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Site Selection of Mechanical Parking System Based on GIS with AFRARBMI

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Abstract

In order to rationalize the site-selection of urban mechanical parking system and relieve the traffic congestion after its completion, this paper proposes a decision method. the attribute data of the site-selection of urban mechanical parking system is established on the basis of the GIS analysis method. Then the relationship between the site-selection and multiple geographical factors are explored by the algorithm for mutual information fuzzy-rough attribute reduction and the Rough Set theory. Finally, the attribute reduction is carried out; thereby, an inductive learning method combined with GIS analysis and deductive reasoning is used to generate the decision trees and decision rules and conduct evaluation and analysis for the site-selection decision. Modeling and simulation for the site-selection of mechanical parking system are put into practice in Lanzhou City. The simulation results show that this method can solve the problem better. It also provides reference for the intelligent transportation system.

Keywords*: site selection, mechanical parking, fuzzy system, mutual information, attribute reduction*

1. Introduction

Parking problem has become a social hot issue in China, which is mainly caused by the excessive land development as well as the imbalance between the static traffic demand caused of the rapid development of cars and the relatively tight supply of parking place. To solve this problem, it is wise to balance the relationship between supply and demand by controlling the traffic demand reasonably and increasing the supply of parking place. The mechanical parking system has various advantages such as small footprint, high safety and reliability, high access efficiency, intelligent parking, etc, so it deserves a serious consideration in building central city area of metropolitan. Therefore, a good site plays an essential role in the performance of the mechanical parking system after its completion.

The development of Traffic Geographic Information System (GIS-T) has provided a powerful analysis tool for the site-selection of urban mechanical parking system. GIS provides various functions such as data input, storage, retrieval, display, etc, for decision supporters. However, it is not efficient enough in analysis, simulation and reasoning, so it is lack of intelligent reasoning in solving complex spatial decision problems. Therefore, in order to solve complex spatial decision problems, it is necessary to study the intelligent decision support system based on GIS. In literature [1], GIS is used as a means of analysis to obtain the geographic information of mechanical parking system, spatial data mining and machine learning algorithm C5 are adopted to analyze and evaluate the planning and site-selection of mechanical parking system.

To sum up, on the basis of the aforementioned study, this paper adopts the model combined with the GIS analysis method and the MIBAFRAR to propose an evaluation and analysis method for the decision-making of mechanical parking system. Besides, examples are given out to demonstrate the specific application of this method.

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2. Literature Review

For the parking site-selection, domestic and foreign research institutions and scholars have made large number of researches. In Parking Generation published by American Institute of Transportation Engineers (ITE), the author summarized the parking demand range, regression formula and curve chart of 64 different types of land. Levinson compared the accessory parking ratio of cities of seven countries in Americas, Europe and Asia, and the results show that the accessory parking ratio is proportional to the urban mechanization level (car ownership rate) [2-3]. Haworth and Hilton studied the relationship between parking lot and the development of market economy [4]. The achievements of Japanese scholars include the probability model based on the travelers' microscopic behavior, the site-selection method of parking lot where the sum of the walking distance after parking is the minimum. These researches emphasize the planning for the parking lot layout [5]. Thomas studied the influence of the parking behavior model with time and cost as the main factors on the layout of parking lot [6].

Chinese scholars have conducted a lot of researches combined on Chinese national conditions and proposed the static traffic incidence models based on the land use and the linear models based on vehicle trip, including the static traffic incidence model and its solution algorithm, multi-objective planning model, the maximum entropy model of the layout of parking facility and the road system coordination, the comprehensive evaluation method of parking planning and the index system of parking social economic evaluation are also among the research subjects of Chinese scholars.

The representative algorithms for fuzzy-rough attributes reduction and their application include the differential matrix algorithm for attribute reduction and its application [7], the information entropy-based algorithm for attribute reduction and its application [8-9], GA-based algorithm for attribute reduction [10-11], the mutual information-based algorithm for attribute reduction and its application [12-13]. Literature [14] proposed a kind of SA rough sets K-means resource dynamic allocation strategy. Literature [15] designed forest resource information integrated embedded technology with GIS. On the basis of the previous researches, this paper proposes the mutual information-based algorithm for fuzzy-rough attribute reduction with the distinctiveness of the site-selection problem of mechanical parking system taken into account, and then applies this algorithm in the decision-making of this problem.

3. Decision Method Based on the GIS and MIBAFRAR

3.1. Decision Modeling

The geographical location-based geographic information constitutes a basic information source for the site-selection decisions of mechanical parking system. It is highly important for the effective extraction of valuable decision-making information apply the great, messy, incomplete and uncertain geographic information to conduct related researches. The trait that rough set theory could depict the incomplete and uncertain information is used to propose the conditional attribute reduction method of decision tables of mechanical parking system site-selection which uses the MIBAFRAR to conduct GIS data analysis. Then adopt the inductive learning algorithm to build decision trees and extract decision rules, thereby further evaluating and analyzing the planning decision of mechanical parking system site-selection.

