


Research Article

Evaluation of High-Quality Development of Manufacturing Industry Using a Novel Grey Dynamic Double Incentive Decision-Making Model

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Received 23 March 2022; Revised 22 April 2022; Accepted 23 April 2022; Published 26 May 2022

Academic Editor: Xunjie Gou

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This paper proposes a novel grey dynamic double incentive decision-making model to evaluate the high-quality development of manufacturing industry. First, we define the concepts of the improved grey incidence analysis and power weight Heronian aggregation (PWAHA) operator. Then, we present the double incentive factors and determine incentive static evaluation values. In addition, we construct the weight vector of the time series. Guided by the incentive static evaluation values and weight vector of the time series, the dynamic evaluation values are produced. Finally, a practical example of the manufacturing industry in the Yangtze River Delta (YRD) demonstrates the effectiveness and application of the proposed model.

1. Introduction

Dynamic multiple attribute decision-making (DMADM) (or called multiple period multiple attribute decision-making) plays an important role in modern decision science [1]. It has become a hot topic in academic research. In recent years, DMADM has received a great deal of attention from researchers in many disciplines [2].

There are many domestic and foreign scholars in the study who carried out a lot. Ma et al. [3] proposed the grey incidence decision-making method embodying development tendency. Liu et al. [4] combined group negotiation and Orness measure constraint to develop a dynamic group grey target decision method. Yu et al. [5] developed the grey incidence decision-making method based on close degree. Shen et al. [6] constructed an improved grey DMADM model to evaluate the core competence of private enterprises in Henan province. Geng et al. [7] employed the enhanced grey possibility clustering model to evaluate Chinese industry linkage ability. Hashemkhani Zolfani et al. [8]

proposed the prospective multiple attribute decision-making (PMADM) model. Jassbi et al. [9] developed a novel DMADM model with future knowledge for supplier selection, which was designed not only to deal with historical data but also to address the problem of considering future information. Venkateswarlu et al. [10] employed grey decision-making method to assess the profitability of Indian non-life insurance companies from 2008 to 2013. Most of the natural phenomena are fuzzy in nature [11, 12]. In light of this, Liu et al. [13] proposed a method for 2-tuple linguistic dynamic multiple attribute decision making with entropy weight. Ashraf et al. [14] developed a novel type-II fuzzy decision support system. Habib et al. [15] proposed the adaptive neuro-fuzzy inference system (ANFIS).

In addition, the aggregation operators are widely used in DMADM problems [16]. In order to consider the impacts of some unreasonable attribute values and objective interrelationships between the attribute values, a wide stream of research has been prompted in the academic community [17]. Different aggregation operators have different

functions, and some aggregation operators can relieve the influences of unreasonable attribute values, such as the power average (PA) operator [18]. In order to eliminate the effect of some unreasonable attribute values, PA operator aggregates the attribute values by allocating weighted vectors based on the support degree between the attributes. The good properties of PA operator have attracted the attention of many scholars. Many extended forms of PA operators have been proposed, such as linguistic power ordered weighted geometric (LPOWG) operator [19], 2-tuple linguistic power average (2TLPA) operator [20], and power geometric operators of trapezoidal intuitionistic fuzzy numbers (TriFNs) [21]. There are also some aggregation operators that can consider the interrelationship of the aggregated arguments, such as Heronian mean (HM) operator and Bonferroni mean (BM) operator [22]. Yu et al. [23] explained that the advantage of HM over BM is that HM can consider the correlation between an attribute and itself.

However, there is an important consideration that is missing, and the following deficiencies are found in existing research. (1) Development trends of the evaluation attribute values are often neglected. In fact, by considering the development trends of evaluation attributes and motivating the development trends positively or negatively, the evaluated object can be guided to develop in a better direction. (2) The impacts of some unreasonable attribute values and objective interrelationships between the attribute values are often considered separately rather than simultaneously. (3) The rationality of weighting methods is controversial. The weighting methods should make the evaluation results more realistic.

Based on the above analysis, a novel decision-making model, which can make up for the deficiencies (mentioned above), is proposed for evaluating the high-quality development of the manufacturing industry in the YRD. The new features of the proposed model and the main advantages of the results over others can be summarized as follows. (1) The proposed model has a new feature of double incentive factors in horizontal and vertical dimensions, respectively. Compared with other decision-making models, the advantage of the results calculated by using the model proposed in this paper is that it can incentivize the evaluated objects to develop in a better direction. (2) The model proposed in this paper improves power weight Heronian aggregation (PWHA) operator that can be applied to real numbers and has the other feature that can take into account the effects caused by unreasonable data and the objective interrelationships between the attribute values. (3) In the novel decision-making model, grey entropy theory and maximizing deviation method are combined to determine the weight vector of time series. This can make the evaluation results over others be more realistic.

