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A hybrid performance evaluation approach for urban logistics using extended cross-efficiency with prospect theory and OWA operator

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ABSTRACT

Urban logistics performance evaluation can provide reference for further improving its level. However, most performance evaluation for urban logistics premises that decision-makers (DMs) are completely rational, which may not conform to the actual situation. Therefore, this article aims to consider the DMs' psychological factors in the performance evaluation of urban logistics. Specifically, the cross-efficiency evaluation (CEE) method with the DMs' psychological factors is used to measure the urban logistics efficiency in the central area of Yangtze River Delta (YRD) urban agglomeration in China in 2019. The main contributions in this article are to propose a hybrid CEE method with prospect theory and ordered weighted average (OWA) operator for urban logistics industry and to expand the evaluation perspectives of urban logistics performance. The main conclusions are obtained: (1) The DMs' optimism level can indeed affect the efficiency value and ranking of urban logistics. (2) The aggregation based on the OWA operator is fair and reasonable because it can make all self-evaluation efficiencies play the same role. (3) To make the efficiencies and rankings of urban logistics in the central area of the YRD have credibility and discrimination, the DMs' optimism level range is best between 0.8 and 0.8177.

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Urban logistics efficiency; cross-efficiency; prospect theory; OWA operator; DEA

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1. Introduction

Logistics industry can drive the transformation of production and circulation modes of other industries, making an increasingly contribution to urban development and construction (Janne & Fredriksson, 2019). Urban development and logistics development are symbiotic. As the main artery of national economy, logistics industry plays an important role in promoting urban economic development. Nevertheless, the logistics performance in China is low and its cost is high as a whole (Zhang et al., 2020), which hinders cities' development to some extent. For the common progress of cities and logistics industry, it is urgent to improve urban logistics performance.

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Effective performance measurement can provide decision support for decision-makers (DMs) to improve the performance. Some scholars utilize logistics efficiency to reflect its performance (Blagojević et al., 2020; Rashidi & Cullinane, 2019). Referring to their practice, this article measures the performance of urban logistics from the perspective of efficiency.

Nowadays, the efficiency has become an important indicator for reflecting the development level of one field (Chen et al., 2020; Sun et al., 2021). Andrejic et al. (2021) pointed out that the operation efficiency has been recognized as a key factor for success and an essential prerequisite for further improvement for companies. It can be seen that efficiency evaluation can reflect the status of the evaluated object and more useful information for improving efficiency can be obtained according to the efficiency results. It needs a suitable evaluation method for reflecting the true situation of the evaluated object. It is well known that there are few DMs with completely rational psychology in the actual decision-making process. Although the efficiency results under the premise of complete rationality are objective, it does not mean that the psychological preferences of decision-making units (DMUs) need not be considered in the efficiency evaluation process (Shi et al., 2021). The analysis and countermeasures conducted according to the efficiency results under the incompletely rational hypothesis premise may be more in tune with reality. Urban logistics belongs to producer service industry and its operation is inseparable from human capital. The DMs' psychological factors play a certain role in the future development plan of urban logistics. Therefore, it is more reasonable to take the DMs' psychological factors into account in the evaluation of urban logistics efficiency.

The Yangtze River Delta (YRD) has become the first region in China to rank among world-class urban agglomerations nowadays. However, compared with the existing developed world-class urban agglomerations, the YRD urban agglomeration is still in development and relevant planning documents are constantly updated. The further development of the YRD urban agglomeration needs to grasp its current situation and adjustable direction. In 2019, the YRD urban agglomeration was expanded from 26 to 41 cities, covering whole Shanghai Municipality, Jiangsu, Zhejiang and Anhui Province. At the same time, the previous 26 cities and one more city constitute the central area of the YRD. Considering that the central area of the YRD is responsible for driving the development of surrounding cities, this article chooses the latest central area of the YRD as the research object.

According to the above analysis, this article decides to achieve the following three aims. First, consider the DMs' psychological factors in the evaluation of urban logistics efficiency to make the evaluation results more consistent with reality. Specifically, introduce the ordered weighted averaging (OWA) operator that reflects the DMs' optimism level into the cross-efficiency evaluation (CEE) method based on the prospect theory that expresses the DMs' behavioural preferences. Second, this article determines the DMs' optimism level range that can completely distinguish the efficiencies of the urban logistics in the central area of the YRD in 2019. Third, analyse the influence degree of the DMs' optimism level on logistics efficiency value of specific cities in the area in 2019. The three aims can be synthesized into one main purpose: use a hybrid CEE method which considers both the behavioural preference and the optimism level of the DMs to measure the urban logistics efficiency in the central area of the YRD in 2019, so as to reflect their more real performance level. Based on this, more realistic countermeasures and suggestions can be put forward to promote the urban logistics' development.

The main contribution and novelty of this article are described as follows:

1. This article proposes a hybrid cross-efficiency evaluation method with the prospect theory and the OWA operator for urban logistics. The optimism level of the DMs is introduced into the prospect theory-based CEE method and measured by the OWA operator. Therefore, the DMs' psychological factors are fully taken into account during the whole process of cross-efficiency evaluation.
2. Taking urban logistics as the research object, this article expands the evaluation perspective of urban logistics performance. To be specific, it has hardly been done to integrate the DMs' behavioural preference and optimism level into the evaluation of urban logistics efficiency.
3. Considering the important strategic position of the central area of the YRD in China's economic development and the update of the cities included in this area in 2019, this article has practical significance to measure and analyse the urban logistics efficiency in the area.

The rest of this article is organized as follows. Section 2 reviews the research perspectives and evaluation methods of urban logistics efficiency. The emphasis is put on the theoretical development and application of the cross-efficiency evaluation method. Section 3 presents the flow chart for measuring the urban logistics efficiency in the central area of the YRD. The specific steps and models are elaborated in detail. Section 4 carries out an analysis on the state of urban logistics in the central area of YRD. After that, the calculation and discussion of urban logistics efficiency in the area are conducted. Section 5 concludes this article and points out the deficiencies.

2. Literature review

At present, some scholars pay attention to the study of urban logistics efficiency. Zhang and Cui (2020) calculated the logistics efficiency of 17 cities in Shandong Province of China through the super-efficiency DEA model. The status quo and spatial characteristics of logistics efficiency in Shandong were reflected. Using stochastic frontier analysis (SFA) method, Wang et al. (2021) measured logistics technology and energy efficiency of 216 prefecture-level cities in China. It was found that their mean values were low and varied greatly. The most methods only evaluate urban logistics efficiency from a completely rational perspective, ignoring the role of the DMs' psychological characteristics in the evaluation process.

