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RESEARCH ARTICLE

Growth analysis of new-energy enterprises in China: A grey possibility degree clustering model for panel data

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ABSTRACT

Growth clustering analysis of new-energy enterprises is an important reference for decision-makers. This study proposes a novel grey clustering model based on the grey probability function from both absolute and incremental perspectives. The model was applied to the cluster analysis of 117 listed new-energy enterprises in China between 2017 and 2021. The results of the grey clustering analysis showed that the proposed model can classify these listed new-energy enterprises into three categories from both absolute and incremental perspectives. In the crossover grey clustering table of the two perspectives, there were 58 new-energy listed enterprises on the diagonal, which belonged to the same level of grey clustering and had growth consistency in both perspectives. Based on the classification, the characteristics of the clusters were analyzed and different development proposals were made accordingly. The study is not only innovative in its clustering methodology, but also contributes to the sustainable development of the new-energy industry by providing decision-makers with reference information on cluster analysis.

KEYWORDS

New energy; Growth; Grey possibility degree; Grey clustering

1 Introduction

In recent decades, driven by economic development and population growth, global energy consumption has increased rapidly (Zhao et al., 2023). This increase in demand is driving the development of low-carbon and new-energy technologies. During the general debate of the *75th United Nations General Assembly* in September 2020, President of the People's Republic of China Xi Jinping announced: "China will scale up its Intended Nationally Determined Contributions by adopting more vigorous policies and measures. We aim to have CO_2 emissions peak before 2030 and achieve carbon neutrality before 2060". Now China has adopted policies and measures to achieve these targets, particularly by promoting technological innovation and green technologies in the new-energy sector. As a result, the

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new-energy industry is thriving and China has become the world's largest energy producer, having made the fastest transition to using energy efficiently (SCIO PRC, 2020).

Cluster analysis of new-energy enterprise growth can provide a valuable reference for subsequent policy formulation. Grey clustering, which includes grey correlation clustering and grey likelihood function clustering, is an important aspect of grey systems theory for uncertainty research. This method is suitable for clustering objects with clear extents and unclear contents, and has been widely used in various applied research fields, particularly in the energy and environmental fields. This study aims to establish a grey possibility degree clustering model and explore crossing grey clustering analysis of new-energy enterprise growth.

1.1 Research progress on financial performance, subsidy policy, and enterprise growth of new energy

New energy refers to the renewable energy sources developed and utilized through adopting new green technologies, such as hydro-power energy, nuclear power energy, wind power energy, solar energy, bio-mass energy and so on (Xue et al., 2019). Since the *18th National Congress of the Communist Party of China* in 2012, China has promoted the development of new energy in a comprehensive, coordinated and sustainable manner. With the increasing importance of new energy, the number of scholars in this field has increased significantly. Most research on new-energy industry focuses on the following aspects: the enterprise growth of energy enterprises, the new-energy subsidy policies from the government (Yu et al., 2021), the financial performance evaluation of new-energy enterprises (Mao et al., 2014), the eco-environmental friendliness of the new-energy sector (Zhang et al., 2015) and so on. For the financial performance evaluation of new-energy enterprises, the evaluation indicators should be constructed from internal and external perspectives (Ren, 2018; Zeng et al., 2013). The internal indicators include technological innovation as well as research and development (R&D) investment; The external indicators include government subsidies (Xia & Li, 2012), protection of intellectual property rights, acquisition, merger of enterprises and political connection (Liu et al., 2018). For the new-energy subsidy policy, there are two different views. One is that the subsidy policy can promote the rapid development of new energy, and the technological innovation investment (Zhang & Bai, 2017), especially in the eastern coastal area (*vs.* non-eastern coastal area) and non-state-owned enterprises (*vs.* state-owned enterprises) (Liu et al., 2022); the other is that government subsidy policy may induce enterprises to take advantage of information asymmetry (Jiang & Yan, 2018), be addicted to rent-seeking subsidies policy-making, abuse government subsidies to reduce the efficiency of capital allocation, then lead to a decline in enterprise performance (Jin, 2018; Lin & Zhang, 2023). As for the eco-environmental friendliness of the new-energy industry, air quality has been significantly improved; the emissions of nitrogen oxides, sulfur dioxide and soot have been rapidly reduced (Yuan et al., 2017; Yan et al., 2023).

New-energy enterprises play a key role in the development of the new-energy industry, and their growth has a significant impact on overall sustainability. Academic interest in firm growth is evident in several studies. Coada & Raob (2010) used panel vector autoregression to confirm the positive influence of R&D investment on enterprise growth across life cycle stages. Gui et al.

