sustainability

MDPI

Article

Using a Novel Grey DANP Model to Identify Interactions between Manufacturing and Logistics Industries in China

Peng Jiang [1,*], Yi-Chung Hu [2,3], Ghi-Feng Yen [2], Hang Jiang [4] and Yu-Jing Chiu [3,*]

1 School of Economics and Management, Dalian Ocean University, Dalian 116023, China
2 College of Management & College of Tourism, Fujian Agriculture and Forestry University, Fuzhou 350002, China; ychu@cycu.edu.tw (Y.-C.H.); gfyen@cycu.edu.tw (G.-F.Y.)
3 Department of Business Administration, Chung Yuan Christian University, Taoyuan City 32023, Taiwan
4 School of Business Administration, Jimei University, Xiamen 361021, China; hangjiang@jmu.edu.cn
* Correspondence: jiangpeng@dlou.edu.cn (P.J.); yujing@cycu.edu.tw (Y.-J.C.); Tel.: +86-411-847-63562 (P.J.)

Received: 25 July 2018; Accepted: 25 September 2018; Published: 27 September 2018

check for updates

Abstract: As a crucial part of producer services, the logistics industry is highly dependent on the manufacturing industry. In general, the interactive development of the logistics and manufacturing industries is essential. Due to the existence of a certain degree of interdependence between any two factors, interaction between the two industries has produced a basis for measurement; identifying the key factors affecting the interaction between the manufacturing and logistics industries is a kind of decision problem in the field of multiple criteria decision making (MCDM). A hybrid MCDM method, DEMATEL-based ANP (DANP) is appropriate to solve this problem. However, DANP uses a direct influence matrix, which involves pairwise comparisons that may be more or less influenced by the respondents. Therefore, we propose a decision model, Grey DANP, which can automatically generate the direct influence matrix. Statistical data for the logistics and manufacturing industries in the China Statistical Yearbook (2006–2015) were used to identify the key factors for interaction between these two industries. The results showed that the key logistics criteria for interaction development are the total number of employees in the transport business, the volume of goods, and the total length of routes. The key manufacturing criteria for interaction development are the gross domestic product and the value added. Therefore, stakeholders should increase the number of employees in the transport industry and freight volumes. Also, the investment in infrastructure should be increased.

Keywords: grey relational analysis; logistics; manufacturing; interaction; DEMATEL; analytic network process

1. Introduction

The development of the manufacturing sector is an important index for measuring the overall strength of a country [1]. The manufacturing industry in China has undergone extensive development in recent decades. At present, China's manufacturing sector includes 31 industries, such as shipbuilding, metals, nuclear power, electronics, information, and the chemical industries, with advanced technology and strong production capacity. In addition, China has tens of thousands of product categories and an efficient supply–production–sales chain that flows from upstream to downstream industries [2]. In particular, China has become a global manufacturing plant. The manufacturing sector plays an important role in China's economy [3].

The development of the logistics industry will become an important industrial sector as well as a new economic growth point of China in the 21st century [4]. It will also improve the operational efficiency of the national economy as a whole, and directly increase the social economic benefits [5]. The sustainable development of various economic sectors will be promoted by the logistics industry. Firstly, it helps the manufacturing industry reduce product costs, thus improving the core competitiveness of manufacturing enterprises [6]. Secondly, it can encourage the development or new formats of many related fields such as the logistics equipment manufacturing industry, e-commerce, and so on [7]. Thirdly, the logistics industry can help the development of traditional transport enterprises by innovating the transportation mode [8].

The value added to the manufacturing sector in China increased from 5.17 trillion Yuan in 2004 to 21.43 trillion Yuan in 2016, with an average annual growth rate of 12.57%. Meanwhile, the value added to the logistics industry rose from 930.65 billion Yuan in 2004 to 3.31 trillion Yuan in 2016, with an average annual growth rate of 11.14%. The proportions of value added from the manufacturing sector and logistics industries to the gross domestic product (GDP) were 28.82% and 4.40%, respectively. Figure 1 shows the value added to the manufacturing and logistics industries and their proportion of the GDP from 2004 to 2016. It can be seen from the chart that although the proportion of GDP in 2016 is slightly lower than that in 2004, these two industries have basically maintained a stable development trend over the past 13 years.

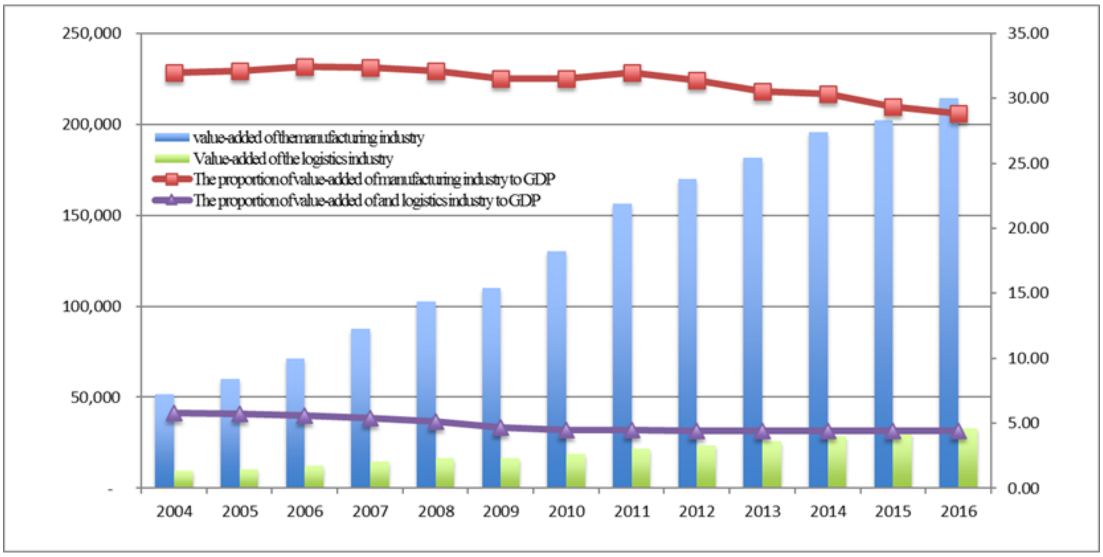

Figure 1. Value added from the manufacturing and logistics industries and their proportion of gross domestic product (GDP) from 2004 to 2016.

As a crucial provider of producer services, the logistics industry is highly dependent on the manufacturing sector [9,10]. Manufacturing is the main source of logistics demand [11], and progress in manufacturing has greatly helped and promoted the logistics sector [12]. In contrast, the development level of the logistics industry is directly related to the efficiency of manufacturers and the benefits that they experience [13].

In general, the interactive development of the logistics and manufacturing industries is essential [14]. As shown in Figure 2, comparing the growth rate of the manufacturing and logistics industries with that of GDP in the period of 2005–2016, it is can be found that the development of the manufacturing and logistics industries keep abreast of the growth of GDP, which means that these two industries had a certain impact on economic development. In addition, from the growth rate between the manufacturing and logistics industries from 2005 to 2016, it is obvious that the development of the logistic industry keeps in step with manufacturing industry. According to the similar development trend of these two industries, we are aware of the close relationship between the manufacturing and the logistics industries, showing an increasing trend of convergence.

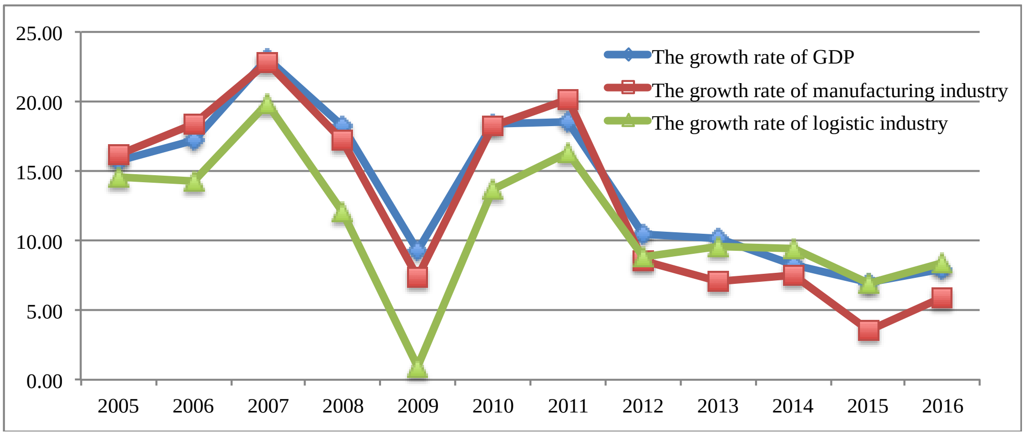

Figure 2. The growth rate of GDP, the manufacturing sector, and the logistics industry.

Different industries are measured by different indicators of performance [15]. Due to the existence of a certain degree of interdependence between any two factors, interaction between the two industries has produced a basis for measurement [16]. Therefore, for the sustainable development of the national economy, it is necessary to identify the key factors affecting the interaction between the two industries. However, the indexes evaluating industrial development are usually derived from statistical data. In previous studies [17–24], entropy is the most commonly used technique for obtaining index weights from statistical data. The entropy method is convenient in use, but it has some shortcomings [25]. For example, it is more suitable for deliberately highlighting attributes such as contractor selection [26]. In addition, if there are negative performance values, entropy will be invalid [27].

Identifying the key factors affecting the interaction between the manufacturing and logistics industries is a kind of decision problem in the field of multiple criteria decision making (MCDM). MCDM methods are often used to deal with the problems that are characterized by several non-commensurable and conflicting (competing) criteria, where there may be no solution that satisfies all of the criteria simultaneously [28]. Since the factors have interdependent impacts [29], a hybrid MCDM model called Decision Making Trial and Evaluation Laboratory (DEMATEL)-based Analytic Hierarchy Process (ANP) (DANP) [30] is suitable for solving such problems. However, DANP uses a direct influence matrix, which involves pairwise comparisons. Thus, what is required is how to generate the direct influence matrix for multiple criteria factors automatically. The grey relational analysis proposed by Deng [31], also known as GRA, can be used to effectively measure the degree of relationships between the given data sequences or patterns [32]. Therefore, we propose the Grey DANP decision model, which applies GRA to measure the criteria relationships and generate the direct influence matrix [33], and identifies the key factors for interaction between manufacturing and logistics industries and determines the causal relationships between any two key factors.

The remainder of this paper is organized as follows. Section 2 reviews the literature on the interaction between the manufacturing and logistics industries. Section 3 introduces the traditional DEMATEL-based ANP (DANP), and Section 4 introduces GRA and the proposed Grey DANP model. Section 5 applies the proposed model to identify key factors affecting the interaction between the two industries in China using statistical data from the yearbook of China. Section 6 discusses the various outcomes, and Section 7 provides the conclusions.

2. Interaction between Manufacturing and Logistics Industries

Previous studies have investigated the interactive development of manufacturing and logistics industries. As a crucial part of the modern economy and a most economical and reasonable service model in industrialization, the logistics industry is developing rapidly worldwide [8]. The interactive development of the two industries is aimed at symbiotic development, with principles of reciprocity and complementarity [34]. Good interaction between the two industries can reduce operating costs, encourage manufacturing productivity, improve core manufacturing competitiveness, and improve logistics service levels [35]. Therefore, the goal of interaction is to achieve a win–win situation [15].

One of the theoretical bases of interaction between the manufacturing and logistics industries is a specification of work [36]. Becker and Murphy [37] believed that a deepening of the division of labor and an increased number of service types would reduce manufacturing costs, which would be an endogenous mechanism for promoting the development of producer services [38]. Furthermore, the division of labor has network effects. The average cost and marginal cost tend to decrease as the level of specialization increases [39]. Logistics has a strong external economy; the improvement of logistics efficiency can reduce transaction costs, and then reduce labor costs [36], which is another theoretical basis of interaction between the manufacturing and logistics industries. The mechanism of interaction between the manufacturing and logistics industries entails two aspects: (1) the method of resource allocation in manufacturing enterprises, and (2) the trade-off in transaction costs between in-house and outsourced logistics [40].