It can be seen that the evaluation methods of urban logistics efficiency mainly include the SFA method and the DEA method. The former can only evaluate the DMUs with multiple inputs and single output and need to presuppose production function forms (Wang et al., 2021). The latter can evaluate the DMUs with multiple inputs and multiple outputs, and directly calculate their efficiencies by using empirical data based on linear programming. Obviously, the latter applies to more situations and the calculation process is simpler. The theory research and application about the DEA method are very extensive (Hassanpour, 2021; Liu et al., 2022). As one of the DEA method, the cross-efficiency evaluation (CEE) method includes two mechanisms: self-evaluation and peer-evaluation (Sexton et al., 1986). Compared with the traditional DEA method, its efficiency results are not only more comprehensive, but also can be fully differentiated (Chen et al., 2020). This method has been recognized and widely studied by many scholars. In the existing literature, its theoretical research includes two directions, namely, avoiding the non-uniqueness of input and output weights used for peer-evaluation (Shi et al., 2021) and determining appropriate weights for aggregating the self-evaluation and peer-evaluation efficiencies (Chen et al., 2020). Its application manifests in many fields, such as logistics performance evaluation (Yang et al., 2019), supplier selection (Goswami & Ghadge, 2020; Soltanifar & Sharafi, 2022) and so on.

For obtaining a unique set of input and output weights for peer-evaluation, it can construct one secondary goal (SG) model based on the self-evaluation efficiency (Doyle & Green, 1994). So far, many SG models have been constructed by researchers from different perspectives (Wu et al., 2021). These research perspectives are mainly divided into the benevolent or aggressive strategy (Chen & Wang, 2020; Wu et al., 2016), the neutral strategy (Shi et al., 2019; Wang & Chin, 2010), and other strategies (Contreras et al., 2021; Liu et al., 2021). Nowadays, more and more scholars have noticed that the DMs' psychological attitudes play an important role in practice (Chen et al., 2020). This feature has been incorporated into the construction of the SG model. For example, Liu et al. (2019) introduced the prospect theory proposed by Kahneman and Tversky (1979) into the objective function of the SG model to reflect the DMs' risk attitudes, developing a prospect cross-efficiency (PCE) model. Subsequently, Shi et al. (2021) extended the PCE model considering that the reference points in the prospect theory might be an interval state rather than an precise one. Since the interval reference points contain parameters and are determined by more than one way, the efficiency results are prone to be inconsistent. In contrast, the PCE model based on the precise reference points can not only obtain clear efficiency results, but also facilitate the efficiency evaluation process.

However, the arithmetic average weights for aggregating the self- and peer-evaluation efficiencies in the prospect theory-based CEE method may underestimate the effectiveness of the self-evaluation efficiency. It is necessary to select one appropriate method for calculating the weights from many information aggregation methods. The Shannon entropy method can objectively compute the weights of criteria based on the initial decision matrix (Blagojević et al., 2020), which has been used to aggregate the cross-efficiencies (Song et al., 2017; Song & Liu, 2018). Also based on the initial decision matrix, the CRITIC (criteria importance through intercriteria correlation) method considers the standard deviation of each criterion and its correlation with other criteria to determine the criteria weights (Mitrović Simić et al., 2020). When use them to aggregate cross-efficiencies, the weights assigned to the self-evaluation efficiencies of all DMUs will be different. The reason is that the self-evaluation efficiencies are located on the diagonal of the initial decision matrix. For assigning reasonable and fair weights to the self- and peer-evaluation efficiencies in the prospect theory-based CEE method, this article considers to use the OWA operator weights that can reflect the DMs' optimism level. There are many research using the OWA operator weights for cross-efficiencies aggregation like Wang and Chin (2011) and Oukil and El-Bouri (2021). The OWA operator weights can give the same weight to the self-evaluation efficiencies of all DMUs and make them play a full role in the final evaluation. More importantly, they can express the DMs' subjective preferences towards the self- and peer-evaluation efficiencies (Puri & Verma, 2020).

In summary, there include three major gaps in the existing literature pertaining to the urban logistics efficiency. First, most studies fail to consider the DMs' psychological factors in the evaluation process of urban logistics efficiency. Second, the prospect theory-based CEE method ignores the role of self-evaluation efficiency and the DMs' subjective preferences towards the self- and peer-evaluation efficiencies. Third, there are few studies on evaluating urban logistics efficiency with the latest central area of the YRD as the research object. Consequently, the main work in this article is to measure and analyse the urban logistics efficiency in the latest central area of the YRD using the prospect theory-based CEE method with the OWA operator that reflects the DMs' subjective preferences.

3. Methodology

The evaluation processes of urban logistics efficiency for the latest central area of the YRD in China are presented in Figure 1, including three phases. The specific steps and methods of each phase will be explained in turn below.

3.1. The first phase

The first phase is to recognize the needs for researching the urban logistics efficiency in the latest central area of the YRD through the realistic background and literature review. The central area of the YRD includes 27 cities after 2019, namely Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, Taizhou_1, Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhoushan, Taizhou_2, Hefei, Chuzhou, Maanshan, Wuhu, Xuancheng, Tongling, Chizhou and Anqing. The logistics industry in each city is viewed as a DMU and there are 27 DMUs. Since there is no clear definition of logistics industry, transportation, storage and postal (TSP) industries are used instead (Deng et al., 2020; Wang et al., 2021). This article selects three inputs and three outputs. It is pointed out that urban logistics takes highway and waterway as the main transportation modes.

3.2. The second phase

In this phase, the cross-efficiency matrix is determined, consisting of the self-evaluation efficiencies by the CCR model and the peer-evaluation efficiencies by the PCE model and the peer-evaluation formula.

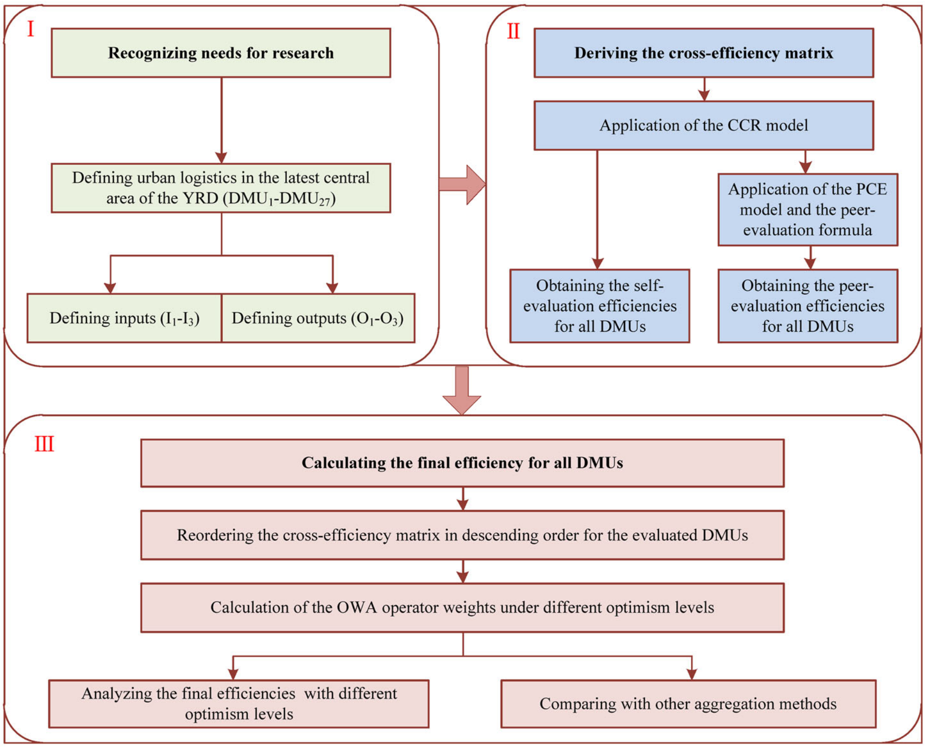

Figure 1. Flow diagram for measuring urban logistics efficiency in the central area of the YRD.
Source: made by authors.