(2012) proposed a four-wheel-drive model including innovation, policy, market dynamics and competition to analyze the dynamic growth mechanism in the new-energy automotive sector. Yuan et al. (2016) contributed to the discourse by building a mechanism model that highlights influential factors, including industrial policy, financial subsidies, R&D investment, ownership structure, and R&D expenditure plus tax deduction. Pan & Feng (2022) extended the discussion by examining the dynamic development and driving factors of new-energy development in China's provinces. Their findings highlighted regional disparities and emphasized the role of technology, economic growth and energy consumption structure. Similarly, Xue et al. (2021) explored factors influencing new-energy development in China using autoregressive distributed lag (ARDL) cointegration and Granger causality analysis, revealing nuanced relationships. Zhou et al. (2020) focused on pattern recognition of China's new-energy product export growth to Belt and Road countries, identifying efficiency factors and highlighting the impact of economic and political institutional distance on technical efficiency. In assessing enterprise growth, Han et al. (2014) structured an index system for the new-energy industry by applying the analytic hierarchy process (AHP) method. Lv & Pan (2017) used factor analysis to evaluate enterprise growth across dimensions for different types of new-energy enterprises. These diverse methodologies contribute to a comprehensive understanding of the complex dynamics affecting the growth of new-energy enterprises (Pan & Feng, 2022).

1.2 Research progress on grey clustering theory methods

To obtain clustering results more effectively, various clustering methods have also been explored in previous works. Dong & Dang (2009) used the principle of maximizing deviations to construct the whitening function of indicator weight, and the grey clustering analysis model was constructed. Song et al. (2010) obtained the weights of indicators based on the degree of difference among decision-makers, and improved the accuracy of the decision conclusion when the group of decision-makers is large. Combining the comprehensive consideration of preferential membership and grey correlation, Gong et al. (2015) improved the grey correlation projection method, and constructed the projection objective function under the combing projection pursuit dynamic cluster method and grey relation projection method. According to the definition of entropy and interval grey numbers, the grey clustering model based on entropy weight and grey numbers was established by Qian et al. (2016). Dang et al. (2017) proposed a new grey cluster evaluation method to accurately cluster in terms of clustering objectives when there are no distinct differences between grey cluster coefficients. Wang (2022) introduced a matrix-based approach to ascertain the necessary algebraic connections among the parameters of grey possibility functions, considering the specified final clustering outcomes in the bidirectional perspective of the grey clustering model. Xiong et al. (2022) extended interval grey numbers from one dimension to two dimensions, introducing a new framework for the construction of kernels and gradations in two-dimensional interval grey numbers.

With the development of society, the previous research of static grey clustering can't effectively cope with the panel data. Some scholars have explored the relational grey clustering methods for the panel data. According to the temporal and spatial characteristics of the multivariate panel data, Qian et al. (2013) proposed the grey matrix relational analysis method to calculate the similarity of the panel data. It is combined with the deviation, difference and discrete degree. Considering the three-dimensional characteristic, the positive and negative relationship of the panel data, Dang (et al., 2017) constructed the panel data grey relational model based on the introduction of grey entropy. To cope with the sample sequence affecting the occurrence order, Luo et al. (2018) established a new grey occurrence model under the panel data based on the dynamic development characteristics of the multivariate panel data. Zeng et al. (2022) focused on the evaluation of the strategic delivery force based on the grey cluster analysis. Their study provided insights into the current state of the strategic delivery force and offered a method for targeted improvement measures. Dong & Shen (2022) studied the innovation capacity of listed banks by using grey cluster analysis and TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution), and provided an effective means to assess the innovation capacity of banks in a period.

In the above literature, the grey relational clustering methods for static and panel data have been analyzed in-depth, but the research on grey possibility degree clustering has rarely been conducted. Geng et al. (2020) defined the development factor to express the development tendency of observed values, and proposed the grey possibility clustering method to solve the problems of panel data. Based on Geng's model, synthetically considering the dynamic development trend, index weight and time point weight, a novel grey possibility clustering method is proposed to solve the panel data problems from two perspectives of absolute and incremental amounts.

The rest of the research is structured as follows: section 2 establishes the novel grey possibility clustering method based on the indicator weight and the time weight; section 3 describes the data collection of new-energy listed enterprises and the basic data analysis; section 4 presents the clustering results from two perspectives and the cross-grey clustering analysis; section 5 summarizes the research conclusions and implications.

2 Methods

In multi-attribute clustering problems of panel data, clustering objects usually adopt a certain development law over a long period. Therefore, to effectively use the dynamic information and development trend of clustering objects, a clustering method based on the grey possibility degree function is specially proposed (Geng et al., 2020; Zeng et al., 2022).

2.1 Absolute amount and incremental amount

Three-dimensional observation data is a collection of data, observation indicators, observation objects, and each data is an observed value associated with a certain indicator of the corresponding object at a certain time. The three-dimensional observation data for panel data can be transformed into a matrix $X_{ijp}^{(0)}$.

$$X_{ijp}^{(0)}=\begin{bmatrix} x_{11p}^{(0)} & x_{12p}^{(0)} & \cdots & x_{1mp}^{(0)} \\ x_{21p}^{(0)} & x_{22p}^{(0)} & \cdots & x_{2mp}^{(0)} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n2p}^{(0)} & x_{n2p}^{(0)} & \cdots & x_{nmp}^{(0)} \end{bmatrix} \tag{1}$$

where, a_i $(i=1,2,\cdots,m)$ denotes the ith observation object, and m is the total number of observation objects; indicator c_j $(j=1,2,\cdots,n)$ denotes the jth characteristic, and n is the total number of indicators. For the pth time point $(p=1,2,\cdots,s)$, $x_{ijp}^{(0)}$ denotes the observed value of the jth indicator of the ith observation object, and is defined as the pth absolute amount, and $X_{ijp}^{(0)}$ is the absolute amount matrix.

