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Research on the Evaluation of Green Innovation Capability of Manufacturing Enterprises in Innovation Network

Jianzhong Xu and Jiaqi Zhai *

School of Economics and Management, Harbin Engineering University, Harbin 150001, China; xujianzhongxjz@163.com

* Correspondence: ceciliazj7@gmail.com; Tel.: +86-1566-345-9896

Received: 27 November 2019; Accepted: 20 January 2020; Published: 22 January 2020



Abstract: The aims of this paper are to objectively evaluate the green innovation ability of manufacturing enterprises in an innovation network and to consider the mutual influence relationship and information randomness of each evaluation index. To do so, 14 indicators were chosen to capture the innovation environment, input, and output, and to construct an evaluation index system. The cloud model method is used to express the evaluation information to assign a quantitative value to qualitative information, and this method is combined with the entropy method to determine the initial weight of the indices. Then, the cloud model and decision-making trial and evaluation laboratory (DEMATEL) method are combined to determine the final comprehensive weight of the indices, and the similarity between each value and ideal value is determined by the cloud distance measurement method and the grey correlation analysis method. Finally, the effectiveness and stability of this method and an accurate numerical method are verified in an empirical analysis that evaluates the green innovation ability of different enterprises. The results demonstrate the superiority of the evaluation system proposed in this paper, which can provide a theoretical basis for the evaluation of the green innovation ability of enterprises.

Keywords: cloud model; innovation network; grey correlation analysis; evaluation of green innovation ability

1. Introduction

With the deepening of economic globalization, numerous manufacturing enterprises have begun to realize that traditional extensive development is difficult to sustain. Moreover, the 19th National Congress highlighted the development concept of “innovation, coordination, green, opening and sharing” [1]. “Green innovation”, representing the combination of innovation-driven and green development strategies, has become the inevitable choice for overcoming bottlenecks regarding resources and the environment [2,3]. With the rapid development of “Internet +” [4,5], a green technology innovation service platform, which represents an important vehicle for information on green technology innovation, can eliminate barriers to the sharing of green innovation information and promote the in-depth development of cloud-based green technology innovation [6]. Therefore, it has considerable theoretical value and practical significance for systematically analyzing and comprehensively evaluating enterprises’ green innovation abilities in an innovation network to effectively enhance the those abilities and realize sustainable development [7,8].

In contrast to traditional technology, green technology innovation seeks to reduce resource consumption and environmental pollution with the new concepts and technologies [9,10]. It requires that enterprises not blindly pursue profit maximization, but also consciously fulfill their social

responsibilities, reduce the environmental externalities of economic development, and obtain corresponding economic benefits. At present, scholars in various countries have begun to refine the evaluation of green innovation ability using specific indicators, and especially quantitative indicators, to empirically evaluate green technology innovation ability. Thus, the design of systems for evaluating green technology innovation tends to be comprehensive and scientific, but most of them focus on evaluating the green technology innovation in a non-networked context, and some are based on the analysis of innovation output [11–13]. For example, according to Garcia Granero, evaluation indicators for green innovation capability include four types: product, process, organization, and marketing [14]. Anthonio (2009) et al. divided innovation ability into three aspects: indirect performance, direct performance, and knowledge output [15]. Rizos established an evaluation index system on the basis of direct performance, indirect performance, knowledge output, ecological performance, and economic performance. In their work, indirect performance refers to the improvement of resource utilization and productivity [16]. Direct performance is mainly reflected in the sales revenue of green technology and the number of innovative products, while knowledge output includes the number of, for example, green patents and monographs. Some scholars argue that green technology innovation ability is not limited to the ability to produce environmental protection products [17–20]. For example, Wield et al. contended that green technology innovation ability should also include the resources, processes, and technologies that operate with reduced energy consumption [21]. Scholars have also evaluated the green innovation ability of enterprises from an input–output perspective. For example, Yin Qun established an evaluation framework of green innovation efficiency based on four categories: resource inputs, nonresource inputs, expected output, and nonexpected output [22]. Wang Hailong and colleagues calculated the efficiency of green innovation in China by the data envelopment analysis (DEA) method from 2007 to 2011 [23]. Hsueh evaluates green supply chain innovation of the construction industry from two aspects of energy and environment by using a multicriteria evaluation model [24]. Enterprises can gain a competitive advantage by developing green product innovation and exploring the key factors of green product evaluation [25]. Cheng Hua and colleagues considered innovation input from capital, human resources, and environmental regulation, and treated environmental performance and economic performance as innovation outputs. Many scholars have also constructed evaluation index systems based on the elements of green innovation capability, such as Yang Lisheng, who defined green technology innovation ability indices based on the six aspects, namely, innovation input ability, management ability, R&D ability, manufacturing ability, entrepreneur innovation consciousness, and marketing capability, and used the comprehensive fuzzy evaluation method to evaluate the green sustainability of enterprises [26]. From the perspective of the green innovation environment of enterprises, Wang Qiang established an evaluation index system including green culture, innovation investment, and resource environment [27].

The methods commonly used for evaluation are generally a combination of subjective and objective, and qualitative and quantitative methods, including DEA [28–31], grey correlation analysis [32,33], entropy [34], the DEMATEL method, panel data, fuzzy comprehensive evaluation [35,36], and the AHP analytic hierarchy process [37]. For example, Gupta et al. used the grey-DEMATEL to determine 21 factors contributing to green innovation [38]. According to panel data, Ghisetti selected nine indicators of energy consumption and environmental pollution to evaluate the efficiency of the green innovation of enterprises [39]. Roberto also used a two-stage model and empirical research to assess the impact of green input on productivity [40]. Liu Chun Xiang (2018) and others used fuzzy comprehensive evaluation and AHP methods to comprehensively evaluate the green innovation ability of pulp and paper enterprises [41]. Ren Yao and Niu Chonghuai evaluated the industrial green innovation efficiency of Shanxi Province based on the DEA–range adjusted measure (RAM) model [42]. Tseng used DEA Malmquist and other productivity index analysis methods to evaluate China’s green innovation ability [43]. However, the aforementioned evaluation methods often inevitably lead to subjective assumptions being made by experts and unreasonable weight allocations, ignoring the randomness of evaluation information and the relationships between indicators [44–46]. Fuzziness and

randomness are interrelated, and although the aforementioned methods have advantages in analyzing complex evaluation factors, it is regrettable that the inherent randomness of the information is ignored. Fortunately, Deyi firstly proposed the cloud model, which describes the relationship between fuzziness and randomness [47–49]. As an effective mathematical method, the cloud model has been used in evaluation fields. For example, based on the cloud model method, Fu et al. (2016) [50] constructed the scheme evaluation system of the sustainable utilization of water resources. Yang et al. (2019) [51] evaluated the vulnerability of debris flow based on the improved entropy method and cloud model. Its numerous advantages have led to the successful application of the cloud model in energy management.