3.2.1. Self-evaluation

The self-evaluation efficiencies of DMUs are obtained from the CCR model, see model (1) (Sexton et al., 1986). Suppose there are n DMUs, denoted by $DMU_j(j = 1, 2, \ldots, n)$, each of which can produce s outputs utilizing m inputs, and the quantity of the ith $(i = 1, 2, \ldots, m)$ input and the rth $(r = 1, 2, \ldots, s)$ of DMU_j are represented by x_{ij} and y_{rj}, respectively. The variables v_{ij} and u_{rj} are the unknown weights attached to x_{ij} and y_{rj}, respectively.

$$
\begin{aligned}
& E_{kk} = \max \sum_{r=1}^{s} u_{rk} y_{rk} \\
& s.t \sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} \leq 0, j = 1, 2, \ldots, n, \\
& \sum_{i=1}^{m} v_{ik} x_{ik} = 1, \\
& u_{rk} \geq 0, r = 1, 2, \ldots, s, \\
& v_{ik} \geq 0, i = 1, 2, \ldots, m.
\end{aligned}
\tag{1}
$$

Set the self-evaluation efficiency of the $DMU_k(k = 1, 2, \ldots, n)$ as $E^*_{kk} = \sum_{r=1}^{s} u^*_{rk} y_{rk}$ under $\sum_{i=1}^{m} v^*_{ik} x_{ik} = 1$, where u^*_{rk} and v^*_{ik} are the optimal output and input weights, respectively. If $E^*_{kk} = 1$, then the $DMU_k(k = 1, 2, \ldots, n)$ is CCR-efficient, otherwise it

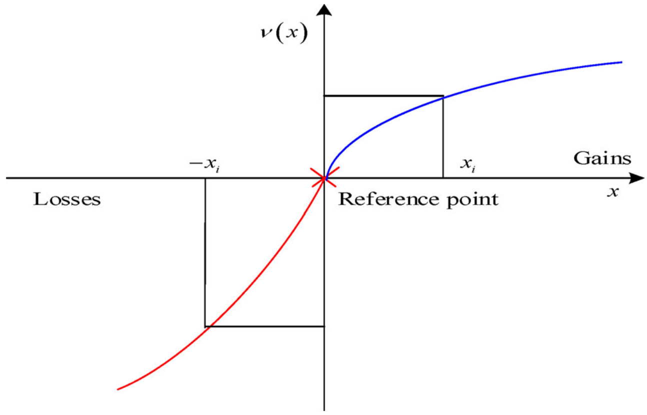

Figure 2. Prospect value curve.
Source: made by authors.

is inefficient. Note that there may be multiple solutions for the optimal output and input weights, and the optimal solution is unique.

3.2.2. PCE model

The aim of SG model is to obtain a unique set of optimal output and input weights, which can improve the effectiveness of peer-evaluation efficiency.

3.2.2.1 Prospect theory. As a descriptive theory of individual risk decision behaviour, the prospect theory developed by Kahneman and Tversky (1979) has been treated as one of the most influential behavioural decision theories (Liu et al., 2019). Prospect theory involves three important principles, see Wang et al. (2021). The principles can be depicted as an asymmetric S-shaped curve, as illustrated in Figure 2. The prospect value function of this curve is described as follows:

$$v(x) = \begin{cases} x^{\alpha}, (x \geq 0) \\ -\lambda(-x)^{\beta}, (x < 0) \end{cases} \tag{2}$$

where $x = x_1 - x_0$ is the difference between the measured value x_1 and the reference point x_0. $x \geq 0$ means that the outcome is regarded as a gain. $x<0$ means that the outcome is regarded as a loss. The parameters α and β represent the concave and convex degree of the value function within the gain and loss domains, respectively, where $0<\alpha<1$ and $0<\beta<1$. The parameter λ is the loss-averse factor and $\lambda>1$ indicates that the value function curve is much steeper for the loss domain than for the gain domain.

3.2.2.2 PCE model. The PCE model determines the input and output weights according to DMUs' own interests and the DMs' psychological attitudes under the risk (Liu et al., 2019).

Define the worst DMU as one has the most input among similar inputs of n DMUs and the least output among similar outputs of n DMUs, and the best DMU as one has the least input among similar inputs of n DMUs and the most output among similar outputs of n DMUs. According to the prospect value function the prospect gain values about DMU_k's ith input and rth output, taking the worst DMU as the reference point, are expressed as follows:

$$V_{Iik}^{+} = (x_i^{-} - x_{ik})^{\alpha}, V_{Ork}^{+} = (y_{rk} - y_r^{-})^{\alpha}, \tag{3}$$

where $x_i^{-} = \max\{x_{ik}|k = 1, 2, \ldots, n\}$ and $y_r^{-} = \min\{y_{rk}|k = 1, 2, \ldots, n\}$ are the ith input and rth output of the defined worst DMU, respectively. And the prospect loss values about DMU_k's ith input and rth output, taking the best DMU as the reference point, are shown as follows:

$$V_{Iik}^{-} = -\lambda\left(x_{ik} - x_i^{+}\right)^{\beta}, V_{Ork}^{-} = -\lambda\left(y_r^{+} - y_{rk}\right)^{\beta}, \tag{4}$$

where $x_i^{+} = \min\{x_{ik}|k = 1, 2, \ldots, n\}$ and $y_r^{+} = \max\{y_{rk}|k = 1, 2, \ldots, n\}$ are the ith input and rth output of the defined best DMU, respectively. In order to maximize DMUs' benefits, the DMs always select the best input and output weights to make the gains of DMU_k maximum and the losses of DMU_k minimum, as follows:

$$\max \sum_{r=1}^{s} u_{rk} V_{Ork}^{+} + \sum_{i=1}^{m} v_{ik} V_{Iik}^{+} \text{ and } \min \sum_{r=1}^{s} u_{rk}(-V_{Ork}^{-}) + \sum_{i=1}^{m} v_{ik}(-V_{Iik}^{-}), \tag{5}$$

Under the above two goals and the DMs' attitude towards gains and losses, Liu et al. (2019) gave the gains of DMUs a weight $\theta(0 \le \theta \le 1)$, on behalf of the DMs' preference for gains and constructed the PCE model, namely model (6).

