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Optimization Algorithms and Digital Management Path Design in Corporate Economic Sustainability

Yuwei Jiao[1,*]
[1] Business School, Hohai University, Nanjing, Jiangsu, 211100, China
Corresponding authors: (e-mail: jiaoyuwei@hhu.edu.cn).

Abstract With the increasing global concern for environmental protection and sustainable resource utilization, companies are facing unprecedented challenges. At the same time, consumers' environmental protection awareness is increasing, which puts forward higher requirements for corporate social responsibility. The study establishes the evaluation index system of enterprise economic sustainable development based on the principle of evaluation index construction. The evaluation indexes are screened by principal component analysis, in which the cumulative contribution rate of total assets contribution, cost and expense profitability, product sales rate, and total capital preservation and value-added rate to the evaluation of enterprise economic sustainable development reaches 95.6%. Aiming at the problems of RBF neural network, the principal component analysis algorithm is introduced, and the genetic algorithm is used to optimize and construct the combined prediction model PCA-GA-RBF, and through the algorithm comparison, it can be seen that this method is able to effectively evaluate the sustainable development of the enterprise's economy, with high accuracy and real-time performance. Combined with the fuzzy set qualitative analysis method for analysis, the results show that there are four types of modes to improve the performance of enterprise sustainable development, based on which the digital management path of the enterprise is proposed to provide reference for the development path of the enterprise.

Index Terms sustainable development, RBF neural network, principal component analysis, digital management

I. Introduction

As a comprehensive concept, sustainable economic development of enterprises advocates that it should take into account the needs of the present without jeopardizing or threatening the interests of future generations, and that it is a development model that combines the present and the future, harmonizes economic growth and environmental protection, and promotes social equity and justice [1]-[3]. This concept takes the promotion of development, social progress and environmental protection as an inseparable whole, and strives to find the optimal balance between the three, so as to jointly build a prosperous, fair and ecologically friendly society [4], [5]. Sustainable economic development focuses on resource conservation and efficient use, encourages technological innovation to improve resource efficiency, emphasizes social justice and inclusive growth, so that the results can benefit more people, and emphasizes environmental protection and ecological restoration, reducing the impact of economic activities on nature, the real implementation of the harmonious coexistence of human beings and nature to achieve sustainable development [6]-[9]. However, in the process of realizing sustainable economic development, enterprises face problems in human, material and financial resources, which seriously impede the sustainable economic development of enterprises [10]-[12].

In the era of artificial intelligence and digitalization, the problems in the process of sustainable economic development of enterprises can be solved [13]. In the field of artificial intelligence, optimization algorithms such as genetic algorithms and artificial neural networks have become important tools in the operation and management of enterprises [14], [15]. The application of optimization algorithms can improve the productivity of enterprises, reduce costs, and enhance the overall competitiveness of enterprises [16]. Digitalization, on the other hand, brings digital management to enterprises, which is a process of strict control and comprehensive optimization of the enterprise management process through the use of modern technical means such as digital technology, information technology and network technology [17]-[19]. The emergence of digital management can not only improve the efficiency of enterprise operation, but also reduce the cost of enterprise operation and enhance the competitiveness of enterprises [20]-[22]. It can be seen that the optimization algorithm and digital management will become an important means to promote the sustainable development of enterprise economy.

The study firstly establishes six evaluation index systems of enterprise economic sustainable development, including total asset contribution, asset liability ratio, cost and expense profitability, product sales rate, total capital preservation and value-added rate, and current asset turnover rate, and constructs the combined prediction model PCA-GA-RBF based on the RBF neural network by introducing the method of principal component analysis and applying the genetic algorithm, and utilizes the principal component analysis to select the evaluation indexes. The evaluation indexes are selected by using principal component analysis, and the validity of PCA-GA-RBF model is verified by the algorithm model comparison experiment. The fuzzy set qualitative comparative analysis method is used to carry out empirical research, and finally the results of the grouping of factors affecting the sustainable development of enterprises are obtained.

II. Measurement of the level of economic sustainability of enterprises based on optimization algorithms

II. A. Construction of the indicator system for the level of sustainable economic development of enterprises

II. A. 1) Principles for the construction of evaluation indicators

1. Combination of scientificity and practicality

The evaluation index system should be constructed in a scientific, objective and real way to measure and reflect the connotation and goal of enterprise sustainable development. At the same time, the designed index system must be practical, if it is not practical, then the constructed index system will have no value for analyzing the sustainable development of enterprises.