In previous studies, many methods have been used to measure the interaction between the manufacturing and logistics industries, and numerous indicators can be used to evaluate manufacturing development and logistics development [36,41,42]. Table 1 shows the methodologies and indicators that have been described in relevant research articles.

Table 1. Methodologies and indicators for measuring the manufacturing and logistics. GDP: gross domestic product.

Method	Indicators for Manufacturing	Indicators for Logistics	Reference
Cointegration	Industrial value added; Gross industrial output value;	Added value of transportation, storage and postal services; Turnover of freight traffic; Total output value of the third industry	[43–47]
Panel data	Total labor productivity; Number of employees	Fixed assets net value	[48,49]
Grey relational model	Gross industrial output value; Industrial added value; Cost utilization ratio; Total investment in fixed assets; Industrial added value rate; The number of workers; Ratio of profits to Total Industrial Costs; All-personnel labor productivity	Logistics freight volume; Freight turnover; Number of employees; Length of transportation routes; Added value; Total investment in fixed assets; Highway mileage; Number of employees in railway transport industry; Number of civilian trucks	[34,41,50–54]
Input–output model	Added value; Intermediate needs rate; Intermediate input rate	Added value; Intermediate needs rate; Intermediate input rate	[55,56]
Data envelopment analysis	Added value; Capital stock; Labor force	Added value; Capital stock; Labor force	[49,57–59]
Principal component analysis	Total retail sales of social consumer goods; GDP; Gross output value	Operating mileage; Quantity of shipments	[60,61]
Coordination degree	Added value; Import and export volume; Manufacturing output	Added value; Total investment in fixed assets; Quantity of shipments;	[62]
System dynamics	Manufacturing output; GDP; Gross industrial output value	Logistics demand; Logistics supply; Total investment in fixed assets; Quantity of shipments	[15,63]
Vector Autoregression model	Added value	Added value	[64]

Duan et al. [65] indicated that the linked development of the manufacturing and logistics industries in Hubei Province was expected to accelerate the construction of supporting industries, cultivate and develop industrial clusters, and promote the development of multilevel logistics service outsourcing. Wang [53] proposed that governments should launch preferential policies, such as financial subsidies, for logistics companies to recruit employees. Peng and Feng [35] asserted that it is necessary to increase investment in logistics infrastructure, strengthen policy guidance, and encourage manufacturing firms to outsource logistics to promote the joint development of the two industries. Zhang [61] argued that manufacturers should focus on promoting informatization and standardization among manufacturers, and third party logistics (TPL) providers should implement Just-in-Time practices to boost the collaborative development of the manufacturing and logistics industries. Chen and Ma [54] noted that effective measures for the interactive development of the two industries include establishing a mechanism to promote the cooperation of the two industries, enacting preferential policies for the two industries, promoting the socialization of manufacturers for logistics needs, and improving TPL service quality.

3. DEMATEL-Based ANP (DANP)

DEMATELcan be applied to construct a network relation map (NRM) [66] for ANP by describing interdependencies visually in the form of networks of explainable nodes and directed arcs [28]. Ou Yang et al. [28] and Tzeng and Huang [66] proposed a novel DANP consisting of DEMETEL and ANP by taking the total influence matrix generated by DEMATEL as the unweighted supermatrix of ANP directly, avoiding the troublesome pairwise comparisons for ANP, particularly for high-order matrices [67]. Hu et al. [29] proposed a variant of DANP using the Borda method [68] to determine the key factors from prominences generated by DEMATEL and relative weights generated by DANP, as shown in Figure 3. To boost the analysis of interdependence among key factors, their DANP variant focused on the causal diagram for key factors rather than all of the factors in the original DANP. These distinctive features lead us to build the proposed decision model on the DANP variant.

To determine the DEMATEL total influence matrix, **T**, the direct influence matrix, **Z**, is first constructed using the degree of effect between each pair of elements taken from respondent questionnaires:

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1n} \\ z_{21} & z_{21} & \cdots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n1} & \cdots & z_{nn} \end{bmatrix}, \tag{1}$$

where n is the number of factors; and z_{ij} represents the extent to which factor i affects factor j, which is specified as a numerical scale. Commonly 0 = no effect, 1 = small effect, 2 = strong effect, and 3 = very strong effect; however, to reduce the effort of filling out questionnaires, this is sometimes shortened to a three-point scale: 0 = no effect, 1 = moderate effect, and 2 = very strong effect [69]. All of the diagonal elements are zero. **Z** is then normalized to produce the normalized direct influence matrix:

$$\mathbf{X} = \lambda \mathbf{Z}, \tag{2}$$

where:

$$\lambda = \frac{1}{\max\limits_{i,j}\left\{ \max \sum\limits_{i=1}^{n} z_{ij}, \max \sum\limits_{j=1}^{n} z_{ij} \right\}}, \tag{3}$$

Then, **T** is generated by X $(1 - \mathrm{X})^{-1}$, and can be treated as an unweighted supermatrix for ANP. A weighted matrix, **W**, can be obtained by normalizing **T**, and the global weight of each factor is obtained by multiplying **W** by itself several times until a limiting supermatrix, **W***, is derived.

Causes and effect can be derived from **T** [70]. For **T**, each row was summed to obtain the value denoted by d, and each column of the total influence matrix was summed to obtain the value denoted by r. Then, $d + r$ is the prominence, and shows the relative importance of the corresponding factor, where larger prominence implies greater importance; meanwhile, $d - r$ is the relation, where a positive relation means the corresponding factor tends to affect other elements actively, which is referred to as a *cause*, and a negative relation means the corresponding factor tends to be affected by other elements, which is referred to as an *effect*.

Since both DEMATEL and ANP provide the importance of each factor, Hu et al. [29] combined them using the Borda method rather than depending only on the degree of importance from ANP. For example, if a factor’s prominence was ranked second in DEMATEL, and fourth in ANP, then its Borda score was six. Thus, a smaller Borda score implied greater importance, which provides a method to select key factors. A causal diagram for key factors can be generated from the relations, following Hu et al. [29].

4. Proposed Decision Model

Since z_{ij} represents the impact on factor j from factor i, it is reasonable to refer to this as a relationship between factors i and j, reflecting the degree of influence or similarity. For example, consider the sales or manufacture of products in a marketplace. A product may be treated as an influential factor, which is described by multiple criteria such as price, size, customer satisfaction, etc. Then, it is worth generating **Z** by exploring the relationships among different products.

GRA can identify relationships between a given reference sequence and several comparative sequences by viewing the reference sequence as the desired goal [32], which can then be used to automatically generate the direct influence matrix.

To perform GRA, we must first compute the grey relational coefficients (GRCs) for each alternative. For the proposed model, we assume there are u ($u \geq 2$) categories that can be defined beforehand, and each factor can be categorized into a single category. Let factor l in category p, which is represented as $\mathbf{x}_{pl} = (x_{pl1}, x_{pl2}, \ldots, x_{pls})$ ($1 \leq l \leq c_p$), be a reference pattern, and let factor i in category q, which is represented as $\mathbf{x}_{qi}$, = $(x_{qi1}, x_{qi2}, \ldots, x_{qis})$ ($1 \leq i \leq c_q$), be a comparative pattern, where c_p and c_q denote the number of factors in categories p and q, respectively; and $c_1 + c_2 + \ldots + c_u = n$.

Since the measurement scales are likely to be different for each criterion, x_{plk} should be normalized following Chang [71], in the case of a benefit criterion:

$$x_{plk} = \frac{x_{plk}}{\max_{pk}}, \text{ for } 1 \leq l \leq c_p,\ 1 \leq k \leq s, \tag{4}$$

where $\max_{pk}$ and $\min_{pk}$ represent the maximum and minimum values, respectively, for criterion k in category p. For a cost criterion, the corresponding normalization is:

$$x_{plk} = \frac{-x_{plk}}{\min_{pk}} + 2, \text{ for } 1 \leq l \leq c_p,\ 1 \leq k \leq s. \tag{5}$$

x_{qik} may be normalized similarly. See Chang [71] for a full explanation of the principles to choose a suitable normalization.

Secondly, it is necessary to compute the grey relational coefficients (GRCs) for each factor. Let ξ_k (x_{qi}, x_{pl}) denote a GRC with respect to x_i, indicating the relationship between x_{qi} and x_{pl} on attribute k ($1 \leq k \leq s$). Then:

$$\xi_k(x_{qi}, x_{pl}) = \frac{\Delta_{\min} + \rho\Delta_{\max}}{\Delta_{isk} + \rho\Delta_{\max}}, \tag{6}$$

where ρ is the discriminative coefficient ($0 \leq \rho \leq 1$), and usually $\rho = 0.5$;

$$\Delta_{\min} = \min_{i=1\ldots c_q} \min_{j=1\ldots s} \left| x_{plj} - x_{qij} \right|; \tag{7}$$

$$\Delta_{\max} = \max_{i=1\ldots c_q} \max_{j=1\ldots s} \left| x_{plj} - x_{qij} \right|; \tag{8}$$

and:

$$\Delta_{ilk} = | x_{plk} - x_{qik} |. \tag{9}$$

The grey relational grade (GRG) indicates the grade of relationship between x_{qi} and x_{pl} and can be represented in this implementation as:

$$z(x_{qi}, x_{pl}) = \sum_{k=1}^{s} w_k \xi_k(x_{qi}, x_{pl}), \tag{10}$$

where w_k is the relative importance of attribute k. $z(x_{qi}, x_{pl})$ ranges from 0 to 1, and the sum of $w_1, w_2, \ldots, w_n$ is one. As a result, **Z** is a partitioned matrix comprising u^2 segments, where each segment represents a relationship between two categories in a system, and the segment related to the relationship between categories p and q is:

$$\mathbf{Z}_{qp} = \begin{bmatrix} z(x_{q1}, x_{p1}) & z(x_{q1}, x_{p2}) & \cdots & z(x_{q1}, x_{pc_p}) \\ z(x_{q2}, x_{p1}) & z(x_{q2}, x_{p2}) & \cdots & z(x_{q2}, x_{pc_p}) \\ \vdots & \vdots & \ddots & \vdots \\ z(x_{qc_q}, x_{p1}) & z(x_{qc_q}, x_{p2}) & \cdots & z(x_{qc_q}, x_{pc_p}) \end{bmatrix}, \text{ for } 1 \leq p, \ldots \leq u. \quad (11)$$

When $p = q$, the corresponding segment is called a grey self-relational matrix. Then, $z(x_{qi}, x_{qi})$ in $\mathbf{Z}_{qq}$ can be set to zero to conform to the requirement of DEMATEL. The novel Grey DANP model is summarized in Figure 3.

