

Low-carbon Cities Evaluation Model Based on RS and SVM

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Abstract: The research on low carbon city is still in the exploratory stage, there is a lack of operational and generalizable evaluation indicator system and evaluation model to guide the transformation and development of low carbon city. An indicator system including low-carbon production, low-carbon consumption, low-carbon environment, low-carbon energy, low-carbon policy and low-carbon technology is established. And then, an evaluation model based on RS and SVM is developed. Experiment results show that the model achieves higher classification accuracy and better generalization performance in the condition of few data.

Keywords Low-carbon Cities, Rough Set, Support Vector Machine, Fuzzy C-mean.

INTRODUCTION

Urban energy consumption is the main source of global carbon emissions, accounting for 75% of the total global carbon emissions. At present, China's total number of cities is 661, urban population is 560 million, and urban energy consumption accounts for over 60% of total energy consumption in the country. Per capita energy consumption is about 3 times of rural per capita energy consumption. Changing the energy structure of cities to build low-carbon cities is the only way to achieve sustainable urban development[Geng, et al.,2017].

Low-carbon city is to build a benign and sustainable energy ecosystem that taking the low-carbon economy as the mode of development and direction, low-carbon life as concept and behavioral characteristics, low-carbon society as the construction sample and blueprint, through the change of "mass production, mass consumption and a lot of waste" of the socio-economic operation Models to optimize energy structure, save energy, reduce emissions, recycle, minimize greenhouse gas emissions, and establish a resource-saving, environment-friendly society[Zhou, et al.2015]. It is of great significance to carry out comprehensive evaluation of low-carbon city: longitudinal quantitative analysis and evaluation of a city's low-carbon construction level will standardize and guide the city to a higher goal; horizontal comparative analysis and evaluation among cities will inspire the builders to explore the potential of development, explore and innovate, and achieve the goal of low-carbon development[Hossny, et al.2018].This paper improves the evaluation index system for low-carbon cities announced by the Chinese Academy of Social Sciences, and sums up the comprehensive evaluation of low-carbon urban construction levels as a multi-category classification problem, adopting an evaluation model based on rough sets and support vector machines, and classifying it into six grades including low-carbon, medium-low carbon, medium-carbon, medium-high carbon, high-carbon and ultra-high-carbon.

LOW-CARBON CITY EVALUATION INDEX SYSTEM

The design of a low-carbon city evaluation index system is the core link for evaluating the city's low-carbon development level [Zhou, et al.2015]. In 2010, the Chinese Academy of Social Sciences announced a new standard system for the evaluation of low-carbon cities. This is by far China's first comprehensive low-carbon city standard. Some indicators of the standard system are too macro, some indicators appear to be redundant, and some have not been specifically quantified. Therefore, there are still some difficulties in operation. In particular, there is no organic synthesis. For this reason, this article has improved the standard system, as shown in Table 1.

The low-carbon city index system includes six subsystems: low-carbon production, low-carbon consumption, low-carbon environment, low-carbon energy, low-carbon policies, and low-carbon technologies. Among them, low-carbon production, low-carbon consumption, and low-carbon environment are the main ways to realize low-carbon cities; low-carbon energy is the core, and it is the basis for realizing low-carbon urban development. It directly determines the level of development of low-carbon cities; low-carbon policies, Low-carbon technologies provide social, legal, and technological solutions to the development of low-carbon cities from the perspective of mechanisms and technologies.

The new indicator system is significantly different from the new standard system for low-carbon cities announced by the Chinese Academy of Social Sciences, which is the inclusion of a low-carbon environment and low-carbon technologies. This is because a low-carbon environment is an effective way for urban carbon sequestration and carbon reduction. Low-carbon technology is an important support and guarantee for realizing urban energy, economy, and society's low carbon. In addition, this paper has embodied low-carbon productivity into three aspects: low-carbon construction, low-carbon transportation, and low-carbon industry.