2. Combination of comprehensiveness and relative independence

Factors affecting the sustainable development of enterprises are very many, and the selected indicators should be comprehensive and complete to reflect the overall characteristics of the level of sustainable development of enterprises. However, the indicators in the indicator system will inevitably overlap in information, so when selecting evaluation indicators, we should try our best to choose indicators with relative independence and a small number of indicators that cover the main aspects affecting the sustainable development of enterprises.

3. Combination of goal orientation and operability

The purpose of the construction of the evaluation index system of enterprise sustainable development is to guide the evaluated enterprises to the road of sustainable development by virtue of the construction process and results of the evaluation index system. At the same time, the selected evaluation indicators should be measurable and easy to quantify as much as possible. However, the qualitative indicators should be measured by grade standards such as “excellent, good, medium, poor and very poor”, so that the qualitative indicators are also operable.

4. Combination of dynamics and statics

The indicator system must contain indicators reflecting the dynamic process of enterprise development, and the ratio and rate of change indicators should be considered comprehensively, so that the indicator system can accurately reflect the process of sustainable development of the enterprise and the dynamic characteristics of its development.

5. Combination of systematic and hierarchical

When constructing indicators, we should start from a systematic perspective and combine a series of indicators of enterprise sustainable development together. At the same time, the indicator system must reflect the intrinsic connection between factors at different levels. Therefore, when constructing the evaluation index system, it can be decomposed into a number of hierarchical structures. At a higher level, some comprehensive indicators should be selected, and the further down the indicators go, the more specific and refined they should be, so that the indicator system can be made more systematic, organized and logical.

II. A. 2) Framework of the evaluation indicator system

Whether the selection of the sustainable development evaluation index system is appropriate or not directly affects the accuracy and reliability of the evaluation results. The evaluation indexes of the enterprise's sustainable development level include the contribution of total assets, asset-liability ratio, cost-expense profit margin, product sales rate, total capital preservation and appreciation rate, and current asset turnover rate.

II. B. Evaluation model based on improved RBF neural network

II. B. 1) Principal component analysis

Due to the large amount of data on various types of influencing factors, it is necessary to select parameters with high correlation performance for analysis and processing.PCA is a process of dimensionality reduction of data by updating the original data into a new set of coordinates through spatial coordinate changes, and at the same time transforming the system's multivariate variables into representative and uncorrelated components under the updated coordinate system.

II. B. 2) RBF Neural Networks

RBF neural network [23] is a three-layer feedforward network, where the first layer is the input layer, the second layer is the hidden layer, and the third layer is the output layer, as shown in Fig. 1, where the output layer results are realized by a linear combination of the hidden layers. In the figure, x_d denotes D-dimensional input parameters, y_m denotes M-dimensional output parameters, h denotes neuron number, and H denotes the number of neuron nodes in the hidden layer. The $\omega_{h,m}$ denotes the weight coefficient from the hth hidden layer neuron to the m th output node, and the initial value is set to 1.

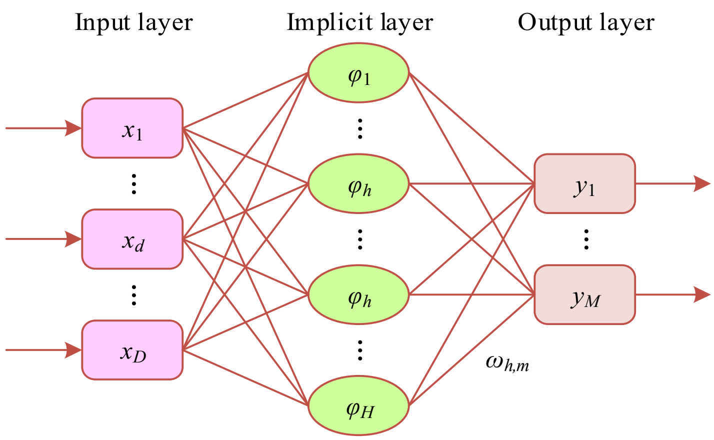

Figure 1: Topology of RBF neural network

The Gaussian kernel function of the hth neuron can be expressed as:

$$\varphi_h(r) = \exp\left(-\frac{r_h^2}{2\sigma_h^2}\right) \tag{1}$$

where r_h denotes the distance from the sample to the centroid, mathematically expressed as a 2-parameter number, and the number of neuron nodes in the hidden layer is set to 30 considering the complexity of the optimization in this paper. The initial value of the expansion constant σ_h for the hth neuron is set to:

$$\sigma_h = \frac{d_{\max}}{\sqrt{2H}} \tag{2}$$

where $d_{\max}$ is the maximum distance between samples. The overall error E of the training samples is defined as:

$$E = \frac{1}{S}\sum_{s=1}^{S}\left[\frac{1}{2}(y_s - y_s^{real})^2\right] \tag{3}$$

where S is the number of training samples and s denotes the number of the sample. The partial derivatives during the update of the weight coefficients $\omega_{h,m}$ are:

$$\frac{\partial E}{\partial \sigma_h} = \frac{1}{S}\sum_{s=1}^{s}\left[\left(y_s - y_s^{real}\right)\omega_{h,m}\varphi_h\left(\frac{r_h^2}{\sigma_h^{\ 3}}\right)\right] \tag{4}$$

where y_{real} denotes the real value of the sample, which is calculated using CFD in this paper. Similarly, the partial derivative of the kernel function width is:

$$\frac{\partial E}{\partial \sigma_h} = \frac{1}{S}\sum_{s=1}^{s}\left[\left(y_s - y_s^{real}\right)\omega_{h,m}\varphi_h\left(\frac{r_h^2}{\sigma_h^{\ 3}}\right)\right] \tag{5}$$

The weight coefficients and kernel function width iterations are implemented using the gradient descent method, i.e:

$$\omega_{h,m}(n+1)=\omega_{h,m}(n)-\alpha\frac{\partial E}{\partial \omega_{h,m}}$$
$$\sigma_h(n+1)=\sigma_h(n)-\alpha\frac{\partial E}{\partial \sigma_h} \tag{6}$$

where n denotes the current value, $n+1$ denotes the corrected value after iteration; α denotes the learning rate, which is fixed at 0.1 in this paper, the number of iteration steps is 100000, and the convergence criterion is that the mean square error is less than 1×10^6.

II. B. 3) PCA-GA-RBF prediction model and parameter selection

RBF neural network algorithm model nonlinear fitting ability, compared with BP neural network, RBF neural network can better achieve the global optimal approximation [24], in the actual computation process, the RBF neural network model exists in the middle of the hidden layer nodes are difficult to determine the number of nodes, the network model is easy to fall into the local optimum, and with the increasing total amount of sample data, it is easy to lead to the complexity of the model structure, prediction With the increasing of the total sample data, it is easy to lead to the complexity of the model structure and the decrease of prediction accuracy.

In this paper, firstly, the principal component analysis is used to reduce the dimensionality of the model input data to reduce the complexity of the model, secondly, the genetic algorithm is used to optimize the RBF neural network, based on the global optimization to get the optimal model parameters, to determine the optimal number of nodes in the hidden layer, so as to achieve the purpose of simplifying the structure of the model, accelerating the speed of convergence, and improving the calculation accuracy.The parameters of the PCA-GA-RBF pavement quality prediction model are selected as follows. The model parameters are selected as follows:

(1) Input layer and output layer node selection

In this paper, six input layer nodes are selected as total asset contribution, asset liability ratio, cost and expense margin, product sales rate, total capital preservation and appreciation rate, and current asset turnover rate, and the economic development detection index (RQI) is the only output layer node.

(2) The number of implied layers and nodes selection

The structure of the RBF neural network algorithm determines that there is only one hidden layer, and the number of nodes in the hidden layer is determined through multiple iterative calculations, without the need for trial calculations and other operations.

(3) RBF neural network radial basis function selection

In this paper, the radial basis function of the hidden layer is selected as Gaussian function. The expression is as follows:

$$\varphi_i(x)=e^{-\frac{\|x-c_i\|^2}{2\sigma_i^2}},\quad i=1,2,\cdots,p \tag{7}$$

II. B. 4) PCA-GA-RBF modeling steps and process

(1) The data related to the enterprise's economic development detection index (RQI), total asset contribution, asset-liability ratio, cost-expense profitability, product sales rate, total capital preservation and appreciation rate, and current asset turnover rate are extracted from the SQL Server pavement performance data management platform respectively.