$$\begin{aligned}
&\max\theta\left(\sum_{r=1}^{s} u_{rk}(y_{rk} - y_r^{-})^{\alpha} + \sum_{i=1}^{m} v_{ik}(x_i^{-} - x_{ik})^{\alpha}\right) - \\
&(1-\theta)\left(\sum_{r=1}^{s} u_{rk}\lambda\left(y_r^{+} - y_{rk}\right)^{\beta} + \sum_{i=1}^{m} v_{ik}\lambda\left(x_{ik} - x_i^{+}\right)^{\beta}\right) \\
&s.t. \sum_{i=1}^{m} v_{ik} x_{ik} = 1, \\
&\sum_{r=1}^{s} u_{rk} y_{rk} = E_{kk}^{*}, \\
&\sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} \le 0, j = 1, 2, \ldots, n, \\
&u_{rk}, v_{ik} \ge 0, r = 1, 2, \ldots, s, i = 1, 2, \ldots, m.
\end{aligned} \tag{6}$$

where E_{kk}^{*} is from model (1). For model (6), there are three situations in terms of the DM's attitude to gains and losses. Firstly, the DMs would like to pay more attention to the gains than losses, which means that $\theta \in (0.5, 1]$. Then, the DMs are more focused on losses when $\theta \in [0, 0.5)$. Finally, if $\theta = 0.5$, the equal importance of gains and losses was taken into account by the DMs. The last case will be adopted in this article without loss of generality.

Table 1. Cross-efficiency matrix.

	Evaluating DMU_k				
Evaluated DMU_j	DMU_1	DMU_2	$\cdots$	DMU_n	Final efficiency
DMU_1	E^*_{11}	E^*_{12}	$\cdots$	E^*_{1n}	$\frac{1}{n}\sum_{k=1}^{n} E^*_{1k}$
DMU_2	E^*_{21}	E^*_{22}	$\cdots$	E^*_{2n}	$\frac{1}{n}\sum_{k=1}^{n} E^*_{2k}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
DMU_n	E^*_{n1}	E^*_{n2}	$\cdots$	E^*_{nn}	$\frac{1}{n}\sum_{k=1}^{n} E^*_{nk}$

Source: made by authors.

3.2.3. Peer-evaluation

Now compute the peer-evaluation efficiency of DMU_j under DMU_k, E_{jk}, according to the following formula (7).

$$E^*_{jk} = \sum_{r=1}^{s} u^*_{rk} y_{rj} / \sum_{i=1}^{m} v^*_{ik} x_{ij}, j = 1, 2, \ldots, n, j \neq k, \tag{7}$$

where u^*_{rk} and v^*_{ik} are the optimal solution from model (7). Thus, DMU_j has $n-1$ peer-evaluation efficiency scores and one self-evaluation efficiency score.

These efficiency scores can be presented in the form of matrix, named $n \times n$ cross-efficiency matrix, as shown in Table 1. The diagonal elements in the cross-efficiency matrix refer to the self-evaluation efficiencies of $DMU_j(j = 1, 2, \ldots, n)$. Besides, the last column of Table 1 lists the traditional algorithm for obtaining the final efficiency values of $DMU_j(j = 1, 2, \ldots, n)$, expressed by the formula $E^*_j = \frac{1}{n}\sum_{k=1}^{n} E^*_{jk}$. It can fully rank all DMUs in accordance with the values of $E^*_j(j = 1, 2, \ldots, n)$.

3.3. The third phase

In this phase, the OWA operator weights (Wang & Chin, 2011) are used to aggregate the cross-efficiencies in Table 1. Then, make an analysis of the final efficiency results with different optimism levels of the DMs and compare the final results under different aggregation methods.

3.3.1. Reordering the cross-efficiencies

Before the application of the OWA operator weights, it needs to reorder the efficiency values in each row of Table 1 in descending order and change the $1/n$ in the last column of Table 1 to the OWA operator weights, see Table 2, where $e_{jk}(j, k = 1, 2, \ldots, n)$ is reordered efficiency value and .. is the OWA operator weight for cross-efficiency of DMU_j. Here, self-evaluation efficiencies of all DMUs are always ranked first, i.e., $e_{j1} = E^*_{jj}$, meaning that the self-evaluation efficiencies are assigned equal weight, w_1, and play the same role in the cross-efficiency aggregation.

3.3.2. OWA operator weights

The relationship between the OWA operator weights and the DMs' optimism level (also called orness degree) is $orness(W) = \frac{1}{n-1}\sum_{k=1}^{n}(n-k)w_k$, where W is the OWA

Table 2. Reordered cross-efficiency matrix.

	Reordered efficiencies in descending order				
	1st	2nd	$\cdots$	nth	
Evaluated DMU_j	w_1	w_2		w_n	Final efficiency
DMU_1	e_{11}	e_{12}	$\cdots$	e_{1n}	$\sum_{k=1}^{n} w_k e_{1k}$
DMU_2	e_{21}	e_{22}	$\cdots$	e_{2n}	$\sum_{k=1}^{n} w_k e_{2k}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
DMU_n	e_{n1}	e_{n2}	$\cdots$	e_{nn}	$\sum_{k=1}^{n} w_k e_{nk}$

Source: made by authors.

operator weights set. Let $orness(W)$ be $\varepsilon(0 \le \varepsilon \le 1)$. The ways to determine the OWA operator weights are as follows (Wang & Chin, 2011).

1. If the weight for the self-evaluation efficiency (i.e., w_1) is given, then $w_i = w_1 - (i-1)d \ge 0$ for $i = 1, 2, \ldots, K(K \le n)$ and $w_i = 0$ for $i = K+1, \ldots, n$, where $K = \min\left(n, \text{int}\left[\frac{2}{w_1}\right]\right)$ and $d = \frac{2(Kw_1 - 1)}{K(K-1)}$. Here, $\text{int}[t]$ is a function rounding t down to the nearest integer.
2. If the orness degree ε is given and in the interval $(0.5, 1)$, then $w_i = w_1 - (i-1)d \ge 0$ for $i = 1, 2, \ldots, K(K \le n)$ and $w_i = 0$ for $i = K+1, \ldots, n$ where $K = \min(n, \text{int}[3n - 1 - 3\varepsilon(n-1)])$, $w_1 = \frac{4(K+1) - 6n + 6\varepsilon(n-1)}{K(K+1)}$ and $d = \frac{2(Kw_1 - 1)}{K(K-1)}$.

There are several special OWA operator weights sets. In the first case, $w_1 = 1$ and $w_k = 0(k \ne 1)$. It means that $orness(W) = 1$ and $\sum_{k=1}^{n} w_k e_{jk} = e_{j1} = E_{jj}^*$ for $j = 1, 2, \ldots, n$, that is, only self-evaluation efficiencies are taken into consideration and the DMs are completely optimistic. Second, $w_n = 1$ and $w_k = 0(k \ne n)$, indicating that $orness(W) = 0$ and the DMs are extremely pessimistic. Third, $w_1 = w_2 = \cdots = w_n = \frac{1}{n}$, which is the traditional aggregation weights set.

3.3.3. Analysis for final efficiency results

After the determination of the OWA operator weights sets with different optimism levels, the final urban logistics efficiencies in the central area of the YRD can be calculated according to Table 2. Then, analyse the final results with different optimism levels and identify the optimism level range that can completely distinguish the efficiencies. In addition, this article respectively use common Shannon entropy and CRITIC method methods to aggregate the cross-efficiencies, the final efficiency results from which will be compared with that form the OWA operator method. Their specific steps see Blagojević et al. (2020) and Mitrović Simić et al. (2020).

