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Supplier Selection in Supply Chain Management with OWA Operator Weights

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Abstract

In the competitive trade world, choosing the best supply chain is a vital problem. One of the most important processes performed in enterprises today is the evaluation, selection and continuous measurement of suppliers. On the other hand, Supplier selection is one of the key issues of Supply Chain Management because the cost of raw materials and component parts constitutes the main cost of a product Management. Moreover finding the best supplier for manufacturing due to preparing raw material is essentially important in much more difficult conditions of competitions. Meanwhile there are different scenarios to supply by suppliers, which can change selection variables like lead-time, transportation cost, transportation path that can affect in supplier selection. In this paper based on OWA operator weights method for supplier selection is introduced.

Keywords: *Supply Chain management, Supplier, OWA Operator, orness degree, aggregation*

1. Introduction

In this competitive worldwide, selecting the best supplier amongst all is vitally important for firms who want to increase procurement quality levels and decrease costs. That is the reason why many companies are working on evaluating and selecting suppliers. [9, 10, 4, 2].

Supplier selection is one of the important aspects of supply chain management. Several factors such as Transportation Lead time, Transportation Cost, Production Lead time, Order Cost, Quality Level, etc. Are determinant in choosing suppliers. Supply chain management (SCM) is one of the most important competitive strategies used by modern enterprises. Meanwhile, supplier selection plays an effective role in the supply chain.

The supplier selection problem is considered as a multiple attributes decision making (MADM) problem affected by several conflicting factors such as price, quality and delivery. Supplier selection requires the information about the potential suppliers' credit history, performance history and other personal information, which are often not available to the public, so that, strengthening partnerships with suppliers is most important for enhancing competitiveness [3]. In the other word, supplier selection is evaluated as a critical factor for the companies desiring to be successful in nowadays competition conditions. [8, 2].

Data envelopment analysis (DEA) developed by Charnes *et al.*, [1], is a methodology for measuring the best relative efficiencies of a group of peer decision-making units (DMUs) that consume multiple inputs to produce multiple outputs with the most favorable input and output weights to each of the DMUs, respectively, and has found significant applications in production economics. It proves to be very effective in identifying DEA efficient units, which

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are those DMUs with the best relative efficiency of one, but is very often unable to distinguish between them any further. To overcome the inability of DEA in discriminating between DEA efficient units, cross-efficiency evaluation, proposed by Sexton *at al.*, [12], is an effective way of ranking decision making units (DMUs). It allows the overall efficiencies of the DMUs to be evaluated through both self- and peer-evaluations.

Existing researches on the cross-efficiency evaluation are mainly focused on either its applications or the calculation of cross-efficiency Matrix. Little attention has been paid to the aggregation process of cross-efficiencies. In our view, the use of equal weights for cross-efficiency aggregation has a significant drawback. That is self-evaluated efficiencies are much less weighted than peer-evaluated efficiencies. This is because each DMU has only one self-evaluated efficiency value, but multiple peer-evaluated efficiency values.

We propose the use of ordered weighted averaging (OWA) operator weights for aggregating cross-efficiencies. The use of OWA operator weights for the cross- efficiency aggregation allows the weights to be reasonably allocated between self-and peer-evaluated efficiencies in terms of the DM's optimism level, characterized by an orness degree. By adjusting the DM's optimism level, self-evaluated efficiencies can play a desirable role in the final overall efficiency assessment or ranking of the DMUs.

2. Supplier Selection

One of the most important process performed in interest today is the evaluation, selection and continuous measurement of supplier. Also the enterprise`s ability to produce a quality product at a reasonable cost and in a timely manner is heavily influenced by its supplier`s capabilities.

On the other hand, supplier selection is one of the key issues of Supply Chain Management (SCM), because the cost of raw materials and component parts constitutes the main cost of a product a management.

