vol.28, No.15, pp.48-52, 2004.

[5] Yang Xue-ming,Yuan Jin-sha, and Wang Jian-feng, A New Spatial Forecasting Method for Distribution Network Based on Cloud Theory, Proceedings of the Chinese Society for Electrical Engineering, vol.26, No.6, pp.30-36, 2006.

[6] Zhong qing, Wu Jie, and Huang Wu-zhong, Researches on Electric Network Planning Based on Spatial Load Forecasting, International Electric Power for China, vol.17, No.4, pp.39-41, 2003.

[7] Wang Tian-hua, Fan Ming-tian, and Wang Ping-yang, The space load forecasting of Network of Distribution Network Based on GIS , Power System Technology, vol.23, No.5, pp.42-47,1999.

[8] Batty M, and Xie Y, From cells to cities, Environment and Planning B: Planning and Design, vol.21, pp.531-548, 1994.

[9] White R, Engelen G, and Uijee I, The use of constrained cellular automata for high-resolution modeling of urban land-use dynamics, Environment and Planning B: Planning and Design, vol.24, pp.323-343, 1997

[10] Wu F, and Webster C J, Simulation of land development through the integration of cellular automata and multi-criteria evaluation, Environment and Planning B: Planning and Design, vol.25, pp.103-126, 1998.

[11] Clarke K C, Hoppen S, and Gaydos L, A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area, Environment and Planning B: Planning and Design, vol.24, pp.247-261, 1997.

[12] Clarke K C, and Gaydos L J, Loose-coupling a cellular automata model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore, International Journal of Geographical Information Science, vol.12, No.7, pp.699-714, 1998.

[13] Hu Mao-gui, Fu Xiao-yang, and Zhang Shu-qing, Land-Cover Simulation and Forcast of Melmeg Wetland Using Cellular Automata, Resources Science, vol.29, No.2, pp.142-148., 2007.

[14] Zhao jing, Chen Hua-gen, and Xu Hui-ping, Simulation of Land Use Evolution Based on Cellular Automata and Artificial Neural Network, Journal of Tongji University (Natural Science), vol.35, No.8, pp.1128-1132, 2007.

[15] Liu Xiao-ping, Li Xia, and Peng Xiao-peng, Niche-based cellular automata for sustainable land use planning, Acta Ecologica Sinica, vol.35, No.8, pp.1128-1132, 2007.

[16] Li Xia, and Ye Jia-an, Cellular automata for simulating complex land use systems using neural networks, Geographical Research, vol.24, No.1, pp.19-27, 2005.

[17] He Chun-yang, Shi Pei-jun, and Chen Jin, Study On Land Use Condition Based On System Dynamic Model and CA, Science in China (Series D)., vol.35, No.5, pp.464-473, 2005.

[18] Yang Xiao-xiong, Liu Yao-lin, and Wang Xiao-hong, Land Utility Planning Layout Model Based on Constrained Conditions Cellular Automata, Geomatics and Information Science of Wuhan University, vol.32, No.12, pp.1164-1168, 2007.

[19] Yang Qing-sehng, and Li Xia, Cellular Automata for Simulating Land Use Changes Based on Support Vector Machine, Journal of Remote Sensing, vol.10, No.6, pp.836-846, 2006.

[20] Newkirk R T, and Wang F, A common knowledge database for remote-sensing and geographic information in a change-detection expert system, Environment and Planning B, vol.17, No.4, pp.395-404,1990.

[21] Li X, and Yeh A G O, Principal component analysis of stacked multi-temporal images for monitoring of rapid urban

expansion in the Pearl River Delta, International Journal of Remote Sensing, vol.19, No.8, pp.1501-1518, 1998.
[22] Openshaw S, Neural network, genetic, and fuzzy logic models of spatial interaction, Environment and Planning A, vol.30, pp.1857-1872, 1998.
[23] Hongchang-Hu, Genxu-Wang, Lajiao-Chen, and Ling-Lu, The LUCC and spatio-temporal variability of climate and their impacts on stream flow in the eco- environment source region of the yellow river, IEEE International, Geoscience and Remote Sensing Symposium, IGARSS, pp.4546-4549,2007.
[24] Shozo Kawamura, Masaki Shirashige, and Takuzo Iwatsubo, Simulation of the nonlinear vibration of a string using the cellular automation method. Applied Acoustics, vol.66, pp.77-87, 2005.
[25] Yang Li-Tu, Wang Jin-feng, Chen Gen-yong, and Wang Jia-yao, Load Spatial Distribution Forecasting Model on Cellular Automata Theory, Proceedings of the Chinese Society for Electrical Engineering, vol.27, No.4, pp.16-20, 2007.
[26] Yongxiu He, Dezhi Li, and Rui Fang. Urban Electric Load Forecasting in China Using Combined Cellular Automata, 2008 International Workshop on Modeling, Simulation and O ptimization.

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