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Published in:
Journal of Coastal Research

DOI:
10.2112/JCR-SI107-000.1

Published: 11/08/2020

Document Version
Peer reviewed version

Inclusive green innovation environment evaluation index: A Study of the logistics companies in Fujian Province

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Abstract

In order to enhance the effectiveness of inclusive green innovation environment evaluation of enterprises from the perspective of strategic management, this paper aims at the inclusive green innovation environment evaluation problems of enterprises under the ecological environmental protection regulations to put forward an inclusive green innovation environment evaluation index system based on multi-layer clustering algorithm. In addition, it designs the multi-layer clustering improvement mode based on the multi-layer clustering algorithm. Finally, it verifies the effectiveness of algorithm through simulation experiment.

Keywords:*Ecological environment, Low carbon operation, Performance evaluation, Hierarchical clustering*

Introduction

The low carbon operation effect refers to the innovation achievement degree generated in the low carbon operation activities. The comprehensive analysis on low carbon operation effect refers to the quantitative calculation and analysis of single content or single index based on their correlation level which reflect the low carbon operation situation and achievement. Its purpose is evaluate and judge the low carbon operation situation and result of enterprises through comprehensive analysis thus to enhance the cognition depth and analysis quality.

The low carbon operation effect evaluation system is a complex system, it is needed to establish an index system for describing the system essence and rule clearly to control it to realize the preset goal. One index can only reflect one certain attribute of the low carbon operation effect evaluation system, therefore, it is needed to process the main indexes to form a new numerical value thus to comprehensively evaluate the low carbon operation effect of enterprises. In addition, the following principles should be obeyed in establishing the evaluation index system: 1) Scientificity, namely the listed indexes should reflect the low carbon operation effect, avoid listing indexes reflecting no low carbon operation effect and adverse effect in enhancing low carbon operation effect. 2) Fairness and reasonableness, namely the evaluation indexes should reflect the low carbon operation effect fairly and reasonably to be helpful for enterprises to make comparison and stimulate the enthusiasm of enterprises in enhancing low carbon operation effect. 3) Operability, namely the indexes are easy for collecting, their correctness and reliability can be guaranteed, the number of indexes should not be too many; in addition, the indexes should not be too complex for calculation. 4) Good guidance, namely the index system should be helpful to guide the low carbon operation work of enterprises to enhance the low carbon operation effect and avoid the ineffective low carbon operation behavior.

Based on the above principles, this paper adopts the production innovation rate, business success rate of innovative products, sales rate of innovative products, number of innovative technologies and innovation frequency of product as the evaluation factors for low carbon operation, establishes the evaluation index of low carbon operation effect and its single-factor evaluation matrix, besides, bases on the fuzzy clustering method of self-organized neural network model to conduct evaluation on low carbon operation effect.

METHODS

The author thinks the green innovation capability of low carbon operation enterprise refers to the capability of enterprise to make technology, management, service, marketing and environmental protection to be continuous and institutional in green innovation for its long-term sustainable development and continuously realizing its economic benefit, environmental benefit and social benefit.

Establishing the green innovation capability evaluation index system for low carbon operation of enterprise

In accordance with the industrial feature of low carbon operation enterprise and its real situation under the ecological environment protection regulations, its green innovation capability can be divided into three relevant levels (as is shown in Figure 1), wherein, these three levels interact with each other and constitute the main structure of green innovation capability of low carbon operation enterprise.

In accordance with the connotation understanding of green innovation capability of low carbon operation enterprise and the availability of empirical data, referring to the continuous green innovation capability index system designed by related scholars and combined with the continuity, institutional nature, systematicness and greenness of continuous green innovation capability, the author conducts evaluation and research from six aspects including green innovation input capability, green innovation management capability, green innovation service capability, green innovation marketing capability, green innovation awareness of entrepreneurs under the ecological environment protection regulations and green innovation environmental protection capability. Meanwhile, the low carbon operation enterprise is a multi-link and multi-layer complex system, based on considering the index diversity and avoiding strong linear relation between the internal indexes of subsystem, the author establishes the green innovation capability evaluation index system of low carbon operation enterprise.