Supplier selection: "The stage in the buying process when the intending buyer chooses the preferred supplier or suppliers from those qualified as suitable." (West Burn Dictionary)

3. OWA Operator and Their Weights Determination Methods

OWA operators, introduced by Yager [11], provide a unified framework for decision making under uncertainty, where different decision criteria such as Maximax (optimistic), Maximin (pessimistic), equally likely (Laplace) are characterized by different OWA operator weights. An OWA operator of *n* is a mapping $F : R^n \rightarrow R^n$ with an associated weight vector $W = \left(w_1, ..., w_n\right)^T$ such that:

$$F\left(a_1, ..., a_n\right) = \sum_{i=1}^{n} w_i b_i = w_1 b_1 + ... + w_n b_n$$
$$1. w_i \in [0,1],\ i = 1, ..., n \qquad (1)$$
$$2. \sum_{i=1}^{n} w_i = 1.$$

Where b_i is the i*th* largest of $a_1, ..., a_n$. We have a oress degree definition as follow [11]:

$$Orness(W) = \frac{1}{n-1} \sum_{i=1}^{n} \left(n-1\right) w_i \qquad (2)$$

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Which lies in the unit interval [0,1]. In this paper we used the minimax model to obtain OWA operator weights as follows [6]:

$$
\begin{aligned}
&Min \quad \delta \\
&subject\ to\ orness(W) = \alpha = \frac{1}{n-1}\sum_{i=1}^{n}(n-i)w_i, \quad 0 \le \alpha \le 1, \\
&\qquad \sum_{i=1}^{n} w_i = 1, \\
&\qquad w_i - w_{i+1} - \delta \le 0, i = 1,...,n-1, \\
&\qquad w_i - w_{i+1} - \delta \ge 0, i = 1,...,n-1, \\
&\qquad w_i \ge 0, i = 1,...,n.
\end{aligned} \tag{3}
$$

This model minimizes the maximum disparity between two adjacent weights. The OWA operator weights determined by the above model have the following characteristics:

- The weights are ordered. That is $w_1 \ge w_2 \ge \cdots \ge w_n \ge 0$ if the orness degree $\alpha > 0.5$ and $0 \le w_1 \le w_2 \le \cdots \le w_n$ if $\alpha \le 0.5$.
- $w_1 = 1$ And $w_j = 0\left(j \ne 1\right)$ if $\alpha = 1$, which means that the DM is purely optimistic and considers only the biggest value $b_1 = \max_i(a_i)$ in decision analysis.
- $w_n = 1$ And $w_j = 0\left(j \ne n\right)$ if $\alpha = 0$, which represents that the DM is purely pessimistic and is only concerned with the most secretive value $b_n = \min_i(a_i)$ when making decision.
- $w_1 = \cdots w_n = \left(1/n\right)$ If $\alpha = 0.5$, which stands for that the DM is neutral and makes use of all the aggregates $b_1 \sim b_n$ equally in decision making.

With regard to the minimax disparity OWA operator weights, we have the following theorems.

Theorem 1. For a given w_1, there exists an integer $k \le n$ such that $w_i = w_1 - (i-1)d \ge 0$, for $i = 1,...,k$ and $w_i = 0$, for $i = k+1,...,n$ where K and are determined by

$$k = \text{Min}\left(n, \text{INT}\left[\frac{2}{w_1}\right]\right) \quad \text{and} \quad d = \frac{2\left(kw_1 - 1\right)}{k\left(k-1\right)}$$

Where INT[x] is a function that rounds x down to the nearest integer.

Proof: see [15].

Theorem 1 shows how the weights for peer-evaluated efficiencies can be determined once the weight for self-evaluated efficiencies are provided. This theorem is particularly useful for the DM to express his/her preference for self-evaluated efficiencies.

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Theorem 2: For a given orness degree $\alpha \in (0,1)$, there exists an integer $k \le n$ such that $w_i = w_1 - (i-1)d \ge 0,$ for $i = 1,...,k$ and $w_i = 0,$ for $i = k+1,...,n$ where K, and w_1 , and are determined by $k = \min(n, \text{INT}[3n-1-3\alpha(n-1)]),$

$$d = \frac{2(kw_1 - 1)}{k(k-1)} \quad \text{And} \quad w_1 = \frac{4(k+1) - 6n + 6\alpha(n-1)}{k(k+1)}$$

Proof : see [15].

Theorem2 shows how the weights for self- and peer-evaluated efficiencies can be determined when the DM's optimism level is given.