Thus, based on the current status of green innovation among manufacturing enterprises in China's innovation network, this paper designs a first-level index based on innovation input, environment, and output, and constructs an innovation evaluation system consisting of 14 s-level indices, including R & D funds, technology investment funds, rental platform equipment funds, and the ability to improve green technology, among others [52,53]. The entropy [54], DEMATEL, and cloud model [55–57] methods are used to calculate the comprehensive weight of the indices, and grey correlation analysis [58] and the cloud model are used to quantitatively evaluate the qualitative indicators.

The contributions of this paper are as follows:

- (1) Combined with the objective of green innovation and the present state of “Internet +” development, this paper establishes a comprehensive evaluation index system for enterprises' green innovation abilities in an innovation network. The index system reflects enterprises' green innovation abilities based on innovation input, environment, and output.
- (2) To obtain a reasonable conversion between quantitative and qualitative information in the process of evaluation, and to fully consider the fuzziness and randomness in the information used in the evaluation, we introduce the cloud model to determine the weightings used in the entropy and DEMATEL methods, which are better suited to deriving the ideal weights in a comprehensive weight method. This represents a scientific and feasible evaluation method that exhibits high classification accuracy for evaluating the ability of manufacturing enterprises in innovation networks to collaboratively produce scientific and technological innovations.

The rest of the paper is organized as follows. In Section 2, we introduce the construction of the index system for green innovation capacity. Section 3 briefly introduces the methods employed, including the cloud model and its calculation, and calculates the comprehensive index weight by combining the entropy and DEMATEL methods. Section 4 evaluates and analyzes the green innovation ability of five companies in an innovation network as examples, and compares the results with those obtained via other accurate numerical methods to verify the accuracy and effectiveness of the proposed method. Finally, Section 5 concludes the work. This paper demonstrates that the evaluation index system devised here for evaluating manufacturing enterprises' green innovation abilities in an innovation network is highly applicable, and the empirical analysis further demonstrates that the method can be used to guide engineering practice.

2. Development of Evaluation Criteria

Establishing evaluation criteria is key to evaluating enterprises' green innovation abilities, and should focus on the following basic principles: goal, system, integrity, and outstanding importance.

In this paper, an evaluation index system is constructed according to the following steps. First, we transform valuable information into indicators by following the relevant literature and collecting information on selected innovation network platforms in China. We then analyze the relevance of this information, and retain useful elements. After collecting the data, we select reasonable indicators, discuss them with experts, optimize the structure of the indicator system, and conduct membership, correlation, and resolution analyses according to principles in the literature on the construction of evaluation indices. Through the above steps, three first-level indices and 14 s-level evaluation indicators

are retained, mainly including green technology improvement ability, green technology absorption ability, green technology investment funds, R&D equipment investment funds, and manufacturing enterprises' overall percentage reductions of energy consumption. The following are the specific meanings and contents of these first-level indicators. The final indicator system constructed in this paper is presented in Table 1.

- (1) Innovation investment. R&D personnel and investment, and expenditures on green technology transformation and green technology imports are often selected as evaluation indicators. An efficient technical team is an important foundation for green innovation research and development. Green technology transformation is extremely beneficial to the upgrading and sustainable development of manufacturing enterprises. To improve market competitiveness, manufacturing enterprises must increase investment in new product development. This paper selects green technology investment and R&D funds, rental platform equipment funds, and investment funds available to enterprise equipment researchers.
- (2) Innovation environment. The innovation environment of enterprises in innovation networks primarily consists of the ability to share and integrate resources in the network, and can be used to reflect the quality of the innovation environment for enterprises involved in innovation activities. The "hard" environment on green technology consists primarily of a comprehensive innovation platform; this is typically a strategic cooperation platform comprising enterprises, R&D institutions, and other hard environments, with a particular focus on capital, talent, equipment, information, and science. The "soft" environment in the context of technological innovation usually refers to the network platform involved in cooperative innovation, mainly including the ability to improve or absorb green technology, for example.
- (3) Innovation output. The output indicators including social and economic benefits. The social dimension consists of two aspects: the public recognition of an enterprise's brand and the cooperative relations between enterprises. The economic benefits consist of three aspects: percentage reduction in comprehensive energy consumption, the reduction of industrial waste, and the percentage change in the unit output value.

Table 1. The indicator system of green innovation ability in an innovation network.

First-Level Indicators	Second-Level Evaluation Indicators
Innovation investment (A1)	Environmental pollution control fund (B1)
	Green technology R & D Fund (B2)
	Green technology investment funds (B3)
	R&D equipment investment funds (B4)
	Platform equipment funds (B5)
	Investment funds available to enterprise researchers (B6)
	Education and training level of R & D personnel (B7)
	Enterprise energy consumption (B8)
Innovation environment (A2)	Green technology improvement ability (B9)
	Green technology absorption ability (B10)
Innovation output (A3)	Percentage reduction in comprehensive energy consumption (B11)
	The reduction of industrial waste (B12)
	The reduction of industrial waste (B13)
	Public recognition of enterprises (B14)

The percentage change in unit output value represents a product's economic output, which can directly reflect the importance of green innovation and its actual benefits.

3. Methodologies

In this part, we propose an evaluation model, including the cloud model and the methods required to obtain indicator weights. By comparing different methods, the cloud model is employed to

express the evaluation information, while we use the entropy weight and DEMATEL to calculate the comprehensive weights of the indices. Finally, we use the cloud distance measurement method to evaluate the performance of the weighting methods.

3.1. Cloud Model and Related Calculation

The theory underlying the cloud model is based on the idea of fuzzy theory [59], as proposed by professor Li [60]. It is a model based on fuzzy mathematics that can find the uncertainty conversion between qualitative and quantitative values [61]. The “cloud” in the model is formed through the condensation of numerous “water droplets,” where the cloud reflects the importance of qualitative indicators and the droplets represent a quantitative description of it. The process of producing these droplets can be used to express the mapping between quantitative values and qualitative indicators.

Let U be a quantitative domain and C a qualitative concept in U . If the uncertainty $\mu(x)$ of element x in U to C is a random number with a stable tendency, the parameter $\mu(x)$ can be described as:

$$\mu(x) : U \rightarrow [0, 1]. \quad \forall x \in U, x \rightarrow \mu(x) \tag{1}$$

Mathematically, the distribution of x can be determined by three characteristics: the expectation parameter Ex , the entropy parameter En , and the hyper entropy parameter He [62–64]. Ex is the expected value of a droplet based on the universe of discourse data, i.e., on the concept and the best representation of qualitative concept. En reflects the distribution of droplets and the range of a droplet in the distribution, which can be determined by the randomness and uncertainty of the concepts. The degree of dispersion of the droplets is denoted by He . This is the membership degree of a random variable, and reflects the thickness of the cloud. The representation method of the cloud model fully shows the randomness of qualitative language, so it is more objective.