The author refers to and collects related materials and information of low carbon operation enterprise, absorbs and refers to the excellent parts of green innovation capability and sustainable development evaluation index of experts and scholars under the ecological environment protection regulations, adopts the frequency statistics method and expert consulting method to firstly select and determine over 50 evaluation indexes and eliminate 21 indexes with insufficient feasibility and correctness, and then conducts analysis on the main components and independence nature of indexes to eliminate 19 indexes, finally retains 12 evaluation indexes and determine the green innovation capability evaluation index system of low carbon operation enterprise after adjustment.

Two -stage clustering detection

In the density clustering process, here adopt the simplified Euclidean distance calculation mode:

$$r(i,j)=\sqrt{\left(K_{1i}-K_{1j}\right)^2+\cdots+\left(K_{mi}-K_{mj}\right)^2} \qquad (1)$$

In the formula (1), K is the spacial projection value of m. Adopt the density clustering to conduct the hidden operation performance defining detection process, namely, base on the data point and its neighbourhood ε for cluster merging, its feature is: base on adjusting the neighbourhood parameter ε to achieve the refined decomposing clustering effect of high-density area, therefore, it is suitable to select the algorithm to be the defined clustering algorithm. Firstly, take any hidden operation performance of rough clustering hierarchy as the clustering center, make similar operation performance search in the given neighbourhood ε, and the similar operation performance number is p.

Under the ecological environment, the density defining detection process of hidden operation performance is composed of two parts: density clustering and hidden operation performance detection. Provided that the gravity set of density clustering is $R=\{R_j\}$, the vector set of pending clustering is $\{S_l\}$. The initial clustering status is $R=\varnothing$, and then the gravity of the vector set $\{S_l\}$ of pending clustering is R_j, $F[S_i]=R_j$, and the number of hidden operation performance sample is k_j in the $\{S_l\}$ corresponding to the gravity R_j, the initial status $k_j=0$, and the density defining clustering process can be described as follows:

Step 1: abstract the operation performance sample S_i non-corresponding to the gravity R_i from the hidden operation performance source data $\{S_l\}$, if the gravity set R exists with another gravity point R_j,, and $S_i\in N\left(R_j\right)$, and then implement the step 2; otherwise, take S_i as the new gravity point, $R=R+S_i$, $R_{ju}=S_{iu}$, $u=1,\cdots,U$, and implement the step 3.

Wherein, $R_{ju}=S_{iu}$, $u=1,\cdots,U$ present that if S_i belongs to no types, take it as the new gravity point.

Step 2: take the gravity point of hidden operation performance S_i as $F[S_i]=R_j$, and update the gravity number as $k_j=k_j+1$.

Step 3: if all samples in the hidden operation performance set correspond to one central point, implement the step 4, otherwise, return to step 1, and continue implement the iterative clustering process.

Step 4: update the gravity attribute of hidden operation performance set:

$$R_{jk}=\sum_{A} S_{ik}/k_j \tag{2}$$

In the formula, $k=1,\cdots,K$, $A=\{S_i|F[S_i]=R_j\}$. If the above process doesn't meet the preset iteration times c, reset the relationship between the hidden operation performance sample set and the gravity set, $F[S_i]=0$, and reset the gravity number $k_j=0$, implement the step 1, and repeat scanning.

Step 5: In accordance with the number k_j of hidden operation performance, conduct effective judgement on the gravity, if $k_j \ge p$, it is effective, otherwise, the gravity is ineffective, for the hidden operation performance relevant with ineffective gravity, the algorithm will repeatedly assign effective gravity relevant with it.

$$F[S_i]=R_j \Rightarrow S_i \in N_\varepsilon(R_j) \Rightarrow dist(S_i,R_j) \le \varepsilon \tag{3}$$

The parameters involved in the algorithm are as follows: distance threshold ε, neighbourhood point lower limit p, preset scanning times c, target attribute number U. The process of detection algorithm is:

Step 1: provided that the hidden operation performance includes mattributes and n sample sets, and conduct normalization processing on all attributes, the calculation process is:

$$x(i,j)=\frac{x^*(i,j)-x_{\min}(i,j)}{x_{\max}(i,j)-x_{\min}(i,j)} \tag{4}$$

In the formula (4), $x_{\max}(i,j)$ and $x_{\min}(i,j)$ respectively represent the upper limit and lower limit of the jth hidden operation performance attributes, $x(i,j)$ represents thejth attribute of ith individual, $x^*(i,j)$ represents the non-normalized measured value.