Theorem 3: If $W^* = (w_1^*,...,w_n^*)^T$ is an optimum solution of LP (6) for a given level of $Orness(W) = \alpha$, then $\hat{W}^* = (\hat{w}_1^*,...,\hat{w}_n^*)^T$ where $\hat{w}_i^* = \hat{w}_{n-i+1}^*, i = 1,...,n,$ is an optimum solution of the LP (6) for $Orness(W) = 1-\alpha,$ and vice versa.

Proof: [13].

Theorem 3 shows that OWA weights have duality property.

3. Cross-efficiency Evaluation

Suppose that there are *n* DMUs are to be evaluated in terms of *m* inputs and *s* outputs. We denote the *i*th input and *r*th output for $DMU_j\ (j = 1,2,...,n)$ as $x_{ij}\ (i = 1,2,...,m)$ and $y_{rj}\ (r = 1,2,...,s),$ respectively. The efficiency rating for any DMU_k, can be computed using the following CCR model in the form of linear programming:

$$\begin{aligned} Max \quad & \theta_{kk} = \sum_{r=1}^{s} u_{rk} y_{rk} \\ s.t. \quad & \sum_{i=1}^{m} v_{ik} x_{ik} = 1, \\ & \sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} \le 0, \quad j = 1,...,n, \\ & u_{rk} \ge 0, \quad r = 1,...,s, \\ & v_{ik} \ge 0, \quad i = 1,...,m. \end{aligned} \tag{4}$$

Let $u_{rk}^*\ (r = 1,...,s)$ and $v_{ik}^*\ (i = 1,...,m)$ be the optimal solution to the above model. Then, $\theta_{kk}^* = \sum_{r=1}^{s} u_{rk}^* y_{rk}$ is referred to as the CCR-efficiency of DMU_k, which is the best relative efficiency that DMU_k can achieve and reflects the self-evaluated efficiency of DMU_k. As such, $\theta_{jk} = \sum_{r=1}^{s} u_{rk}^* y_{rj} \Big/ \sum_{i=1}^{m} v_{ik}^* x_{ik}$ is referred to as a cross-efficiency value of DMU_j and reflects the peer evaluation of DMU_k to $DMU_j\ (j = 1,...,n;\ j \ne k)$.

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Model (4) is solved *n* times, each time for one different DMU. As a result, there will be *n* sets of input and output weights available for *n* DMUs and each DMU will have $(n-1)$ cross-efficiency values plus one CCR-efficiency value, where $\theta_{kk}\ (k=1,...,n)$ are the CCR-efficiencies of the *n* DMUs, *i.e.*, $\theta_{kk}=\theta^{*}_{kk}$.

Table 1. Cross-efficiency Matrix for *n* DMU

DMU	Target DMU				Average
	1^{st}	2^{nd}	...	n^{th}	Cross-efficiency
1	θ_{11}	θ_{12}	$\cdots$	θ_{1n}	$\frac{1}{n}\sum_{k=1}^{n}\theta_{1k}$
2	θ_{21}	θ_{22}	$\cdots$	θ_{2n}	$\frac{1}{n}\sum_{k=1}^{n}\theta_{2k}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
n	θ_{n1}	θ_{n2}	$\cdots$	θ_{nn}	$\frac{1}{n}\sum_{k=1}^{n}\theta_{nk}$

It is noticed that model (4) may have multiple optimal solutions. This non-uniqueness of input and output weights would damage the use of cross-efficiency evaluation if it were not resolved. To resolve this problem, one remedy suggested by Sexton [15], is to introduce a secondary goal which optimizes the input and output weights while keeping unchanged the CCR-efficiency determined by model (4). The most commonly used secondary goals were suggested by Doyle & Green [5]. Models that they suggested are called Aggressive and Benevolent formulation.

The aggressive formulation for cross-efficiency evaluation which aims to minimize the cross-efficiencies of the other DMUs in some way, the benevolent formulation for cross-efficiency evaluation which maximizes the cross-efficiencies of the other DMUs to some extent. Since the two models optimize the input and output weights in two different ways, there is thus no guarantee that they can lead to the same efficiency ranking or conclusion for the *n* DMUs.

In this paper we use neutral cross-efficiency formulation, which is neither aggressive nor benevolent [14]. Each DMU determines the weights only from its own point of view without considering their impacts on the other DMUs. This good feature enables the decision maker (DM) not to make a difficult choice between the aggressive and benevolent formulations.