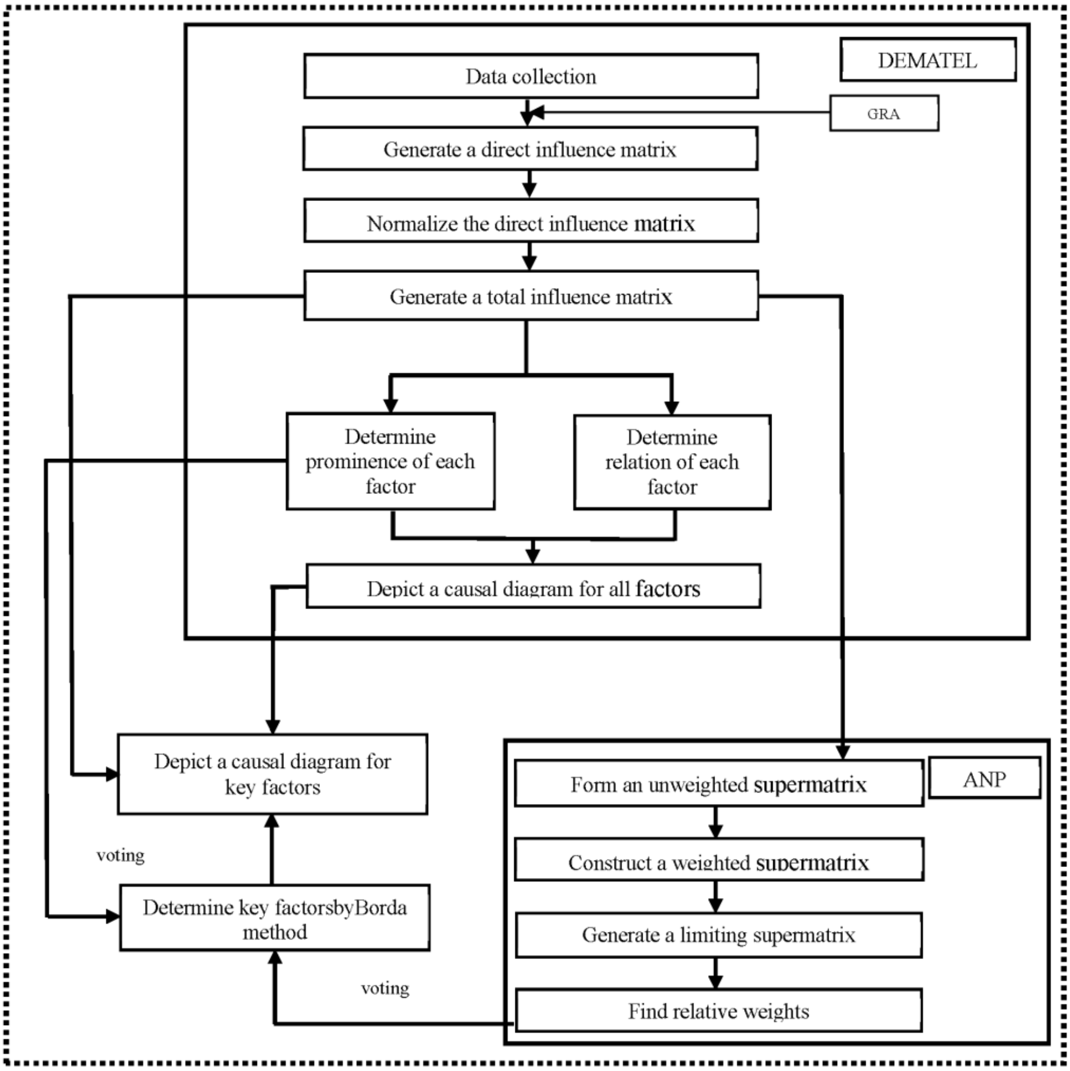

Figure 3. The framework of the proposed Grey DANP.

5. Empirical Study

5.1. Case Study

Governments regularly publish statistics on their domestic industry and economy, and these may be used to analyze the current state of economic development. Since these historical data are objective rather than subjective, we use them to evaluate the development of the logistics industry in China.

Tables 2 and 3 describe the factors associated with data collected from the ***China Statistical Yearbook*** for the period 2006–2015, and the manufacturing (X_1) and logistics (X_2) industries (i.e., $r = 2$), where X_1 and X_2 include five ($c_1 = 5$) and eight ($c_2 = 8$) alternatives, respectively. Therefore, $n = 13$. Each factor was described for 10 consecutive years (i.e., $s = 10$).

Table 2. Selected factors for logistics and manufacturing industries.

Industry	Factor
Logistics Industry (X_1) Aspect 1	Value added of transportation, storage, and postal services (100 million CNY) (x_{11})
	Total investment in fixed assets in transportation, storage, and postal services (100 million CNY) (x_{12})
	Volume of goods (100 million km) (x_{13})
	Volume of freight traffic (10,000 tons) (x_{14})
	Total number of employment in transport business (x_{15})
	Express volume (10,000 pieces) (x_{16})
	The total length of routes (km) (x_{17})
	Business outlets (x_{18})
Manufacturing Industry (X_2) Aspect 2	Employment in the secondary industry (million) (x_{21})
	Value added (100 million CNY) (x_{22})
	Gross domestic product (100 million CNY) (x_{23})
	Total investment in fixed assets (100 million CNY) (x_{24})
	Number of industrial enterprises (x_{25})

Table 3. Collected data for logistics and manufacturing industries.

Factor	Year									
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
x_{11}	12,186.3	14,605.1	16,367.6	16,522.4	18,783.6	21,842	23,763.2	26,042.7	28,500.9	30,488
x_{12}	12,138.12	14,154.01	17,024.36	24,974.67	30,074.48	28,291.66	31,444.9	36,790.12	43,215.67	49,200.04
x_{13}	88,839.85	101,418.8	110,300	122,133.3	141,837.4	159,323.6	173,804.5	168,013.8	181,667.7	178,355.9
x_{14}	2,037,060	2,275,822	2,585,937	2,825,222	3,241,807	3,696,961	4,100,436	4,098,900	416,7296	4,175,886
x_{15}	2,150,224	2,406,000	2,729,629	2,988,852	3,432,503	3,906,418	4,329,449	4,329,747	4,420,680	4,433,930
x_{16}	26,988.04	120,189.6	151,329.3	185,785.8	233,892	367,311.1	568,548	918,674.9	1,395,925	2,066,637
x_{17}	3,369,392	3,532,980	3,693,464	4,027,751	4,635,569	5,140,272	5,855,107	5,897,229	6,305,556	6,376,429
x_{18}	62,799	70,655	69,146	65,672	75,739	78,667	95,572	125,115	137,562	188,637
x_{21}	18,894.5	20,186	20,553.4	21,080.2	21,842.1	22,544	23,241	23,170	23,099	22,693
x_{22}	92,238.4	111,693.9	131,727.6	138,095.5	165,126.4	195,142.8	208,905.6	222,337.6	233,856.4	236,506
x_{23}	104,361.8	126,633.6	149,956.6	160,171.7	191,629.8	227,038.8	244,643.3	261,956.1	277,571.8	282,040
x_{24}	34,089.51	44,505.13	56,702.36	70,612.9	88,619.2	102,712.9	124,550	147,705	167,025.3	180,370.4
x_{25}	301,961	336,768	426,113	434,364	452,872	325,609	343,769	369,813	377,888	383,148

For DANP, the direct influence matrix is obtained by survey. In contrast, the proposed Grey DANP can use the objective historical data to hand, where $\mathbf{Z}$ can be automatically obtained by GRA by partitioning into four segments (i.e., $\mathbf{Z}_{11}$, $\mathbf{Z}_{12}$, $\mathbf{Z}_{21}$, and $\mathbf{Z}_{22}$).

5.2. Generating the Initial Direct Influence Matrix Using GRA

Since the measurement scales are different for the criteria in this study, the raw data should be normalized. The criteria selected to describe the development of the logistics and manufacturing industries were all benefit criteria (the larger-the-better attributes), so Equation (4) is suitable for normalization, as shown in Table 4.

Table 4. The results of normalization.

Factor	Year									
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
x_{11}	0.3997	0.4790	0.5369	0.5419	0.6161	0.7164	0.7794	0.8542	0.9348	1.0000
x_{12}	0.2467	0.2877	0.3460	0.5076	0.6113	0.5750	0.6391	0.7478	0.8784	1.0000
x_{13}	0.4890	0.5583	0.6072	0.6723	0.7808	0.8770	0.9567	0.9248	1.0000	0.9818
x_{14}	0.4878	0.5450	0.6193	0.6766	0.7763	0.8853	0.9819	0.9816	0.9979	1.0000
x_{15}	0.4849	0.5426	0.6156	0.6741	0.7741	0.8810	0.9764	0.9765	0.9970	1.0000
x_{16}	0.0131	0.0582	0.0732	0.0899	0.1132	0.1777	0.2751	0.4445	0.6755	1.0000
x_{17}	0.5284	0.5541	0.5792	0.6317	0.7270	0.8061	0.9182	0.9248	0.9889	1.0000
x_{18}	0.3329	0.3746	0.3666	0.3481	0.4015	0.4170	0.5066	0.6633	0.7292	1.0000
x_{21}	0.8326	0.8895	0.9057	0.9289	0.9625	0.9934	1.0241	1.0210	1.0179	1.0000
x_{22}	0.3900	0.4723	0.5570	0.5839	0.6982	0.8251	0.8833	0.9401	0.9888	1.0000
x_{23}	0.3700	0.4490	0.5317	0.5679	0.6794	0.8050	0.8674	0.9288	0.9842	1.0000
x_{24}	0.1890	0.2467	0.3144	0.3915	0.4913	0.5695	0.6905	0.8189	0.9260	1.0000
x_{25}	0.6668	0.7436	0.9409	0.9591	1.0000	0.7190	0.7591	0.8166	0.8344	0.8460

GRGs for $\mathbf{Z}_{11}$, $\mathbf{Z}_{12}$, $\mathbf{Z}_{21}$, and $\mathbf{Z}_{22}$ were calculated using Equations (6)–(10). The manufacturing factors were selected as an example to illustrate the operation steps.

First, we set x_{21} as the reference sequence and the other factors in aspect 2 as the comparability sequences. Parameters Δ_{1lk}, $\Delta_{\max}$, and $\Delta_{\min}$, and subsequently all of the grey relational coefficients were calculated using equations (6)–(9). For example, $\Delta_{212} = |0.8326 - 0.3900| = 0.4426$, $\Delta_{\max} = 0.6436$, and $\Delta_{min} = 0$; so $\xi_1(x_{21},x_{22}) = (0 + 0.5 \times 0.6436)/(0.4426 + 0.5 \times 0.6436) = 0.4210$. The complete grey relational coefficients $\xi_k(x_{21},x_{2l})$ are shown in Table 5, and Table 6 showed the results for $\xi_k(x_{2i},x_{2l})$.

Table 5. Calculating the grey relational coefficient (GRC) by treating x_{21} as the reference sequence.

Reference Sequence	Comparative Sequence	GRC									
		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
	x_{22}	0.4210	0.4354	0.4799	0.4826	0.5490	0.6566	0.6956	0.7991	0.9171	1.0000
	x_{23}	0.4103	0.4221	0.4625	0.4713	0.5320	0.6307	0.6725	0.7772	0.9051	1.0000
	x_{24}	0.3333	0.3336	0.3524	0.3745	0.4058	0.4315	0.4910	0.6142	0.7779	1.0000
	x_{25}	0.6599	0.6881	0.9014	0.9142	0.8956	0.5397	0.5483	0.6115	0.6369	0.6764

Table 6. Calculating the grey relational grade (GRG) by treating x_{2i} as the reference sequence.

Reference Sequence	Comparative Sequence	GRC										GRG
		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	
x_{21}	x_{21}	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	x_{22}	0.4210	0.4354	0.4799	0.4826	0.5490	0.6566	0.6956	0.7991	0.9171	1.0000	0.6436
	x_{23}	0.4103	0.4221	0.4625	0.4713	0.5320	0.6307	0.6725	0.7772	0.9051	1.0000	0.6284
	x_{24}	0.3333	0.3336	0.3524	0.3745	0.4058	0.4315	0.4910	0.6142	0.7779	1.0000	0.5114
	x_{25}	0.6599	0.6881	0.9014	0.9142	0.8956	0.5397	0.5483	0.6115	0.6369	0.6764	0.7072
x_{22}	x_{21}	0.3333	0.3466	0.3882	0.3908	0.4557	0.5680	0.6111	0.7322	0.8838	1.0000	0.5710
	x_{22}	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	x_{23}	0.9172	0.9048	0.8975	0.9326	0.9219	0.9167	0.9330	0.9514	0.9795	1.0000	0.9355
	x_{24}	0.5240	0.4953	0.4770	0.5349	0.5169	0.4640	0.5344	0.6461	0.7790	1.0000	0.5972
	x_{25}	0.4443	0.4492	0.3656	0.3710	0.4231	0.6759	0.6405	0.6418	0.5891	0.5897	0.5190
x_{23}	x_{21}	0.3333	0.3443	0.3821	0.3905	0.4497	0.5510	0.5961	0.7149	0.8727	1.0000	0.5635
	x_{22}	0.9205	0.9086	0.9014	0.9353	0.9250	0.9200	0.9357	0.9534	0.9803	1.0000	0.9380
	x_{23}	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	x_{24}	0.5610	0.5335	0.5156	0.5673	0.5515	0.4955	0.5667	0.6779	0.7991	1.0000	0.6268
	x_{25}	0.4380	0.4398	0.3611	0.3715	0.4191	0.7290	0.6811	0.6734	0.6070	0.6004	0.5320
x_{24}	x_{21}	0.3333	0.3336	0.3524	0.3745	0.4058	0.4315	0.4910	0.6142	0.7779	1.0000	0.5114
	x_{22}	0.6155	0.5880	0.5702	0.6258	0.6087	0.5573	0.6254	0.7264	0.8368	1.0000	0.6754
	x_{23}	0.6400	0.6141	0.5969	0.6459	0.6311	0.5774	0.6453	0.7454	0.8470	1.0000	0.6943
	x_{24}	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	x_{25}	0.4025	0.3931	0.3393	0.3618	0.3875	0.6828	0.8244	0.9929	0.7785	0.6764	0.5839
x_{25}	x_{21}	0.6587	0.6873	0.9056	0.9188	0.8997	0.5369	0.5457	0.6096	0.6353	0.6754	0.7073
	x_{22}	0.5348	0.5398	0.4526	0.4583	0.5131	0.7525	0.7213	0.7225	0.6748	0.6754	0.6045
	x_{23}	0.5173	0.5191	0.4368	0.4479	0.4979	0.7904	0.7485	0.7417	0.6816	0.6754	0.6057
	x_{24}	0.3989	0.3895	0.3358	0.3582	0.3839	0.6819	0.8265	1.0000	0.7795	0.6754	0.5830
	x_{25}	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

To compute the GRGs, the importance of all of the attributes (i.e., years) was assumed to be equal. From Equation (10), $z(x_{2i},x_{2l})$ are shown in the last column of Table 6. Since $p = 2$ and $q = 2$, Table 7 shows the grey self-relational matrix of $z(x_{2i},x_{2l})$.