3.1.1. Evaluation Scale of Cloud Model

In scheme evaluation, n (generally odd) semantic evaluation scales are given for experts to evaluate each index in the scheme. The effective domain is $U = [X_{\min}, X_{\max}]$ (generally set by experts). The generated n clouds correspond to n semantic scales one by one. If a middle cloud is denoted by $E_0(Ex_0, En_0, He_0)$, then the adjacent clouds can be defined as, respectively,

$$E_{-1}(Ex_{-1}, En_{-1}, He_{-1}), E_1(Ex_1, En_1, He_1), \dots, \tag{2}$$

$$E_{(1-n)/2}(Ex_{(1-n)/2}, En_{(1-n)/2}, He_{(1-n)/2}), E_{(n-1)/2}(Ex_{(n-1)/2}, En_{(n-1)/2}, He_{(n-1)/2}) \tag{3}$$

Generally, we generate five clouds by the golden section method, and, according to expert evaluation, we select $[X_{\min}, X_{\max}]$ as $[0,1]$, and $He_0 = 0.05$. For a given He_0 , $He_{-1} = He_1 = He_0/0.618$. The method for calculating the numerical characteristics of a cloud is shown in Table 2. The calculated cloud evaluation scale is as follows: excellent $E_2(1,0.103,0.016)$, good $E_1(0.691,0.064,0.016)$, medium $E_0(0.5,0.039,0.01)$, poor $E_{-1}(0.309,0.064,0.016)$, and very poor $E_{-2}(0,0.103,0.026)$. Figure 1 shows the five clouds used in the cloud evaluation model.

Table 2. The calculation method of the characteristics of the cloud.

Cloud	Ex	En	He
$E_2(Ex_2, En_2, He_2)$	X_{\max}	En_1	$He_1/0.618$
$E_1(Ex_1, En_1, He_1)$	$Ex_0 + 0.382 \times (X_{\max} + X_{\min})/2$	$0.382 \times (X_{\max} - X_{\min})/6$	$He_0/0.618$
$E_0(Ex_0, En_0, He_0)$	$(X_{\max} + X_{\min})/2$	$0.618 En_1$	He_0
$E_{-1}(Ex_{-1}, En_{-1}, He_{-1})$	$Ex_0 - 0.382 \times (X_{\max} + X_{\min})/2$	$0.382 \times (X_{\max} - X_{\min})/6$	$He_0/0.618$
$E_{-2}(Ex_{-2}, En_{-2}, He_{-2})$	X_{\min}	$En_1/0.618$	$He_1/0.618$

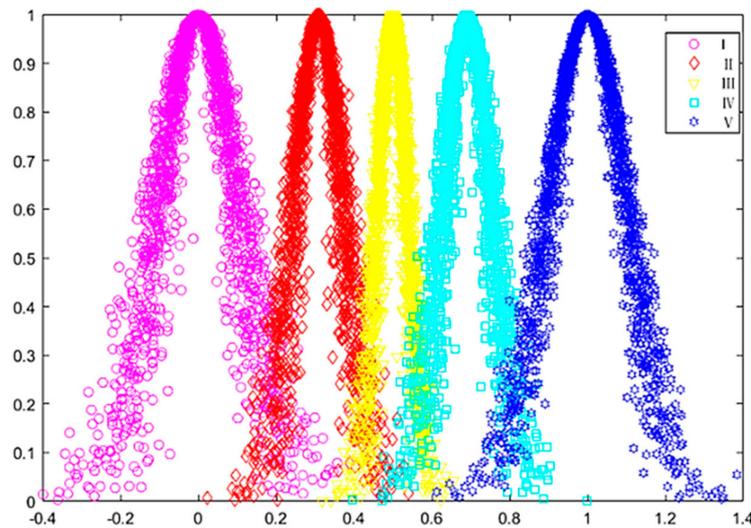


Figure 1. Five clouds of scoring levels.

3.1.2. Cloud Integration

According to the steps above, we determine that each expert’s linguistic assessment has n fundamental clouds, i.e., $y_1 = (Ex_1, En_1, He_1), y_2 = (Ex_2, En_2, He_2), \dots, y_n = (Ex_n, En_n, He_n)$, where n is the number of experts. These basic clouds can generate a floating cloud. If the generated floating cloud can be represented as $Y = (Ex, En, He)$, then:

$$\begin{cases} Ex = \omega_1 Ex_1 + \omega_2 Ex_2 + \dots + \omega_n Ex_n \\ En = \sqrt{(\omega_1 Ex_1)^2 + (\omega_2 Ex_2)^2 + \dots + (\omega_n Ex_n)^2} \\ He = \sqrt{(\omega_1 Ex_1)^2 + (\omega_2 Ex_2)^2 + \dots + (\omega_n Ex_n)^2} \end{cases} \quad (4)$$

In the above equation, $\omega_i, i = 1, 2, \dots, n$ denotes the corresponding indicator weight. When the weight values of each cloud model are equal, that is, $\omega_n = 1/n$, $Y = (Ex, En, He)$, then the integrated cloud is:

$$\begin{cases} Ex = (Ex_1 + Ex_2 + \dots + Ex_n) / n \\ En = \sqrt{(Ex_1)^2 + (Ex_2)^2 + \dots + (Ex_n)^2} / n \\ He = \sqrt{(\omega_1 Ex_1)^2 + (\omega_2 Ex_2)^2 + \dots + (\omega_n Ex_n)^2} / n \end{cases} \quad (5)$$

3.1.3. The Positive Cloud Generator

The cloud generator is a cloud generation algorithm that is implemented in software. Cloud generators can reveal the relationship between qualitative concepts and quantitative characteristics, which including two common types: forward and backward cloud generators. The processes of the positive cloud generator is shown in Figure 2.

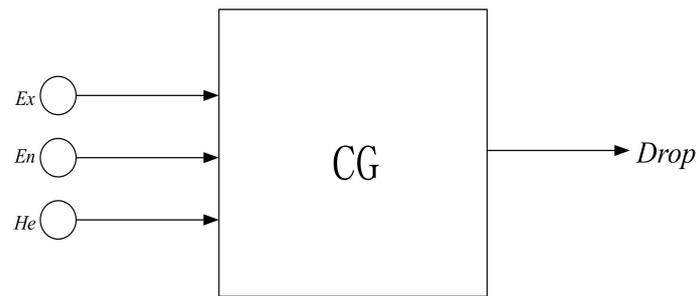


Figure 2. The positive cloud generator.

Specifically, the forward cloud generator makes it easier to transform qualitative concepts into quantitative features. The backward cloud generator can also transform the quantitative characteristic into a qualitative concept. Using generators, the required cloud drops can be produced. The algorithm flow of the positive cloud generator is shown in Figure 3.