Step 2: Provided that m-dimensional projection vector is a, wherein, the linear projection feature values of $a = a_1, \cdots, a_m$, x_{ij} are as follows:

$$z_i = \sum_{j=1}^{m} A \times x_{ij}, i = 1, 2, \cdots, n \tag{5}$$

In the formula (5), A represents unit matrix and z_i represents projection value.

Step 3: implement the above density clustering in each dimensional space, delete the nonexistent clustering attributes and update the attribute set $P = \{p_1, p_2, \cdots, p_k\}$, $\exists p \in P$. Implement the above clustering operation on each dimension, if there exists with no clustering, there will exist with no hidden operation performance, end and exit from the algorithm. On the contrary, if there exists with $l > 1$ clustering, there will exist with hidden operation performance.

Step 4: If there exist with clustering in each components $a_1, \cdots, a_m$ of projection vector a, there will exist with clustering, and then implement the density clustering process, if there exists with $l' > 1$ clustering, there will exist with hidden operation performance.

The principle of the algorithm detection process: firstly, base on the hierarchical agglomerative clustering algorithm to realize the rough clustering of hidden operation performance, and then lock on the hierarchy of target and implement the density clustering process. In this process, project the high-dimensional data to judge whether there exists with multiple clustering based on single attribute thus to judge whether there exists with hidden operation performance, and then combine the attributes with single clustering to establish the multi-dimensional space and repeatedly implement the above judgement on the multi-dimensional space, therefore, the high-dimensional data can be expandable in the above algorithm.

Experiment analysis

In consideration of the insufficient feasibility to obtain large number of empirical research samples, this paper mainly centers on Fujian in the region selection of sample enterprises in order to reduce the model error and increase the correctness of empirical result. Therefore, this paper conducts empirical analysis by taking low carbon operation enterprises in Fujian as examples, the statistical data are mainly from Fujian Statistical Yearbook(2019) and materials related to logistics industry, meanwhile, it adopts the questionnaire and field visit to collect partial data and information, and finally select 45 low carbon operation enterprises as samples, wherein, select 30 enterprises randomly to be the learning samples and select 15 to be the detection samples. In the training process, this paperclassify the sample data by aid of MATBLE tool and conduct fitting on data samples.

The experiment result in Figure 2 shows that in the forward-backward compressed clustering network model training and testing processes of green innovation capability evaluation of enterprises, the fitting degrees of the model in actual output and expected output are very approximate, which can realize the recognition efficiency of over 95% of sample data and can meet the precision requirement of green innovation evaluation of logistics enterprises under the ecological environment protection regulations.

The main purpose of training the forward-backward compressed clustering network model of green innovation capability evaluation of enterprises under the ecological environment protection regulations is to guarantee the model has good input sample generalization performance. Namely, it is not only needed to evaluate the fitting performance of samples but also the approximation performance of samples. The main reason is that even if the training error is small in each group of samples, it does not mean the approximation performance of the model is good, because there exists with the fitting phenomenon, namely the MSE index of the model can not fully reflect the performance of the model. It is also needed to verify the training effectiveness of forward-backward compressed clustering network model of green innovation capability evaluation of enterprises under the ecological environment protection regulations. Based on the 30 groups of test data for verification and calculate to get the error of mean square of the model to be 3.8652 e-05, which meets the requirement of error termination based on the minimum network training. The experiment shows that the sample error is mostly distributed between the internal of [0.001, 0.01], and the cross-verification process is passed. Wherein, the verification results of 15 groups test samples is as shown in table1.