Table 7. An example of the grey self-relational matrix for the manufacturing industry.

	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
x_{21}	0.0000	0.6436	0.6284	0.5114	0.7072
x_{22}	0.5710	0.0000	0.9355	0.5972	0.5190
x_{23}	0.5635	0.9380	0.0000	0.6268	0.5320
x_{24}	0.5114	0.6754	0.6943	0.0000	0.5839
x_{25}	0.7073	0.6045	0.6057	0.5830	0.0000

Finally, in this case, $u = 2$, so **Z** has four matrix segments, where each matrix segment represents a relationship between the logistics and manufacturing industries. The partitioned matrix represents the relationships between any two factors among the industries, and may be used to generate the initial direct influence matrix. Therefore, $z(x_{qi},x_{qi})$ was set to zero to conform to the requirements of DEMATEL, and the segments related to the relationships between the logistics and manufacturing industries were obtained using Equation (11), as shown in Table 8.

Table 8. The initial direct influence matrix.

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
x_{11}	0.0000	0.7534	0.7375	0.7291	0.7342	0.4478	0.7816	0.6395	0.7600	0.7560	0.4369	0.7184	0.5218
x_{12}	0.7404	0.0000	0.5751	0.5731	0.5761	0.5014	0.6086	0.7197	0.8475	0.8537	0.4638	0.9026	0.6347
x_{13}	0.7827	0.6497	0.0000	0.9616	0.9647	0.4512	0.9228	0.5893	0.8124	0.8181	0.4648	0.8811	0.6481
x_{14}	0.7764	0.6487	0.9621	0.0000	0.9918	0.4552	0.9037	0.5910	0.5185	0.5215	0.4781	0.5529	0.6727
x_{15}	0.7799	0.6503	0.9649	0.9918	0.0000	0.4552	0.9071	0.5920	0.8199	0.8206	0.5692	0.8456	0.7088
x_{16}	0.5068	0.5785	0.4538	0.4552	0.4564	0.0000	0.4665	0.6416	0.7291	0.7342	0.4478	0.7816	0.6395
x_{17}	0.8090	0.6623	0.9168	0.8954	0.8995	0.4462	0.0000	0.5890	0.5731	0.5761	0.5014	0.6086	0.7197
x_{18}	0.6133	0.7111	0.5031	0.5047	0.5071	0.5575	0.5223	0.0000	0.9617	0.9647	0.4512	0.9228	0.5893
x_{21}	0.6407	0.5704	0.7407	0.7600	0.7560	0.4369	0.7184	0.5218	0.0000	0.6436	0.6284	0.5114	0.7072
x_{22}	0.8728	0.7040	0.8549	0.8475	0.8537	0.4638	0.9026	0.6347	0.5710	0.0000	0.9355	0.5972	0.5190
x_{23}	0.8798	0.7204	0.8255	0.8124	0.8181	0.4648	0.8811	0.6481	0.5635	0.9380	0.0000	0.6268	0.5320
x_{24}	0.6756	0.8095	0.5227	0.5185	0.5215	0.4781	0.5529	0.6727	0.5114	0.6754	0.6943	0.0000	0.5839
x_{25}	0.7297	0.6560	0.7033	0.6892	0.6898	0.4784	0.7108	0.5958	0.7073	0.6045	0.6057	0.5830	0.0000

5.3. Determining the Total Influence Matrix

Following the DEMATEL method, the normalized direct influence matrix was obtained using Equation (2), as shown in Table 9. Since $\mathbf{T} = \mathbf{X}\,(\mathbf{I} - \mathbf{X})^{-1}$, the total influence matrix is shown in Table 10, and the prominence and relation of each factor are shown in Table 11.

Table 9. The normalized direct influence matrix.

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
x_{11}	0.0000	0.0827	0.0810	0.0801	0.0806	0.0492	0.0858	0.0702	0.0835	0.0830	0.0480	0.0789	0.0573
x_{12}	0.0813	0.0000	0.0632	0.0629	0.0633	0.0551	0.0668	0.0790	0.0931	0.0938	0.0509	0.0991	0.0697
x_{13}	0.0860	0.0714	0.0000	0.1056	0.1059	0.0496	0.1013	0.0647	0.0892	0.0899	0.0511	0.0968	0.0712
x_{14}	0.0853	0.0712	0.1057	0.0000	0.1089	0.0500	0.0993	0.0649	0.0569	0.0573	0.0525	0.0607	0.0739
x_{15}	0.0857	0.0714	0.1060	0.1089	0.0000	0.0500	0.0996	0.0650	0.0901	0.0901	0.0625	0.0929	0.0778
x_{16}	0.0557	0.0635	0.0498	0.0500	0.0501	0.0000	0.0512	0.0705	0.0801	0.0806	0.0492	0.0858	0.0702
x_{17}	0.0889	0.0727	0.1007	0.0983	0.0988	0.0490	0.0000	0.0647	0.0629	0.0633	0.0551	0.0668	0.0790
x_{18}	0.0674	0.0781	0.0553	0.0554	0.0557	0.0612	0.0574	0.0000	0.1056	0.1060	0.0496	0.1013	0.0647
x_{21}	0.0704	0.0626	0.0813	0.0835	0.0830	0.0480	0.0789	0.0573	0.0000	0.0707	0.0690	0.0562	0.0777
x_{22}	0.0959	0.0773	0.0939	0.0931	0.0938	0.0509	0.0991	0.0697	0.0627	0.0000	0.1027	0.0656	0.0570
x_{23}	0.0966	0.0791	0.0907	0.0892	0.0899	0.0511	0.0968	0.0712	0.0619	0.1030	0.0000	0.0688	0.0584
x_{24}	0.0742	0.0889	0.0574	0.0569	0.0573	0.0525	0.0607	0.0739	0.0562	0.0742	0.0763	0.0000	0.0641
x_{25}	0.0801	0.0720	0.0772	0.0757	0.0758	0.0525	0.0781	0.0654	0.0777	0.0664	0.0665	0.0640	0.0000

Table 10. The total influence matrix.

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}	d
x_{11}	0.6129	0.6414	0.6893	0.6873	0.6897	0.4457	0.6998	0.5838	0.6557	0.6869	0.5186	0.6621	0.5779	8.1512
x_{12}	0.6820	0.5602	0.6668	0.6654	0.6676	0.4475	0.6766	0.5870	0.6586	0.6908	0.5179	0.6738	0.5833	8.0774
x_{13}	0.7590	0.6930	0.6824	0.7766	0.7789	0.4892	0.7812	0.6351	0.7226	0.7580	0.5729	0.7406	0.6471	9.0367
x_{14}	0.6999	0.6386	0.7195	0.6227	0.7229	0.4515	0.7204	0.5857	0.6411	0.6728	0.5273	0.6549	0.5995	8.2570
x_{15}	0.7704	0.7036	0.7898	0.7909	0.6948	0.4970	0.7916	0.6450	0.7340	0.7697	0.5914	0.7482	0.6624	9.1890
x_{16}	0.5784	0.5450	0.5733	0.5724	0.5741	0.3427	0.5803	0.5111	0.5709	0.5989	0.4538	0.5846	0.5147	7.0004
x_{17}	0.7104	0.6469	0.7226	0.7194	0.7217	0.4556	0.6375	0.5920	0.6530	0.6852	0.5356	0.6669	0.6102	8.3569
x_{18}	0.6552	0.6190	0.6449	0.6439	0.6459	0.4434	0.6532	0.5014	0.6554	0.6868	0.5062	0.6614	0.5664	7.8830
x_{21}	0.6545	0.6010	0.6659	0.6665	0.6680	0.4284	0.6699	0.5514	0.5550	0.6515	0.5176	0.6181	0.5746	7.8224
x_{22}	0.7592	0.6899	0.7595	0.7573	0.7600	0.4846	0.7710	0.6321	0.6917	0.6683	0.6099	0.7059	0.6264	8.9158
x_{23}	0.7559	0.6880	0.7525	0.7499	0.7525	0.4822	0.7648	0.6301	0.6873	0.7579	0.5138	0.7049	0.6242	8.8640
x_{24}	0.6234	0.5932	0.6088	0.6072	0.6092	0.4108	0.6178	0.5380	0.5770	0.6222	0.4981	0.5331	0.5329	7.3717
x_{25}	0.6685	0.6148	0.6675	0.6649	0.6668	0.4365	0.6744	0.5638	0.6332	0.6541	0.5199	0.6311	0.5075	7.9031
r	8.9296	8.2346	8.9428	8.9244	8.9522	5.8153	9.0384	7.5566	8.4356	8.9032	6.8830	8.5857	7.6271	

Table 11. Prominence and relation of each factor.

Factor	d	r	$d+r$	$d-r$
x_{11}	8.1512	8.9296	17.0808	−0.7784
x_{12}	8.0774	8.2346	16.3120	−0.1571
x_{13}	9.0367	8.9428	17.9795	0.0939
x_{14}	8.2570	8.9244	17.1814	−0.6675
x_{15}	9.1890	8.9522	18.1412	0.2368
x_{16}	7.0004	5.8153	12.8157	1.1852
x_{17}	8.3569	9.0384	17.3953	−0.6815
x_{18}	7.8830	7.5566	15.4396	0.3264
x_{21}	7.8224	8.4356	16.2580	−0.6133
x_{22}	8.9158	8.9032	17.8190	0.0126
x_{23}	8.8640	6.8830	15.7470	1.9810
x_{24}	7.3717	8.5857	15.9574	−1.2140
x_{25}	7.9031	7.6271	15.5302	0.2760

5.4. Deriving the Limiting Supermatrix

Table 12 shows the weighted supermatrix, which is obtained by normalizing the total influence matrix, and Table 13 shows the limiting supermatrix derived from the weighted supermatrix. Table 14 shows the overall rankings for factors, which are arranged in ascending order of the Borda score of each factor.

Table 12. The weighted supermatrix for factors.