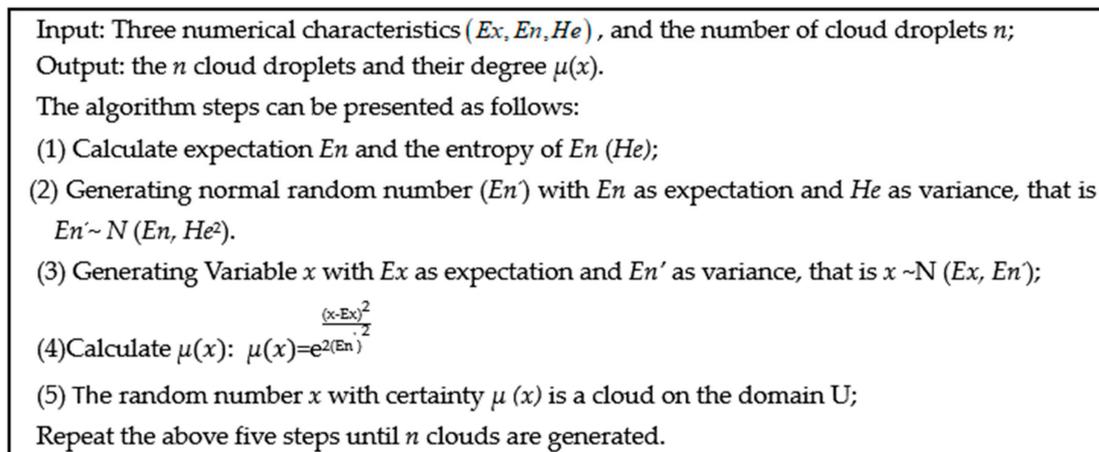


Figure 3. The positive cloud generator.

3.1.4. Measurement of Cloud Distance

Cloud distance refers to the distance between two clouds. The specific steps of this algorithm are as follows:

- (1) Input the eigenvalues $E_1 (Ex_1, En_1, He_1)$, $E_2 (Ex_2, En_2, He_2)$ and cloud drop number n of the two clouds;
- (2) The two clouds generate n cloud droplets respectively through the positive cloud generator.
- (3) Arrange each cloud drop from small to large in abscissa;
- (4) Screen the cloud drops and keep them falling in the range of $[Ex - 3En, Ex + 3En]$;
- (5) Set the number of cloud drops of the two clouds after screening to n_1 and n_2 respectively. Suppose $n_1 > n_2$ randomly select n_2 cloud drops from n_1 cloud drops of the first cloud, then sort the cloud drops from small to large in abscissa, and keep them in the set $Drop1$ and $Drop2$; if $n_1 < n_2$, do the opposite;
- (6) Calculate the distance between each cloud drop ($x, (x)$) in drop1 and drop2 in corresponding order;

$$d(E_1, E_2) = d(Drop1, Drop2) = \frac{1}{n_2} \sum_{k=1}^{n_2} \sqrt{(x_{1k} - x_{2k})^2 - (\mu(x)_{1k} - \mu(x)_{2k})^2} \quad (6)$$

- (7) Output the distance $D(E_1, E_2)$ between two clouds.

The algorithm fully considers the randomness of the cloud model, and its calculation results also reflect that when the super entropy of the two clouds is large, the distance between the two clouds is also greater.

3.2. Determine the Evaluation Index Weights

In 1948, the American mathematician Shannon first applied cloud models in information theory, using them as a measure of the uncertainty between things and problems [65]. In information theory, entropy can quantitatively express the disorder and effectiveness of a system. Any information has redundancy, and its size is related to the probability or uncertainty of each symbol in the information. The entropy method is a method to give weight to the evaluation index objectively. It determines the weight of each index by the information provided by the observation value of the index [66]. This method can help prevent human factors from influencing the weights of evaluation indices, meaning that the evaluation results are reasonable.

To obtain an index weighting that comprehensively captures subjective and objective factors, the cloud model and entropy weighting method were employed, as in the following steps.

Step 1: Let $E_{ij}(Ex_{ij}, En_{ij}, He_{ij})$ be the evaluation value of the j -th ($j = 1, 2, \dots, n$) index in the i -th ($i = 1, 2, \dots, m$) enterprise, where $d(E_{ij}, E_j^*)$ represents the distance between the evaluation value and the ideal. The larger $d(E_{ij}, E_j^*)$ is, the less similar the two clouds are. The judgment matrix $E = (E_{ij})_{m \times n}$ composed of m evaluation schemes and n evaluation indices is established. Next, transform it into the distance measure matrix $D = (d(E_{ij}, E_j^*))_{ij, m \times n}$:

$$E_{ij} = \begin{pmatrix} E'_{11} & \cdots & E'_{1i} \\ \vdots & \ddots & \vdots \\ E'_{j1} & \cdots & E'_{ij} \end{pmatrix} \tag{7}$$

where n is the number of indices and m is the number of enterprises.

(2) Due to the differences in properties and units of evaluation indices, it is necessary to standardize matrix D to obtain dimensionless index matrix P_{ij} :

$$P_{ij} = \frac{d(E_{ij}, E_j^*)_{ij}}{\sum_{i=1}^n d(E_{ij}, E_j^*)_{ij}} \quad i = 1, 2, \dots, m. \quad j = 1, 2, \dots, n \tag{8}$$

(3) The entropy of the j -th evaluation indices is:

$$S_{ij} = -\frac{1}{\ln m} \sum_{i=1}^m (P_{ij} \cdot \ln P_{ij}) \tag{9}$$

In Formula (6), $\frac{1}{\ln m}$ is Boltzmann's constant, where entropy guarantees that $0 \leq S_{ij} \leq 1$.

(4) Get the initial weight of each indicator by the above entropy:

$$\omega_s = \frac{1 - S_{ij}}{\sum_{i=1}^n (1 - S_{ij})} \quad j = 1, 2, \dots, n \tag{10}$$

3.3. Using the Cloud Model—Applying the DEMATEL Method to Modify the Weighting

The DEMATEL method is a method for visualizing the relationships between factors in an understandable way. It can transform the causal relationship between factors into a comprehensive model to assist in decision-making processes. In general, when using the DEMATEL method to

estimate the relationship between factors, the following steps are included: measure the strength and direction between factors; construct and normalize an initial direct relationship matrix; determine the overall relationship matrix and the importance and weights of factors.

However, there are different aspects of uncertainty in complex decision-making processes, including the formalization of qualitative or quantitative standards and the preferences of decision makers. In this sense, the analysis approach of the DEMATEL method is more comprehensive. Therefore, we use this method to analyze the direct and indirect effects of various influencing factors. Moreover, the cloud model is employed to represent and address fuzzy linguistic information, and the DEMATEL method is employed to analyze the relationships among indicators and to calculate the weights.