To do this end, the remainder of this paper is organized as follows. In Section 2, a novel grey dynamic double incentive decision-making model is constructed. A case study of high-quality development of manufacturing industry in the YRD is employed in Section 3 to illustrate how the proposed model can be implemented. Section 4 comprises conclusions for this paper.

2. Grey Dynamic Double Incentive Decision-Making Model

In this section, we first define the grey incidence analysis based on the exponential function. Moreover, with the help of power Heronian aggregation (PHA) operator and attribute weights, we introduce the traditional PWHA operator applied to fuzzy numbers into real numbers and put forward the improved PWHA operator suitable for real numbers. Then, we define the double incentive factors to give incentives to the evaluated objects and combine grey entropy theory and maximizing deviation method to determine the weight vector of the time series. Finally, a novel grey dynamic double incentive decision-making model is constructed, which can guide the evaluated objects to develop in a better direction.

2.1. The Attribute Weights Determined by Grey Incidence Analysis Based on Exponential Function

Definition 1. Assume that $x_{ij}(t)$ and $y_{ij}(t)$ ($i = 1, 2, \dots, m$; $j = 1, 2, \dots, n$; $t = 1, 2, \dots, p$) stand for the original and normative attribute values of the j th attribute of the evaluated object i at time t , respectively. Then,

$$X(t) = \begin{bmatrix} x_{11}(t) & \cdots & x_{1j}(t) & \cdots & x_{1n}(t) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i1}(t) & \cdots & x_{ij}(t) & \cdots & x_{in}(t) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{m1}(t) & \cdots & x_{mj}(t) & \cdots & x_{mn}(t) \end{bmatrix}, \quad (1)$$

$$Y(t) = \begin{bmatrix} y_{11}(t) & \cdots & y_{1j}(t) & \cdots & y_{1n}(t) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ y_{i1}(t) & \cdots & y_{ij}(t) & \cdots & y_{in}(t) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ y_{m1}(t) & \cdots & y_{mj}(t) & \cdots & y_{mn}(t) \end{bmatrix},$$

are called as the original and normative attribute matrices, respectively.

When the property of the attribute is benefit-type, $y_{ij}(t)$ is as follows:

$$y_{ij}(t) = \frac{x_{ij}(t) - \min_i x_{ij}(t)}{\max_i x_{ij}(t) - \min_i x_{ij}(t)}. \quad (2)$$

When the property of the attribute is cost-type, $y_{ij}(t)$ can be written as follows:

$$y_{ij}(t) = \frac{\max_i x_{ij}(t) - x_{ij}(t)}{\max_i x_{ij}(t) - \min_i x_{ij}(t)}. \quad (3)$$

Relevant research shows that Deng's degree of grey incidence does not reflect the situation where the incidence between the two series is close to 0 or no correlation [6]. More importantly, the value of Deng's degree of grey incidence is between 0.3333 and 1, so the degree of

discrimination is not high [3]. Considering that the grey incidence analysis based on exponential function has a satisfactory discrimination, the paper employs it to assign weights to attributes. It can be defined as follows.

$$\delta_{ij}^+(t) = \exp\left(\frac{|y_{ij}(t) - y_{0j}^+(t)| - \min_i \min_j |y_{ij}(t) - y_{0j}^+(t)|}{\min_i \min_j |y_{ij}(t) - y_{0j}^+(t)| + \xi \max_i \max_j |y_{ij}(t) - y_{0j}^+(t)|}\right), \quad (4)$$

is called as the grey incidence coefficient of the j th indicator of the evaluated object i at time t and ξ is known as the distinguishing coefficient, which is generally taken as 0.5.