Table 1 Evaluation indicator system of low-carbon cities

Low-carbon production	Low-carbon building	Energy-saving building development proportion C1
		Low carbonization rate of construction C2
	Low-carbon traffic	The number of buses per 10,000 people C3
		The proportion of new energy vehicles C4
		The proportion of public transport passenger traffic (except taxi) C5
	Low-carbon industry	Tertiary industry's share of GDP C6
		The proportion of environmental protection industry in GDP C7
		The proportion of high-tech industries in GDP C8
	Low-carbon consumption	
Low-carbon energy	Energy structure	Non-fossil energy consumption C13
		New energy consumption ratio C14
	Low-carbon efficiency	Energy consumption per unit of GDP C15
		Carbon emissions per unit of GDP C16
Low-carbon policy	Policy planning	Low-carbon construction related standards C17
		Low-carbon incentive supervision mechanism C18
	Public education	Low carbon concept popularization rate C19
		Low carbon awareness C20
Low-carbon technology		
Low-carbon environment	Green carbon sink	Low-carbon R&D expenditure as a percentage of fiscal expenditure C21
		Greenhouse gas capture and storage ratio C22
		Smart energy-saving technology usage C23
	Pollution control	Renewable energy technology usage C24
		Heavy pollution industry clean production technology utilization rate C25
		Per capita green area C26
		Forest cover rate C27
		Comprehensive utilization of industrial solid waste C28
		Industrial exhaust gas dust emission standards C29
		The harmless treatment rate of urban living garbage C30
		The number of days that air quality reaches Grade 2 and above C31

LOW CARBON CITY EVALUATION MODEL BASED ON RS AND SVM

SVM effectively solves the problems of finite sample, high dimensionality, nonlinearity, local optimal solution and so on [Li, et al.2015]. However, there are two problems:

(1) Due to the low number of evaluation indicators in low-carbon cities, the amount of input data at the SVM model input end Too large, the system structure is too complex, it is difficult to obtain good results in terms of speed and accuracy;

(2) As the SVM is a supervised learning mechanism, it is required to use identification samples for training, artificial identification of low-carbon city development level is not only a heavy workload, And the identification results may be different due to people's subjective feelings. Pure non-supervisory mechanisms often result in inaccuracies in the actual classification due to the reduction of the amount of available information.

For the first problem, this paper introduces rough sets for attribute reduction in SVM model and

synthesizes the respective advantages of RS and SVM. First, the rough set is used as a preprocessing to eliminate attributes that are not related to the decision information and then used to reduce the attributes. The resulting training samples were trained and tested on support vector machines[Sidheswar, et al.2018].

For the second problem, this paper introduces the semi-supervised improvement of fuzzy c-means (FCM) clustering in SVM model. First, based on prior knowledge, find out the initial cluster centers of various types and then use them. FCM clustering technology automatically identifies other samples, and finally trains multi-layer SVM classifiers to complete the division of low-carbon urban development grades[Murat, et al.2018] .

In addition, the optimal classification hyperplane of SVM is mainly determined by the support vector, and those samples farther from the optimal classification hyperplane have little effect on SVM training. If these samples can be taken out in advance, it will be able to greatly reduce the amount of calculations, thereby improving the SVM training speed. FCM clustering is a soft division of the sample. It does not force the

classification of the sample. Instead, it uses a concept of subordination to evaluate the extent to which the sample belongs to a certain category. Therefore, this paper uses FCM to preprocess the training sample and remove the larger sample [Sheeja T.K., et al.2018]. Here

is the degree of membership of the i -th sample point belonging to the j -th cluster center, generally taken as $= 0.8$.