(2) The Min-Max Normalization method is used to standardize the whole modeling data, which can be expressed as follows:

$$y_n=\frac{y-y_{\min}}{y_{\max}-y_{\min}} \tag{8}$$

where y_n is the normalized data, y is the original data, $y_{\max}$ and $y_{\min}$ are the maximum and minimum values of y respectively.

(3) Using principal component analysis to analyze and calculate the data of total asset contribution (S1), asset-liability ratio (S2), cost-expense margin (S3), product sales rate (S4), total capital preservation and appreciation rate (S5), and turnover rate of current assets (S6), we reduce the number of variables on the input side of the model, and realize the dimensionality reduction without reducing the information of the original data, so that we can use the results of the calculation as the input variables of the model, and the economic development detection index (RQI) as the model output variables;

(4) Select the radial basis function, this paper selects the implicit layer radial basis function as Gaussian function. The expression is as follows:

$$\varphi_i(x) = e^{-\frac{\|x-c_i\|^2}{2\sigma_i^2}}, \quad i = 1, 2, \cdots, p \tag{9}$$

(5) Apply genetic algorithm for global optimization calculation to get the optimal model parameters lambda, alpha.
(6) The calculated optimal model parameters are used as PCA-GA-RBF neural network model parameters to construct the combined prediction model.

II. C. Model Testing and Analysis

II. C. 1) Selection of evaluation indicators by principal component analysis

The evaluation indicators are analyzed using the proposed principal component analysis method of enterprise economic sustainable development evaluation indicators, and the indicators with the greatest contribution to the evaluation of enterprise economic sustainable development are screened out, and the results of the principal component analysis are shown in Figure 2. The results show that the cumulative contribution rate of the principal component indicators of total asset contribution, cost and expense margin, product sales rate, and total capital preservation and appreciation rate to the evaluation of enterprise economic sustainable development has been as high as 95.6%, which exceeds the set threshold of cumulative contribution rate. This indicates that the four indicators have been able to effectively represent the important information contained in all the indicators.

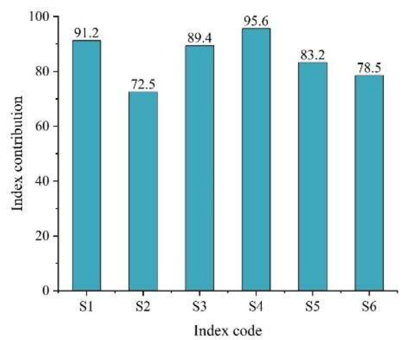

Figure 2: The main component analysis results in the evaluation index

II. C. 2) Analysis of the results of the level of economic sustainability of enterprises

Select 40 groups of test samples, using the combined prediction model PCA-GA-RBF constructed in this paper to evaluate the sustainable development of the enterprise's economy, the change curve of the mean square error during the model training process is shown in Fig. 3, and the results show that the original RBF neural network reaches convergence after about 45 iterations, while it only needs about 30 iterations to reach convergence after optimization of genetic algorithms, which suggests that genetic algorithms can effectively This indicates that the genetic algorithm can effectively improve the convergence speed of RBF neural network and reduce the model training time. Moreover, the RBF neural network optimized by genetic algorithm is always lower than the original RBF neural network, which indicates that genetic algorithm can improve the prediction accuracy of the model.

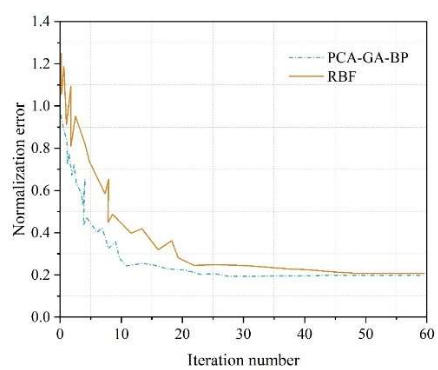

Figure 3: Model mean square error curve

The evaluation accuracy of enterprise economic sustainable development of the test group data is shown in Fig. 4, and the results show that the original RBF neural network has a higher evaluation accuracy of enterprise economic sustainable development, which are all higher than 83%, but the evaluation accuracy of the combined prediction model PCA-GA-RBF is better than the original RBF neural network. The statistical results show that in the test samples, the combined prediction model PCA-GA-RBF has a high approximation accuracy for 36 groups with evaluation accuracy greater than 92%, and 30 of them have an evaluation accuracy greater than 96%, which demonstrates that the prediction model PCA-GA-RBF has a high approximation accuracy.