According to Definition 2, the weight of each attribute at time t can be obtained as follows:

$$w(t) = [w_1(t) \ \dots \ w_j(t) \ \dots \ w_n(t)] \\ = \left[\frac{\sum_{i=1}^m \delta_{i1}^+(t)}{\sum_{i=1}^m \sum_{j=1}^n \delta_{ij}^+(t)} \ \dots \ \frac{\sum_{i=1}^m \delta_{ij}^+(t)}{\sum_{i=1}^m \sum_{j=1}^n \delta_{ij}^+(t)} \ \dots \ \frac{\sum_{i=1}^m \delta_{in}^+(t)}{\sum_{i=1}^m \sum_{j=1}^n \delta_{ij}^+(t)} \right]. \quad (5)$$

Definition 2. $y_{ij}(t)$ is shown in Definition 1. Let $y^+(t) = [y_{01}^+(t) \ \dots \ y_{0j}^+(t) \ \dots \ y_{0n}^+(t)]$ be the data sequence of the positive ideal system's behavioral characteristics where $y_{0j}^+(t) = \max\{y_{1j}(t), \dots, y_{ij}(t), \dots, y_{mj}(t)\}$. Then,

2.2. The Static Evaluation Values Determined by the Improved PWHA Operator. The PWHA operator could take into account the objective interrelationships between the attributes and the effects caused by unreasonable data [22, 24]. Here, we propose the improved PWHA operator applied to real numbers. Moreover, the improved PWHA operator is used to aggregate the value of $y_{ij}(t)$, and then static evaluation values can be obtained, as shown below.

Definition 3. $y_{ij}(t)$ is shown in Definition 1. $w(t)$ is shown in formula (6). Let $p, q \geq 0$. Then,

$$\left(\frac{2}{n(n+1)} \sum_{j=1}^n \sum_{r=j}^n \left(\frac{nw_j(t)(1+T(y_{ij}(t)))}{\sum_{k=1}^n w_k(t)(1+T(y_{ik}(t)))} y_{ij}(t) \right)^p \left(\frac{mw_r(t)(1+T(y_{rk}(t)))}{\sum_{k=1}^n w_k(t)(1+T(y_{ik}(t)))} y_{ir}(t) \right)^q \right)^{1/p+q}, \quad (6)$$

is called as the improved PWHA ^{p,q} ($y_{i1}(t), y_{i2}(t), \dots, y_{in}(t)$) operator where

$$\begin{cases} T(y_{ij}(t)) = \sum_{h=1, h \neq j}^n \text{Sup}(y_{ij}(t), y_{ih}(t)), \\ \text{Sup}(y_{ij}(t), y_{ih}(t)) = 1 - d(y_{ij}(t), y_{ih}(t)), \\ d(y_{ij}(t), y_{ih}(t)) = |y_{ij}(t) - y_{ih}(t)|. \end{cases} \quad (7)$$

Here, $\text{Sup}(y_{ij}(t), y_{ih}(t))$ represents the support degree for $y_{ij}(t)$ from $y_{ih}(t)$. The improved PWHA operator is an extended version of PWHA in the field of real numbers. Considering that real numbers are different from fuzzy numbers, we define $d(y_{ij}(t), y_{ih}(t)) = |y_{ij}(t) - y_{ih}(t)|$, which is different from the traditional PWHA operator applied to fuzzy numbers. In addition, p and q are often taken as $p = q = 1$. $\text{Sup}(y_{ij}(t), y_{ih}(t))$ satisfies the following properties.

Theorem 1. $\text{Sup}(y_{ij}(t), y_{ih}(t)) \in [0, 1]$.

Theorem 2. $\text{Sup}(y_{ij}(t), y_{ih}(t)) = \text{Sup}(y_{ih}(t), y_{ij}(t))$.

Theorem 3. If $d(y_{ij}(t), y_{ih}(t)) \leq d(y_{il}(t), y_{iq}(t))$, then $\text{Sup}(y_{ij}(t), y_{ih}(t)) \geq \text{Sup}(y_{il}(t), y_{iq}(t))$.

Definition 4. Let the improved PWHA ^{p,q} ($y_{i1}(t), y_{i2}(t), \dots, y_{in}(t)$) be $y_i(t)$. Then,

$$Y = \begin{bmatrix} y_1(1) & \dots & y_1(t) & \dots & y_1(p) \\ \dots & \dots & \dots & \dots & \dots \\ y_i(1) & \dots & y_i(t) & \dots & y_i(p) \\ \dots & \dots & \dots & \dots & \dots \\ y_m(1) & \dots & y_m(t) & \dots & y_m(p) \end{bmatrix}, \quad (8)$$

is called as the static evaluation value matrix composed of the static value $y_i(t)$.

2.3. The Double Incentive Factors. In order to incentivize the evaluated objects, we define the double incentive factors in horizontal and vertical dimensions, as shown below.