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
x_{11}	0.0686	0.0779	0.0771	0.0770	0.0770	0.0766	0.0774	0.0773	0.0777	0.0771	0.0753	0.0771	0.0758
x_{12}	0.0764	0.0680	0.0746	0.0746	0.0746	0.0770	0.0749	0.0777	0.0781	0.0776	0.0752	0.0785	0.0765
x_{13}	0.0850	0.0842	0.0763	0.0870	0.0870	0.0841	0.0864	0.0840	0.0857	0.0851	0.0832	0.0863	0.0848
x_{14}	0.0784	0.0776	0.0805	0.0698	0.0807	0.0776	0.0797	0.0775	0.0760	0.0756	0.0766	0.0763	0.0786
x_{15}	0.0863	0.0854	0.0883	0.0886	0.0776	0.0855	0.0876	0.0854	0.0870	0.0865	0.0859	0.0871	0.0869
x_{16}	0.0648	0.0662	0.0641	0.0641	0.0641	0.0589	0.0642	0.0676	0.0677	0.0673	0.0659	0.0681	0.0675
x_{17}	0.0796	0.0786	0.0808	0.0806	0.0806	0.0783	0.0705	0.0783	0.0774	0.0770	0.0778	0.0777	0.0800
x_{18}	0.0734	0.0752	0.0721	0.0721	0.0722	0.0763	0.0723	0.0663	0.0777	0.0771	0.0735	0.0770	0.0743
x_{21}	0.0733	0.0730	0.0745	0.0747	0.0746	0.0737	0.0741	0.0730	0.0658	0.0732	0.0752	0.0720	0.0753
x_{22}	0.0850	0.0838	0.0849	0.0849	0.0849	0.0833	0.0853	0.0836	0.0820	0.0751	0.0886	0.0822	0.0821
x_{23}	0.0846	0.0835	0.0841	0.0840	0.0841	0.0829	0.0846	0.0834	0.0815	0.0851	0.0746	0.0821	0.0818
x_{24}	0.0698	0.0720	0.0681	0.0680	0.0681	0.0706	0.0684	0.0712	0.0684	0.0699	0.0724	0.0621	0.0699
x_{25}	0.0749	0.0747	0.0746	0.0745	0.0745	0.0751	0.0746	0.0746	0.0751	0.0735	0.0755	0.0735	0.0665

Table 13. The limited supermatrix for factors.

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
x_{11}	0.0763	0.0763	0.0763	0.0763	0.0763	0.0763	0.0763	0.0763	0.0763	0.0763	0.0763	0.0763	0.0763
x_{12}	0.0756	0.0756	0.0756	0.0756	0.0756	0.0756	0.0756	0.0756	0.0756	0.0756	0.0756	0.0756	0.0756
x_{13}	0.0845	0.0845	0.0845	0.0845	0.0845	0.0845	0.0845	0.0845	0.0845	0.0845	0.0845	0.0845	0.0845
x_{14}	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773	0.0773
x_{15}	0.0859	0.0859	0.0859	0.0859	0.0859	0.0859	0.0859	0.0859	0.0859	0.0859	0.0859	0.0859	0.0859
x_{16}	0.0655	0.0655	0.0655	0.0655	0.0655	0.0655	0.0655	0.0655	0.0655	0.0655	0.0655	0.0655	0.0655
x_{17}	0.0783	0.0783	0.0783	0.0783	0.0783	0.0783	0.0783	0.0783	0.0783	0.0783	0.0783	0.0783	0.0783
x_{18}	0.0738	0.0738	0.0738	0.0738	0.0738	0.0738	0.0738	0.0737	0.0738	0.0738	0.0737	0.0738	0.0738
x_{21}	0.0733	0.0733	0.0733	0.0733	0.0733	0.0733	0.0733	0.0733	0.0733	0.0733	0.0733	0.0733	0.0733
x_{22}	0.0835	0.0835	0.0835	0.0835	0.0835	0.0835	0.0835	0.0835	0.0835	0.0835	0.0835	0.0835	0.0835
x_{23}	0.0828	0.0828	0.0828	0.0828	0.0828	0.0828	0.0828	0.0828	0.0828	0.0828	0.0828	0.0828	0.0828
x_{24}	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692
x_{25}	0.0740	0.0740	0.0740	0.0740	0.0740	0.0740	0.0740	0.0740	0.0740	0.0740	0.0740	0.0740	0.0740

Table 14. The overall ranking for the factors.

Factor	DEMATEL	DANP	Sum of Rankings (Borda Score)	Overall Rankings	Intra Industry Rankings
x_{11}	6	7	13	6	5
x_{12}	7	8	15	8	6
x_{13}	2	2	4	2	2
x_{14}	5	6	11	5	4
x_{15}	1	1	2	1	1
x_{16}	13	13	26	13	8
x_{17}	4	5	9	4	3
x_{18}	12	10	22	12	7
x_{21}	8	11	19	9	3
x_{22}	3	3	6	3	1
x_{23}	10	4	14	7	2
x_{24}	9	12	21	11	5
x_{25}	11	9	20	10	4

Considering the industry differences, it is reasonable to choose key factors for each industry. The key criteria in the logistics industry for interaction development are the total number of employment in transport business (x_{15}), the volume of goods (x_{13}), and the total length of routes (x_{17}). The key criteria in the manufacturing industry for interaction development are the gross domestic product (x_{23}) and value added (x_{22}).

5.5. Depicting the Causal Diagram

Figure 4 shows the causal diagram corresponding to the total influence matrix that is shown in Table 10.

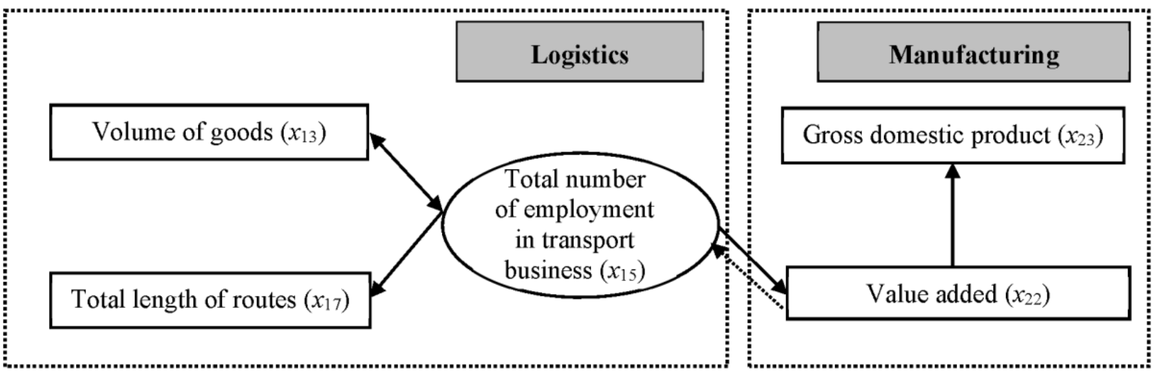

Figure 4. The causal diagram for key factors.

The influences between the volume of goods (x_{13}) and total number of employment in the transport business (x_{15}) are the two critical factors affecting the development of the logistics industry and facilitating the other key factors. Since the relation (i.e., $d - r$) of x_{13} and x_{15} are both greater than zero, x_{13} and x_{15} are appropriate to be the start.

The impact on x_{15} from the logistics industry is x_{13}, whereas it is interesting to know which factor in the manufacturing industry has the largest influence on x_{15}. Table 10 shows that x_{22} has the largest impacts on x_{15}. Thus, it is reasonable to presume that the "gross domestic product" and "value added" can be helpful to boost the "total number of employment in transport business". Figure 4 shows the impacts from x_{22} as a dashed line.

6. Managerial Implications

Both the manufacturing and logistics industries play a vital role in economic growth. The empirical results demonstrate that the development of the manufacturing industry can affect that of the logistics industry. Rapid economic growth can fuel the rapid growth of the logistics industry, and the logistics industry plays a crucial role in both microeconomic and macroeconomic aspects. Logistics is a service industry, and so provides substantial contributions to society, such as the promotion of infrastructure construction, employment, and consumption. Thus, governments attach great importance to the development of the logistics industry. However, due to the late start of modern logistics, the development of the logistics industry has been somewhat deficient. Therefore, ensuring the healthy development of the logistics industry in China has become a critical issue.

The five key factors determined by the Grey DANP (GDANP) are reasonable, because the total number of employees in the transport business was the most important criterion, with other key factors being the volume of goods, the total length of routes, GDP, and value added. As mentioned previously, the manufacturing industry can boost the development of the logistics industry mainly by eliciting an impact of x_{22} on x_{15}. Furthermore, the logistics factor influencing the development of the manufacturing industry is the total number of employees in the transport business. Manufacturing factors could promote the growth of the logistics industry, and logistics factors could promote growth in manufacturing as well, which is in agreement with past studies [15,34,35]. The five key factors and two results are discussed as follows.

First, from the perspective of the logistics industry, the total number of employees in the transport business represents the total productivity of the transport industry. Within the industry, the number of employees directly affects the volume of goods, and vice versa.

Hiring sufficient labor can enable the logistics industry to expand its operations and extend the total length of routes. For example, the rapid growth of e-commerce in China has led to a surge in the volume of express business, which has led to a marked rapid increase in the demand for air cargo. Therefore, various airlines have increased their aircraft acquisition to increase their market share. However, China faces a substantial shortage of domestic pilots. As Bloomberg reported, "Chinese airlines must hire almost 100 pilots a week for the next 20 years to meet [the] skyrocketing travel demand". This shortage severely limits business route extension.

The number of employees certainly affects value added. Labor is one of the most important essential productive factors. Sufficient labor resources in logistics can drive industrial output. Logistics providers can help manufacturers deliver products to the market to meet the growing consumer demand. Therefore, smooth and timely logistics service is essential for guaranteeing the delivery of products to the market. An adequate numbers of employees can ensure the successful implementation of services. Good outsourcing logistics services enable manufacturers to focus on their core business, and the value added by the manufacturer increases accordingly, which tends to increase profits. Problems with logistics tend to cascade into a host of related problems, such as a backlog of inventory. When this occurs, manufacturers must reduce production, which has a negative impact on manufacturing output.

Second, from the perspective of the manufacturing industry, value added affects the total number of employees in transport. Growing value added in manufacturing tends to increase logistics service demand. Logistics providers may need to hire additional workers to cope with the rapid growth of value added. However, output growth tends to drive consumption, and increasing consumption promotes employment. Furthermore, the quality of the labor force tends to rise accordingly. As Figure 4 shows, once the performance of x_{22} is improved, the performance of x_{23} tends to improve as well.

The improvement of x_{15} tends to improve the performance of other key factors. Therefore, the stakeholders (i.e., the Chinese government and logistics providers) should focus on this factor. To effectively improve x_{15}, logistics providers should accurately determine the number of employees that are required to guarantee normal operation, and the government should take effective measures to ensure the labor supply and improve the quality of the labor force. Logistics providers should also expand their distribution network, increasing their total length of routes, which tends to increase the number of employees. Furthermore, manufacturers should spare no effort in increasing GDP and value added. This ensures the competitive advantage and competitiveness of enterprises, and it promotes employment in the logistics industry, as well as other productive industries.

7. Conclusions

The purpose of this research was to identify the key factors affecting the interaction between the manufacturing and logistics industries using statistical data. GRA and DANP were combined to determine the key factors and identify how they affected each other. The proposed Grey DANP model has several distinct features in addition to the usual DANP strengths.

- The proposed method allows the use of historical statistical data as input, rather than respondent questionnaires. This will significantly expand the application scope, because data collection is greatly simplified, and is typically more objective.
- The proposed decision model applies GRA to measure the relationships among all of the factors, generating the initial direct influence matrix automatically, thereby avoiding the requirement for individual respondents to fill out tedious DEMATEL questionnaires. This will greatly improve the validity of the resultant data. Furthermore, the proposed model is not sensitive with the discriminative coefficient. An experiment in which the discriminative coefficient was taken as 0.1 and 0.9, respectively, is shown in the Appendix A.
- Causal relationships between any two factors in different categories can be determined visually, and negative values, which often occur in statistical data, can be accommodated by the proposed method, whereas negative values are not allowed by the previous methods that have been applied to obtain the relative weight, such as Entropy, analytic hierarchy process (AHP), ANP, etc.

Although the proposed Grey DANP model overcomes many of the shortcomings of the other methods, it must be extended in a number of ways. First, we selected just seven logistics and five manufacturing indicators for the example case. Other measurable indicators should also be considered. Second, if the attributes are not of equal weight, the method to calculate the weights for each attribute in the GRG process should be investigated.