In our point of view, when a DMU is given an opportunity to decide a set of input and output weights, what the DMU is concerned most about is whether the weights can be as favorable as possible to itself. It should not care too much about how to be aggressive or benevolent to the other DMUs. The neutral cross-efficiency evaluation of DMU_k is as follow:

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$$
\begin{aligned}
Max \quad & \delta \\
s.t. \quad & \sum_{i=1}^{m} v_{ik}\tilde{x}_{ik} = 1 \\
& \sum_{r=1}^{s} u_{rk}\tilde{y}_{rk} = \theta_{kk}^{*} \\
& \sum_{r=1}^{s} u_{rk}\tilde{y}_{rj} - \sum_{i=1}^{m} v_{ik}\tilde{x}_{ij} \le 0, \quad j = 1,\dots,n;\, j \ne k, \\
& u_{rk} y_{rk} - \delta \ge 0, \quad r = 1,\dots,s, \\
& v_{ik} \ge 0, \quad i = 1,\dots,m, \\
& \delta \ge 0.
\end{aligned}
\tag{5}
$$

where $u_{rk}(r=1,\dots,s)$ and $v_{ik}(i=1,\dots,m)$ and δ are decision variables. Like all DEA models for cross-efficiency evaluation, model (5) needs to be solved *n* times, each time for one DMU. Accordingly, there will be *n* sets of input and output weights available for cross-efficiency evaluation.

4. Neutral Cross-efficiency Aggregation by OWA Operator Weights

The self-evaluation allows the efficiencies of the DMUs to be evaluated with the most favorable weights so that each of them can achieve its best possible relative efficiency, whereas the peer-evaluation requires the efficiency of each DMU to be evaluated with the weights determined by the other DMUs. The self-evaluated efficiency and peer-evaluated efficiencies of each DMU are then averaged as the overall efficiency of the DMU. Traditional approaches for the cross-efficiency evaluation do not differentiate between self-evaluated and peer-evaluated efficiencies and aggregate them equally. The most extensively used approach is to aggregate cross efficiencies with equal weights. Our literature review reveals that only Wu *et. al.*, [6, 7] determined ultimate cross-efficiency by weighting *n* cross-efficiency scores rather than simply averageing them. The weights they utilized for aggregation were determined in terms of the nucleolus solution and the Shapley value in cooperative game, respectively.

A significant drawback with these approaches is that the weight assigned to the self-evaluated efficiency of each DMU is fixed and has no way of incorporating the DM`s subjective preferences into the aggregation. When they are simply averaged together, the weight assigned to the self-evaluated efficiency is only*1/n* if there are *n* DMUs to be evaluated, whereas the remaining weights *(n-1)/n* are all given to those peer-evaluated efficiencies. Quiet obviously,self-evaluated efficiencies fail to play a sufficient role in the final overall assessment and ranking. More importantly, the use of equal weights for aggregation has no way to take into consideration the decision maker (DM)’s subjective preferences on the best relative efficiencies in the final overall assessment and ranking.

To reflect the DM`s subjective preferences on different efficiencies, we propose the use of OWA operator weights for cross-efficiency aggregation.

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4.1. The Algorithm of using OWA Operator Weights

1- At first, cross-efficiency are measured by model (5);
2- Then cross-efficiency matrix are transposed;
3- In this stage, we re-ordered each rows of transpose matrix, the aim of this work is to implement the OWA operator. In fact, these sorted values are b_i in OWA operator definition;
4- In this stage, we get aggregation cross-efficiency from product of each row in OWA operator weight. These values are obtained using $\bar{\theta}_i = \sum_{k=1}^{n} w_k \vartheta_{ik}$
5- Finally, we select best supplier.