Definition 5. $y_i(t)$ is shown in Definition 4. α ($0 \leq \alpha \leq 1$) and β ($0 \leq \beta \leq 1$) are parameters. Then,

$$\Delta_{\uparrow} y_i(t) = \begin{cases} 0, & t = 1, \\ \alpha \frac{y_i(t) - y_i(t-1)}{t - (t-1)}, & t = 2, \dots, p, \end{cases} \tag{9}$$

$$\Delta_{\rightarrow} y_i(t) = \begin{cases} 0, & t = 1 \\ \beta \left[\frac{y_i(t) - y_i(t-1)}{t - (t-1)} - \frac{1}{m-1} \sum_{g=1, g \neq i}^m \frac{y_g(t) - y_g(t-1)}{t - (t-1)} \right], & t = 2, \dots, p, \end{cases} \tag{10}$$

are called as the absolute growth rate and relative growth rate of $y_i(t)$ within $[t-1, t]$, respectively. α and β indicate the degree of subjective preference for the absolute growth trend and relative growth trend of $y_i(t)$, respectively. And, $\alpha + \beta = 1$; generally let $\alpha = \beta = 0.5$.

In the vertical dimension, $\Delta_{\uparrow} y_i(t)$ represents the development status of the static evaluation value $y_i(t)$ within $[t-1, t]$. (1) When $\Delta_{\uparrow} y_i(t) > 0$, there is a positive incentive for the upward development state of $y_i(t)$ within $[t-1, t]$. (2) When $\Delta_{\uparrow} y_i(t) < 0$, there is a negative incentive for the downward development state of $y_i(t)$ within $[t-1, t]$. (3) When $\Delta_{\uparrow} y_i(t) = 0$, there is no incentive for $y_i(t)$ that does not change within $[t-1, t]$.

In the horizontal dimension, $\Delta_{\rightarrow} y_i(t)$ represents the degree of difference in the development status of the static evaluation value $y_i(t)$ within $[t-1, t]$, compared with other evaluated objects. (1) When $\Delta_{\rightarrow} y_i(t) > 0$, there is a positive incentive for $y_i(t)$. (2) When $\Delta_{\rightarrow} y_i(t) < 0$, there is a negative incentive for $y_i(t)$. (3) When $\Delta_{\rightarrow} y_i(t) = 0$, there is no incentive for $y_i(t)$.

Definition 6. $y_i(t)$ is shown in Definition 4. $\Delta_{\uparrow} y_i(t)$ and $\Delta_{\rightarrow} y_i(t)$ are shown in Definition 5, respectively. Then,

$$y_i^*(t) = y_i(t) + \Delta_{\uparrow} y_i(t) + \Delta_{\rightarrow} y_i(t), \tag{11}$$

$$Y^* = \begin{bmatrix} y_1^*(1) & \dots & y_1^*(t) & \dots & y_1^*(p) \\ \dots & \dots & \dots & \dots & \dots \\ y_i^*(1) & \dots & y_i^*(t) & \dots & y_i^*(p) \\ \dots & \dots & \dots & \dots & \dots \\ y_m^*(1) & \dots & y_m^*(t) & \dots & y_m^*(p) \end{bmatrix}, \tag{12}$$

are called as the incentive static evaluation value of the evaluated object i at time t and incentive static evaluation value matrix composed of $y_i^*(t)$, respectively.

2.4. The Dynamic Evaluation Values Determined by Grey Entropy and Maximizing Deviation. Here, we combine grey entropy theory and maximizing deviation method to determine the weight vector of time series.

Definition 7. $y_i^*(t)$ is shown in Definition 6. Let $y_0^+ = [y_0^+(1) \dots y_0^+(t) \dots y_0^+(p)]$ be the data sequence of the positive ideal static evaluation value, and let $y_0^- = [y_0^-(1) \dots y_0^-(t) \dots y_0^-(p)]$ be the data sequence of the negative ideal static evaluation value, respectively, where $y_0^+(t) = \max\{y_1^*(t), \dots, y_i^*(t), \dots, y_m^*(t)\}$ and $y_0^-(t) = \min\{y_1^*(t), \dots, y_i^*(t), \dots, y_m^*(t)\}$. Let $u = [u(1) \dots u(t) \dots u(p)]$ be the weight vector of time series, which can be solved by the following nonlinear programming ($0 < \theta < 1/2$):

$$\begin{aligned} & \max \left\{ \theta \sum_{t=1}^p \sum_{i=1}^m u(t) |y_i^*(t) - y_0^+(t)| \right. \\ & \quad - \theta \sum_{t=1}^p \sum_{i=1}^m u(t) |y_i^*(t) - y_0^-(t)| \\ & \quad \left. - (1 - 2\theta) \sum_{t=1}^p u(t) \ln u(t) \right\}, \tag{13} \\ & \text{s.t. } \sum_{t=1}^p u(t) = 1, u(t) \geq 0, t = 1, 2, \dots, p. \end{aligned}$$