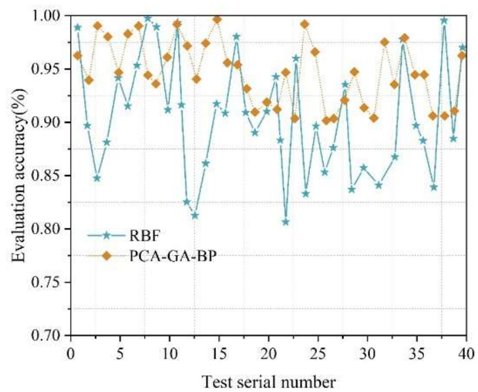

Figure 4: Model evaluation accuracy curve

III. Digital Management Path for Sustainable Economic Development of Enterprises

III. A. Qualitative comparative analysis methods

III. A. 1) Specific steps of the fsQCA methodology

The Qualitative Comparative Analysis (QCA) method, first proposed by American sociologist Charles Larkin in 1987, is a comparative analysis method based on case data [25]. Compared with other research methods, the main advantage of the QCA method is that it develops a logical analysis of the link between factors and outcomes, it exists different combinations of factors that may produce the same outcome, combines traditional qualitative and quantitative methods, and incorporates the cross terms of all the elements into the research model while dealing with the causal relationship between antecedent and outcome variables, the method is more in line with the reality and the logic of the research .

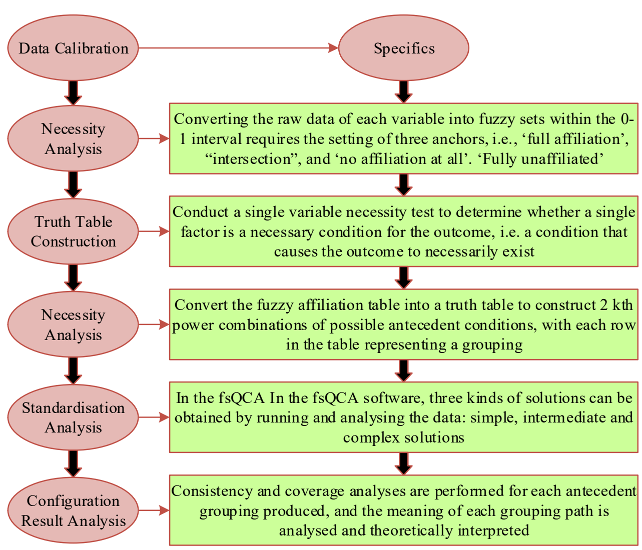

Figure 5: Specific operation steps of fsQCA method

In addition, the QCA research method includes three analytical tools: clear set qualitative comparative analysis (csQCA), fuzzy set qualitative comparative analysis (fsQCA), and multi-valued set qualitative comparative analysis (mvQCA). fsQCA is able to use all numbers in the range of 0 to 1 to arbitrarily assign a value to the variable, which breaks the technical limitation that the variables of csQCA and mvQCA can only take the values of 0 and 1, and makes it possible to deal with medium-sized sample size, while including all cross terms of elements into the research model. This makes it more superior than regression analysis when dealing with medium sample sizes, and it is valuable in research design. fsQCA procedure is shown in Figure 5.

III. A. 2) Applicability of fsQCA methodology

1. The fsQCA method is characterized by multiple concurrency. Compared with traditional research methods, fsQCA method considers that antecedent conditions do not independently influence the outcome variables, and abandons the study of the net effect of a single conditional variable on the outcome variables, and focuses instead on the interdependence of factors and the multiple concurrent causal associations constructed by different combinations of conditions. The level of enterprise digital innovation is synergistically affected by internal and external factors. fsQCA method can effectively deal with the effects of three or more variables on digital management based on a holistic perspective, make up for this shortcoming, and cope with the complexity of the antecedent conditions of enterprise digital innovation.