For the $(p-1)$th time point $(p=1,2,\cdots,s)$, $x_{ij(p-1)}^{(0)}$ denotes the observed value for the jth indicator of the ith observation object, and is defined as the $(p-1)$th absolute amount. The incremental amount $v_{ijp}^{(0)}$ can be calculated by Eq.(2).

$$v_{ijp}^{(0)} = \begin{cases} 0 \quad , & p=1 \\ \dfrac{x_{ijp}^{(0)} - x_{ij(p-1)}^{(0)}}{p-(p-1)} \quad , & p=2,3,\cdots,t \end{cases} \tag{2}$$

The incremental amount of three-dimensional observation data for panel data can be transformed into the matrix $V_{ijp}^{(0)}$.

$$V_{ijp}^{(0)} = \begin{bmatrix} v_{11p}^{(0)} & v_{12p}^{(0)} & \cdots & v_{1mp}^{(0)} \\ v_{11p}^{(0)} & v_{22p}^{(0)} & \cdots & v_{2mp}^{(0)} \\ \vdots & \vdots & \ddots & \vdots \\ v_{11p}^{(0)} & v_{n2p}^{(0)} & \cdots & v_{nmp}^{(0)} \end{bmatrix} \tag{3}$$

According to the characteristics of observed objects, the time-point features of observed objects are defined into two categories: absolute amount and incremental amount of panel data; they can be written as R_1 and R_2. For the time point feature R_k $(k=1,2)$, $y_{ijp}^{(0)}(k)$ denotes the jth indicator value corresponding to the ith observed object, and p is the serial number of time points. Based on the aforementioned analysis, two equations can be derived: $y_{ijp}^{(0)}(1)= x_{ijp}^{(0)}$, $y_{ijp}^{(0)}(2)= v_{ijp}^{(0)}$.

2.2 Information aggregation

According to w^p $(p=1,2,\cdots,t)$, which is the weight of the pth time calculated based on grey entropy and time-temperature (Geng et al., 2020), and $y_{ijp}^{(0)}(k)$ which denotes the jth feature value corresponding to the ith observation object, p is the serial number of time points, the aggregated data $u_{ij}^{(0)}(k)$ is calculated by Eq.(4).

$$u_{ij}^{(0)}(k) = \sum_{p=1}^{t} y_{ijp}^{(0)}(k) \times w^p \tag{4}$$

Where $u_{ij}^{(0)}(k)$ indicates the jth indicator value corresponding to the ith observation object, and k is the serial number of time point features.

The standardization data of aggregated information can be written as $u_{ij}(k)(k=1,2)$, and the three-dimensional standardization data can be transformed into the matrix $U_{ij}(k)$.

$$U_{ij}^{(0)}(k) = \begin{bmatrix} u_{11}^{(0)}(k) & u_{12}^{(0)}(k) & \cdots & u_{1m}^{(0)}(k) \\ u_{21}^{(0)}(k) & u_{22}^{(0)}(k) & \cdots & u_{2m}^{(0)}(k) \\ \vdots & \vdots & \ddots & \vdots \\ u_{n1}^{(0)}(k) & u_{n2}^{(0)}(k) & \cdots & u_{nm}^{(0)}(k) \end{bmatrix} \tag{5}$$

For the benefit indicator, where a higher value of the indicator is preferred, the standardization function is as follows:

$$u_{ij}(k)=\frac{u_{ij}^{(0)}(k)-\min_i(u_{ij}^{(0)}(k))}{\max_i(u_{ij}^{(0)}(k))-\min_i(u_{ij}^{(0)}(k))}\times 100 \tag{6}$$

For the cost indicator, where a smaller value of the indicator is preferred, the standardization function is as follows:

$$u_{ij}(k)=\frac{\max_i(u_{ij}^{(0)}(k))-u_{ij}^{(0)}(k)}{\max_i(u_{ij}^{(0)}(k))-\min_i(u_{ij}^{(0)}(k))}\times 100 \tag{7}$$

2.3 Determine the grey possibility degree and clustering

Assuming that the total number of clustering objects is *m*, the total number of clustering indicators is *n*, and the total number of different grey clusters is *e*; the following steps are taken to determine the grey possibility degree (Luo et al., 2018; Dong & Shen, 2022):

① According to the grey clusters, the data of each clustering indicator is divided into *e* grades, and the values of vector (λ_1, λ_2, ⋯, λ_e) are the center marks of the corresponding grey cluster.