By constructing the Lagrange function to solve the above nonlinear programming, the expression of u is found as follows:

$$\begin{cases} u = [u(1) \dots u(t) \dots u(p)] = \left[\frac{f(1)}{\sum_{t=1}^p f(t)} \dots \frac{f(t)}{\sum_{t=1}^p f(t)} \dots \frac{f(p)}{\sum_{t=1}^p f(t)} \right], \\ f(t) = \exp \left(\frac{\theta}{1 - 2\theta} \left(\sum_{i=1}^m |y_i^*(t) - y_0^+(t)| - \sum_{i=1}^m |y_i^*(t) - y_0^-(t)| \right) - 1 \right). \end{cases} \tag{14}$$

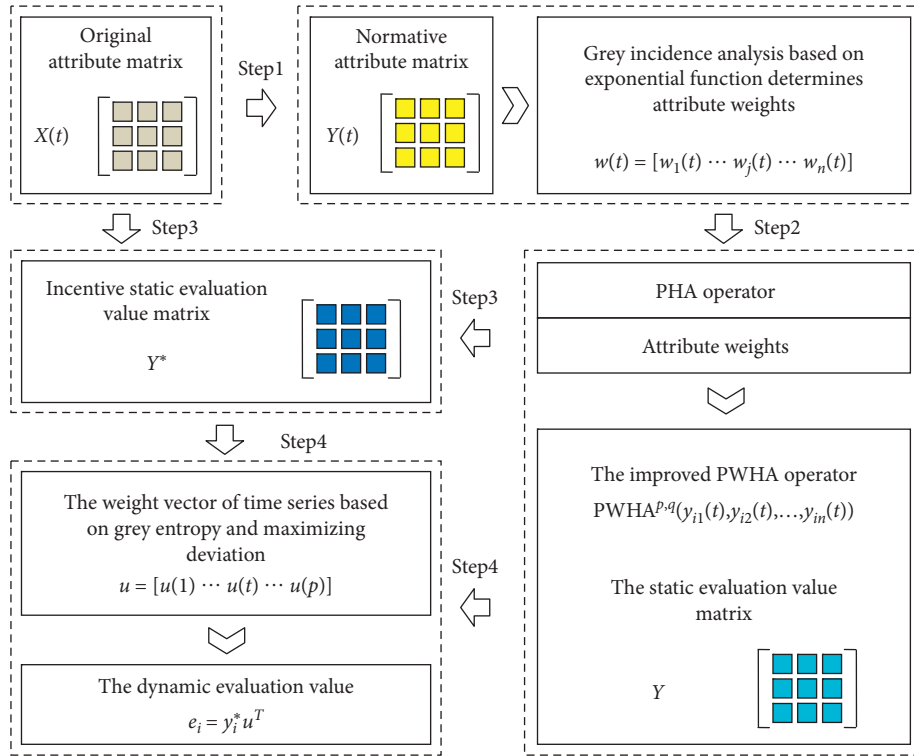


FIGURE 1: The operating process of the model proposed in the paper.

Definition 8. u is shown in Definition 7. Let $y_i^* = [y_i^*(1) \cdots y_i^*(t) \cdots y_i^*(p)]$. Then,

$$e_i = y_i^* u^T = y_i^*(1)u(1) + \cdots + y_i^*(t)u(t) + \cdots + y_i^*(p)u(p), \quad (15)$$

is called as the dynamic evaluation value. The larger the value of e_i , the better the performance of evaluated object i during $t \in [1, p]$, and vice versa.

2.5. The Steps of Grey Dynamic Double Incentive Decision-Making Model. In summary, the grey dynamic double incentive decision-making model has a clear operating process, as shown in Figure 1.

Step 1. Obtain the normative attribute matrix $Y(t)$ and use grey incidence analysis based on exponential function to determine the attribute weights $w(t)$.

Step 2. Use the improved PWHA operator to aggregate the value of $y_{ij}(t)$ and obtain the static evaluation value matrix Y .