The specific analysis steps are as follows:

- (1) Construct the initial direct relation matrix. Suppose that K experts are asked to indicate the direct influences among j -th factors $B_j = \{B_1, B_2, \dots, B_n\}$, then determine the relationship among all evaluation factors in this system and establish an assessment standard. To facilitate evaluation, influence was divided into five levels, which are represented by five symbols (I, II, III, IV, and V, respectively). The original evaluation number is then converted into a cloud evaluation value. Levels of influence are determined based on the expert evaluation. Then, five symbols are converted into cloud evaluation values (Table 3).
- (2) According to the results of the questionnaire, the relationships among all of the factors that involved green innovation are derived, and the direct relationship matrix R^k of each expert is modeled as follows:

$$R^k = \begin{bmatrix} 0 & r_{12}^k & \dots & r_{1n}^k \\ r_{21}^k & 0 & \dots & r_{2n}^k \\ \dots & \dots & \ddots & \dots \\ r_{n2}^k & r_{n2}^k & \dots & 0 \end{bmatrix} \tag{11}$$

where $r_{ij}^k(\text{Ex}_{ij}^k, \text{En}_{ij}^k, \text{He}_{ij}^k)$ ($k = 1, 2, \dots, K$) represents the evaluation cloud of the k -th expert on the relationship between evaluation indicators, and the diagonal elements of the evaluation matrix are all zero. Then, we aggregate the qualitative evaluation results of decision makers using Equation (12), and the initial direct relation matrix can be obtained:

$$R = \frac{1}{K}(R^1 + R^2 + \dots + R^K) \tag{12}$$

- (3) In this study, the cloud evaluation scale r^* (0,0.103,0.026) is used as the evaluation value of the reference cloud to calculate the distance between each indicator and the benchmark cloud: the greater the cloud distance, the greater the influence. The cloud distance measurement matrix is obtained by (13):

$$D = \left(d(r_{ij}, r_j^*) \right)_{m \times n} \tag{13}$$

- (4) Using (14) and (15) to normalize the matrix D , a standardized direct relation matrix is obtained:

$$d'_{\max} = \max_{1 \leq i \leq n} \sum_{j=1}^m d(r_{ij}, r_j^*)_{ij} \tag{14}$$

$$N = D/d'_{\max} \tag{15}$$

- (5) We calculate the direct/indirect influence matrix, which reflects the interaction between matrix elements, and the total relation matrix T can be expressed as:

$$T = N(1 - N)^{-1} \tag{16}$$

- (6) Calculate the average of the matrix T and use it as a threshold t [67–69]. Only the value greater than the threshold value in the T matrix is retained, and the factor less than the threshold value is set to 0. Accordingly, matrix T' is obtained.
- (7) Find the sum of rows R_j and columns C_j of the matrix T' . The importance of each factor is as follows:

$$\lambda = \sqrt{(R_j + C_j)^2 + (R_j - C_j)^2} \quad j = 1, 2, \dots, n \tag{17}$$

where R_j is the sum of influences of F_j on other factors and C_j is the total influences of other factors on F_j . In addition, $R_j + C_j$ shows the importance of the factor F_j to the system. In contrast, $R_j - C_j$ represents the net effect of the factor F_j on the system.

- (8) Draw the causality graph, which takes the center degree $R_j + C_j$ of each factor as the abscissa and the cause degree $R_j - C_j$ as the ordinate.
- (9) The relative importance of each factor is as follows:

$$\lambda'_j = \frac{\lambda_j}{\sum_{j=1}^m \lambda_j} \quad j = 1, 2, \dots, n \tag{18}$$

- (10) We then determine the combined weights of the evaluation indices ω_j for the assessment of green innovation ability of manufacturing companies based on the DEMATEL and entropy weighting methods. The combined weights ω_j of the evaluation criteria can be determined by integrating the weight of DEMATEL λ'_j and entropy weighting ω_s methods:

$$\omega_j = \alpha \lambda'_j + (1 - \alpha) \omega_s \quad j = 1, 2, \dots, n \quad 0 \leq \alpha \leq 1 \tag{19}$$

where $0 \leq \alpha \leq 1$ is the combined coefficient.

Table 3. The cloud evaluation scale.

Linguistic Scales	Number	Clouds
None Influence (N)	I	$E_{-2}(0,0.103,0.026)$
Very Low Influence (VL)	II	$E_{-1}(0.309,0.064,0.016)$
Low Influence (L)	III	$E_0(0.5,0.039,0.01)$
High Influence (H)	IV	$E_1(0.691,0.064,0.016)$
Very High Influence (VH)	V	$E_2(1,0.103,0.016)$

3.4. Cloud Model and Grey Relation Analysis Method

Grey relational analysis is a method for solving the multicriteria decision-making (MCDM) problem with multiple attributes in uncertain situations. In the analysis, an ideal solution is required, and we can judge the pros and cons of the scheme by comparing the correlation between each scheme and the ideal solution. The greater the degree of relevance, the closer the scheme is to the ideal solution, and the better the scheme is evaluated. In this paper, by calculating the distance and the grey correlation between the cloud evaluation value of each enterprise and the ideal cloud evaluation value, we can more intuitively compare enterprise performance. Grey relation analysis comprises three steps: the normalization of data, calculation of the relationship coefficient, and the grey relational degree.

Step 1. Generate the ideal solution.

Let $M_i = [E_{i1}, E_{i2}, \dots, E_{in}]$ represent the integrated evaluation value of all experts for i ($i = 1, 2, \dots, m$) enterprises. We find the ideal solution in the matrix $A_0 = [E_{01}, E_{02}, \dots, E_{0n}]$, where $E_{0j}(1,0.103,0.016)$ is the reference of the j -th evaluation index, which is the maximum value of each evaluation index.

Step 2. Calculate the grey relational coefficient ξ_{ij} of indices using Equations (20)–(23).

$$\xi_{ij} = \frac{\Delta_{\min} + \rho \Delta_{\max}}{\Delta_i(k) + \rho \Delta_{\max}} \quad (20)$$

$$\Delta_i(k) = d(E_{ij}, E_{0j}) \quad (21)$$

$$\Delta_{\min} = \min_i \left[\min_j (d(E_{ij}, E_{0j})) \right] \quad (22)$$

$$\Delta_{\max} = \max_i \left[\max_j (d(E_{ij}, E_{0j})) \right] \quad (23)$$

where ρ ($0 \leq \rho \leq 1$) is the resolution coefficient and indicates the importance of Δ_{\max} . The smaller ρ is, the higher its distinguish ability. $d(E_{ij}, E_{0j})$ is the distance between the cloud assessment value and the ideal value. In most situations, $\rho = 0.5$, because the value usually provides good discrimination.

Step 3. Calculating grey correlation degree γ_i .

The grey correlation coefficient can be obtained by summing up the grey correlation coefficient ξ_{ij} using Equation (24):

$$\gamma_i = \sum_{j=1}^n \omega_j \xi_{ij} \quad (24)$$

where ω_j is the weight of j-th evaluation index, and γ_i is the grey relational degree, which represents the magnitude of the measured correlation between the reference and comparison sequences. Moreover, the cloud evaluation value of the enterprise with the highest relational degree is the best solution. Therefore, when γ_i is larger, the cloud evaluation value of the enterprise and the ideal value are highly related. In contrast, when γ_i is lower, these two values are less related.

4. A Case Study

To verify the validity of the above framework in a real-world decision-making environment, this section applies it to the evaluation of manufacturing enterprises' innovation abilities on a cloud platform. The manufacturing enterprises' abilities on the platform are then ranked using grey relation analysis.

4.1. Data Collection and Analysis

To conduct a comprehensive evaluation of the five manufacturing enterprises selected in this paper, 35 experienced experts were invited to form an expert committee to ensure the professional and effective evaluation of the results. After a discussion, the committee finally determined a set of evaluation index systems applicable to the innovation ability of manufacturing enterprises under the network innovation platform, including R & D equipment investment (B_4), expenses for renting platform equipment (B_5), enterprise energy consumption (B_8), and green technology absorption capacity (B_{10}), as shown in Table 2.