②λ_0 denotes the center mark of the leftward continuation grey cluster, which can be written as *0*th grey cluster; λ_{e+1} denotes the center mark of the grey cluster continuing to the right, which can be written as *(e+1)*th grey cluster. The grey clusters are divided into different intervals:

$[\lambda_0, \lambda_1]$, $[\lambda_1, \lambda_2]$, ⋯ , $[\lambda_{f-1}, \lambda_f]$, ⋯ , $[\lambda_{e-1}, \lambda_e]$, $[\lambda_e, \lambda_{e+1}]$.

The possibility degree function can be explicitly calculated as follows.

$$\theta_{ij}^{f}(k)=\begin{cases} 0 \ , & x\notin\left[\lambda_{f-1},\lambda_{f+1}\right] \\ \dfrac{u_{ij}(k)-\lambda_{f-1}}{\lambda_f-\lambda_{f-1}}, & x\in\left[\lambda_{f-1},\lambda_f\right] \\ \dfrac{\lambda_{f+1}-x}{\lambda_{f+1}-\lambda_f}, & x\in\left[\lambda_f,\lambda_{f+1}\right] \end{cases} \tag{8}$$

Where $\theta_{ij}^{f}(k)$ indicates the grey possibility degree function value of the *j*th clustering indicator corresponding to the *i*th clustering object, *f* is the serial number of grey clusters, and *k* is the serial number of time point features.

The value of $\theta_{ij}^{f}(k)$ is calculated by the above possibility functions, then $\delta_i^{f}(k)$ can be calculated explicitly as follows:

$$\delta_i^{f}(k)=\sum_{j=1}^{m}\theta_{ij}^{f}(k)\times w_j \tag{9}$$

Where $\delta_i^{f}(k)$ indicates the grey clustering coefficient of the *f*th grey cluster corresponding to the *i*th clustering object, and *k* is the serial number of time point features. w_j denotes the indicator weight based on best-worst method (BWM). Determine the best clustering coefficient to the *i*th clustering object: if $\delta_i^*(k) = \max_{1 \le f \le e} \left\{ \delta_i^f \right\}$, then the *i*th clustering object belongs to the *f*th grey cluster.

3 Data

3.1 Indicators and data collection

This research is about the enterprise growth of the new-energy industry based on the grey possibility degree clustering method. To analyze the enterprise growth, ten indicators are employed for the grey clustering analysis of new-energy enterprises (Yuan et al, 2016; Pan & Feng, 2022). Ten indicators and their weights based on BWM are shown in Table 1 (Rezaei, 2016).

Table 1 The clustering indicator system of enterprise growth

Indicators	Weight	Indicator type
C1: R&D intensity	0.159	Benefit indicator
C2: Total assets	0.074	Benefit indicator
C3: Profit-to-cost ratio	0.098	Benefit indicator
C4: Profit margin on net assets	0.110	Benefit indicator
C5: Current ratio	0.083	Benefit indicator
C6: Debt-to-assets ratio	0.073	Benefit indicator
C7: Technical assets ratio	0.121	Benefit indicator
C8: Operating revenue	0.098	Benefit indicator
C9: Net profit	0.122	Benefit indicator
C10: Management fee	0.062	Cost indicator

There are 157 Chinese listed enterprises of new-energy conception on the Shanghai and Shenzhen stock exchanges on the Tonghuasun website. Based on the time span and data integrity of the samples, 117 listed enterprises were finally selected for the study of the growth potential of the new-energy industry. The research period is from 2017 to 2021 and has 16 quarters: IV-2017, I-2018, II-2018, III-2018, IV-2018, I-2019, II-2019, III-2019, IV-2019, I-2020, II-2020, III-2020, IV-2020, I-2021, II-2021, III-2021. All data were collected from the quarterly financial reports of listed enterprises and the EPS Data Platform.