The design is shown as follows: gather the information of multiple layers in the condition attribute table of the planning mechanical parking system site-selection by GIS analysis. Let the urgency degree in planning as the decision-making attributes to form the learning data. Then find out the site-selection of mechanical parking system by the attribute reduction algorithm based on the MI RS theory, and conduct attribute reduction with the relational knowledge of various geographical factors. Finally, the Inductive Learning algorithm combined the geographic information analysis and deductive reasoning is used to generate decision trees and decision rules for the evaluation and analysis of site-selection decisions.

Combined the spatial data analysis and inductive learning method, the specific steps of this method are shown as follow steps：

Step 1 extract the related geographic information data in planning of mechanical parking system

Step 2 analyze the geographic information

Step 3 establish the decision-making knowledge data

Step 4 conduct the knowledge attribute reduction based on the MI fuzzy-rough set

Step 5 obtain the decision-making knowledge of the relation between mechanical parking system and geographic factors

Step 6 conduct inductive learning + deductive reasoning

Step 7 carry out the evaluation and analysis of the site-selection decision

3.2. The Extraction of the Attribute Information

The location of the mechanical parking system is closely related with the building distribution with different functions as the source of parking demand in its service radius [11]. Based on the road traffic survey knowledge of the research problems, the spatial data includes the distribution map of shared mechanical parking system, the road net map of the major traffic routes connected to the shared mechanical parking system, the distribution map of buildings in the service radius. Establish feature layers with different types are established, as shown in Figure 1. The attributes of site-selection factors contained by each layer are as shown in Table 1.

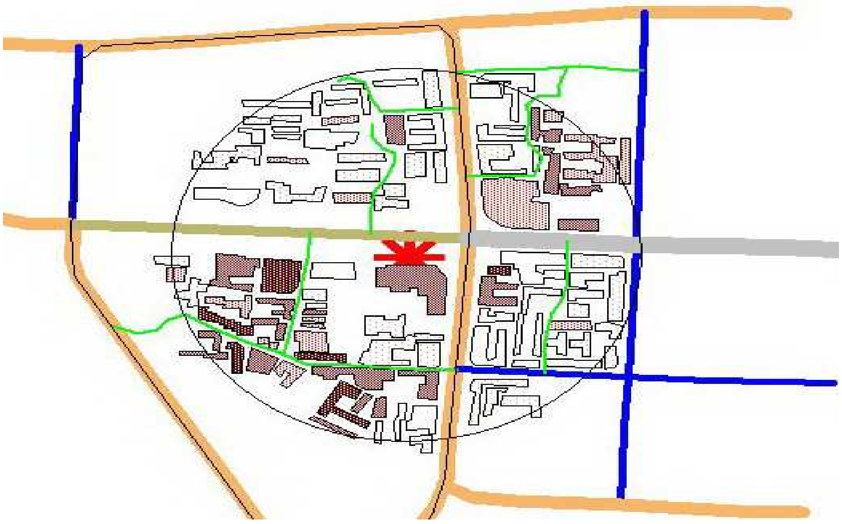

Figure 1. Site selection factors' layer establishing

Table 1. Attributes in every layer

Layer	Attribute
mechanical parking system	ID capacity service hours fees convenience security
the road net	road ID road lane survey flow road lane entrance connected main roads
buildings within the service radius	building name the mall area ① demand for ① residential area② demand for② office area③ demand for③ dining area④ demand for④

As shown in Figure 1 and Table 1, the primary feature layers and location factors attributes contain the following three aspects. 1) the attributes of mechanical parking system layers include its ID, capacity, service hours, fees, convenience (access time) , security; 2) the attributes of the road net layer of the major traffic routes connected to the shared mechanical parking system including its ID, road lane, survey flow, the convenience of the entrance of the cutting shared mechanical parking system, the number of the connected main roads; 3) the attributes of the distribution layer of buildings within the service radius including the name of the building, the mall area, residential area, office area, dining area, and calculation of parking demand for different purposes in accordance with the statistical data of the characteristics of parking behavior.

4. Algorithm for Fuzzy-Rough Attributes Reduction

In this paper, based on the concepts and principles of information entropy and conditional entropy of fuzzy rough set , the concept of mutual information is introduced when the mutual information is used to measure the relative importance of the fuzzy attribute in fuzzy decision tables. Therefore, the Algorithm for Fuzzy-Rough Attribute Reduction Based on Mutual Information (AFRARBMI) is proposed.