4.2. Calculation of Evaluation Value $E(E_{ij})$ of Each Index B (B_i)

Using the described evaluation method, we evaluated the innovation ability of five manufacturing enterprises using the network platform. The index weightings were obtained via a questionnaire. To comprehensively account for expert authority, 35 Chinese experts in the field of green innovation were selected to conduct face-to-face interviews, with experts with greater authority theoretically deriving the index weight. These 35 respondents were graded from 1–5 on E in terms of the importance

of the 14 s-level indices F_j ($j = 1, 2, \dots, 14$), and each grade had a set of digital characteristics (Ex_{ij}^k , En_{ij}^k , and He_{ij}^k). According to the questionnaire data and Equation (1), the semantic evaluation data for the ability of green innovation of enterprises A_i ($i = 1, 2, \dots, 5$) in the innovation network by the expert group were obtained, and then transformed into cloud evaluation values using MATLAB software (Math Works, Natick, America). Here, $E_2(1, 0.103, 0.016)$, $E_1(0.691, 0.064, 0.016)$, $E_0(0.5, 0.039, 0.01)$, $E_{-1}(0.309, 0.064, 0.016)$, and $E_{-2}(0, 0.103, 0.026)$ correspond to five semantic evaluation grades, i.e., excellent, good, medium, poor, and very poor. The total cloud evaluation value can be obtained using Equation (2), as shown in Table 4.

Table 4. Total cloud evaluation value of all enterprise evaluation indices.

	B₁	B₂	...	B₁₄
A1	(0.049, 0.016, 0.004)	(0.084, 0.0271, 0.0068)	...	(0.054, 0.0175, 0.0044)
A2	(0.052, 0.0168, 0.0042)	(0.057, 0.0182, 0.0046)	...	(0.059, 0.0189, 0.0047)
A3	(0.057, 0.0182, 0.0046)	(0.084, 0.0271, 0.0068)	...	(0.052, 0.0168, 0.0042)
A4	(0.054, 0.0175, 0.0044)	(0.059, 0.0189, 0.0047)	...	(0.054, 0.0175, 0.0044)
A5	(0.087, 0.0283, 0.0071)	(0.055, 0.0186, 0.0047)	...	(0.059, 0.0189, 0.0047)

4.3. Weight Determined

4.3.1. Determine the Initial Weight by the Entropy Method

In this study, the cloud evaluation scale $E^*(1, 0.103, 0.016)$ was taken as the evaluation value of the reference cloud, and the cloud distance matrix between the cloud assessment values of five enterprises and the benchmark cloud E^* could be calculated by using the measurement algorithm for cloud distance and Equation (3), as shown in Table 5. The initial weight values of 14 indices were obtained using Equations (5)–(7); the results are shown in Table 6.

Table 5. Total evaluation data of each evaluation index for five enterprises.

B₁	B₂	B₃	...	B₁₃	B₁₄
0.0009	0.0011	0.0012	...	0.0013	0.0014
0.0013	0.0013	0.0014	...	0.0013	0.0014
0.0015	0.0014	0.0014	...	0.0013	0.0015
0.0013	0.0011	0.0013	...	0.0011	0.0013
0.0011	0.0013	0.0012	...	0.0010	0.0015

Table 6. Initial weight value ω_s of each index.

Index	ω_s	Index	ω_s
B ₁	0.084	B ₈	0.025
B ₂	0.020	B ₉	0.059
B ₃	0.014	B ₁₀	0.074
B ₄	0.150	B ₁₁	0.025
B ₅	0.082	B ₁₂	0.034
B ₆	0.115	B ₁₃	0.044
B ₇	0.261	B ₁₄	0.014

4.3.2. Using the DEMATEL Method to Determine Relative Importance

The expert committee constructed a direct relation matrix for the evaluation indices for green innovation capability using the linguistic scale given in Table 3. The direct relation matrix given by each expert can be summarized by Equation (9), and the cloud evaluation matrix of the total initial direct relationship of evaluation indices R provided by experts is listed in Table 7. The initial cloud relation matrices given by each expert are not listed to avoid including unnecessary information.

Table 7. Cloud evaluation matrix R of total initial direct relationship.

	B₁	B₂	...	B₁₄
B ₁	(0, 0, 0)	(0.846, 0.0271, 0.0068)	...	(0.343, 0.0203, 0.0051)
B ₂	(0.405, 0.0168, 0.0042)	(0, 0, 0)	...	(0.462, 0.0143, 0.0036)
B ₃	(0.347, 0.0189, 0.0047)	(0.646, 0.0193, 0.0049)	...	(0.443, 0.0151, 0.0038)
B ₄	(0.424, 0.016, 0.004)	(0.596, 0.0168, 0.0042)	...	(0.405, 0.0168, 0.0042)
B ₅	(0.385, 0.0175, 0.0044)	(0.807, 0.0261, 0.0066)	...	(0.519, 0.0168, 0.0042)
B ₆	(0.576, 0.016, 0.004)	(0.726, 0.023, 0.0058)	...	(0.481, 0.0182, 0.0046)
B ₇	(0.596, 0.0168, 0.0042)	(0.707, 0.0224, 0.0057)	...	(0.443, 0.0168, 0.0042)
B ₈	(0.634, 0.0182, 0.0046)	(0.634, 0.0182, 0.0046)	...	(0.596, 0.0182, 0.0046)
B ₉	(0.385, 0.0175, 0.0044)	(0.519, 0.0133, 0.0034)	...	(0.366, 0.0182, 0.0046)
B ₁₀	(0.443, 0.0151, 0.0038)	(0.576, 0.016, 0.004)	...	(0.385, 0.0175, 0.0044)
B ₁₁	(0.424, 0.016, 0.004)	(0.557, 0.0151, 0.0038)	...	(0.385, 0.0175, 0.0044)
B ₁₂	(0.443, 0.0151, 0.0038)	(0.615, 0.0175, 0.0044)	...	(0.385, 0.0175, 0.0044)
B ₁₃	(0.405, 0.0168, 0.0042)	(0.576, 0.016, 0.004)	...	(0.462, 0.0189, 0.0047)
B ₁₄	(0.557, 0.0151, 0.0038)	(0.734, 0.0227, 0.0057)	...	(0, 0, 0)

According to the cloud distance measurement algorithm, after converting the above matrix to the cloud distance measurement matrix, the cloud distance measurement matrix could be standardized using to Equation (9). The cloud evaluation scale E^* (0, 0.103, 0.016) was taken as the evaluation value of the reference cloud, and the relative importance of indices could be obtained using Equations (10)–(14), as shown in Table 8. The threshold value was 0.4629; the causality diagram is shown in Figure 4.

Table 8. Relative importance λ_j' of evaluation indices.