2. fsQCA method focuses on the asymmetry of causal conditions. Compared with the general assumption of consistency of causality in linear regression analysis, it emphasizes more on the fact that causal variables with correlation in one group condition may not be correlated or even have opposite relationship in another group condition, which better illustrates the difference between cases and the group effect of interconnection among the influencing factors. Enterprises in the process of digital management, the degree and direction of the influence of each influencing factor may be different, which is conducive to deepening the understanding of the enterprise digital management influencing factors.

3. fsQCA method produces results with equivalence. Equivalence means that the same results can be obtained for different groupings. This indicates that there may be multiple ways to obtain the expected or undesirable results, and there is no single optimal solution derived from the analysis of traditional methods. Different paths formed by combining different factors can drive enterprises to achieve a high level of digital management, that is to say, enterprises can achieve a high level of digital management through multiple paths, which is more in line with the actual situation of the development of enterprise digital management.

Based on the above analysis, in view of the theoretical gap of multi-factor dependency analysis in the research related to enterprise digital management, this paper chooses fsQCA method to explore the combination of digital management influencing factors, and dig deeper into the complex causal relationship of enterprise digital management.

III. A. 3) fsQCA metrics

Whether the factors are necessary for the outcome to occur, that is, factors that cause the outcome to necessarily exist. In this case, consistency is used to determine the proportion of cases with a particular antecedent or combination of antecedents showing the same outcome, and coverage is used to determine how strongly different groupings of conditions explain the outcome. The closer consistency is to 1, the more likely it is that a particular antecedent condition is a subset of the outcome; the closer coverage is to 1, the stronger the antecedent condition explains the outcome variable.

The formulas for consistency and coverage are given below:

$$Consistency\left(X_i \le Y_i\right) = \sum\left[\min\left(X_i, Y_i\right)\right] / \sum\left(X_i\right) \tag{10}$$

$$Coverage\left(X_i \le Y_i\right) = \sum\left[\min\left(X_i, Y_i\right)\right] / \sum\left(Y_i\right) \tag{11}$$

where X_i is the calibration value of the condition factor and Y_i is the calibration value of the outcome variable.

Based on Fiss's study, the consistency of the antecedent condition is not less than 0.9, which can be regarded as a necessary condition for the outcome variable.

III. B. Qualitative analysis of fuzzy sets

Taking sustainability performance as the outcome variable, seven variables such as connectivity capability (CC), intelligence capability (IC), analytical capability (AC), internal green management (IGM), external green management (EGM), executive green cognition (EGC), and environmental dynamics (ED) are selected as the conditional variables, to further explore the driving mechanism that triggers the sustainability performance, and to search for the trigger of high corporate economic sustainability performance and find the digital management paths that trigger high corporate economic performance.

III. B. 1) Variable calibration

According to the results of existing studies, the criteria of complete affiliation point (95%), complete non-affiliation point (5%), and crossover point (50%) proposed by the researchers for fsQCA research on questionnaire scales are more mature and used by most scholars, therefore, based on the actual distribution of the data in the present study, three qualitative anchors will be set up, which will be at the 95% percentile and the 5% percentile of the variables, respectively, 50% percentile, and 5% percentile for data calibration of variables. Specifically, the continuous variables of the variables connectivity, intelligence, analytical ability, internal green management, external green management, executives' green cognition, environmental dynamics, and the outcome variable sustainability performance will be averaged, and then the anchors will be selected and calibrated according to the criteria of complete affiliation point (95%), complete disaffiliation point (5%), and crossover point (50%), and the results are shown in Table 1, in which SDP is sustainable development performance.

Table 1: Collection, calibration, and descriptive statistics

Set	Fuzzy set calibration				Descriptive analysis		
	Completely unaffiliated	Crossing point	Full membership	Mean	Standard deviation	Maximum value	Minimum value
CC	2.739	5.721	7.029	5.289	1.273	8.000	1.000
IC	3.072	5.721	7.029	5.501	1.17	8.000	1.000
AC	1.572	5.054	6.696	4.943	1.507	8.000	1.000
IGM	2.405	5.61	6.585	5.148	1.293	8.000	1.571
EGM	2.918	5.516	6.491	5.203	1.122	8.000	1.861
EGC	1.832	5.054	6.529	4.476	1.77	8.000	1.000
ED	1.929	3.483	6.315	3.98	1.602	8.000	1.301
SDP	2.855	5.487	6.479	5.273	1.076	8.000	1.745