4. Empirical analysis

4.1. Definition of inputs and outputs about urban logistics

Referring to the indicators in existing studies on regional logistics efficiency, this article determines respectively three kinds of inputs and outputs, and their variables and meanings are shown in Table 3.

Table 3. The input-output index system of urban logistics.

	Index names	Variables	Remarks
Input	Average wage of employees in urban non-private units in logistics industry. (CNY)	X_1	As a producer service industry, logistics cannot do without labor force. Average wage can reflect its investment in human capital (Deng et al., 2020). This article represents the labor input of urban logistics by the average annual wage of urban non-private employees in TSP industries.
	Fixed assets investment in logistics industry. (100 million CNY)	X_2	It is a capital input indicator and the main mode to form logistics industry capital (Chen, 2018; Zheng et al., 2020). This article defines it as the annual fixed asset investment of TSP industries in each city.
	Length of transport routes. (km)	X_3	This is an infrastructure indicator, consisting of the highway and inland waterway mileages in TSP industries at year-end in each city, which can reflect the development scale of urban transportation infrastructure (Chen, 2018; Deng et al., 2020).
Output	Gross product of logistics industry. (100 million CNY)	Y_1	It denotes the economic benefit of logistics industry in a city and shows directly its development level (Deng et al., 2020; Zheng et al., 2020). It is represented by TSP industries gross product.
	Freight traffic. (10000 tons)	Y_2	The freight traffic of urban logistics is defined as the actual completed tasks transported mainly by highway and waterway in this article, representing their transport capacity (Chen, 2018; Zheng et al., 2020).
	Freight turnover. (10000 ton-km)	Y_3	Joint assessment of this index and freight traffic will correctly reflect the transport situation and economic benefits (Zhang et al., 2020; Zhang & Cui, 2020). It is composed of the turnover of freight traffic by highway and waterway.

Source: made by authors.

Table 4. Descriptive statistics on index of urban logistics in the central area of the YRD.

	X_1	X_2	X_3	Y_1	Y_2	Y_3
Max	160256	1036	30779	1650	108731	297260000
Min	58669	52	2795	44	7279	816458
Average	86470	319	13942	266	26390	19550929
SD	21470	273	6567	310	20261	55477858

Source: made by authors.

4.2. Analyzing the state of urban logistics in the central area of YRD

As the latest central area of the YRD was determined in 2019, this subsection will analyse the urban logistics status of the area in 2019 and the efficiency below is also in terms of 2019. The data of inputs and outputs are obtained from each city's Statistical Yearbook of 2020, and their descriptive statistics are shown in Table 4. Note that several missing indicator values were replaced by their values in the nearest year or mean values in their region. There is an obvious gap and a large dispersion in the inputs or outputs of logistics industry in each city, reflecting the characteristics of unbalanced development. Although the central area of the YRD has been participating in regional integration development, its internal development is uneven. In addition, the inputs of more than half of urban logistics industries are below their average, while the outputs of less than one-third of urban logistics industries are above their average. It indicates that there is still room for improvement in urban logistics output. Shanghai, Nanjing, Hangzhou, Ningbo and Hefei have higher inputs and higher outputs in logistics industry. Suzhou, Wenzhou and Taizhou_2 have higher inputs and lower outputs in logistics industry. Zhoushan' logistics industry has lower inputs and higher outputs. Other cities' logistics industries have lower inputs and

Table 5. Part of cross-efficiency matrix of urban logistics in the central area of the YRD.

	Evaluating DMU							
Evaluated DMU	Shanghai	Nanjing	Wuxi	Changzhou	Suzhou	Nanong	Yancheng	Yangzhou
Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Nanjing	0.46	0.46	0.31	0.31	0.32	0.32	0.32	0.32
Wuxi	0.25	0.25	0.75	0.75	0.68	0.64	0.60	0.64
Changzhou	0.20	0.20	0.38	0.42	0.42	0.34	0.33	0.34
Suzhou	0.31	0.31	0.55	0.74	0.77	0.41	0.37	0.41
Nantong	0.09	0.09	0.32	0.33	0.41	0.46	0.45	0.46
Yancheng	0.07	0.07	0.31	0.27	0.36	0.58	0.59	0.58
Yangzhou	0.11	0.11	0.37	0.37	0.39	0.41	0.39	0.41

Source: made by authors.

lower outputs. Comparatively speaking, the urban logistics industries located in Anhui Province are deficient in investment.

4.3. Deriving the cross-efficiency matrix

Since there are multiple parameters to be set in the PCE model, this article makes $\theta = 0.5$, $\alpha = 0.89$, $\beta = 0.92$ and $\lambda = 2.25$ by referring to the practices of some scholars, which does not lose generality (Liu et al., 2019). Then, use MATLAB software to deal with models (1), (6) and (7) to obtain the cross-efficiency matrix of urban logistics industries in the central area of the YRD, part of which are shown in Table 5. The values on the main diagonal are the self-evaluation efficiencies, which are always no lower than other values in their row.

4.4. Calculating the OWA operator weights under different optimism levels

Firstly, it needs to reorder the self- and peer-evaluation efficiencies for all evaluated urban logistics industries in descending order, and then the OWA operator weight $w_1 - w_{27}$ should be assigned successively. Next, calculate the OWA operator weights under different orness degrees according to the methods in Section 3.3.2 and the values are shown in Table 6. There are two special sets of OWA operator weights. One is the case with an orness degree of 1. The other is the case with an orness degree of 0.5.

4.5. Analyzing the final efficiency of urban logistics in the central area of YRD

4.5.1. Discussion of the final efficiencies with different optimism levels

According to the formula in the last column in Table 2, the final efficiency values of urban logistics in the central area of the YRD in 2019 under different optimism levels are obtained, which are presented in Table 7. Obviously, the logistics efficiency values of multiple cities (Shanghai, Taizhou_1, Ningbo and Zhoushan) are all 1 in the case that the DM is completely optimistic, meaning that they cannot be further distinguished in the ranking. It can be found that the efficiency difference is not strong enough when the orness degree is between 0.8177 and 1, that is, more than one urban logistics industry are ranked first. When the orness degree is less than 0.8177, it can fully rank the efficiencies of urban logistics industries in the central area of the

Table 6. The OWA operator weights under different optimism levels.