Step 3. Obtain the incentive static evaluation value $y_i^*(t)$ and incentive static evaluation value matrix Y^* .

Step 4. By combining grey entropy theory and maximizing deviation method, produce the dynamic evaluation value e_i to rank the evaluated object i .



FIGURE 2: Geographical distribution of the YRD.

3. Case Analysis

The manufacturing industry is the mainstay of China's economy [25, 26]. The YRD is China's largest economic zone and one of the important manufacturing areas in China [27]. According to the outline of regional integration development plan for the Yangtze River Delta approved by the Chinese government in 2019, the YRD includes Shanghai, Jiangsu, Zhejiang, and Anhui, as shown in Figure 2. The coordinated development and low-carbon economy of Shanghai, Jiangsu, Zhejiang, and Anhui provinces in the YRD have been the strategy of the Chinese government. In

TABLE 1: Evaluation indicator system of high-quality development of manufacturing industry.

First-level indicators	Secondary-level indicators
R&D and innovation ability	Ratio of innovation output
	Ratio of R&D output
	R&D investment intensity
Processing and manufacturing ability	Ratio of new product main business income
	Ratio of low value added manufacturing assets
	Ratio of low value added manufacturing labor
	Ratio of cost-to-operating income
Brand marketing ability	Ratio of low value added manufacturing main business income
	Manufacturing competitiveness index
	Main business income per unit of current assets
Environmental protection ability	Ratio of the effective brand registration
	Ratio of product sales
	Industrial wastewater discharge per unit of main business income
	Industrial exhaust emissions per unit of main business income
	Industrial solid waste discharge per unit of main business income

TABLE 2: Static evaluation values of the evaluated objects from 2011 to 2017.

Objects	$y_i(t)$						
	2011	2012	2013	2014	2015	2016	2017
Shanghai	0.9601	0.9596	0.9599	0.9815	0.9313	0.9577	0.9397
Jiangsu	0.5106	0.5456	0.5591	0.5426	0.5840	0.5330	0.4537
Zhejiang	0.4167	0.3811	0.4201	0.3520	0.3368	0.3545	0.4121
Anhui	0.1809	0.2175	0.1876	0.2214	0.2676	0.3669	0.4378

TABLE 3: Absolute growth rate of $y_i(t)$.

Objects	$\Delta_{\uparrow} y_i(t)$						
	2011	2012	2013	2014	2015	2016	2017
Shanghai	0.0000	-0.0002	0.0001	0.0108	-0.0251	0.0132	-0.0090
Jiangsu	0.0000	0.0175	0.0067	-0.0082	0.0207	-0.0255	-0.0396
Zhejiang	0.0000	-0.0178	0.0195	-0.0341	-0.0076	0.0089	0.0288
Anhui	0.0000	0.0183	-0.0150	0.0169	0.0231	0.0497	0.0354

China, the development of the manufacturing industry is vital to the regional economy [28, 29]. Moreover, the main source of economy in the YRD is the manufacturing industry. So, the paper takes Shanghai, Jiangsu, Zhejiang, and Anhui in the YRD as objects to evaluate the high-quality development of manufacturing industry.

3.1. Selection of Evaluation Attributes and Data Sources. According to the Global Value Chain (GVC), Made in China 2025 document, and smile curve theory, this paper selects the evaluation indicators from four perspectives as shown in Table 1. The basic data are collected from the relevant statistical yearbooks between 2012 and 2018.

3.2. Evaluation Procedure

Step 1. The original attribute matrix is processed by equations (2) and (3), and then the normative attribute matrix is obtained. Here, we take the data in 2017 as an example to

show the working methodology. The evaluated object i takes 1, 2, 3, 4 to represent Shanghai, Jiangsu, Zhejiang, and Anhui. According to the calculated normative attribute matrix and Definition 2, the weight of each attribute in 2017 is [0.0829, 0.0692, 0.0550, 0.0586, 0.0539, 0.0575, 0.0553, 0.0527, 0.0747, 0.0706, 0.0674, 0.0572, 0.0853, 0.0707, 0.0889].

Step 2. According to the attribute weights and normative attribute matrices from 2011 to 2017, we can obtain the static evaluation values by formulas (6)–(8), as shown in Table 2.

Step 3. According to formulas (10)–(13) and the above data, we can get $\Delta_{\uparrow} y_i(t)$ and $\Delta_{\downarrow} y_i(t)$ and incentive static evaluation values $y_i^*(t)$, as shown in Tables 3–5.