This requires re-ordered efficiencies of each DMU from the biggest to the smallest. Evidently, self-evaluated efficiencies are always ranked in the first place. In order to determine the weights of OWA operators, it is necessary for the DM to provide his/her preferences on different or optimism level towards the best relative efficiencies. In the following, we provide some very special OWA operator weights for the cross-efficieny aggregation:

- $w_1 = 1$ And $w_j = 0\left(j \neq 1\right)$. In this case, $orness(W) = 1$, $\bar{\theta}_i = \sum_{k=1}^{n} w_k \vartheta_{ik} = \vartheta_{i1} = \theta_{ii}^*$, for. $i = 1,...,n$. The DM considers only self evaluated efficiencies which means that the DM is purely optimistic.
- $w_n = 1$ And $w_j = 0\left(j \neq n\right)$. In this case, $orness(W) = 0$, $\bar{\theta}_i = \sum_{k=1}^{n} w_k \vartheta_{ik} = \vartheta_{i1} = \min_i\left(\theta_{ik}\right)$ for $i = 1,...,n$. The DM chooses the least efficiency value of each DMU as its overall efficiency which means that the DM is purely pessimistic.
- $w_1 = \cdots w_n = \left(1/n\right)$. In this case, $orness(W) = 0.5$, $\bar{\theta}_i = \sum_{k=1}^{n} w_k \vartheta_{ik} = 1/n \sum_{k=1}^{n} \theta_{ik}$ for $i = 1,...,n$. $\alpha = 0.5$, which is the average cross-efficiency value in the traditional aggregation in the cross-efficiency evaluation is only a special case of the use of OWA operator weights for cross-efficiency aggregation.

Table 2. Re-ordered cross-efficiency Matrix of the n DMUs

DMU	Re-ordered efficiencies in descending order				Weighted average cross-efficiency
	1st w_1	2nd w_2	...	nth w_3	
1	ϑ_{11}	ϑ_{12}	…	ϑ_{1n}	$\sum_{k=1}^{n} w_k \theta_{1k}$
2	ϑ_{21}	ϑ_{22}	…	ϑ_{2n}	$\sum_{k=1}^{n} w_k \theta_{2k}$
⋮	⋮	⋮	⋮	⋮	⋮
n	ϑ_{n1}	ϑ_{n2}	…	ϑ_{nn}	$\sum_{k=1}^{n} w_k \theta_{nk}$

4. An Illustrative Example

In this section, we provide a numerical example to illustrate potential applications of OWA operator weight to find the best supplier. In this example we want to select best box suppliers among 12 suppliers. Factors considered in order to select best supplier are as follows:
The data set for the 12 box supplier is documented in Table (3), where price (USD), distance (kilometer) and preparation time (Hour) are treated as inputs, quality and services are viewed as outputs. One of the inputs was a price that specified by the supplier, and varies between 32 to 36.5 USD, another input is blowover distance to the target box is delivered to the factory. Preparation time, time interval between the request and the delivery of an order based is specified at the time in the Table (3), quality and services are the outputs that have been determined by experts in the number 1 to 9.

Table 3. Data for 12 Box Supplier

Supplier	Inputs and Outputs				
	Price	Distance	Preparation Time	Quality	Services
1	32.5	65	48	7	6
2	320	680	72	6	6
3	320	800	72	4	8
4	330	1100	84	3	4
5	330	800	72	5	5
6	325	700	12	3	8
7	365	940	84	1	4
8	360	940	72	1	3
9	350	1300	96	3	1
10	340	1400	96	2	1
11	365	85	48	8	7
12	325	450	24	2	2

Table 4 shows the neutral cross-efficiency matrix of the 12 box suppliers obtained by solving model (5) for each of the 12 suppliers respectively. The average neutral cross-efficiency values of 12 suppliers are provided in the last column of Table 4, which shows that supplier 2, 3, 4, 5 and 12 are the best supplier due to its biggest average cross-efficiency value. Such a selection, however, fails to take into consideration the DM`s subjective preference. This drawback can be well overcome by using OWA operator weights for cross-efficiency aggregation.

To take into account the DM`s optimism level towards the best relative efficiencies in the final selection of the best supplier, we re-order the efficiencies of each supplier according to algorithm 4-1 in descending order in Table 5. For an extremely optimistic DM, he/she does not consider peer-evaluated efficiencies in the final selection at all. In other words, the DM assigns the whole weight of one to self-evaluated efficiencies and zero weights to all peer-evaluated efficiencies. The DM`s optimism level is orness (W)=1. In this case, the DM does not want to the CCR-efficient suppliers to be discriminated by their peer-evaluated efficiencies(See column 2 of Table 6). In the traditional equal aggregation of cross-efficiencies, the weight assigned to the self-evaluated efficiencies is only 8.3% (=1/12), (See column 5 of Table 6).