Author Contributions: P.J. and Y.-C.H. conceived the research; G.-F.Y. and H.J. collected and analyzed data, and performed the experiments; P.J. and Y.-C.H. wrote the paper; and Y.-J.C. revised the paper. All authors have read and approved the final version.

Funding: This research is partially funded by the Research project of China Logistics Society, Grant/Award Number: 2018CSLKT3-200, and Ministry of Science and Technology of Taiwan under grant MOST104-2410-H-033-023-MY2.

Acknowledgments: The authors would like to thank the anonymous referees and the editors for their valuable comments. This research is partially funded by the Research project of China Logistics Society, Grant/Award Number: 2018CSLKT3-200, and Ministry of Science and Technology of Taiwan under grant MOST104-2410-H-033-023-MY2.

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

Appendix A

According to Equations (6)–(9), the initial direct influence matrix can be generated by GRA, and the two initial direct influence matrices are shown in Tables A1 and A2, respectively.

Table A1. The initial direct influence matrix (ρ = 0.1).

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
x_{11}	0.0000	0.4606	0.3870	0.3971	0.4027	0.2019	0.4561	0.3190	0.4790	0.4710	0.1985	0.4085	0.2371
x_{12}	0.4473	0.0000	0.2465	0.2682	0.2700	0.2276	0.2930	0.4003	0.5643	0.5761	0.2089	0.7003	0.3251
x_{13}	0.4448	0.3041	0.0000	0.8504	0.8596	0.1850	0.7293	0.2619	0.5074	0.5167	0.2094	0.6696	0.3443
x_{14}	0.4516	0.3204	0.8517	0.0000	0.9608	0.2054	0.6801	0.2813	0.2429	0.2446	0.2167	0.2644	0.3502
x_{15}	0.4562	0.3216	0.8602	0.9605	0.0000	0.2053	0.6864	0.2821	0.6103	0.6119	0.3414	0.6756	0.4896
x_{16}	0.2290	0.2705	0.1863	0.2054	0.2059	0.0000	0.2100	0.3245	0.3971	0.4027	0.2019	0.4561	0.3190
x_{17}	0.4936	0.3334	0.7147	0.6619	0.6693	0.2012	0.0000	0.2766	0.2682	0.2700	0.2276	0.2930	0.4003
x_{18}	0.2997	0.3919	0.2058	0.2313	0.2326	0.2680	0.2379	0.0000	0.8505	0.8597	0.1850	0.7294	0.2619
x_{21}	0.3235	0.2710	0.4288	0.4790	0.4710	0.1985	0.4085	0.2371	0.0000	0.3491	0.3346	0.2454	0.3724
x_{22}	0.6318	0.3728	0.5716	0.5643	0.5761	0.2089	0.7003	0.3251	0.2961	0.0000	0.7543	0.2877	0.1882
x_{23}	0.6331	0.3918	0.5314	0.5074	0.5167	0.2094	0.6696	0.3443	0.2887	0.7619	0.0000	0.3081	0.2012
x_{24}	0.3844	0.5173	0.2208	0.2429	0.2446	0.2167	0.2644	0.3502	0.2454	0.3467	0.3631	0.0000	0.2999
x_{25}	0.4492	0.3314	0.3348	0.3167	0.3176	0.1772	0.3506	0.2541	0.3806	0.2539	0.2607	0.3069	0.0000

Table A2. The initial direct influence matrix (ρ = 0.9).

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
x_{11}	0.0000	0.8384	0.8313	0.8239	0.8277	0.5768	0.8627	0.7527	0.8411	0.8384	0.5640	0.8129	0.6507
x_{12}	0.8284	0.0000	0.7009	0.6968	0.6995	0.6299	0.7272	0.8154	0.9073	0.9113	0.5932	0.9412	0.7461
x_{13}	0.8638	0.7639	0.0000	0.9779	0.9797	0.5825	0.9548	0.7121	0.8837	0.8876	0.5943	0.9267	0.7557
x_{14}	0.8587	0.7618	0.9782	0.0000	0.9954	0.5842	0.9432	0.7117	0.6437	0.6465	0.6064	0.6750	0.7789
x_{15}	0.8612	0.7631	0.9798	0.9954	0.0000	0.5842	0.9453	0.7126	0.8825	0.8828	0.6757	0.8979	0.7935
x_{16}	0.6365	0.7020	0.5851	0.5842	0.5855	0.0000	0.5963	0.7545	0.8239	0.8277	0.5768	0.8627	0.7527
x_{17}	0.8818	0.7722	0.9512	0.9380	0.9406	0.5751	0.0000	0.7115	0.6968	0.6995	0.6299	0.7272	0.8154
x_{18}	0.7304	0.8087	0.6332	0.6315	0.6338	0.6801	0.6504	0.0000	0.9779	0.9797	0.5825	0.9548	0.7121
x_{21}	0.7530	0.6926	0.8292	0.8411	0.8384	0.5640	0.8129	0.6507	0.0000	0.7495	0.7369	0.6329	0.8062
x_{22}	0.9226	0.8047	0.9123	0.9073	0.9113	0.5932	0.9412	0.7461	0.6837	0.0000	0.9628	0.7171	0.6535
x_{23}	0.9278	0.8169	0.8922	0.8837	0.8876	0.5943	0.9267	0.7557	0.6776	0.9644	0.0000	0.7427	0.6630
x_{24}	0.7763	0.8801	0.6496	0.6437	0.6465	0.6064	0.6750	0.7789	0.6329	0.7828	0.7978	0.0000	0.6943
x_{25}	0.8176	0.7623	0.8080	0.7982	0.7985	0.6112	0.8121	0.7177	0.8055	0.7274	0.7265	0.6923	0.0000

Following the DEMATEL method, the normalized direct influence matrix was obtained using Equation (2), as shown in Tables A3 and A4, respectively.

Table A3. The normalized direct influence matrix (ρ = 0.1).

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
x_{11}	0.0000	0.0709	0.0595	0.0611	0.0619	0.0311	0.0702	0.0491	0.0737	0.0724	0.0305	0.0628	0.0365
x_{12}	0.0688	0.0000	0.0379	0.0413	0.0415	0.0350	0.0451	0.0616	0.0868	0.0886	0.0321	0.1077	0.0500
x_{13}	0.0684	0.0468	0.0000	0.1308	0.1322	0.0285	0.1122	0.0403	0.0781	0.0795	0.0322	0.1030	0.0530
x_{14}	0.0695	0.0493	0.1310	0.0000	0.1478	0.0316	0.1046	0.0433	0.0374	0.0376	0.0333	0.0407	0.0539
x_{15}	0.0702	0.0495	0.1323	0.1477	0.0000	0.0316	0.1056	0.0434	0.0939	0.0941	0.0525	0.1039	0.0753
x_{16}	0.0352	0.0416	0.0287	0.0316	0.0317	0.0000	0.0323	0.0499	0.0611	0.0619	0.0311	0.0702	0.0491
x_{17}	0.0759	0.0513	0.1099	0.1018	0.1030	0.0309	0.0000	0.0425	0.0413	0.0415	0.0350	0.0451	0.0616
x_{18}	0.0461	0.0603	0.0317	0.0356	0.0358	0.0412	0.0366	0.0000	0.1308	0.1322	0.0285	0.1122	0.0403
x_{21}	0.0498	0.0417	0.0660	0.0737	0.0724	0.0305	0.0628	0.0365	0.0000	0.0537	0.0515	0.0377	0.0573
x_{22}	0.0972	0.0573	0.0879	0.0868	0.0886	0.0321	0.1077	0.0500	0.0455	0.0000	0.1160	0.0443	0.0289
x_{23}	0.0974	0.0603	0.0817	0.0781	0.0795	0.0322	0.1030	0.0530	0.0444	0.1172	0.0000	0.0474	0.0309
x_{24}	0.0591	0.0796	0.0340	0.0374	0.0376	0.0333	0.0407	0.0539	0.0377	0.0533	0.0558	0.0000	0.0461
x_{25}	0.0691	0.0510	0.0515	0.0487	0.0488	0.0273	0.0539	0.0391	0.0585	0.0390	0.0401	0.0472	0.0000

Table A4. The normalized direct influence matrix (ρ = 0.9).

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
x_{11}	0.0000	0.0841	0.0833	0.0826	0.0830	0.0578	0.0865	0.0755	0.0843	0.0841	0.0565	0.0815	0.0652
x_{12}	0.0831	0.0000	0.0703	0.0699	0.0701	0.0632	0.0729	0.0818	0.0910	0.0914	0.0595	0.0944	0.0748
x_{13}	0.0866	0.0766	0.0000	0.0980	0.0982	0.0584	0.0957	0.0714	0.0886	0.0890	0.0596	0.0929	0.0758
x_{14}	0.0861	0.0764	0.0981	0.0000	0.0998	0.0586	0.0946	0.0714	0.0645	0.0648	0.0608	0.0677	0.0781
x_{15}	0.0863	0.0765	0.0982	0.0998	0.0000	0.0586	0.0948	0.0714	0.0885	0.0885	0.0677	0.0900	0.0796
x_{16}	0.0638	0.0704	0.0587	0.0586	0.0587	0.0000	0.0598	0.0756	0.0826	0.0830	0.0578	0.0865	0.0755
x_{17}	0.0884	0.0774	0.0954	0.0940	0.0943	0.0577	0.0000	0.0713	0.0699	0.0701	0.0632	0.0729	0.0818
x_{18}	0.0732	0.0811	0.0635	0.0633	0.0635	0.0682	0.0652	0.0000	0.0980	0.0982	0.0584	0.0957	0.0714
x_{21}	0.0755	0.0694	0.0831	0.0843	0.0841	0.0565	0.0815	0.0652	0.0000	0.0751	0.0739	0.0635	0.0808
x_{22}	0.0925	0.0807	0.0915	0.0910	0.0914	0.0595	0.0944	0.0748	0.0685	0.0000	0.0965	0.0719	0.0655
x_{23}	0.0930	0.0819	0.0895	0.0886	0.0890	0.0596	0.0929	0.0758	0.0679	0.0967	0.0000	0.0745	0.0665
x_{24}	0.0778	0.0882	0.0651	0.0645	0.0648	0.0608	0.0677	0.0781	0.0635	0.0785	0.0800	0.0000	0.0696
x_{25}	0.0820	0.0764	0.0810	0.0800	0.0801	0.0613	0.0814	0.0720	0.0808	0.0729	0.0728	0.0694	0.0000

Since $\mathbf{T} = \mathbf{X}\,(\mathbf{I} - \mathbf{X})^{-1}$, the total influence matrices for ρ = 0.1 and ρ = 0.9 are shown in Tables A5 and A6, respectively.

Table A5. The total influence matrix (ρ = 0.1).