III. B. 2) Analysis of necessary conditions

Generally based on the consistency value, when the consistency value of the variable is tested to be greater than 0.9, the variable is considered to be a superset of the result, i.e., if the variable appears, the result must appear, so it should be excluded from the truth table analysis. Necessary condition analysis is required before the group analysis, and the results of the necessary condition analysis are shown in Table 2. Necessary condition analysis is used to determine the extent to which each single variable explains the results. The results of the analysis show that the consistency values are less than 0.9, and that the seven antecedent conditions are not and do not approximate the necessary conditions for sustainable development performance; therefore, the variables can be subjected to the next step of the grouping analysis.

Table 2: The necessity of the fsQCA method is tested for a single condition

Conditional variable	Sustainable development performance	
	Consistency	Coverage ratio
CC	0.773	0.881
~CC	0.67	0.709
IC	0.817	0.87
~IC	0.615	0.696
AC	0.875	0.85
~AC	0.54	0.681
IGM	0.832	0.891
~IGM	0.609	0.685
EGM	0.822	0.861
~EGM	0.587	0.676
EGC	0.766	0.841
~EGC	0.588	0.647
ED	0.749	0.79
~ED	0.597	0.686

III. B. 3) Configuration analysis

In this paper, fsQCA 3.0 software is used to analyze the environmental groupings that lead to high sustainability performance, and these different groupings all lead to the same outcome. These groupings are also named based on group theorizing. The study involves 7 conditional variables, using fsQCA3.0 software to construct the truth matrix of 2k combinations of conditions, k is the number of antecedent conditions, the case frequency threshold is set to 2, the original consistency threshold is set to 0.8, and the PRI consistency threshold is set to 0.75, and the software fsQCA3.0 is run to construct the truth table of sustainability performance, to determine whether the consistency of the collected data is naturally broken or not. The grouping analysis is shown in Table 3. S1a sub-grouping other auxiliary conditions are high connectivity; S1b other auxiliary conditions are high intelligence; grouping S2 refers to high connectivity and high intelligence as the core conditions, and complementary high analytical ability and high external green management can improve the sustainable development performance. Configuration S3 refers to high connectivity capability, high intelligence capability, high analytical capability, high internal green management, high executive green cognition and non-high external green management as the core conditions, and complementary non-high environmental dynamics can enhance sustainable development performance.

By comparing the parsimonious solution with the intermediate solution, the conditions that appear in both the intermediate and parsimonious solutions are core conditions for that solution, but the conditions that appear only in the intermediate solution and not in the parsimonious solution are edge conditions. The results show that the consistency of the solutions for each grouping of states is above 0.8, and the total consistency is also above 0.8, indicating that each grouping of states is a sufficient condition for the results. Coverage represents the degree to which a particular group state explains the results, similar to R^2 in regression analysis. General coverage consists of raw coverage, unique coverage, and total coverage. Raw coverage represents the extent to which a particular grouping explains the results without excluding the overlap with other groupings, unique coverage excludes the overlap with other groupings and focuses on the explanation of the results by a single grouping, and total coverage is the extent to which all groupings explain the results. It can also be seen from the table that the raw coverage of the solutions of the groupings is good, indicating that the groupings have some explanatory strength for the results. Among them, there are five groupings that produce high sustainability performance, and since S1a and S1b have the same core conditions, they constitute second-order equivalent groupings.

Table 3: The group state of high sustainable development performance in fsQCA

Combinatorial configuration	Sustainable development performance				
	S1a	S1b	S2	S3	S4
Connection ability	●		◎	◎	□
Intelligent ability		●	◎	◎	◎
Analytical ability	◎	◎	●	◎	◎
Internal green management	◎	◎	□	◎	□
External green management	●	●	●	★	★
Executive green cognition	◎	◎	□	◎	□
Environmental dynamics	●	●	□	□	□
Consistency	0.995	0.992	0.978	0.994	0.975
Primary coverage	0.448	0.459	0.248	0.234	0.239
Unique coverage	0.027	0.027	0.033	0.025	0.032
Overall consistency			0.974		
Overall coverage			0.615		

Note: ◎ indicates that the core condition exists, ★ indicates that the core condition does not exist, □ indicates that the auxiliary condition does not exist, and ● indicates that the auxiliary condition exists.