Set the domain of discourse. $U=\{x_1,x_2,\cdots,x_n\}$, P and Q have equivalence relation on U . $X=\{X_1,X_2\cdots,X_m\}$, $Y=\{Y_1,Y_2,\cdots,Y_n\}$ are the fuzzy attribute division derived by P and Q from U . To solve the problem, assume that $\forall X_i\in X$, $\forall Y_i\in Y$ are definable collection, and for $\forall X_i\in X$, $\forall Y_i\in Y$ and $x_k\in U$, its fuzzy membership function is formula (1).

$$\mu_{X_i}(x_k)=\begin{cases}1, & x_k\in X_i\\ 0, & x_k\notin X_i\end{cases},\quad \mu_{Y_i}(x_k)=\begin{cases}1, & x_k\in Y_j\\ 0, & x_k\notin Y_j\end{cases} \tag{1}$$

The fuzzy probability distribution constituted by the subset of P, Q in U could be expressed as the following formula (2) and formula (3).

$$p(X_i)=\frac{\sum_{k=1}^{|U|}\mu_{X_i}(x_k)}{|U|}\qquad i=1,2,\cdots,n \tag{2}$$

$$p(Y_j)=\frac{\sum_{k=1}^{|U|}\mu_{Y_j}(x_k)}{|U|}\qquad j=1,2,\cdots,m \tag{3}$$

The entropy $H(P)$ of the knowledge P can be expressed as the following formula (4), and the conditional entropy of knowledge Q with respect to knowledge P can be expressed as the following formula (5).

$$H(P)=-\sum_{i=1}^{n}\frac{\sum_{k=1}^{|U|}\mu_{X_i}(x_k)}{|U|}\log\frac{\sum_{k=1}^{|U|}\mu_{X_i}(x_k)}{|U|} \tag{4}$$

$$\begin{aligned}H(Q|P)&=-\sum_{i=1}^{n}p(X_i)\sum_{j=1}^{m}\frac{p(Y_j\cap X_i)}{p(X_i)}\log\frac{p(Y_j\cap X_i)}{p(X_i)}\\ &=-\sum_{i=1}^{n}\frac{\sum_{k=1}^{|U|}\mu_{X_i}(x_k)}{|U|}\sum_{j=1}^{m}\frac{\sum_{k=1}^{|U|}\mu_{X_i}\cap Y_j(x_k)}{\sum_{k=1}^{|U|}\mu_{X_i}(x_k)}\log\frac{\sum_{k=1}^{|U|}\mu_{X_i}\cap Y_j(x_k)}{\sum_{k=1}^{|U|}\mu_{X_i}(x_k)}\end{aligned} \tag{5}$$

Definition 1 (Fuzzy decision table): assume that the universe $U=\{x_1,x_2,\cdots,x_N\}$, the fuzzy attribute set $\tilde{A}$ is constituted by the fuzzy variable attributes $\{\tilde{A}^1,\tilde{A}^2,\cdots,\tilde{A}^m,\tilde{A}^{m+1}\}$, where $D=\{\tilde{A}^{m+1}\}$ is the fuzzy decision attribute and $C=\{\tilde{A}^1,\tilde{A}^2,\cdots,\tilde{A}^m\}$ is the fuzzy conditional attribute. Every fuzzy attribute could divide the universe into p_j fuzzy equivalence classes, expressed as $\{\tilde{F}_j^1,F_j^2,\cdots F_j^{p_j}\}$ $(j=1,2,\cdots,m+1)$, where $\tilde{F}_j^i\left(1<i<p_j\right)$ is a fuzzy set. The information system $S=(U,\tilde{A})$ constituted by such a universe and the fuzzy attribute sets is called the fuzzy decision table.

When P and Q are the fuzzy equivalence relation composed by fuzzy attributes, namely, $U/Ind(P)=\{\tilde{X}_1,\tilde{X}_2,\cdots,\tilde{X}_n\}$, $U/Ind(Q)=\{\tilde{Y}_1,\tilde{Y}_2,\cdots,\tilde{Y}_n\}$. The entropy $H(P)$ P of the knowledge P can be expressed as the following formula (6), the conditional entropy of knowledge Q with respect to knowledge P can be expressed as the following formula (7). In a subset of U,

$$H(P)=-\sum_{i=1}^{n}\frac{\sum_{k=1}^{|U|}\mu_{\tilde{X}_i}(x_k)}{|U|}\log\frac{\sum_{k=1}^{|U|}\mu_{\tilde{X}_i}(x_k)}{|U|} \tag{6}$$

$$H(Q|P)=-\sum_{i=1}^{n}\frac{\sum_{k=1}^{|U|}\mu_{\tilde{X}_i}(x_k)}{|U|}\sum_{j=1}^{m}\frac{\sum_{k=1}^{|U|}\mu_{\tilde{X}_i}\cap Y_j(x_k)}{\sum_{k=1}^{|U|}\mu_{\tilde{X}_i}(x_k)}\log\frac{\sum_{k=1}^{|U|}\mu_{\tilde{X}_i}\cap Y_j(x_k)}{\sum_{k=1}^{|U|}\mu_{\tilde{X}_i}(x_k)} \tag{7}$$