ε	1	0.9744	0.9	0.85	0.83	0.82	0.8177	0.81	0.8	0.5
w_1	1.000	0.500	0.204	0.146	0.131	0.125	0.123	0.119	0.114	0.037
w_2	0	0.333	0.181	0.135	0.122	0.116	0.115	0.111	0.107	0.037
w_3	0	0.167	0.158	0.123	0.113	0.108	0.107	0.104	0.100	0.037
w_4	0	0	0.134	0.112	0.104	0.100	0.099	0.096	0.093	0.037
w_5	0	0	0.111	0.100	0.094	0.092	0.091	0.089	0.086	0.037
w_6	0	0	0.088	0.088	0.085	0.083	0.083	0.081	0.079	0.037
w_7	0	0	0.064	0.077	0.076	0.075	0.075	0.074	0.073	0.037
w_8	0	0	0.041	0.065	0.067	0.067	0.067	0.066	0.066	0.037
w_9	0	0	0.018	0.054	0.057	0.058	0.058	0.059	0.059	0.037
w_{10}	0	0	0	0.042	0.048	0.050	0.050	0.051	0.052	0.037
w_{11}	0	0	0	0.031	0.039	0.042	0.042	0.044	0.045	0.037
w_{12}	0	0	0	0.019	0.030	0.033	0.034	0.036	0.038	0.037
w_{13}	0	0	0	0.008	0.021	0.025	0.026	0.029	0.031	0.037
w_{14}	0	0	0	0	0.011	0.017	0.018	0.021	0.025	0.037
w_{15}	0	0	0	0	0.002	0.009	0.010	0.014	0.018	0.037
w_{16}	0	0	0	0	0	0.000	0.002	0.006	0.011	0.037
w_{17}	0	0	0	0	0	0	0	0	0.004	0.037
w_{18}	0	0	0	0	0	0	0	0	0	0.037
w_{19}	0	0	0	0	0	0	0	0	0	0.037
w_{20}	0	0	0	0	0	0	0	0	0	0.037
w_{21}	0	0	0	0	0	0	0	0	0	0.037
w_{22}	0	0	0	0	0	0	0	0	0	0.037
w_{23}	0	0	0	0	0	0	0	0	0	0.037
w_{24}	0	0	0	0	0	0	0	0	0	0.037
w_{25}	0	0	0	0	0	0	0	0	0	0.037
w_{26}	0	0	0	0	0	0	0	0	0	0.037
w_{27}	0	0	0	0	0	0	0	0	0	0.037

Source: made by authors.

YRD. Given that the important role of the self-evaluation efficiency, the weight assigned to it should be not less than the arithmetic average weight. Due to the property of OWA operator weights, the weight assigned to self-evaluation efficiency increases with the improvement of optimism level. Therefore, the ideal optimism level of the DMs should be between 0.5 and 0.8177 in order to fully distinguish the urban logistics efficiency in the central area of the YRD. The corresponding weight rang for the self-evaluation efficiency is between 0.037 and 0.123. In addition, there is a big gap between the urban logistics efficiency values, which reflects the characteristics of unbalanced development in the central area of the YRD.

Figure 3 clearly shows the changes of urban logistics efficiencies in the central area of the YRD as the optimism level decreases. It is found that when the orness degree drops from 1 to 0.85, the logistics efficiency values of Nanjing, Suzhou, Zhenjiang, Hangzhou and Tongling decline significantly, indicating that the optimism level of the DMs has a significant impact on them. When the orness degree decreases from 0.85 to 0.8, the logistics efficiency values of all cities in the central area of the YRD are relatively stable with little change, showing that the results in this optimism interval are relatively credible. The logistics efficiency values of all cities in the area have obvious downward trends when the orness degree drops from 0.8 to 0.5, reflecting the importance of the self-evaluation efficiency to the final efficiency results. Overall, the urban logistics efficiency in the area decreases with the reduction of the optimism level. It can be seen that the DMs' optimism level should not be too high or too low, that is to say, it is better to maintain a moderate level. Combined with the above analysis, the DMs' optimism level is best between 0.8 and 0.8177, thus the urban logistics

Table 7. The final efficiency results of urban logistics in the central area of the YRD.

ε	1		0.9744		0.9		0.85		0.83	
Shanghai	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
Nanjing	0.4585	21	0.4507	21	0.4027	22	0.3830	24	0.3772	24
Wuxi	0.7540	11	0.7528	11	0.7102	12	0.6922	11	0.6859	11
Changzhou	0.4205	23	0.4204	23	0.3999	24	0.3868	23	0.3825	23
Suzhou	0.7722	8	0.7660	9	0.6610	15	0.6025	16	0.5844	17
Nantong	0.4600	20	0.4600	20	0.4593	20	0.4574	20	0.4561	20
Yancheng	0.5895	18	0.5895	18	0.5875	18	0.5860	17	0.5847	16
Yangzhou	0.4059	24	0.4059	24	0.4040	21	0.4006	21	0.3990	21
Zhenjiang	0.9540	6	0.9175	6	0.7328	10	0.6416	14	0.6143	14
Taizhou$_1$	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
Hangzhou	0.4497	22	0.4374	22	0.4018	23	0.3904	22	0.3870	22
Ningbo	1.0000	1	1.0000	1	0.9986	4	0.9949	4	0.9922	4
Wenzhou	0.2827	25	0.2776	25	0.2622	26	0.2569	26	0.2552	26
Jiaxing	0.7316	13	0.7316	13	0.7302	11	0.7270	10	0.7251	10
Huzhou	0.6654	16	0.6653	16	0.6647	14	0.6617	13	0.6595	13
Shaoxing	0.2665	26	0.2665	26	0.2651	25	0.2621	25	0.2608	25
Jinhua	0.2561	27	0.2536	27	0.2470	27	0.2451	27	0.2444	27
Zhoushan	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
Taizhou$_2$	0.6188	17	0.6172	17	0.6130	16	0.6102	15	0.6090	15
Hefei	0.7573	10	0.7573	10	0.7562	8	0.7546	8	0.7537	8
Chuzhou	0.8124	7	0.8124	7	0.8089	6	0.8028	6	0.7994	6
Maanshan	0.5085	19	0.5085	19	0.5081	19	0.5070	19	0.5060	19
Wuhu	0.9880	5	0.9880	5	0.9868	5	0.9846	5	0.9829	5
Xuancheng	0.7701	9	0.7701	8	0.7692	7	0.7675	7	0.7663	7
Tongling	0.7293	14	0.6888	15	0.6074	17	0.5854	18	0.5783	18
Chizhou	0.6979	15	0.6956	14	0.6893	13	0.6852	12	0.6826	12
Anqing	0.7352	12	0.7352	12	0.7333	9	0.7296	9	0.7275	9

Table 7. The final efficiency results of urban logistics in the central area of the YRD. (Continued).