3.2 Descriptive statistics analysis

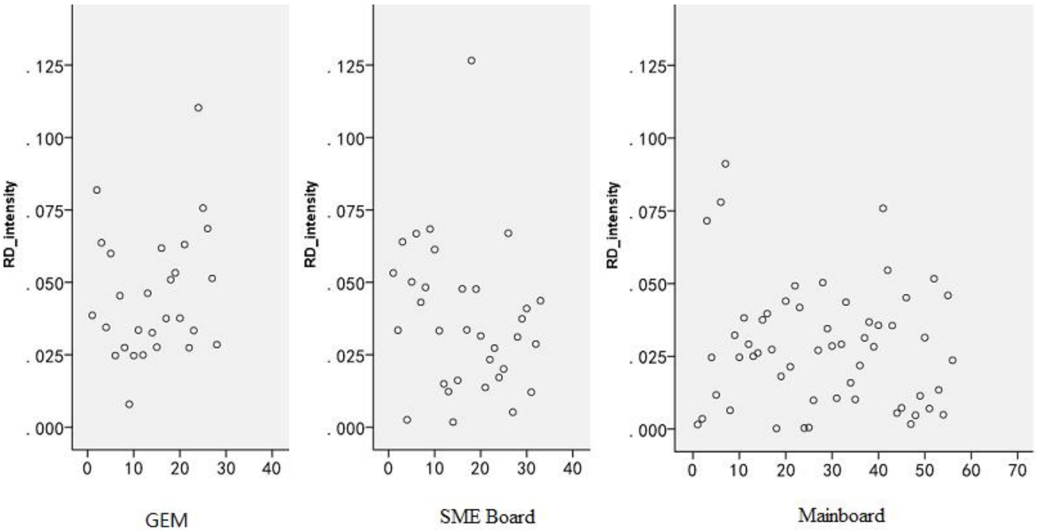
R&D intensity (C1), profit-to-cost ratio (C3), profit margin on net assets (C4), current ratio (C5), debt-to-assets ratio (C6), and technical assets ratio (C7) were expressed as percentages; the units of other indicators were different. According to the descriptive statistical analysis of the aggregated data exhibited in Table 2, there are little differences in the mean values and standard deviations of indicators C1, C5 and C7; there are certain differences in the mean values and standard deviations of indicators C3, C4 and C6; but there are significant differences in the mean values and standard deviations of indicators C2, C8, C9 and C10. In particular, the minimum value of indicator C8 is 23,215 and the maximum value of indicator C8 is 23,489,428, and this shows that there are significant gaps between 117 new-energy enterprises. To narrow down the significant gaps for the accurate clustering analysis, 117 new-energy enterprises were divided into three categories: 56 listed enterprises on Mainboard, 33 listed enterprises on the Small and Medium Enterprise (SME) board, and 28 listed enterprises on the Growth Enterprise Market (GEM).

Table 2 Descriptive statistics analysis of aggregated data

Indicators	Mean	Median	SD	Min	Max
C1	0.035	0.032	0.023	0.000	0.127
C2	4,058,468	1,057,865	10,713,710	103,119	92,143,615
C3	12.858	9.804	34.067	-104.824	314.430
C4	1.600	3.827	24.327	-249.182	40.081
C5	1.537	1.311	0.822	0.217	6.048
C6	51.813	52.189	15.812	12.063	89.201
C7	0.042	0.033	0.042	0.002	0.311
C8	1,036,158	275,148	2,673,271	23,215	23,489,428
C9	62,269	17,634	159,891	-180,215	1,384,034
C10	35,671	13,998	78,540	1625	704,831

3.3 Scatter diagram analysis of R&D intensity

The scatter diagrams of the aggregated data (56 listed enterprises on the Mainboard, 33 listed enterprises on the SME board, and 28 listed enterprises on the GEM) are exhibited in Figure 1. R&D intensity, that is the ratio of R&D expense to operating revenue, is an important indicator of innovation and technological progress, and is closely related to the long-term competitiveness and sustainable development of enterprises in economic theory. As shown in Figure 1, the R&D intensities of most of China's new-energy enterprises are measured between 0.0 and 0.08. According to relevant international standards, R&D intensity had reached to 2%, and the enterprise could stay alive; R&D intensity had increased to 5%, and the enterprise was dynamic and competitive. As exhibited in Figure 1, the R&D intensities of 56 listed enterprises on the Mainboard board are between 0.02 and 0.05; the R&D intensities of 33 listed enterprises on the SME board are between 0.02 and 0.07; the R&D intensities of 28 listed enterprises on the GEM are between 0.025 and 0.075. The R&D intensities of new energy enterprises were moderate, and the new-energy enterprises grew at a medium speed; the new-energy enterprises on Mainboard paid less attention to technological innovation, the ratio of R&D expense to operating revenue was slightly smaller, and the new-energy enterprises grew at a slightly slow pace.