Definition 2 (mutual information of fuzzy attributes and fuzzy decision attribute): assume the fuzzy decision table. $S=(U,\tilde{A})$, R is a collection of fuzzy conditional attributes, and the importance $SGF\left(\tilde{A}^j,R,D\right)$ of any attribute $\tilde{A}^j\in C-R$ is defined as the following formula (8).

$$SGF\left(\tilde{A}^j,R,D\right)=I\left(R\cup\{\tilde{A}^j\};D\right)-I(R;D)=H(D|R)-H\left(D|R\cup\{\tilde{A}^j\}\right) \tag{8}$$

If $R=\phi$, and $SGF\left(\tilde{A}^j,R,D\right)=SGF\left(\tilde{A}^j,D\right)$. Then

$$SGF\left(\tilde{A}^j,D\right)=H(D)-H\left(D|\tilde{A}^j\right)=I\left(\tilde{A}^j;D\right) \tag{9}$$

Formula (9) is the mutual information of fuzzy attribute $\tilde{A}^j$ and fuzzy condition D.

After analysis, the steps of AFRARBMI are summarized as follows:

Step 1. Calculate the mutual information $I(C;D)=H(D)-H(D|C)$ of conditional attribute C and decision attribute D in the fuzzy decision table. T.

Step 2. Let $R=\phi$ and repeat the following steps for the condition attribute sets, $C-R$:

① For each fuzzy attribute $\tilde{A}^j\in C-R$, calculate the conditional mutual information. $I\left(\tilde{A}^j;D|R\right)$;

② Select the attribute which enables the conditional mutual information $I\left(\tilde{A}^j;D|R\right)$ to reach its maximum value, denoted as $\tilde{A}^j$. Then update R by $\tilde{A}^j$, where $R=R\cup\{\tilde{A}^j\}$. If there are more than 1 attributes, select the one with the minimum of similarity number, as $\tilde{A}^j$;

③ If $I(C;D)=I(R;D)$ or $\left|I(C;D)-I(R;D)\right|\le\varepsilon$ (ε is the accuracy range of allowable error; usually, to facilitate the calculation, take $\varepsilon=0.001$), terminate it; otherwise, transfer to *Step* 1);

Step 3. R is the relative reduction of condition attribute C relative to a decision attribute D.

In addition, what should be noted is that Wong and Ziarko have proved that to seek the minimum attribute reduction belongs to the NP-hard problem [16]. Therefore, the reduction obtained using AFRARBMI algorithm is just a relative reduction.

5. Case Studies

5.1. Research Object

The research object is the parking planning for the central city area of the Chengguan District in Lanzhou, as shown in Figure 2, a total of 37 mechanical parking systems. The data of simulation test is as shown in Table 2.

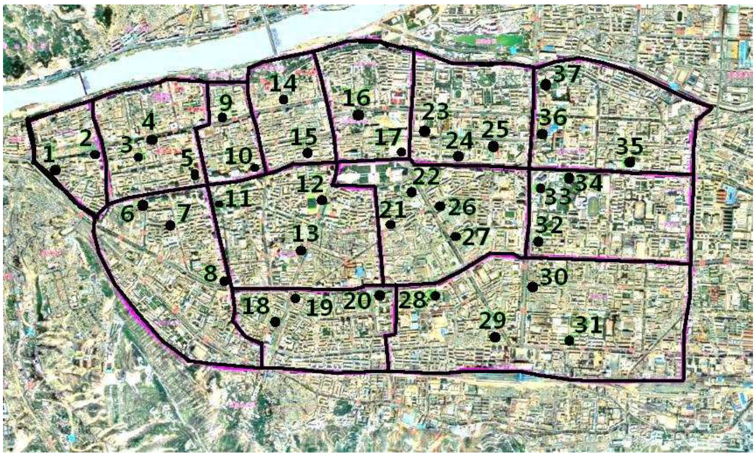

Figure 2. Mechanical parking system distribution planning in central city area

5.2. Computational Analysis

Adopt the AFRARBMI algorithm is adopted to carry out the reduction for the fuzzy decision table (Table 2) of the research object. There are 8 condition attributes in table 2, $C=${parking capacity, charging standard, access time, total parking demand for shopping malls, total parking demand for residence, total parking demand for office, total parking demand for restaurant, observed traffic flow of the connecting roads}. The planning period category is the decision attribute D. The parking capacity, total parking demand for shopping malls, total parking demand for residence, total parking demand for office, total parking demand for restaurant, observed traffic flow of the connecting roads all have 3 fuzzy equivalence classes. Charging standard and access time have 2 fuzzy equivalence classes.

The specific steps of the reduction for the fuzzy decision table of parking systems in planning using AFRARBMI algorithm are shown as follows:

Step 1: calculate the mutual information $I(C;D)=0.1936$ of condition attribute C and decision attribute D in Table 2.