Conclusion

This paper aims at the inclusive green innovation environment evaluation problems of enterprises to put forward an inclusive green innovation environment evaluation index system based on forward-backward compressed clustering filtering algorithm under the ecological environment protection regulations, conducts evaluation and research from six aspects including green innovation input capability, green innovation management capability, green innovation service capability, green innovation marketing capability, green innovation awareness of entrepreneurs under the ecological environment protection regulations and green innovation environmental protection capability, and puts forward a forward-backward compressed clustering filtering algorithm to effectively solve the noise and uncertainty problems existed in green innovation evaluation collection of enterprises and realize effective estimation on the green innovation evaluation equilibrium model under the ecological environment protection regulations.

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FIGURES

FIGURES

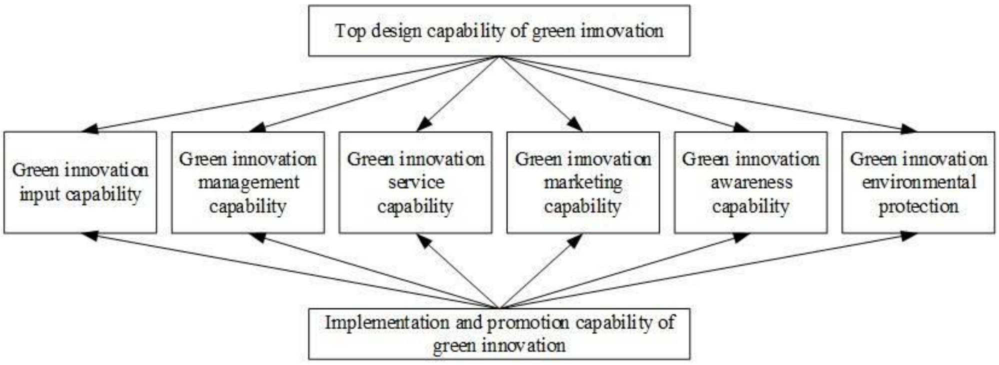

Fig. 1. Green innovation capability structure model of low carbon operation enterprise

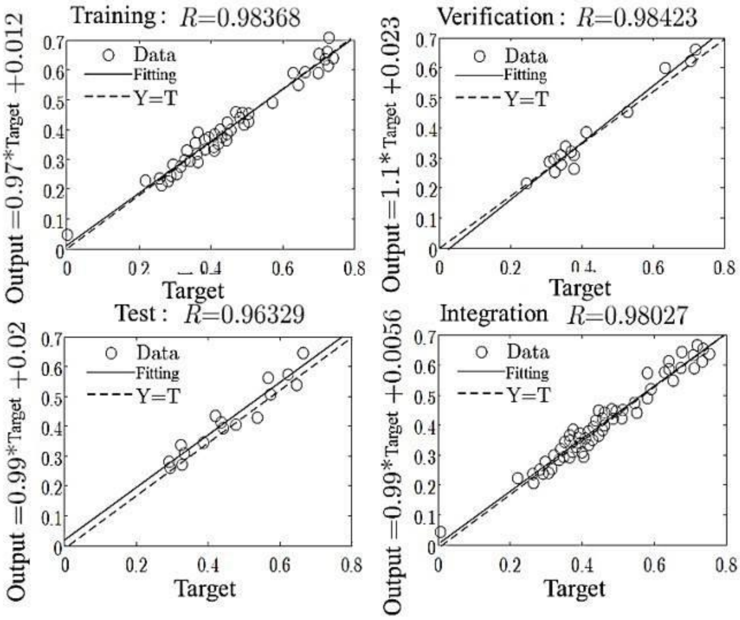

Fig.2. Network approximation information

Serial number	Actual value	Expected value	Absolute value
1	0.6012	0.6078	0.0086
2	0.3112	0.3120	0.0018
3	0.4152	0.4127	0.0035
4	0.4880	0.4958	0.0068
5	0.3951	0.4136	0.0175
6	0.3072	0.3086	0.0024
7	0.6627	0.6711	0.0074
8	0.2535	0.2520	0.0025
9	0.3021	0.2946	0.0045
10	0.3554	0.3516	0.0048
11	0.3757	0.3711	0.0056
12	0.3711	0.3680	0.0021
13	0.5044	0.5062	0.0028
14	0.3158	0.3045	0.0123
15	0.5973	0.6125	0.0142

Table1 Effectiveness verification data