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}	d
x_{11}	0.1720	0.2066	0.2459	0.2518	0.2537	0.1132	0.2563	0.1659	0.2318	0.2442	0.1489	0.2302	0.1623	2.6829
x_{12}	0.2348	0.1409	0.2206	0.2279	0.2293	0.1165	0.2297	0.1769	0.2420	0.2577	0.1515	0.2677	0.1722	2.6676
x_{13}	0.2938	0.2315	0.2608	0.3827	0.3854	0.1380	0.3603	0.1967	0.2871	0.3056	0.1895	0.3207	0.2215	3.5735
x_{14}	0.2695	0.2123	0.3511	0.2409	0.3712	0.1287	0.3275	0.1817	0.2322	0.2471	0.1705	0.2466	0.2047	3.1840
x_{15}	0.3165	0.2505	0.4006	0.4193	0.2923	0.1506	0.3784	0.2136	0.3191	0.3389	0.2215	0.3406	0.2551	3.8971
x_{16}	0.1634	0.1464	0.1674	0.1733	0.1742	0.0629	0.1728	0.1378	0.1805	0.1920	0.1211	0.1940	0.1415	2.0273
x_{17}	0.2620	0.2040	0.3162	0.3146	0.3169	0.1219	0.2162	0.1724	0.2220	0.2361	0.1632	0.2355	0.2006	2.9815
x_{18}	0.2227	0.2036	0.2234	0.2316	0.2330	0.1260	0.2313	0.1243	0.2875	0.3039	0.1568	0.2777	0.1688	2.7905
x_{21}	0.2116	0.1727	0.2453	0.2559	0.2560	0.1082	0.2430	0.1479	0.1541	0.2185	0.1608	0.1984	0.1752	2.5477
x_{22}	0.3091	0.2312	0.3259	0.3300	0.3332	0.1356	0.3445	0.1978	0.2481	0.2257	0.2547	0.2577	0.1883	3.3817
x_{23}	0.3041	0.2298	0.3137	0.3157	0.3185	0.1333	0.3340	0.1970	0.2425	0.3257	0.1474	0.2553	0.1858	3.3029
x_{24}	0.1992	0.1918	0.1874	0.1938	0.1950	0.1015	0.1958	0.1511	0.1732	0.2001	0.1512	0.1431	0.1481	2.2312
x_{25}	0.2100	0.1673	0.2087	0.2101	0.2112	0.0967	0.2121	0.1383	0.1933	0.1873	0.1376	0.1895	0.1072	2.2693
r	3.1688	2.5886	3.4670	3.5474	3.5699	1.5332	3.5018	2.2013	3.0135	3.2827	2.1746	3.1570	2.3314	

Table A6. The total influence matrix (ρ = 0.9).

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}	d
x_{11}	0.9829	1.0125	1.0529	1.0497	1.0521	0.7820	1.0637	0.9521	1.0186	1.0570	0.8665	1.0278	0.9452	12.8631
x_{12}	1.0539	0.9300	1.0356	1.0327	1.0350	0.7828	1.0461	0.9529	1.0191	1.0581	0.8651	1.0335	0.9484	12.7932
x_{13}	1.1284	1.0685	1.0416	1.1282	1.1306	0.8309	1.1376	1.0074	1.0846	1.1262	0.9236	1.1008	1.0134	13.7219
x_{14}	1.0614	1.0049	1.0649	0.9731	1.0659	0.7818	1.0701	0.9477	1.0011	1.0397	0.8687	1.0154	0.9556	12.8502
x_{15}	1.1375	1.0773	1.1404	1.1389	1.0504	0.8379	1.1463	1.0158	1.0934	1.1351	0.9382	1.1073	1.0249	13.8435
x_{16}	0.9449	0.9079	0.9336	0.9312	0.9331	0.6552	0.9420	0.8649	0.9237	0.9591	0.7875	0.9374	0.8660	11.5866
x_{17}	1.0779	1.0197	1.0770	1.0733	1.0756	0.7918	0.9982	0.9607	1.0193	1.0586	0.8829	1.0337	0.9717	13.0404
x_{18}	1.0223	0.9829	1.0066	1.0039	1.0061	0.7701	1.0161	0.8566	1.0029	1.0409	0.8454	1.0121	0.9246	12.4905
x_{21}	1.0244	0.9723	1.0245	1.0230	1.0248	0.7593	1.0310	0.9172	0.9130	1.0205	0.8575	0.9839	0.9327	12.4842
x_{22}	1.1247	1.0634	1.1165	1.1134	1.1159	0.8251	1.1277	1.0023	1.0589	1.0361	0.9474	1.0743	0.9960	13.6018
x_{23}	1.1223	1.0619	1.1120	1.1086	1.1111	0.8232	1.1236	1.0007	1.0557	1.1216	0.8571	1.0739	0.9943	13.5662
x_{24}	0.9890	0.9535	0.9710	0.9680	0.9702	0.7359	0.9810	0.8955	0.9375	0.9871	0.8323	0.8887	0.8891	11.9988
x_{25}	1.0449	0.9927	1.0373	1.0339	1.0360	0.7747	1.0457	0.9367	1.0023	1.0338	0.8690	1.0039	0.8714	12.6823
r	13.7146	13.0477	13.6139	13.5779	13.6068	10.1508	13.7292	12.3105	13.1300	13.6737	11.3413	13.2927	12.3333	

Tables A7 and A8, respectively, show the limiting supermatrices derived from the weighted supermatrices for ρ = 0.1 and ρ = 0.9, respectively. Table A9 shows the overall rankings and intra-industry rankings for factors, arranging in ascending order of the Borda score of each factor.

Table A7. The limiting supermatrix (ρ = 0.1).

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
x_{11}	0.0716	0.0716	0.0716	0.0716	0.0716	0.0716	0.0716	0.0716	0.0716	0.0716	0.0716	0.0716	0.0716
x_{12}	0.0708	0.0708	0.0708	0.0708	0.0708	0.0708	0.0708	0.0708	0.0708	0.0708	0.0708	0.0708	0.0708
x_{13}	0.0945	0.0945	0.0945	0.0945	0.0945	0.0945	0.0945	0.0945	0.0945	0.0945	0.0945	0.0945	0.0945
x_{14}	0.0850	0.0850	0.0850	0.0850	0.0850	0.0850	0.0850	0.0850	0.0850	0.0850	0.0850	0.0850	0.0850
x_{15}	0.1031	0.1031	0.1032	0.1032	0.1031	0.1031	0.1031	0.1031	0.1032	0.1032	0.1031	0.1032	0.1032
x_{16}	0.0539	0.0539	0.0539	0.0539	0.0539	0.0539	0.0539	0.0539	0.0539	0.0539	0.0539	0.0539	0.0539
x_{17}	0.0796	0.0796	0.0796	0.0796	0.0796	0.0796	0.0796	0.0796	0.0796	0.0796	0.0797	0.0796	0.0796
x_{18}	0.0738	0.0738	0.0738	0.0738	0.0738	0.0738	0.0738	0.0738	0.0738	0.0738	0.0737	0.0738	0.0738
x_{21}	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684	0.0684
x_{22}	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909
x_{23}	0.0875	0.0875	0.0875	0.0875	0.0875	0.0875	0.0875	0.0875	0.0875	0.0875	0.0875	0.0875	0.0875
x_{24}	0.0604	0.0604	0.0603	0.0603	0.0603	0.0604	0.0603	0.0604	0.0603	0.0603	0.0604	0.0603	0.0604
x_{25}	0.0605	0.0605	0.0605	0.0605	0.0605	0.0605	0.0605	0.0605	0.0605	0.0605	0.0605	0.0605	0.0605

Table A8. The limiting supermatrix (ρ = 0.9).

	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}
x_{11}	0.0768	0.0768	0.0768	0.0768	0.0768	0.0768	0.0768	0.0768	0.0768	0.0768	0.0768	0.0768	0.0768
x_{12}	0.0764	0.0764	0.0764	0.0764	0.0764	0.0764	0.0764	0.0764	0.0764	0.0764	0.0764	0.0764	0.0764
x_{13}	0.0819	0.0819	0.0819	0.0819	0.0819	0.0819	0.0819	0.0819	0.0819	0.0819	0.0819	0.0819	0.0819
x_{14}	0.0767	0.0767	0.0767	0.0767	0.0767	0.0767	0.0767	0.0767	0.0767	0.0767	0.0767	0.0767	0.0767
x_{15}	0.0826	0.0826	0.0826	0.0826	0.0826	0.0826	0.0826	0.0826	0.0826	0.0826	0.0826	0.0826	0.0826
x_{16}	0.0691	0.0691	0.0691	0.0691	0.0691	0.0691	0.0691	0.0691	0.0691	0.0691	0.0691	0.0691	0.0691
x_{17}	0.0779	0.0779	0.0779	0.0779	0.0779	0.0779	0.0779	0.0779	0.0779	0.0779	0.0779	0.0779	0.0779
x_{18}	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745
x_{21}	0.0746	0.0746	0.0746	0.0746	0.0746	0.0746	0.0746	0.0746	0.0746	0.0746	0.0746	0.0746	0.0746
x_{22}	0.0812	0.0812	0.0812	0.0812	0.0812	0.0812	0.0812	0.0812	0.0812	0.0812	0.0812	0.0812	0.0812
x_{23}	0.0809	0.0809	0.0809	0.0809	0.0809	0.0809	0.0809	0.0809	0.0809	0.0809	0.0809	0.0809	0.0809
x_{24}	0.0717	0.0717	0.0717	0.0717	0.0717	0.0717	0.0717	0.0717	0.0717	0.0717	0.0717	0.0717	0.0717
x_{25}	0.0757	0.0757	0.0757	0.0757	0.0757	0.0757	0.0757	0.0757	0.0757	0.0757	0.0757	0.0757	0.0757

Table A9. The overall rankings and intra-industry rankings for factors.

Criteria	ρ = 0.1		ρ = 0.5		ρ = 0.9	
	Overall Rankings	Intra-Industry Rankings	Overall Rankings	Intra-Industry Rankings	Overall Rankings	Intra-Industry Rankings
x_{11}	7	5	6	5	5	4
x_{12}	10	7	8	6	7	6
x_{13}	2	**2**	2	**2**	2	**2**
x_{14}	5	4	5	4	6	5
x_{15}	1	**1**	1	**1**	1	**1**
x_{16}	13	8	13	8	13	8
x_{17}	4	**3**	4	**3**	4	**3**
x_{18}	9	6	12	7	12	7
x_{21}	8	3	9	3	9	3
x_{22}	3	**1**	3	**1**	3	**1**
x_{23}	6	**2**	7	**2**	7	**2**
x_{24}	11	4	11	5	11	5
x_{25}	12	5	10	4	10	4

According to Table A9, it is found that whether the discriminative coefficient is 0.1, 0.5, or 0.9, the key factors remain unchanged. This experiment proves that the proposed model is not sensitive to the discriminative coefficient.

References

1. Szirmai, A.; Verspagen, B. Manufacturing and economic growth in developing countries, 1950–2005. *Struct. Chang. Econ. Dyn.* **2015**, *34*, 46–59. [CrossRef]
2. Chiang, S.-H.; Hwang, J.-T. An investigation of urban agglomeration economies in Taiwanese manufacturing. *J. Taiwan Land Res.* **2007**, *10*, 127–149.
3. Fagerberg, J.; Verspagen, B. Technology-gaps, innovation-diffusion and transformation: An evolutionary interpretation. *Res. Policy* **2002**, *31*, 1291–1304. [CrossRef]