Indicator	λ_j'	Indicator	λ_j'
B ₁	0.0692	B ₈	0.0329
B ₂	0.097	B ₉	0.0742
B ₃	0.1203	B ₁₀	0.1001
B ₄	0.0641	B ₁₁	0.0617
B ₅	0.0714	B ₁₂	0.0827
B ₆	0.0836	B ₁₃	0.0566
B ₇	0.0281	B ₁₄	0.058

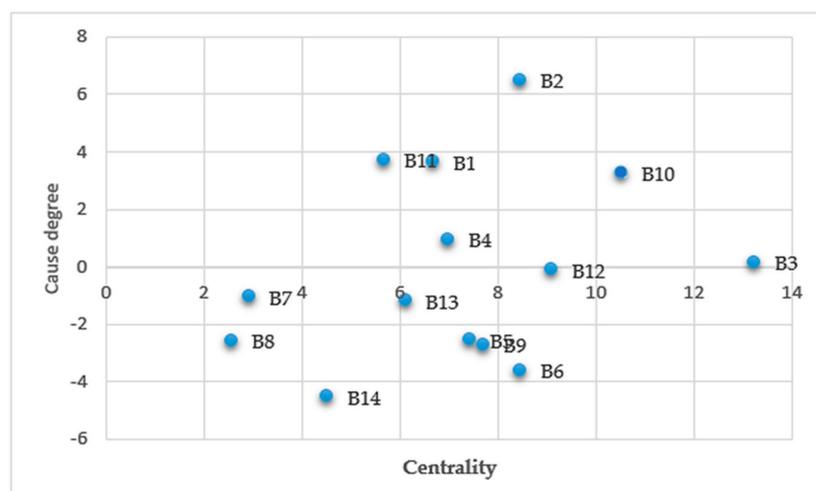


Figure 4. The causality graph.

4.3.3. Determine the Comprehensive Weight

Let α be 0, 0.2, 0.5, 0.8, or 1. The final integrated weights of each index ω_j can be obtained by Equation (14); all results are shown in Table 9.

Table 9. The comprehensive weight ω_j of the index in the case of different α

	$\alpha = 0$	$\alpha = 0.2$	$\alpha = 0.5$	$\alpha = 0.8$	$\alpha = 1$
B1	0.1676	0.1479	0.1184	0.0888	0.0692
B2	0.1218	0.1169	0.1094	0.102	0.097
B3	0.0861	0.093	0.1032	0.1135	0.1203
B4	0.0433	0.0474	0.0537	0.0599	0.0641
B5	0.0477	0.0524	0.0595	0.0666	0.0714
B6	0.052	0.0583	0.0678	0.0773	0.0836
B7	0.0177	0.0198	0.0229	0.0261	0.0281
B8	0.037	0.0362	0.035	0.0337	0.0329
B9	0.0525	0.0568	0.0634	0.0699	0.0742
B10	0.1524	0.142	0.1263	0.1106	0.1001
B11	0.0988	0.0914	0.0802	0.0691	0.0617
B12	0.0799	0.0804	0.0813	0.0821	0.0827
B13	0.0319	0.0368	0.0442	0.0516	0.0566
B14	0.0114	0.0207	0.0347	0.0487	0.058

4.4. Discussion

4.4.1. Calculate the Correlation Degree of Each Index

Let α equal 0, 0.2, 0.5, 0.8, or 1. The correlation coefficient of each index was obtained according to the steps introduced in Section 3.3; the final integrated weights were obtained using Equations (15)–(18), as shown in Table 10.

Table 10. Correlation coefficient ξ_{ij} of evaluation indices in different α cases.

	B₁	B₂	B₃	...	B₁₂	B₁₃	B₁₄
$\alpha = 0$	0.953	0.837	0.482	...	0.774	0.631	0.672
$\alpha = 0.2$	0.695	0.651	0.594	...	0.519	0.494	0.562
$\alpha = 0.5$	0.953	0.494	0.414	...	0.719	0.672	0.651
$\alpha = 0.8$	0.719	0.532	0.547	...	0.612	0.651	0.631
$\alpha = 1$	0.672	0.532	0.612	...	0.494	0.594	0.594

The grey correlation degree refers to a process that evaluates the weighted sum of grey correlation coefficients. The correlation degree was calculated by Equation (19) and is displayed in Table 11.

Table 11. Correlation degree γ_i of evaluation indices in different α cases.

	A₁	A₂	A₃	A₄	A₅
$\alpha = 0$	0.8425	0.7349	0.7794	0.7326	0.7803
$\alpha = 0.2$	0.8332	0.7384	0.7791	0.7497	0.78
$\alpha = 0.5$	0.8192	0.7437	0.7797	0.7555	0.7835
$\alpha = 0.8$	0.8052	0.749	0.7793	0.7612	0.788
$\alpha = 1$	0.7959	0.7525	0.7791	0.7683	0.7876

Figure 2 demonstrates that when influence α of the correlation between the evaluation indices on the weight increases, manufacturing enterprises' green innovation abilities in the innovation network change as follows: $A_1 > A_5 > A_3 > A_2 > A_4$ to $A_1 > A_5 > A_3 > A_4 > A_2$. In the case of a large correlation between evaluation indices, the green innovation capability of enterprise A_2 is better than that of A_4 . When the correlation between evaluation indices does not have a substantial impact on the weight, the green innovation ability of enterprise A_4 is better than that of A_2 .

It is clear from Table 11 that when $\alpha = 0.5$ and $\alpha = 0.8$, the correlation between enterprise A_2 and A_4 is relatively small, so it is difficult to distinguish between the advantages and disadvantages of the two enterprises. Furthermore, we discuss two cases of $\alpha = 0.5$ and $\alpha = 0.8$, and Equation (1) was

employed to integrate the cloud evaluation values of all evaluation indices of each manufacturing enterprise, as shown in Tables 12 and 13. Then, to more intuitively compare A_2 and A_4 , according to the cloud model's eigenvalues of enterprises A_2 and A_4 ($\alpha = 0.5$ and $\alpha = 0.8$), the MATLAB software was used to draw the corresponding cloud charts of the two enterprises. The results are presented in Figures 5 and 6.

Table 12. Total evaluation cloud of enterprises at $\alpha = 0.5$.

	A_1	A_2	A_3	A_4	A_5
Ex	0.0628	0.0519	0.0558	0.0518	0.0584
En	0.0062	0.0051	0.0054	0.0052	0.0061
He	0.0016	0.0012	0.0014	0.0013	0.0015

Table 13. Total evaluation cloud of enterprises at $\alpha = 0.8$.

	A_1	A_2	A_3	A_4	A_5
Ex	0.0641	0.052	0.0561	0.0528	0.0574
En	0.0061	0.0047	0.0052	0.0046	0.0053
He	0.0015	0.0012	0.0013	0.0011	0.0014

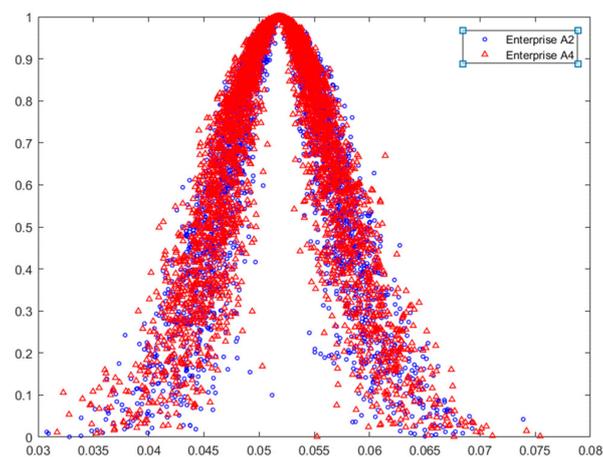


Figure 5. Comparison cloud of A_2 and A_4 at $\alpha = 0.5$.