Step 2: let $R=\phi$, calculate the condition mutual information $I(\tilde{A}^j;D|R)$ when $\forall\tilde{A}^j\in C-R$, shown as follows:

As $I(\tilde{A}^1;D)=0.0516$, $I(\tilde{A}^2;D)=-0.0078$, $I(\tilde{A}^3;D)=0.1569$, $I(\tilde{A}^4;D)=-0.1077$, $I(\tilde{A}^5;D)=0.1901$, $I(\tilde{A}^6;D)=0.2415$, $I(\tilde{A}^7;D)=0.2003$, $I(\tilde{A}^8;D)=0.0621$。

Table 2. Fuzzy decision database sets

No.	capacity			Fees		access time		demand for			demand for			demand for			demand for			survey flow			planning period		
	S	**M**	**B**	**S**	**B**	**S**	**B**	**S**	**M**	**B**	**S**	**M**	**B**	**S**	**M**	**B**	**S**	**M**	**B**	**S**	**M**	**B**	**forward**	**metaphase**	**recent**
1	0.5	1	0.9	0.8	0.4	0.7	0.8	1	0.7	0.5	1	0.5	0.4	1	0.7	0.5	0.2	0.9	0.6	1	0.9	0.7	1	0.8	0.6
2	0.2	0.9	1	1	0.3	1	0.6	0	0.8	1	0	1	0.8	0.2	1	0.8	0	1	0.8	0.7	1	0.9	0.1	0.8	1
3	0.5	1	0.9	0.2	0.6	0.5	0.9	0.9	0.8	0.6	0.6	0.7	0.5	0.9	0.7	0.5	0	1	0.8	1	0.9	0.8	1	0.8	0.6
4	0.5	1	0.9	0	0.9	0.5	0.9	0.1	1	0.9	0.1	0.9	0.6	0.3	1	0.8	0	1	0.9	0.9	1	0.9	0.5	1	0.9
5	1	0.8	0.6	0.8	0.4	0.7	0.8	0	0.8	1	0	1	0.8	0.1	1	0.9	0	1	0.8	0.6	1	1	0.1	0.8	1
6	0.5	1	0.9	0.2	0.6	0.5	0.9	0	0.9	1	0	1	0.7	0.2	1	0.8	0	1	0.7	0.9	1	0.9	0.1	0.8	1
7	0.8	0.9	0.8	1	0.3	1	0.6	0	0.8	1	0	1	0.8	0.1	1	0.9	0	0.6	1	0.6	1	1	0.1	0.8	1
8	0.2	0.9	1	1	0.3	1	0.6	0.5	0.9	0.7	0	1	0.7	0.3	1	0.8	0	1	0.8	0.7	1	0.9	0.5	1	0.9
9	0.8	0.9	0.8	0.5	0.5	0.9	0.7	0.6	0.9	0.7	0	1	0.7	0.4	1	0.7	0	1	0.7	0.9	1	0.8	0.5	1	0.9
10	0.5	1	0.9	1	0.3	1	0.6	0.1	1	0.9	0	1	0.8	0.1	1	0.9	0	1	0.9	0.5	0.9	1	0.1	0.8	1
11	0.2	0.9	1	1	0.3	1	0.6	0.2	1	0.8	0	0.5	1	0.2	1	0.8	0	1	0.7	0.6	1	1	0.1	0.8	1
12	0.5	1	0.9	0.2	0.6	0.5	0.9	0	0.9	0.9	0	1	0.8	0	0.9	0.9	0	1	0.8	0.6	1	1	0.1	0.8	1
13	0.2	0.9	1	0.2	0.6	0.5	0.9	1	0.7	0.5	0.5	0.7	0.5	0.8	0.8	0.6	0	1	0.8	1	0.9	0.8	1	0.8	0.6
14	1	0.8	0.6	0.2	0.6	0.5	0.9	0.8	0.9	0.6	0	1	0.7	0.4	1	0.7	0	1	0.9	0.7	1	0.9	0.5	1	0.9
15	0.5	1	0.9	0	1	0.5	0.9	0	0.9	1	0	0.7	1	0.4	1	0.7	0	1	0.8	0.3	0.9	1	0.1	0.8	1