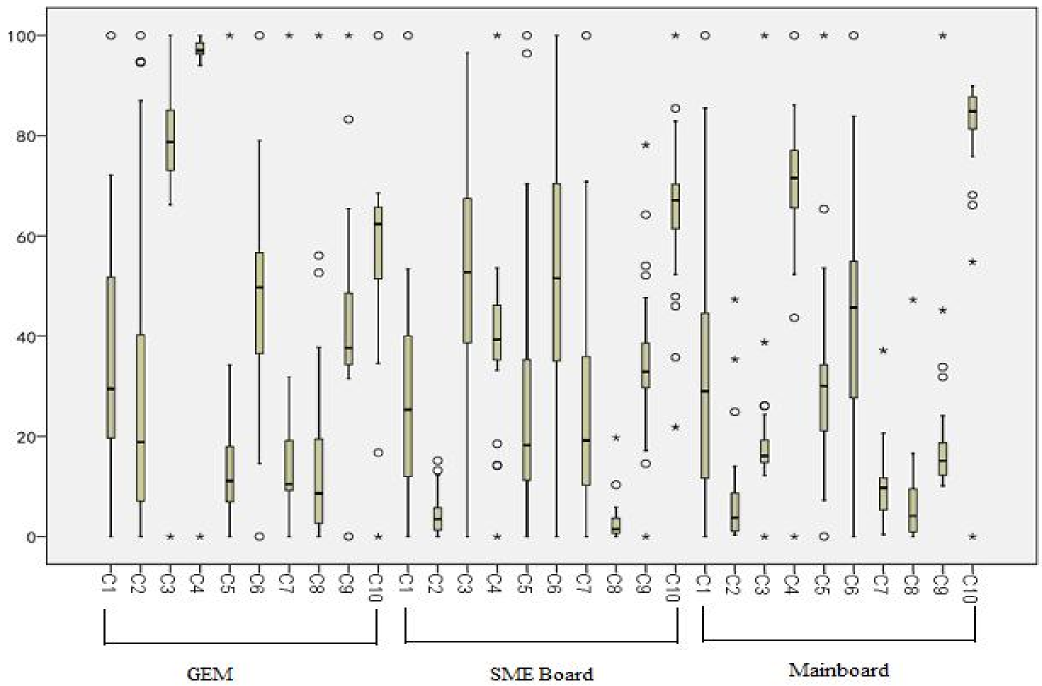
GEM: Growth Enterprise Market; SME: Small and Medium Enterprise

Figure 1 Scatter diagrams of the aggregated data of 117 Chinese new-energy enterprises

3.4 Distribution analysis of the aggregated data

To conduct a grey clustering analysis of 117 listed new-energy enterprises, the absolute amount attribute of enterprise growth was classified into three grey clusters: high, medium and low; and the incremental amount attribute of enterprise growth was classified into three grey clusters: fast, medium and slow.

Due to the different sizes of the 117 new-energy enterprises, there were significant gaps in the same indicator among the three boards, and it was not appropriate to adopt the same centre mark of the corresponding grey cluster for the three boards. In order to obtain the appropriate midpoint of the corresponding grey cluster, three box-and-whisker charts were drawn corresponding to the three boards to analyze the distribution situation of the aggregated data. To facilitate comparison in the same coordinates, all data were normalized between 0 and 100. As shown in Figure 2, the median of the same indicator is different. For the indicator of C4, the value ranges of three boxes were: (96-97), (35-39), (65-72), with no overlap between the boxes. Based on the analysis of the distribution characteristics and the advice of the decision maker, it was appropriate to adopt different mid-points of the corresponding grey clusters for three panels. For each board, the midpoints of the three grey clusters corresponding to each indicator per board were written as three percentiles (20th, 50th and 80th percentiles). For the outliers above the box and whiskers, the probability function value was defined as 1, corresponding to the "better" grey cluster and the "fast" grey cluster; for the outliers below the box and whiskers, the probability function value was defined as 1, corresponding to the "low" grey cluster and the "slow" grey cluster.



GEM: Growth Enterprise Market; SME: Small and Medium Enterprise

Figure 2 Box and whiskers diagrams corresponding to three boards

4 Results

4.1 Grey clustering result

According to the grey clustering method and center marks of different grey clusters, the grey clustering possibility degree function of enterprise growth could be constructed. By combining the grey clustering possibility degree function and the weights, the grey clustering coefficient of each grey cluster could be obtained, and 117 listed enterprises were divided into different grey clusters.

Due to the existence of three grey clusters in both the absolute amount perspective and the incremental amount dynamic development of new-energy listed enterprises, the combination of grey clusters from two different amounts yielded nine grey cluster crossing subspaces, which could be presented in a two-dimensional table. As shown in Table 3, the grey clustering results of absolute amount and incremental amount categorize 117 listed new-energy enterprises into nine grey cluster crossing subspaces. Among them, 58 new-energy enterprises lay on the diagonal line. This meant that they belonged to the same grey cluster level in terms of both absolute amount and incremental amount.

Table 3 Grey clustering evaluation of the listed new-energy enterprises

Incremental amount	Absolute amount		
	Low	Medium	High

Slow	002006, 002012, 002074, 002121, 002309, 002451, 002580, 002594, 002610, 002623, 300062, 300068, 300093,300187, 3000393, 300499, 00021, 600290, 600537, 600550, 03686, 603333, 603105, 603507, 603595, 000601	002053, 02218, 002298, 002389, 002516, 300457, 600066, 600522, 601137, 000055	002056, 002531, 300037, 300234, 300484, 600011, 600674, 600770, 600875, 600886, 603988, 000027, 000973
Medium	002221, 300001, 300080, 300117, 600098, 600339, 601218, 603969, 000040, 000793	002079, 002130, 002226, 002922, 300082, 300118, 300129, 300217, 300450, 300569, 600482, 600499, 600517, 600590, 601222, 601311, 000065	002518, 300014, 00642, 601208
Fast	002011, 002147, 002506, 300064, 300335, 600268, 600416, 600869, 000507, 000669, 000826	002141, 002371, 002407, 002487, 300073, 300095, 600075, 600487, 600884, 601908, 000990	002080, 002460, 002601, 300207, 300274, 300305, 300316, 600900, 601012, 601669, 601985, 603659, 000012, 000625, 000959

Number in the table is the stock code of the enterprise

4.2 Grey clustering analysis

Based on the results of the above classification, we analyzed the characteristics of each classification. First, the common characteristics of the three main categories that determined the amount of growth in absolute terms were identified. The specific characteristics of the nine categories of the detailed classification are then presented in Table 4.