The results of the fsQCA analysis show that among the four types of patterns for enhancing sustainability performance, the original coverage of pattern 1 is greater than the other three groups, indicating that the explanatory power of pattern 1 is greater than the explanatory power of the other three triggering patterns. Model 1, which contains two sub-groupings (S1a and S1b), has the same core conditions of high analytical capability, high internal green management and high executive green perception, and the same auxiliary conditions of high external green management and high environmental dynamics. both S1a and S1b emphasize internal green management and external green management of the enterprise, which suggests that the green supply chain management plays an important role in data empowerment to promote sustainable development performance S1a and S1b both emphasize on internal green management and external green management, indicating that green supply chain management plays an important role in data empowerment to promote sustainability performance.

III. C. Digital management path design

1. Establishment of digital hardware and software foundation

Digital management is built on the basis of the enterprise's advanced technology, tools and equipment and talents. The digital management of enterprises needs to rely on a series of digital technology and advanced equipment to realize, which is the hard foundation for the realization of digital management, such as the Internet-based computing model cloud computing, with the collection, storage and processing of large amounts of data big data technology, artificial intelligence that can simulate human beings through machine learning and language processing and other technologies, through the network to connect a variety of equipment to achieve automated control and intelligent operation of the Internet, blockchain technology to help enterprises achieve information security of transaction cooperation, etc. Enterprises need to combine their business development and the development of advanced tools and equipment and human resources. Internet, blockchain technology that helps enterprises realize information security and transaction cooperation, etc. Enterprises need to combine their own business development and ability to choose the technology and tools suitable for development to practice and apply.

2. Reform digital management and operation mode

Enterprise digital management involves the reform of enterprise organizational structure, business model, product innovation, process optimization, talent training, etc. To realize the enterprise digital management and operation mode, it is necessary to sort out each business process and standardize the management process of the business module, and establish a digital management and operation system on the basis of this, including digital internal management, digital supply chain management, digital production, digital product management, digital market operation, digital order management, digital customer management and other systems. At present, the degree of digitization of small and medium-sized enterprises in different industries is different, and the direction of digital core inputs varies to some extent, in which digital management, digital supply chain, digital production, digital operation and digital marketing have always been an important focus. Digital management uses digital technologies such as big data and artificial intelligence to build an efficient management system, which can effectively reduce the risk of enterprise management, reduce uncertainty in operation, and lay a solid foundation for enterprise development.

3. Build a digital asset system

In the era of the digital economy, data, as a key element of enterprise digital management, always runs through all the processes of enterprise business. With the development of digital management, enterprises must build a digital asset system to realize the use of digital assets to achieve the role of driving the growth of enterprise benefits. The construction of the digital asset system includes the enterprise's asset digitization and digital assetization. Asset digitization is the enterprise digital marking of assets, and make it have the nature of trading and circulation, realize the efficient and convenient management of enterprise resources, can measure the overall assets of the enterprise at the same time, for the implementation of the enterprise digital strategy to provide the basis; digital assetization is the enterprise's data resources into the process of the characteristics of the asset, the same has the nature of the transaction and circulation, so that the data of this element to produce measurable value, to help enterprises use the data to achieve growth and efficiency. Digital assetization is the process of transforming enterprise data resources into assets, which also has the nature of trading and circulation, so that the element of data can generate measurable value, help enterprises utilize data to generate more value-added benefits, and provide elemental support for the digital transformation of enterprises.

IV. Conclusion

The study is based on the principle of evaluation index construction, the evaluation index system of enterprise sustainable development level. After the optimization process of principal component analysis and RBF algorithm, the combined prediction model PCA-GA-RBF is established. The model uses principal component analysis to screen out total asset contribution, cost and expense margin, product sales rate, and total capital preservation and appreciation rate as important indicators, and the prediction model PCA-GA-RBF is more efficient in operation, and the accuracy is greater than 92% for all the test samples. fsQCA analysis shows that there are four types of modes to improve the sustainability performance of the enterprise, of which mode 1 contains two sub-models. Models S1a “Connectivity * Analytical Capabilities * Internal Green Management * External Green Management * Executive Green Perception * Environmental Dynamics” and S1b “Intelligent Capabilities * Analytical Capabilities * Internal Green Management * External Green Management * Executive Green Perception * Environmental Dynamics”.

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