16	0.2	0.9	1	1	0.3	1	0.6	0.3	1	0.8	0	1	0.8	0.2	1	0.8	0	1	0.7	0.7	1	0.9	0.1	0.8	1
17	0.8	0.9	0.8	1	0.3	1	0.6	0.6	0.9	0.7	0	1	0.7	0.5	0.9	0.7	0	1	0.8	0.9	1	0.8	0.5	1	0.9
18	1	0.8	0.6	0.8	0.4	0.7	0.8	0.2	1	0.8	0	1	0.9	0	0.7	1	0.2	0.9	0.6	0.7	1	0.9	0.1	0.8	1
19	0.5	1	0.9	0.2	0.6	0.5	0.9	0.9	0.8	0.6	0.1	0.9	0.6	1	0.7	0.5	0	1	0.7	0.9	1	0.9	1	0.8	0.6
20	1	0.8	0.6	0.5	0.5	0.9	0.7	0	0.9	1	0	1	0.8	0.3	1	0.8	0.2	0.9	0.6	0.6	1	1	0.1	0.8	1
21	0.8	0.9	0.8	0.5	0.5	0.9	0.7	0.4	1	0.7	0	0.9	0.6	0.4	1	0.7	0	0.9	0.9	1	0.9	0.8	0.5	1	0.9
22	0.1	0.8	1	0.2	0.6	0.5	0.9	0	0.7	1	0	1	0.9	0.6	0.9	0.7	0	1	0.7	0.8	1	0.9	0.1	0.8	1
23	0.8	0.9	0.8	0.2	0.6	0.5	0.9	0.7	0.9	0.6	0	0.8	0.9	0.1	1	0.9	0	0.5	1	0.8	1	0.9	0.1	0.8	1
24	0.5	1	0.9	0.2	0.6	0.1	1	0.9	0.8	0.6	0.1	0.9	0.6	0.9	0.8	0.6	0	1	0.8	1	0.9	0.7	1	0.8	0.6
25	0.5	1	0.9	0.2	0.6	0.5	0.9	0.3	1	0.8	0	0.9	0.9	0	0.7	1	0	0.9	0.9	0.7	1	1	0.1	0.8	1
26	0.5	1	0.9	0.2	0.6	0.5	0.9	0.2	1	0.9	0	1	0.8	0	0.8	1	0	1	0.8	0.8	1	0.9	0.1	0.8	1
27	0.5	1	0.9	0	1	0.5	0.9	0.1	1	0.9	0	1	0.8	0.1	1	0.9	0	1	0.7	0.7	1	0.9	0.1	0.8	1
28	0.8	0.9	0.8	0.2	0.6	0.5	0.9	1	0.8	0.5	0.5	0.7	0.5	0.9	0.8	0.6	0.2	0.9	0.6	1	0.9	0.8	1	0.8	0.6
29	0.1	0.8	1	0.2	0.6	0.5	0.9	0.6	0.9	0.7	0.8	0.6	0.4	0.9	0.8	0.5	0.8	0.7	0.5	1	0.9	0.7	1	0.8	0.6
30	0.5	1	0.9	0.2	0.6	0.1	1	0.1	1	0.9	0	1	0.8	0.2	1	0.8	0.2	0.9	0.6	0.6	1	1	0.1	0.8	1
31	0.5	1	0.9	0	0.9	0.5	0.9	0.9	0.8	0.6	0.1	0.9	0.6	0.8	0.8	0.6	0.4	0.8	0.6	0.9	1	0.9	1	0.8	0.6
32	0.5	1	0.9	0.2	0.6	0.5	0.9	0	0.9	1	0.1	0.9	0.6	0	0.7	1	0.8	0.7	0.5	0.7	1	0.9	0.1	0.8	1
33	0.2	0.9	1	0.2	0.6	0.1	1	0.5	0.9	0.7	0	1	0.8	0.4	1	0.7	0.3	0.9	0.6	0.9	1	0.9	0.5	1	0.9
34	0.5	1	0.9	0	0.9	0.5	0.9	0	0.7	1	0	0.9	0.9	0	0.9	0.9	0.9	0.6	0.4	0.7	1	0.9	0.1	0.8	1
35	0.5	1	0.9	0.2	0.6	0.5	0.9	0.9	0.8	0.6	0.5	0.7	0.5	0.9	0.8	0.6	1	0.6	0.4	1	0.9	0.7	1	0.8	0.6
36	0.8	0.9	0.8	0.8	0.4	0.7	0.8	0.1	1	0.9	0	0.6	1	0.3	1	0.8	0	1	0.9	0.8	1	0.9	0.1	0.8	1
37	0.8	0.9	0.8	0.8	0.4	0.7	0.8	0.2	1	0.8	0	1	0.8	0	0.8	1	1	0.5	0.4	0.7	1	0.9	0.1	0.8	1