Enterprises in categories I, II and III, which were characterized by high absolute amounts, shared several common characteristics. First, they had a sound development base, which provided a solid foundation for sustainable growth and adaptability in the dynamic new-energy sector. Second, these enterprises had significant development potential, suggesting untapped opportunities for further expansion and market dominance. Third, there was a clear improvement in financial status, suggesting greater stability and resilience in the face of market challenges. Finally, a notable commonality was an emphasis on R&D, demonstrating a strategic commitment to technological advancement. The possession of a wealth of intangible assets, including intellectual property, further strengthened their competitive position in the industry. These enterprises continued to gain market share, reflecting successful strategies in response to market demands. Importantly, their positive influence in the industry contributed significantly to the overall development of the new-energy sector.

Enterprises in categories IV, V and VI, which were characterized by medium absolute values, shared key characteristics that were essential for sustainable success. First, they had a moderate development base, achieving a harmonious balance between stability and adaptability. Second, a significant improvement in financial status underscored their positive trajectory in overcoming market challenges, demonstrating resilience. Third, a commitment to R&D strengthened their competitive edge and ensured continuous innovation. Significantly, the expansion of their market share was indicative of effective strategies in response to evolving market demands. In addition, these enterprises had a remarkable development momentum, laying a solid foundation for future growth. Their ability to balance stability, innovation and strategic adaptation positioned them favorably in the dynamic business landscape, ready to seize emerging opportunities for further development.

Enterprises in categories VII, VIII and IX, which were characterized by low absolute amounts, shared common characteristics that were crucial for their unique development paths. First, a weak development base was a challenge, highlighting the need to build a solid foundation for growth. Second, despite their small size, some of them had a strong capacity for technological innovation, underlining their resilience and adaptability. This characteristic put them in an advantageous position to face challenges. Third, there was evidence of untapped potential for future growth. Although some enterprises were currently small in absolute terms, their robust technological capabilities provided a foundation for significant and impactful future development, offering optimism for their continued relevance and competitiveness in the ever-evolving business landscape.

Table 4 Characteristics of nine categories of the listed new-energy enterprises

Category	Absolute amount	Incremental amount	Characteristics
I	High	Fast	Huge development potential, better financial status, highly valued R&D, abundant intangible assets, high and growing market share
II	High	Medium	Large scale, stable market share, medium enterprise growth rate and moderate development momentum, medium R&D expenditure
III	High	Slow	Large scale, stable market share, better financial status, slow enterprise growth rate, low development momentum
IV	Medium	Fast	Medium size, better financial status, high return on R&D investment, increasing market share, strong development momentum
V	Medium	Medium	Medium size, stable market share, medium growth rate, moderate development momentum, medium R&D expenditure
VI	Medium	Slow	Medium size, declining market share, weak technological innovation capacity and low development momentum
VII	Low	Fast	Small size, better financial status, strong technological innovation capability and development momentum, increasing market share
VIII	Low	Medium	Small size, average technological innovation capacity and insufficient development momentum, medium R&D expenditure
IX	Low	Slow	Small size, declining market share, weak technological innovation capacity and low development momentum

4.3 Recommendations

Based on the results of grey clustering, we conducted an economic theory analysis of the characteristics of each classification. The common characteristics of enterprises in categories I, II and III are consistent with the economic theory of innovation in emerging industries, which emphasizes the importance of technological innovation and R&D investment for enterprise growth. The characteristics of enterprises in categories IV, V and VI are consistent with the theory of industrial organization regarding the relationship between enterprise size and market share. Based on the above analyses and and the characteristics of the different classified enterprises (Table 4), the following recommendations are made.

Category I enterprises have special characteristics, especially rapid growth in volume. To accelerate growth and enhance product competitiveness, these enterprises should emphasize technological innovation, understand market consumer needs, vigorously develop core business technologies, leverage internal resources, and strengthen overall competitiveness in the new-energy field. Category II enterprises are characterized by a balanced approach, with enterprises showing moderate incremental growth. These enterprises have characteristics such as a solid development foundation, substantial scale, stable market share and positive influence in the new-energy field. Enterprises with moderate growth speed, indicating moderate development momentum, should prioritize technological innovation, increase R&D investment, optimize current resource utilization to gradually increase growth speed, and enhance the competitiveness of key products for rapid growth. Category III enterprises faced the challenge of slow incremental volume growth. To overcome the hurdle of slow incremental growth, these enterprises should optimize the integration of enterprise resources, prioritize R&D investment, focus on high-tech products, and develop new business channels to enhance enterprise growth.