ε	0.82		0.8177		0.81		0.8		0.5	
Shanghai	1.0000	1	1.0000	1	1.0000	1	1.0000	1	0.9242	1
Nanjing	0.3747	24	0.3741	24	0.3723	24	0.3702	24	0.3121	22
Wuxi	0.6829	11	0.6822	11	0.6800	11	0.6773	11	0.5488	9
Changzhou	0.3804	23	0.3800	23	0.3784	23	0.3765	23	0.3048	23
Suzhou	0.5761	17	0.5743	17	0.5683	18	0.5609	18	0.3989	17
Nantong	0.4553	20	0.4550	20	0.4543	20	0.4534	20	0.3646	20
Yancheng	0.5838	16	0.5836	16	0.5826	16	0.5813	15	0.4385	16
Yangzhou	0.3983	21	0.3981	21	0.3975	21	0.3967	21	0.3291	21
Zhenjiang	0.6019	15	0.5992	15	0.5904	15	0.5797	16	0.3670	19
Taizhou$_1$	1.0000	1	0.9998	3	0.9994	3	0.9986	3	0.8229	2
Hangzhou	0.3854	22	0.3850	22	0.3837	22	0.3820	22	0.3037	24
Ningbo	0.9905	4	0.9900	4	0.9885	4	0.9864	4	0.7992	3
Wenzhou	0.2544	26	0.2542	26	0.2535	26	0.2526	26	0.2000	26
Jiaxing	0.7240	10	0.7237	10	0.7225	10	0.7206	9	0.5583	8
Huzhou	0.6583	13	0.6580	13	0.6570	13	0.6556	13	0.5014	12
Shaoxing	0.2602	25	0.2600	25	0.2595	25	0.2588	25	0.1895	27
Jinhua	0.2441	27	0.2440	27	0.2437	27	0.2434	27	0.2075	25
Zhoushan	1.0000	1	0.9999	2	0.9997	2	0.9993	2	0.7952	4
Taizhou$_2$	0.6082	14	0.6079	14	0.6068	14	0.6051	14	0.4473	14
Hefei	0.7531	8	0.7528	8	0.7520	8	0.7507	8	0.6155	6
Chuzhou	0.7976	6	0.7969	6	0.7948	6	0.7915	6	0.5740	7
Maanshan	0.5055	19	0.5053	19	0.5045	19	0.5033	19	0.3810	18
Wuhu	0.9819	5	0.9813	5	0.9794	5	0.9761	5	0.7394	5
Xuancheng	0.7656	7	0.7651	7	0.7635	7	0.7608	7	0.5481	10
Tongling	0.5750	18	0.5742	18	0.5717	17	0.5685	17	0.4397	15
Chizhou	0.6811	12	0.6807	12	0.6794	12	0.6771	12	0.4877	13
Anqing	0.7263	9	0.7257	9	0.7237	9	0.7204	10	0.5233	11

Source: made by authors.

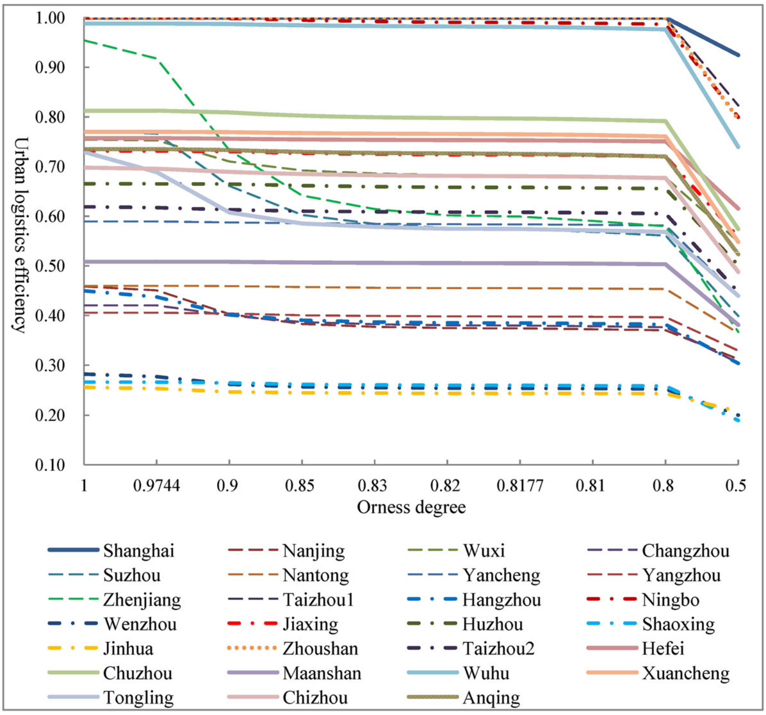

Figure 3. The change of efficiency value when decreasing optimism level.
Source: made by authors.

efficiencies in the area are more credible and can be fully differentiated. Correspondingly, the weight rang for the self-evaluation efficiency is best 0.114 and 0.123.

Besides, the logistics efficiencies in Shanghai, Taizhou_1, Ningbo, Zhoushan and Wuhu are always in the top five, and ones in Wenzhou, Shaoxing and Jinhua are always in the bottom three. It manifests that it is feasible to use the OWA operator weights to aggregate the cross-efficiencies by the PCE model to a certain extent. According to the analysis in Section 4.2, the logistics industries in Shanghai and Ningbo with high inputs and high outputs and Taizhou_1 and Wuhu with low inputs and low outputs have higher resource utilization levels. Zhoushan's higher logistics efficiency is consistent with its actual situation of low inputs and high outputs. The resource utilization levels of logistics industry in Wenzhou, Shaoxing and Jinhua are poor. Especially the logistics industry in Wenzhou may have a large number of input resources redundant.

The ranking changes of urban logistics efficiency in the central area of the YRD with the optimism level from 1 to 0.5 are displayed in Figure 4. It can be seen that the rankings of logistics efficiency in Suzhou, Zhenjiang, Jiaxing, Huzhou, Hefei and Tongling fluctuate greatly. It illustrates that the DMs' optimism level will affect the efficiency ranking and the DMs have an important role in the overall situation. In addition, it is found that more than two-thirds of urban logistic efficiency rankings remain almost unchanged between the orness degree of 0.8 and 0.8177, testifying that this optimism level range is convincing. The logistics efficiency ranking in Shanghai has not been affected by the optimism level and consistently ranked first, thus it can serve as a benchmark to learn for other cities. The logistics efficiency rankings of