Obviously, when $I\left(\tilde{A}^{6};D\right)=0.2415$, the attribute enabling the condition mutual information to reach the maximum value is the total parking demand for office. The updated $R=\phi\cup\left\{\tilde{A}^{6}\right\}=\left\{\tilde{A}^{6}\right\}$, then obtained $I\left(R;D\right)=I\left(\left\{\tilde{A}^{6}\right\};D\right)=0.2415$。

By that analogy, solve the next attribute $I\left(\tilde{A}^{j};D\middle|\left\{\tilde{A}^{6}\right\}\right)$ enabling to reach its maximum value, $I\left(\tilde{A}^{1};D\middle|R\right)=0.0833$, $I\left(\tilde{A}^{2};D\middle|R\right)=-0.0418$, $I\left(\tilde{A}^{3};D\middle|R\right)=-0.0002$, $I\left(\tilde{A}^{4};D\middle|R\right)=0.1051$, $I\left(\tilde{A}^{5};D\middle|R\right)=0.1073$, $I\left(\tilde{A}^{6};D\middle|R\right)=0.1564$, $I\left(\tilde{A}^{7};D\middle|R\right)=-0.0018$, $I\left(\tilde{A}^{8};D\middle|R\right)=0.1970$。

Obviously, $I\left(\tilde{A}^{8};D\right)$ has the maximum value, so the attribute enabling the conditional mutual information to reach its maximum value is the observed traffic flow of the connecting roads. The updated $R=\left\{\tilde{A}^{6},\tilde{A}^{8}\right\}$, and solve the $I\left(R;D\right)=I\left(\left\{\tilde{A}^{6},\tilde{A}^{8}\right\};D\right)=$ 0.1528.

Then, conduct the successive iterative operation $I\left(\tilde{A}^{j};D\middle|\left\{\tilde{A}^{6},\tilde{A}^{8}\right\}\right)$ to solve that the attribute enabling the conditional mutual information to reach its maximum value is the total parking demand for shopping malls. The updated $R=\left\{\tilde{A}^{6},\tilde{A}^{8},\tilde{A}^{4}\right\}$, and solve the $I\left(R;D\right)=I\left(\left\{\tilde{A}^{6},\tilde{A}^{8},\tilde{A}^{4}\right\};D\right)=$ 0.1800.

Carry out loop iteration to solve the next attribute $I\left(\tilde{A}^{j};D\left|\left\{\tilde{A}^{6},\tilde{A}^{8},\tilde{A}^{4}\right\}\right.\right)$ enabling to reach its maximum value is the total parking demand for restaurant. The updated $R=\left\{\tilde{A}^{6},\tilde{A}^{8},\tilde{A}^{4},\tilde{A}^{7}\right\}$ and solve the $I\left(R;D\right)=I\left(\left\{\tilde{A}^{6},\tilde{A}^{8},\tilde{A}^{4},\tilde{A}^{7}\right\};D\right)=$ 0.1931.

Therefore, $\left|I\left(C;D\right)-I\left(R;D\right)\right|$ is in the margin of error, i.e. $\left|I\left(C;D\right)-I\left(R;D\right)\right|\le\varepsilon$ ($\varepsilon=10^{-3}$). At this time, the attribute set { total parking demand for shopping malls, total parking demand for office, total parking demand for restaurant, observed traffic flow of the connecting roads } is the relative reduction of the original fuzzy decision table, as shown in table 3.