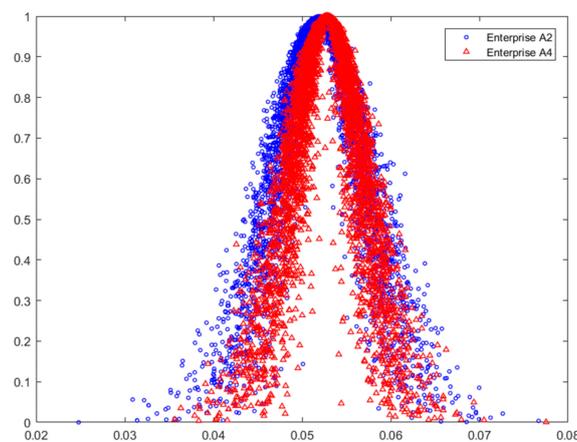


Figure 6. Comparison cloud of A_2 and A_4 at $\alpha = 0.8$.

In Tables 12 and 13, the ranking obtained from the cloud model evaluation is consistent with that calculated by the grey correlation analysis. Although the expectations E_x of A_2 and A_4 are similar, Figure 5 demonstrates that the thickness and span of A_4 are greater than that of A_2 , indicating that

A_2 has a high level of recognition by experts, and A_2 has good green innovation ability. As shown in Tables 12 and 13, as the association between enterprises increases, their optimal ranking changes from $A_1 > A_5 > A_3 > A_2 > A_4$ to $A_1 > A_5 > A_3 > A_4 > A_2$. According to the computations, the entropy value and super entropy value of enterprise A_2 both increase, but the entropy value and super entropy value of A_4 decrease, which reflects the considerable influence of the relationship with each index on A_4 . Figure 6 also shows that as α increases, the cloud span and thickness of A_4 decrease, i.e., the uncertainty of the enterprise decreases, and the design enterprise becomes reliable.

4.4.2. Validation Analysis of Cloud Model—Grey Correlation Analysis Method

To demonstrate the rationality and feasibility of the information processing of the cloud model, we performed a comparison with the results of an accurate numerical method. Values of 1, 3, 5, 7, and 9 were used to represent very poor, poor, medium, good, and excellent, respectively, and the group decision value was obtained by taking the arithmetic average. Then, the correlation degree of each scheme under different values of α was obtained by grey correlation analysis. The ranking of the enterprises is shown in Table 14.

Table 14. Correlation degree with different weights using the accurate value method.

	A_1	A_2	A_3	A_4	A_5
$\alpha = 0$	0.7515	0.5698	0.6239	0.5682	0.6381
$\alpha = 0.2$	0.7451	0.5686	0.6247	0.5704	0.6271
$\alpha = 0.5$	0.7355	0.5667	0.6107	0.5736	0.626
$\alpha = 0.8$	0.7258	0.5649	0.5943	0.5767	0.6272
$\alpha = 1$	0.7194	0.5637	0.5833	0.5789	0.628

Based on the ranking result, when the influence of correlation on the index weight increases, the capability of green innovation changes from $A_1 > A_5 > A_3 > A_2 > A_4$ to $A_1 > A_5 > A_3 > A_4 > A_2$. When $\alpha = 0.5$ and $\alpha = 0.8$, the correlation between A_2 and A_4 is relatively high, and the numerical method cannot compare the entropy and super entropy evaluation value through the cloud model graph, so it cannot directly reflect the judgments of experts on the green innovation ability of enterprises. Therefore, we conclude that the method described in this paper is useful, and that it provides a more sensitive method than the accurate numerical method in response to changes in parameter α .

5. Conclusions

Evaluating manufacturing enterprises' green innovation abilities in networks is a complex problem, since it depends on many factors. In this paper, the uncertainty of the evaluation index system was quantified using the cloud model and entropy theory, and the evaluation method of green innovation ability of manufacturing enterprises based on the cloud distance algorithm and grey correlation analysis was proposed. The primary novelty of this study is that it more objectively and effectively evaluates innovation capability, which was quantified by employing evaluation indicators described by cloud characteristics. The major contributions are as follows:

- (1) An evaluation index system was constructed based on previous studies, empirical research, and expert opinions. Fourteen factors influencing the green innovation ability of enterprises in a network were considered, which were divided into three categories: innovation input, innovation environment, and innovation output. The characteristics of cloud platforms were also considered, as they can provide a theoretical basis for improving the evaluation of green innovation systems in innovation networks.
- (2) A model for evaluating green innovation capability was established. In this model, the DEMATEL and entropy methods were employed to determine the index weights while considering the relationships among factors, which reduced the influence of experts' subjective judgment, and thereby, more objectively expressed the evaluation information.

- (3) The established model was applied to an empirical analysis: the evaluation of the manufacturing enterprises' green innovation abilities in a network. The application results could be used to compare the advantages and disadvantages of enterprises. The empirical study illustrates that this method can better assess manufacturing enterprises and continuously encourage them to provide better green innovation services, thus providing a prerequisite for the sustainable development of green innovation cooperation, and serving as a reference for decision makers.
- (4) However, this paper suffers from some limitations and shortcomings. Some factors may have been ignored in the formulation of the indicator system, which could have biased the evaluation results. The green innovation under the network environment involves many subjects. Therefore, we hope to conduct in-depth research incorporating environmental science, humanities, economics, and other aspects to explore more evaluation indices of green innovation and establish a general and flexible index system. Furthermore, the study only considers Chinese manufacturing companies as research objects, and the applicability of the conclusions obtained in other regions and industries remains to be further tested. Future research will consider expanding the sample scope.

In conclusion, this paper provides a method for evaluating manufacturing enterprises' green innovation abilities in networks. It is also useful for decision makers to judge the green innovation ability of an enterprise using the network platform and selected partners. We suggest that the Chinese government actively provide a platform and policy support for cooperation concerning green innovation through a network platform.

Author Contributions: Conceptualization, J.X.; and J.Z.; Formal analysis, J.Z.; Investigation, J.X.; Methodology, J.Z.; Writing—original draft, J.Z.; Writing—review & editing, J.Z.; Supervision: J.X. All authors have read and agreed to the published version of the manuscript.

Funding: The key research topics of economic and social development in Heilongjiang Province: 19023, National Natural Science Foundation emergency management project: 71841054, Natural Science Foundation of Heilongjiang Province: LH2019G014, The 2019 Annual Basic Project of the Party's Political Construction Research Center of the Ministry of Industry and Information Technology: 19GZY411

Conflicts of Interest: The authors declare no conflict of interest.

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