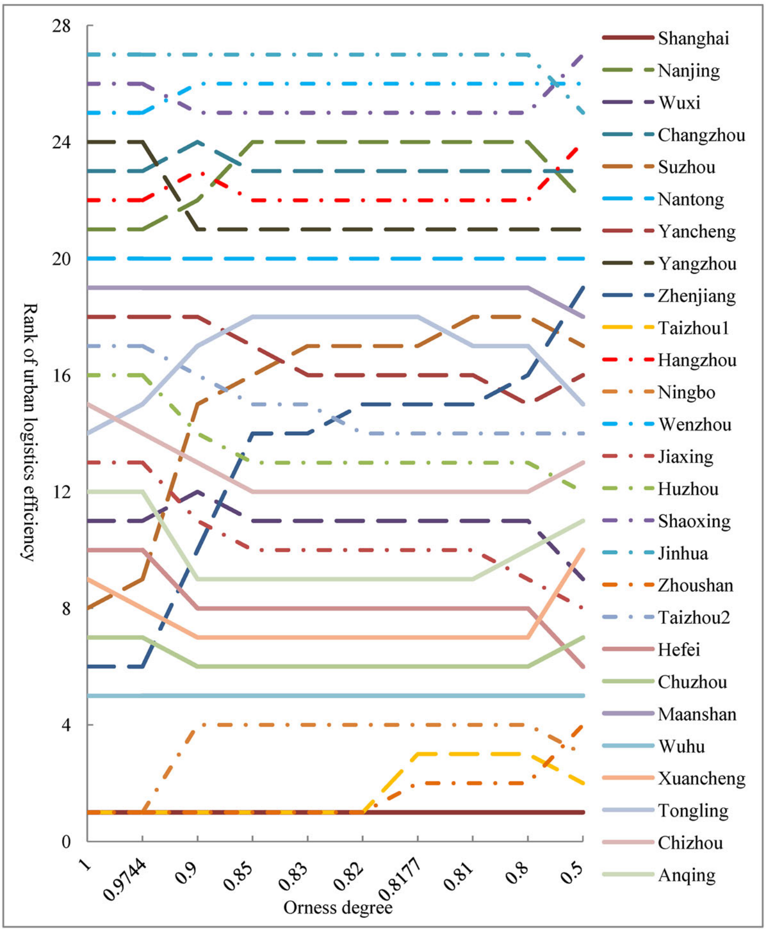

Figure 4. The change of efficiency ranking when decreasing optimism level.
Source: made by authors.

Taizhou$_1$, Ningbo, Zhoushan and Wuhu closely follow that of Shanghai, so they can also be as benchmarks. Wenzhou logistics efficiency ranking is relatively low. The reason may be that Wenzhou City has just joined the YRD integration development strategy and the advantages have not been reflected.

4.5.2. Comparison with Shannon entropy and CRITIC methods

This subsection conducts a comparative analysis of efficiency results under Shannon entropy, CRITIC, OWA operator aggregation methods. Note that the first two methods, taking the original cross-efficiency matrix as their calculation basis, are objective methods. The weights calculated by Shannon entropy method are 0.011, 0.011, 0.039, 0.031, 0.032, 0.047, etc., which will in turn be assigned to the cross-efficiency values of each evaluated urban logistics. The weights by the CRITIC method are 0.050, 0.050, 0.037, 0.064, 0.055, 0.028, etc. Obviously, the self-evaluation logistics efficiency in each evaluated city is given different weight and even some self-evaluation efficiencies' weights are less than 0.037, which shows that the self-evaluation efficiency does not play the same role and may cause unfair evaluation results. In contrast, the

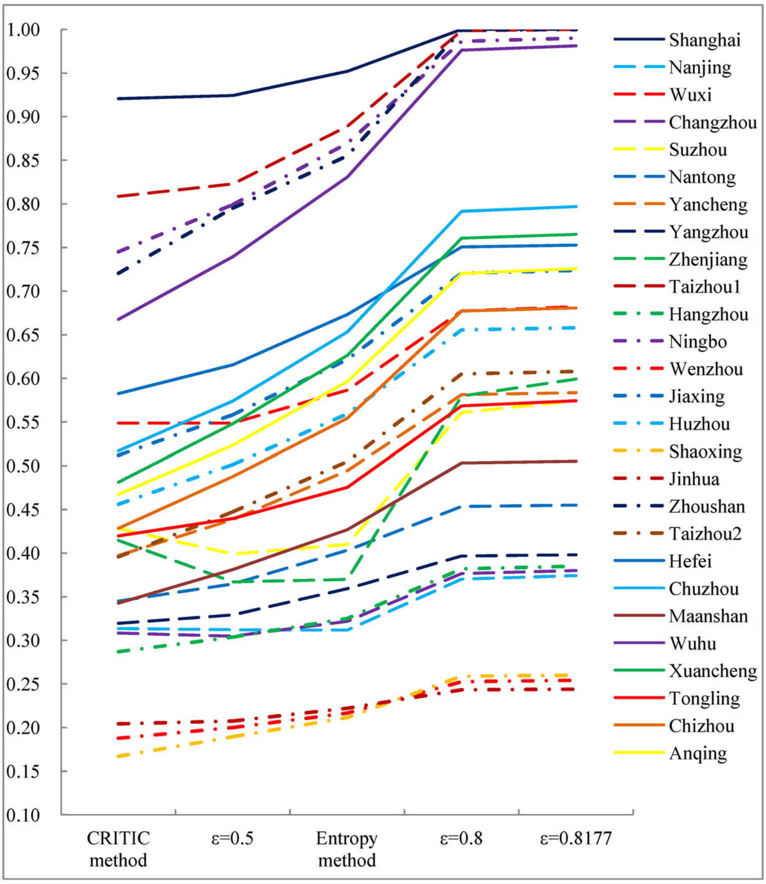

Figure 5. Comparison with urban logistics efficiency values under different aggregation methods.
Source: made by authors.

weights for the self-evaluation efficiencies calculated by the OWA operator are fairer because they are the same. The cities with top five and bottom three in logistics efficiency under the two methods are the same as those based on the OWA operator. It can be seen that the OWA operator weights have reliability and superiority.

The results under the three aggregation methods are depicted in Figure 5 for discussion. In this article, the efficiency results based on the OWA operator with optimism level of 0.5, 0.8 and 0.8177 are taken as examples. It is found that the logistics industries of 85% cities in the central area of the YRD have the lowest efficiency values under the CRITIC method and may be underestimated in this case. Almost all cities' logistics efficiency values under Shannon entropy method fall between the results under the optimistic levels of 0.5 and 0.8. It can be seen that the efficiency results obtained based on objective methods are generally low.

5. Conclusion

This article uses a hybrid cross-efficiency evaluation method which combines the prospect theory with the OWA operator weights to measure the urban logistics performance of the central area of the YRD urban agglomeration in 2019. It is realized that the DMs' psychological factors are considered in the efficiency evaluation of urban logistics and their behavioural preference and optimism level are simultaneously viewed in the process of cross-efficiency evaluation. After empirical analysis, we come to four conclusions: (1) The DMs' optimism level can indeed affect the efficiency value and ranking of urban logistics. The final efficiency results increase with the optimism level. (2) The aggregation based on the OWA operator is more fair and reasonable. The OWA operator weights can make the self-evaluation logistics efficiencies of all cities in the central area of the YRD play the same role and help them play a full role in the final efficiency calculation. (3) To make the efficiencies and rankings of urban logistics industries in the central area of the YRD have high credibility and discrimination, the DMs' optimism level range is best between 0.8 and 0.8177. Correspondingly, the weight range for the self-evaluation efficiency is between 0.114 and 0.123. (4) Shanghai logistics efficiency always ranks first, which can serve as a benchmark to learn for other cities in the central area of the YRD. Zhoushan is located in the Ningbo metropolis and their logistics efficiency levels are both high, thus the Ningbo metropolis can be as the learning benchmark for other metropolis in the YRD urban agglomeration.

There are some deficiencies in this article. On the one hand, the parameters values in the PCE model just conform to a general condition, which may have limitations. In the future, a sensitivity analysis in terms of each parameter will be carried out to explore the impact of each parameter on urban logistics efficiency. On the other hand, almost all the indicators in this article are macro and may cause obvious differences due to different regions. It may not fully reflect the inputs and outputs of urban logistics industry. Future work is to study more intensity indicators about urban logistics industry to replace macro indicators.

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