4. Qiu, Y.; Lu, H.-P.; Wang, H.-W. Prediction method for regional logistics. *Tsinghua Sci. Technol.* **2008**, *5*, 660–668. [CrossRef]
5. Cui, H.-K.; Zhang, L.; Jiang, Z.-J. Interactive analysis of logistics industry and economic development in China's western region. *Technoecon. Manag. Res.* **2015**, *2*, 101–105.
6. Sandberg, E.; Abrahamsson, M. Logistics capabilities for sustainable competitive advantage. *Int. J. Logist.* **2011**, *14*, 61–75. [CrossRef]
7. Marasco, A. Third-party logistics: A literature review. *Int. J. Prod. Econ.* **2008**, *113*, 127–147. [CrossRef]
8. Wang, Z.-Z. Interactive development of manufacturing and logistics: A literature review. *J. Manag.* **2014**, *27*, 41–47, 57.
9. Chan, J.W.K. Competitive strategies and manufacturing logistics: An empirical study of Hong Kong manufacturers. *Int. J. Phys. Distrib. Logist. Manag.* **2005**, *35*, 20–43. [CrossRef]
10. Voordijk, H. Obstacles and preconditions for logistics and manufacturing improvements in Africa—A case study. *Int. J. Oper. Prod. Manag.* **1999**, *19*, 293–307. [CrossRef]
11. Mortensen, O.; Lemoine, O.W. Integration between manufacturers and third party logistics providers? *Int. J. Oper. Prod. Manag.* **2008**, *28*, 331–359. [CrossRef]
12. Hertz, S.; Alfredsson, M. Strategic development of third party logistics providers. *Ind. Mark. Manag.* **2003**, *32*, 139–149. [CrossRef]
13. Choi, T.M.; Wallace, S.W.; Wang, Y.-L. Risk management and coordination in service supply chains: Information, logistics and outsourcing. *J. Oper. Res. Soc.* **2016**, *67*, 159–164. [CrossRef]
14. Hwang, B.N.; Chen, T.T.; Lin, J.T. 3PL selection criteria in integrated circuit manufacturing industry in Taiwan. *Supply Chain Manag. Int. J.* **2016**, *21*, 103–124. [CrossRef]
15. Wang, Z.-Z. Self-organized evolutionary dynamic model for the development of manufacturing and logistics. *Stat. Decis.* **2014**, *17*, 36–39.
16. Jiang, P.; Hu, Y.-C.; Yen, G.-F. Applying grey relational analysis to find interactions between manufacturing and logistics industries in Taiwan. *Adv. Manag. Appl. Econ.* **2017**, *7*, 21–40.
17. Hsu, P.-F.; Chien, P.-C. Optimal selection of media agencies for an advertiser using the GRA and Entropy. *J. Grey Syst.* **2008**, *20*, 27–38.
18. Hsu, P.-F.; Kuo, M.-H. An application of the GRA & Entropy to select a city in China for an international business office center. *J. Grey Syst.* **2007**, *19*, 269–282.
19. Kuo, Y.; Yang, T.; Huang, G.-W. The use of grey relational analysis in solving multiple attribute decision-making problems. *Comput. Ind. Eng.* **2008**, *55*, 80–93. [CrossRef]
20. Rajesh, S.; Rajakarunakaran, S.; Sudhkarapandian, R. Optimization of the red mud-aluminum composite in the turning process by the Grey relational analysis with entropy. *J. Compos. Mater.* **2014**, *48*, 2097–2105. [CrossRef]
21. Shuai, J.-J.; Wu, W.-W. Evaluating the influence of E-marketing on hotel performance by DEA and grey entropy. *Expert Syst. Appl.* **2011**, *38*, 8763–8769. [CrossRef]
22. Sun, C.-C. Combining grey relation analysis and entropy model for evaluating the operational performance: An empirical study. *Qual. Quant.* **2014**, *48*, 1589–1600. [CrossRef]
23. Verma, A.; Sarangi, S.; Kolekar, M.H. Stator winding fault prediction of induction motors using multiscale entropy and grey fuzzy optimization methods. *Comput. Electr. Eng.* **2014**, *40*, 2246–2258. [CrossRef]
24. Wu, W.-W. An integrated solution for benchmarking using DEA, gray entropy, and Borda count. *Serv. Ind. J.* **2012**, *32*, 321–335. [CrossRef]
25. Machado, J.A.T. Entropy analysis of systems exhibiting negative probabilities. *Commun. Nonlinear Sci. Numer. Simul.* **2016**, *36*, 58–64. [CrossRef]
26. Stosic, D.; Stosic, D.; Ludermir, T.; de Oliveira, W.; Stosic, T. Foreign exchange rate entropy evolution during financial crises. *Phys. A Stat. Mech. Its Appl.* **2016**, *449*, 233–239. [CrossRef]
27. Xu, M.-J.; Shang, P.-J.; Huang, J.-J. Modified generalized sample entropy and surrogate data analysis for stock markets. *Commun. Nonlinear Sci. Numer. Simul.* **2016**, *35*, 17–24. [CrossRef]
28. Ouyang, Y.-P.; Shieh, H.-M.; Tzeng, G.-H. A VIKOR technique based on DEMATEL and ANP for information security risk control assessment. *Inf. Sci.* **2013**, *232*, 482–500. [CrossRef]
29. Hu, Y.-C.; Chiu, Y.-J.; Hsu, C.-S.; Chang, Y.-Y. Identifying key factors of introducing GPS-based fleet management systems to the logistics industry. *Math. Probl. Eng.* **2015**, *2015*, 413203. [CrossRef]

30. Ouyang, Y.-P.; Shieh, H.-M.; Leu, J.-D.; Tzeng, G.-H. A novel hybrid MCDM model combined with DEMATEL and ANP with applications. *Int. J. Oper. Res.* **2008**, *5*, 160–168.
31. Deng, J.-L. Control problems of grey systems. *Syst. Control Lett.* **1982**, *1*, 288–294.
32. Hu, Y.-C.; Chen, R.-S.; Hsu, Y.-T.; Tzeng, G.-H. Grey self-organizing feature maps. *Neurocomputing* **2002**, *48*, 863–877. [CrossRef]
33. Jiang, P.; Hu, Y.-C.; Yen, G.-F.; Tsao, S.-J. Green supplier selection for sustainable development of the automotive industry using gray decision-making. *Sustain. Dev.* **2018**. [CrossRef]
34. Wang, Z.-Z.; Chen, G.-Y. Analysis on the evolutionary game of interactive development between manufacturing and logistics industry. *Econ. Issues China* **2012**, *2*, 86–97.
35. Peng, B.-H.; Feng, L.-Q. A study on the symbiotic mechanism of modern logistics industry and advanced manufacturing. *J. Bus. Econ.* **2010**, *1*, 18–25.
36. Wang, X.; Li, W. Analysis on the grey correlation between manufacturing and logistics industry in Dongguan. In Proceedings of the 2013 9th International Conference on Computational Intelligence and Security, Emeishan, China, 14–15 December 2013.
37. Becker, G.S.; Murphy, K.M. The division of labor, coordination costs, and knowledge. *Q. J. Econ.* **1992**, *107*, 1137–1160. [CrossRef]
38. Gu, N.-H.; Bi, D.-D.; Ren, W.-B. Relationship between producer services' development and manufacturing's competence in china during transition period—An empirical research based on panel data. *China Ind. Econ.* **2006**, *9*, 14–21.
39. Yang, X.-K. New development of enterprise theory. *Econ. Res. J.* **1994**, *7*, 60–65.
40. Wang, Z. The sources and innovation in the interactive development of the manufacturing and logistics industry. *China Bus. Mark.* **2009**, *23*, 16–19.
41. Wang, Z.-Z.; Chen, G.-Y. Empirical analysis of interactive development between manufacturing sub-sectors and logistics industry: Based on gray correlational model. *J. Shanghai Univ. Financ. Econ.* **2010**, *12*, 65–74.
42. Fan, J.; Lin, L.-S.; Gu, C.M. Research on manufacturing and logistics linkage development based on the grey correlation model—Case study of Zhejiang Province. In Proceedings of the 2nd International Conference of Electrical and Electronics Engineering, Macau, China, 1–2 December 2011.
43. Hou, H.-C. An analysis of the development of the linkage about logistics industry and manufacturing industry in Henan. *Enterp. Vitality* **2010**, *4*, 10–14.
44. Gan, W.-H.; Wang, J. An empirical study on the relationship between logistics industry and manufacturing industry in Jiangxi Province. *Commer. Times* **2010**, *17*, 27–28.
45. Wei, Q. Empirical study of linkage evolvement between manufacturing and logistics industry. *J. Zhongnan Univ. Econ. Law* **2011**, *1*, 115–119.
46. Ge, J.-T.; Liu, L.-H.; Chen, N.-N. An empirical analysis on the interactive development of manufacturing and logistics industry. *Logist. Eng. Manag.* **2012**, *34*, 19–21.
47. Chai, G.-J.; Li, W.-H.; Wei, J.-G.; Li, D. Inner Mongolia's modern logistics industry and manufacturing linkage relationship. *Logist. Manag.* **2012**, *6*, 34–37.
48. Wang, J.; Liang, H.-Y. An empirical research on the influence of logistics development on the efficiency of manufacturing industry. *China Bus. Mark.* **2012**, *26*, 27–32.
49. Yang, J. Research on the relationship between logistics industry and manufacturing efficiency in regional disparity perspective—An empirical research derived from panel data of China's provinces. *J. Guangxi Econ. Manag. Cadre Coll.* **2011**, *23*, 71–76.
50. Yuan, K.-Z. Research on the development of Yangtze River Delta manufacturing industry and regional logistics-based on gray relational analysis. *Econ. Soc. Dev.* **2007**, *5*, 65–70.
51. Han, X.-L.; Wang, L.; Tian, N.-J.; Tong, F.-T. The quantitative analysing on coordinated development between manufacture and logistics. *Value Eng.* **2009**, *28*, 84–86.
52. Li, S.-Q.; Su, K.-T. Gray relational analysis on the development of Guangdong manufacturing industry and logistics industry. *China Collect. Econ.* **2009**, *15*, 104–105.
53. Wang, Z.-Z. Empirical study of spatio-temporal differentiation of interactive development between manufacturing and logistics industry—Based on gray relational model. *J. Fujian Normal Univ. (Philos. Soc. Sci. Ed.)* **2012**, *3*, 31–39.
54. Chen, Z.-G.; Ma, J.-S. Correlativity analysis of manufacturing and logistics industries in Yunnan Province. *Logist. Technol.* **2011**, *30*, 79–82.

55. Wang, W.; Liu, W. Analytical method of contribution of production's logistic service to the market competitiveness of manufacturing. *Soft Sci.* **2010**, *24*, 15–19.
56. Su, Q.; Zhang, Y. International comparison and research on the interactive development of manufacturing and logistics industries. *China Soft Sci.* **2011**, *5*, 37–45.
57. Shi, G.-H.; Zhao, M. Evaluation of coordinated development between logistics and manufacturing in Jiangsu Province based on DEA. *Sci. Technol. Manag. Res.* **2010**, *30*, 62–65.
58. Fan, M. Research on operation efficiency and development strategy of Chinese urban agglomeration logistics industry—Based on industry operation and interactive development. *Soft Sci.* **2010**, *24*, 11–16.
59. Cui, X.-D. Analysis on interactive performance between manufacturing industry and logistics industry based on DEA- GRA model: Evidence from Tianjin. *Sci. Technol. Manag. Res.* **2011**, *31*, 96–100.
60. Wang, J.-X. Research on the Model of Synergetic Development of Logistics Industry and Manufacturing Industry in China. Unpublished Master's Dissertation, Wuhan University of Science and Technology, Wuhan, China, 2010.
61. Zhang, K.-J. The Econometric Analysis of Coordinated Development of Manufacturing and Logistics Industry—Case Study of Hangzhou. Unpublished Master's Dissertation, Zhejiang Gongshang University, Zhejiang, China, 2011.
62. Zhu, L. Research on Collaborative Development between Logistics and Manufacturing. Unpublished Master's Dissertation, Dalian Maritime University, Dalian, China, 2010.
63. Fu, Y.-J. An empirical study on the relationship between manufacturing industry and logistics industry based on system dynamics. *Port Econ.* **2011**, *8*, 43–46.
64. Wang, Z.-Z.; Chen, G.-Y. Study on the modes and relationship of interactive development between manufacturing and logistics industry—Based on the analysis of impulse response function and variance decomposition of VAR model. *Luojia Manag. Rev.* **2011**, *2*, 79–93.
65. Duan, Y.-L.; Fan, R.; Li, Z.-C. The coordinated development between manufacturing industry and logistics service industry in Hubei. *Logist. Technol.* **2009**, *9*, 11–14.
66. Tzeng, G.-H.; Huang, J.-J. *Multiple Attribute Decision Making: Methods and Applications*; CRC Press: Boca Raton, FL, USA, 2011.
67. Xu, Z.; Wei, C. A consistency improving method in the analytic hierarchy process. *Eur. J. Oper. Res.* **1999**, *116*, 443–449.
68. Heckelman, J. Probabilistic Borda rule voting. *Soc. Choice Welf.* **2003**, *21*, 455–468. [CrossRef]
69. Hu, Y.-C.; Jiang, P.; Yen, G.-F.; Chan, K.-C. Evaluating key factors of developing green logistics for logistics providers in China using multiple criteria decision making. *Int. J. Manag. Theory Pract.* **2016**, *17*, 73–91.
70. Lin, C.-L.; Hsieh, M.-S.; Tzeng, G.-H. Evaluating vehicle telematics system by using a novel MCDM techniques with dependence and feedback. *Expert Syst. Appl.* **2010**, *37*, 6723–6736. [CrossRef]
71. Chang, W.-C. Improvement on Grey Relational Generating Operation. In Proceedings of the 4th Conference on Grey System Theory and Applications, Kaohsiung City, Taiwan, 22 October 1998.