Step 4. Considering that there is no preference in terms of maximizing deviation and grey entropy, we choose $\theta = 1/3$. According to formula (14) and Table 5, we can get the weight vector of time series as [0.1197, 0.1370, 0.0953, 0.1827, 0.1295, 0.1768, 0.1590]. Furthermore, according to formula

TABLE 4: Relative growth rate of $y_i(t)$

Objects	$\Delta \rightarrow y_i(t)$						
	2011	2012	2013	2014	2015	2016	2017
Shanghai	0.0000	-0.0031	-0.0018	0.0096	-0.0186	0.0011	-0.0086
Jiangsu	0.0000	0.0087	0.0026	-0.0031	0.0119	-0.0247	-0.0290
Zhejiang	0.0000	-0.0148	0.0111	-0.0203	-0.0069	-0.0018	0.0166
Anhui	0.0000	0.0093	-0.0119	0.0137	0.0136	0.0254	0.0210

TABLE 5: Incentive static evaluation values of the evaluated objects from 2011 to 2017.

Objects	$y_i^*(t)$						
	2011	2012	2013	2014	2015	2016	2017
Shanghai	0.9601	0.9562	0.9582	1.0020	0.8875	0.9720	0.9221
Jiangsu	0.5106	0.5718	0.5683	0.5313	0.6166	0.4829	0.3851
Zhejiang	0.4167	0.3484	0.4508	0.2976	0.3222	0.3615	0.4575
Anhui	0.1809	0.2451	0.1607	0.2520	0.3042	0.4420	0.4942

TABLE 6: Dynamic evaluation values of the evaluated objects.

Dynamic evaluation values/ranking	Shanghai ($e1$)	Jiangsu ($e2$)	Zhejiang ($e3$)	Anhui ($e4$)
Dynamic evaluation values	0.9537	0.5172	0.3733	0.3127
Ranking	$e1 > e2 > e3 > e4$			

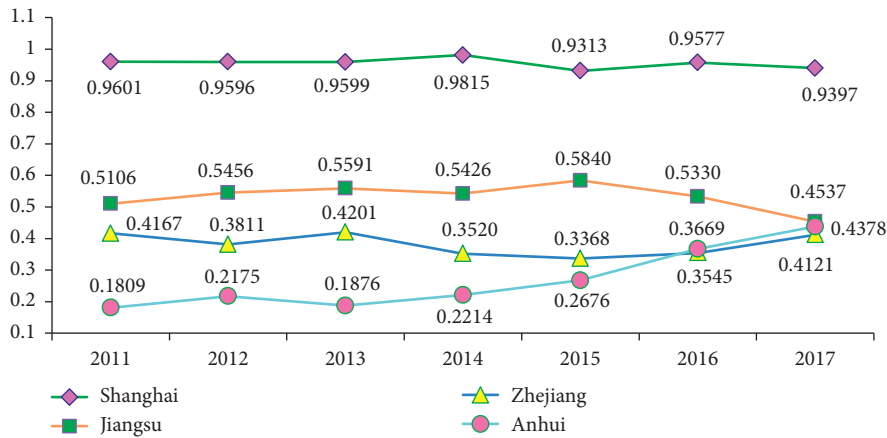


FIGURE 3: Before the incentive (static evaluation values).

(15), we can get the dynamic evaluation values of the evaluated objects, as shown in Table 6.

According to Table 6, the ranking result is $e1 > e2 > e3 > e4$. The high-quality development of manufacturing industry can be classified into three levels. The first level is Shanghai. Shanghai has the largest dynamic evaluation value, and its performance is the best in the high-quality development of manufacturing industry. The second level is Jiangsu. The third level is Zhejiang and Anhui. The dynamic evaluation values of Zhejiang and Anhui are very close, and Anhui is lower than Zhejiang. In fact, the comprehensive development level of Shanghai's economy and other aspects

is the best in the YRD. Anhui has just been included in the YRD by the Chinese government in 2019, and its development in various aspects has a gap compared with Shanghai, Zhejiang, and Jiangsu. The high-quality development of Anhui's manufacturing industry needs to be further improved.

3.3. Comparison Analysis. In order to embody the effectiveness of our proposed method, we first compare static evaluation values before and after the incentive, as shown in Figure 3 and Figure 4.