Table 3. Fuzzy information sheet reduced

No.	demand for ①			demand for ③			demand for ④			survey flow			planning period		
	S	M	B	S	M	B	S	M	B	S	M	B	forward	metaphase	recent
1	1	0.7	0.5	1	0.7	0.5	0.2	0.9	0.6	1	0.9	0.7	1	0.8	0.6
2	0	0.8	1	0.2	1	0.8	0	1	0.8	0.7	1	0.9	0.1	0.8	1
3	0.9	0.8	0.6	0.9	0.7	0.5	0	1	0.8	1	0.9	0.8	1	0.8	0.6
4	0.1	1	0.9	0.3	1	0.8	0	1	0.9	0.9	1	0.9	0.5	1	0.9
5	0	0.8	1	0.1	1	0.9	0	1	0.8	0.6	1	1	0.1	0.8	1
6	0	0.9	1	0.2	1	0.8	0	1	0.7	0.9	1	0.9	0.1	0.8	1
7	0	0.8	1	0.1	1	0.9	0	0.6	1	0.6	1	1	0.1	0.8	1
8	0.5	0.9	0.7	0.3	1	0.8	0	1	0.8	0.7	1	0.9	0.5	1	0.9
9	0.6	0.9	0.7	0.4	1	0.7	0	1	0.7	0.9	1	0.8	0.5	1	0.9
10	0.1	1	0.9	0.1	1	0.9	0	1	0.9	0.5	0.9	1	0.1	0.8	1
11	0.2	1	0.8	0.2	1	0.8	0	1	0.7	0.6	1	1	0.1	0.8	1
12	0	0.9	0.9	0	0.9	0.9	0	1	0.8	0.6	1	1	0.1	0.8	1
13	1	0.7	0.5	0.8	0.8	0.6	0	1	0.8	1	0.9	0.8	1	0.8	0.6
14	0.8	0.9	0.6	0.4	1	0.7	0	1	0.9	0.7	1	0.9	0.5	1	0.9
15	0	0.9	1	0.4	1	0.7	0	1	0.8	0.3	0.9	1	0.1	0.8	1
16	0.3	1	0.8	0.2	1	0.8	0	1	0.7	0.7	1	0.9	0.1	0.8	1
17	0.6	0.9	0.7	0.5	0.9	0.7	0	1	0.8	0.9	1	0.8	0.5	1	0.9
18	0.2	1	0.8	0	0.7	1	0.2	0.9	0.6	0.7	1	0.9	0.1	0.8	1
19	0.9	0.8	0.6	1	0.7	0.5	0	1	0.7	0.9	1	0.9	1	0.8	0.6
20	0	0.9	1	0.3	1	0.8	0.2	0.9	0.6	0.6	1	1	0.1	0.8	1
21	0.4	1	0.7	0.4	1	0.7	0	0.9	0.9	1	0.9	0.8	0.5	1	0.9
22	0	0.7	1	0.6	0.9	0.7	0	1	0.7	0.8	1	0.9	0.1	0.8	1
23	0.7	0.9	0.6	0.1	1	0.9	0	0.5	1	0.8	1	0.9	0.1	0.8	1
24	0.9	0.8	0.6	0.9	0.8	0.6	0	1	0.8	1	0.9	0.7	1	0.8	0.6
25	0.3	1	0.8	0	0.7	1	0	0.9	0.9	0.7	1	1	0.1	0.8	1
26	0.2	1	0.9	0	0.8	1	0	1	0.8	0.8	1	0.9	0.1	0.8	1
27	0.1	1	0.9	0.1	1	0.9	0	1	0.7	0.7	1	0.9	0.1	0.8	1
28	1	0.8	0.5	0.9	0.8	0.6	0.2	0.9	0.6	1	0.9	0.8	1	0.8	0.6
29	0.6	0.9	0.7	0.9	0.8	0.5	0.8	0.7	0.5	1	0.9	0.7	1	0.8	0.6
30	0.1	1	0.9	0.2	1	0.8	0.2	0.9	0.6	0.6	1	1	0.1	0.8	1
31	0.9	0.8	0.6	0.8	0.8	0.6	0.4	0.8	0.6	0.9	1	0.9	1	0.8	0.6
32	0	0.9	1	0	0.7	1	0.8	0.7	0.5	0.7	1	0.9	0.1	0.8	1
33	0.5	0.9	0.7	0.4	1	0.7	0.3	0.9	0.6	0.9	1	0.9	0.5	1	0.9
34	0	0.7	1	0	0.9	0.9	0.9	0.6	0.4	0.7	1	0.9	0.1	0.8	1
35	0.9	0.8	0.6	0.9	0.8	0.6	1	0.6	0.4	1	0.9	0.7	1	0.8	0.6
36	0.1	1	0.9	0.3	1	0.8	0	1	0.9	0.8	1	0.9	0.1	0.8	1
37	0.2	1	0.8	0	0.8	1	1	0.5	0.4	0.7	1	0.9	0.1	0.8	1

5.3. Analysis and Evaluation

Reconstruct the decision table of the site-selection of mechanical parking system are constructed according to the rules after reduction, and then adopt the C5 algorithm is adopted to conduct inductive learning for the decision attribute-based urgency degree of construction (planning period), coupled with the evaluation of the decision.

Literature [1] adopts the GIS data analysis and inductive learning method to conduct comparison for the site-selection of mechanical parking system and the decision rules of the related geographical factors. The results indicate that the pre and post errors are consistent, 2.7%. However, the learning accuracy of the latter one has been improved, 98.1%, and its decisions conditional attribute has decreased, which (C4 parking demand for shopping malls, C6 parking demand for office) owns simplicity, intuitive nature, scientificity and rationality. The specific results of the comparison are as shown in Table 4.

Table 4. Result comparison

Item	Condition attribute	Learning accuracy	Attribute			Decision tree		Modeling time
			C4	C6	C9	size	error	
Literature[1] method	8	97.3%	62%	100%	76%	4	1(2.7%)	0.13s
AFRARBMI method	4	98.1%	76%	100%	-	3	1(2.7%)	0.02s

In the research on the site-selection of mechanical parking system, the GIS-based analysis of the road traffic investigation and data statistic are conducted, and the further refinement of the research object results in the obtained data information more comprehensive and complex, therefore, the algorithm for fuzzy-rough attribute reduction (AFRAR) can provide a convenient and accurate basis for decision-making.

6. Conclusion

Based on the GIS analysis method and the algorithm for mutual information fuzzy-rough attribute reduction, this paper proposes a method model for the reduction and analysis of the site-selection factors, and achieves the decision analysis and evaluation for the site-selection of mechanical parking system. The research results show that this method realizes the mutual promotion for both rough set theory and fuzzy system theory, and improves the intelligence level of GIS data analysis and decision support. Although the research subject is the site-selection of mechanical parking system, this method has a certain universal significance. It has been proved that it has great potential in wide application in the site-selection of resources and facilities as well as the spatial decision support. Therefore, it has higher application value in urban intelligent transportation system.

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