The basic steps of the model are shown in Figure 1:

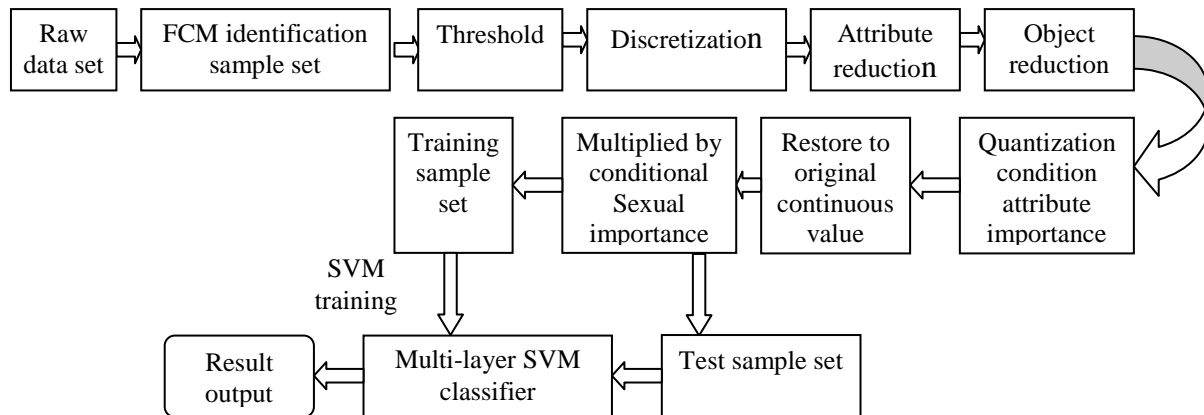


Figure 1 Low-carbon cities evaluation model based on RS and SVM

Note: When the range of values of each attribute is different, in order to avoid the advantage of the attribute with a large value range, the data needs to be thresholded so that all the attribute values fall in the same interval; the rough set can only process discrete data. It is necessary to discretize all continuous attribute values. Discrete processing and attribute reduction will produce a large number of redundant or incompatible objects, object reduction can solve this situation; In order to enhance the impact of important attributes on the decision results, the importance of the attribute is used as the weight of each condition attribute.

EMPIRICAL ANALYSIS

Data collection

Most of the data in this article come from "China Statistical Yearbook," "China City Statistical Yearbook," and "China Energy Statistical Yearbook". Some of the indicators are obtained through questionnaire surveys, and some indicator data (such as indicators under the low-carbon policy). Because there is no statistical data, it is obtained through consultation with experts in this field. This article has collected 50 cities related data, which are all complete records. The sample set is divided into two parts: training set (40) and test set (10).

Data preprocessing

(1) Threshold processing to make all index values fall in the same interval [0,1]

(2) According to the automatic identification of training samples by FCM, 25 samples are most likely to be support vectors, 2 low-carbon cities, 3 low-medium-carbon cities, 7 medium-carbon cities, 10 high-medium-carbon cities, 2 high-carbon cities and 1 ultra-high-carbon cities. The test set has the

following identification results: 1 low-carbon cities, 2 low-medium-carbon cities, 2 medium-carbon cities, 3 high-medium-carbon cities, 1 high-carbon cities and 1 ultra-high-carbon cities.

(3) The rough set data processing tool ROSETTA is used to reduce the attribute of the decision system. The algorithms used to reduce the attributes include: genetic algorithm, dynamic reduction algorithm, expansion method, etc. After many tests, it will be dynamic. The combination of reduction method and genetic algorithm for reduction is better than simply using one method. It can solve the conflict problem of reduced rules better. A total of 167 reduction sets were obtained, one of which was chosen based on the conditional attributes for decision support and importance. {C1,C5,C6,C11,C13, C15, C22, C27, C31};

(4) After removing redundant or incompatible samples, the sample set changes from 25 records to 24 records.

(5) The importance of each attribute in the reduction set was {0.05, 0.05, 0.1, 0.15, 0.2, 0.2, 0.05, 0.1, 0.1}.

(6) Restore the discretized attribute value in the reduced set to a continuous value and multiply its importance matrix to obtain a sample set with fewer attributes and objects and weights.