Category IV enterprises are characterized by rapid volume growth. To become more like Category I, these enterprises should focus on developing new business channels, tapping broader markets, increasing market share, maintaining core competitive superiority, producing in large quantities to exploit economies of scale, and establishing technical advantages in products. Enterprises in category V showed moderate growth in volume. To accelerate enterprise growth, these enterprises should increase R&D investment, introduce new technologies, integrate internal resources, and improve the utilization efficiency of existing resources. Category VI enterprises had slow incremental amount growth. To accelerate incremental amount growth, they are advised to prioritize R&D, eliminate obsolete products and develop new products to create new profit growth points. To improve absolute development amounts, these enterprises should enhance the competitiveness of core products, strengthen marketing ability to expand market share, and improve customer satisfaction.

Category VII enterprises had rapid growth in incremental amounts. To maintain incremental amounts, these enterprises should continuously increase R&D investment, improve the technological content of existing products, and continuously develop new products. To increase absolute development amounts, they are advised to strengthen marketing ability, increase the market share of core products, perfect the modern enterprise structure, develop brand cultivation, and strengthen the enterprise's influence in the new-energy field. Enterprises in category VIII have shown medium growth in the amount of development. Improvement initiatives must be carried out by focusing on technical research, improving the technological content of existing products, strengthening the integration of internal resources, and improving the utilization efficiency of existing resources. To cope with the low absolute quantity, enterprises should improve marketing ability, stabilize the existing market share, expand current resources and gradually improve the enterprise's influence in the market. Category IX enterprises had slow incremental quantity growth. To reverse this unfavorable situation, decision makers should take various measures to promote comprehensive development: integrate internal resources, analyze existing technical advantages and product characteristics, implement precision marketing in specific market segments to improve market share and competitive position, and introduce advanced technology to upgrade products.

5 Conclusions and implications

It is the government's commitment to strive for a peak in carbon dioxide emissions before 2030 and carbon neutrality by 2060 in order to ensure global energy security and tackle global climate change. In order to achieve this goal, the growth of new-energy enterprises is an important reference for decision makers. Aiming at systematic clustering problems for the panel at a certain period, a novel grey clustering model was built based on the perspective that the dynamic development trend reflected the implicit relationship between clustering objects. Then, 117 new-energy listed enterprises were clustered and analyzed based on the constructed model, and the following conclusions were obtained. (1) From the perspective of absolute amount and incremental amount, the novel model was constructed based on the grey possibility degree function. (2) According to the scatter diagrams of R&D intensity, the enterprises on GEM paid much more attention to technological innovation, and R&D intensity was larger. The enterprises listed on SME board paid more attention to technological innovation, and the R&D intensity was moderate. The enterprises on the mainboard paid less attention to technological innovation, and the ratio of R&D expenditure to operating revenue was slightly lower. (3) Grey clustering analysis, considering both absolute and incremental amounts, categorized 117 listed enterprises into nine sub-spaces. 58 enterprises aligned along the diagonal line, sharing the same grey cluster for both absolute and incremental amounts. 24 enterprises belonged to opposite grey clusters, indicating significant differences in company growth in terms of absolute and incremental amounts. (4) Under the absolute amount perspective, the common characteristics of enterprises were analyzed by category, and recommendations were presented for the development of each type of enterprise by combining the specific characteristics of the nine classifications under the relative amount perspective.

The insight of this study is that through grey cluster analysis we can better understand the growth path of new-energy enterprises. For policymakers, understanding the growth characteristics and differences of different types of enterprises will help formulate appropriate policies and measures. Meanwhile, the results of the study also suggest that innovation and technology investment play an important role in driving enterprise growth. Government support and subsidy policies also have an impact on the development of new-energy enterprises. In the context of pursuing sustainable development and achieving the goal of carbon neutrality, the continued promotion of green technology and innovation is crucial for the growth of new-energy enterprises. Policymakers should strengthen support and guidance for new-energy enterprises to promote their sustainable development. This includes the provision of financial support, tax incentives, research and development grants and market access facilitation. Governments should also increase support for R&D and innovation in new-energy technologies, encourage enterprises to increase their technological investment and promote technological progress and innovation. Policymakers should also aim to provide guidance and direction to help new-energy enterprises overcome the challenges and difficulties they face. This could include providing professional advisory services, promoting cooperation and experience sharing among enterprises, and establishing good policy communication channels. By establishing good cooperation and information-sharing mechanisms, it can promote mutual benefits and common development among new-energy enterprises, and promote the sustainable development of the whole industry.

The healthy and rapid growth of new-energy enterprises is an important task for promoting the comprehensive, coordinated and sustainable development of the energy industry. In future research, we will further explore the endogenous growth force of new-energy enterprises, consider the impact of national industrial policy support on enterprise growth, and pay attention to the research of technological innovation characteristics of new-energy enterprises based on the combination of internal and external perspectives, so as to promote new-energy enterprises to generate the motive force and creativity for sustainable development.

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