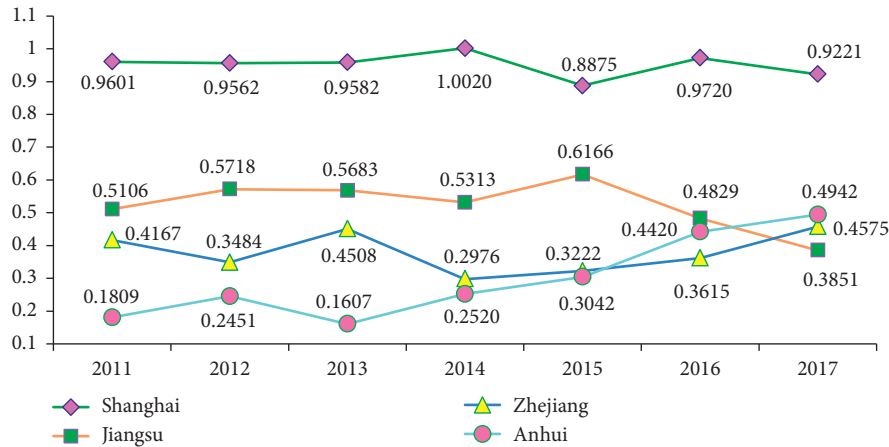


FIGURE 4: After the incentive (static evaluation values).

TABLE 7: Comparative analysis based on different methods.

Literature	Main methods	Shanghai (e_1)	Jiangsu (e_2)	Zhejiang (e_3)	Anhui (e_4)
Literature [6]	Traditional grey dynamic decision-making model, TOPSIS	0.8815	0.5290	0.2532	0.3605
This paper	Novel grey dynamic incentive decision-making model, the improved PWHA operator	0.9537	0.5172	0.3733	0.3127

We use the data in 2017 as an example to illustrate the role of the incentive. Before the incentive, the ranking of the static evaluation values in 2017 was $y_1(t) > y_2(t) > y_4(t) > y_3(t)$. After the incentive, the ranking of the static evaluation values in 2017 was $y_1^*(t) > y_4^*(t) > y_3^*(t) > y_2^*(t)$. The reason why the ranking of Anhui rose from third to second was that Anhui received a vertical positive incentive (0.0354) as well as a horizontal positive incentive (0.0210). Similarly, the reason why the ranking of Jiangsu dropped from second to fourth was that Jiangsu received a vertical negative incentive (-0.0396) as well as a horizontal negative incentive (-0.0290). The result of the ranking after the incentive is added to the role of management, which can guide the evaluated object to develop in a better direction.

In addition, in order to further demonstrate preponderance of the proposed model in this paper, the results based on the models developed in literature [6] are made. According to Table 7, we can see that Zhejiang and Anhui are ranked differently. There are two reasons for the different rankings. (1) The incentive plays a role. (2) The model proposed in this paper considers both the impacts of some unreasonable attribute values and objective interrelationships between the attribute values.

4. Conclusions

The purpose of this study is to take the YRD as an example to evaluate high-quality development of the manufacturing industry by constructing a novel grey dynamic double incentive decision-making model. The paper is a pioneer in the

integration of the grey incidence analysis, the improved PWHA operator, and the double incentive factors to construct incentive static evaluation values and further proposes the grey dynamic double incentive decision-making model. The model proposed in the paper can consider the impact of some unreasonable attribute values, the impact of objective interrelationships between the attribute values, and incentivize evaluated objects to develop in a better direction. The model is reasonable and effective, which not only helps improve the stability and adaptability of the decision-making but also makes the evaluation results be more realistic with reality.

Through case analysis, the performance of Shanghai, Jiangsu, Zhejiang, and Anhui in the high-quality development of the manufacturing industry can be clearly obtained. We get the following results: high-quality development of the manufacturing industry in the YRD can be classified into three levels. Shanghai is on the first level, which is the best performer in the high-quality development of the manufacturing industry in the YRD. Jiangsu is on the second level. Zhejiang and Anhui are on the third level, and Anhui is the worst performer.

Based on the analysis of our model and case analysis, the study of this paper has the following significance. On the one hand, the model enriches and widens the application field and scope of grey incidence analysis and PWHA operator. On the other hand, the evaluation results of Shanghai, Jiangsu, Zhejiang, and Anhui can help the relevant government to put forward some policies and suggestions to speed up the high-quality development of manufacturing industry in the lower ranking provinces.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The relevant research studies done in this paper are supported by the National Social Science Foundation of China (19BJL052) and Royal Society and NSFC International Exchanges project (IEC\NSFC\170391).

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