SVM training and testing

The development level of low-carbon cities has six evaluation levels. This is a multi-classification problem. In this paper, binary tree-based SVMs are used to achieve multi-classification, and five-layer SVM classifiers are constructed to obtain SVM1, SVM2, SVM3, SVM4, and SVM5. The main training process is: For the i ($i = 1, 2, 3, 4, 5$) SVM, the decision attribute value corresponding to the training

sample in the i -th class is set to +1, and the decision attribute values of other samples are Set to -1. The training sample's condition attribute values and the i -th corresponding decision attribute values are sent to five SVMs for training. Its test procedure is: first input the sample to be tested into SVM1, if its output is +1, it is judged that its level is low carbon, and the test process ends; otherwise, it is input into SVM2 if its output +1, then it is judged as low- medium - carbon, the test process is over; otherwise, it is input into SVM3. If its output is +1, it is judged to be medium-carbon, and the test process ends; otherwise, it is input again. To SVM4, if its output is +1, it is judged to be high-medium-carbon, and the test process ends; otherwise, it is input into SVM5, if its output is +1, it is judged as high-carbon, otherwise it is judged It is ultra-high carbon.

This paper uses RBF kernel function $k(x, y) = \exp[-\|x - y\|^2 / (2\delta^2)]$, x, y input for training set, δ is the width of radial basis function. After many tests, the value of δ is 0.4100652, and the error penalty factor C is 941857063. The classification effect is the best.

Test results and analysis

SVM1 test sample set = {1 low-carbon, 2 low-medium carbon, 2 medium-carbon, 3 high- medium carbon, 1 high-carbon, 1 ultra-high carbon}

The output of SVM1 is = {+1, -1, -1, -1, -1, -1, -1, -1, -1, -1}

SVM1 correctly differentiates samples of low-carbon and other grades (medium-low carbon, medium-carbon, medium-high carbon, high-carbon, and ultra-high carbon).

SVM2 test sample set = {2 low-medium carbon, 2 medium carbon, 3 high-medium carbon, 1 high carbon, 1 ultra high carbon}

The output of SVM2 is = { -1, -1, +1, -1, -1, -1, +1, -1, -1}

SVM2 correctly differentiates between low-medium carbon and other grades (medium carbon, high-medium carbon, high-carbon, and ultra-high carbon).

SVM3 test sample set = {2 medium carbons, 3 high-medium carbons, 1 high carbon, 1 ultra-high carbon}

The output of SVM3 is = {+1, -1, -1, -1, +1, +1, -1}

SVM3 misjudges one sample of high carbon in the class as medium carbon.

SVM4 test sample set = {2 high-medium carbon, 1 high carbon, 1 ultra-high carbon}

The output of SVM4 is = { -1, +1, -1, +1}

SVM4 correctly distinguishes between high-medium carbon and other grades (high-carbon, ultra-high-carbon) samples.

SVM4 test sample set = {1 high carbon, 1 ultra-high carbon}

The output of SVM4 is = { -1, +1}

SVM4 correctly differentiates between high carbon and ultra-high carbon samples.

CONCLUSIONS

To improve the low-carbon city evaluation system announced by the Chinese Academy of Social Sciences, a more complete indicator system has been constructed, including low-carbon production, low-carbon consumption, low-carbon environment, low-carbon energy, low-carbon policies, and low-carbon technologies. system.

A comprehensive evaluation model for low-carbon cities based on rough sets and support vector machines is proposed. The model has the following advantages:

(1) Manual identification training samples are avoided, the workload is reduced, and the identification results are more objective;

(2) Picking out the samples that are most likely to be support vectors, reducing the training set, and reducing the amount of calculations, thereby improving the training speed and accuracy of the SVM;

(3) After using RS method to remove redundant information, the training sample set is simplified, the training time of the system is shortened, and the classification performance is improved.

(4) The SVM is a post-processing information system with fault tolerance and anti-jamming capabilities. In a small sample, it shows good generalization performance.

The test results show that the model has a higher classification accuracy and can be better applied in the evaluation of low carbon city development level.

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