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Table 4. Neutral Cross-efficieny Matrix of 12 Box Supplier

Supplier	1	2	3	4	5	6	7	8	9	10	11	12	Ave
1	1.0000	0.3561	0.3251	0.1461	0.2621	0.3291	0.1191	0.0951	0.0691	0.0501	1.0000	0.1830	0.3278
2	0.9712	0.9272	1.0000	0.5422	0.7492	0.9262	0.3872	0.3072	0.2492	0.2012	1.0000	0.3042	**0.6303**
3	0.9713	0.9273	1.0000	0.5423	0.7493	0.9263	0.3873	0.3073	0.2493	0.2013	1.0000	0.3043	**0.6303**
4	0.9714	0.9274	1.0000	0.5424	0.7494	0.9264	0.3874	0.3074	0.2494	0.2014	1.0000	0.3040	**0.6303**
5	0.9715	0.9275	1.0000	0.5425	0.7495	0.9265	0.3875	0.3075	0.2495	0.2015	1.0000	0.3040	**0.6303**
6	0.9206	0.6506	0.5526	0.3176	0.5366	1.0000	0.1706	0.1606	0.2136	0.1526	1.0000	0.0500	0.4768
7	0.7387	0.7507	1.0000	0.4857	0.6067	0.9857	0.4387	0.3337	0.1147	0.1187	0.7677	0.2460	0.5484
8	0.7438	0.7508	1.0000	0.4848	0.6068	1.0000	0.4388	0.3348	0.1148	0.1178	0.7738	0.2250	0.5484
9	0.9839	0.8569	0.5709	0.4159	0.6919	0.4219	0.1259	0.1279	0.3919	0.2689	1.0000	0.2810	0.5106
10	0.9831	0.8561	0.5701	0.4151	0.6911	0.4211	0.1251	0.1271	0.3911	0.2681	1.0000	0.2810	0.5106
11	0.9731	0.9171	0.9371	0.5231	0.7411	0.8521	0.3481	0.2811	0.2701	0.2111	1.0000	0.3010	0.6128
12	0.9711	0.9271	1.0000	0.5421	0.7491	0.9261	0.3871	0.3071	0.2491	0.2011	1.0000	0.3040	**0.6303**

Table 5. Re-ordered Neutral cross-efficiency of the 12 Box Supplier

Supplier	1	2	3	4	5	6	7	8	9	10	11	12
1	1.0000	0.9839	0.9831	0.9731	0.9715	0.9714	0.9713	0.9712	0.9711	0.9206	0.7438	0.7387
2	0.9275	0.9274	0.9273	0.9272	0.9271	0.9171	0.8569	0.8561	0.7508	0.7507	0.6506	0.3561
3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9371	0.5709	0.5701	0.5526	0.3251
4	0.5425	0.5424	0.5423	0.5422	0.5421	0.5231	0.4857	0.4848	0.4159	0.4151	0.3176	0.1461
5	0.7495	0.7494	0.7493	0.7492	0.7491	0.7411	0.6919	0.6911	0.6068	0.6067	0.3566	0.2621
6	1.0000	1.0000	0.9857	0.9265	0.9264	0.9263	0.9262	0.9261	0.8521	0.4219	0.4211	0.3291
7	0.4388	0.4387	0.3875	0.3874	0.3873	0.3872	0.3871	0.3481	0.1259	0.1251	0.1706	0.1191
8	0.3348	0.3337	0.3075	0.3074	0.3073	0.3072	0.3071	0.2811	0.1279	0.1271	0.1606	0.0951
9	0.3919	0.3911	0.2701	0.2495	0.2494	0.2493	0.2492	0.2491	0.2136	0.1148	0.1147	0.0691
10	0.2689	0.2681	0.2111	0.2015	0.2014	0.2013	0.2012	0.2011	0.1526	0.1188	0.1187	0.0501
11	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.7738	0.7677
12	0.3043	0.3042	0.3040	0.3040	0.3040	0.3010	0.2810	0.2810	0.2460	0.2250	0.1803	0.0500

For an optimistic DM, he/she may wish the self-evaluated efficiencies to play a more role in the final overall efficiency assessment. For example, the DM may wish the weight for the self-evaluated efficiencies to account for 40% rather than 8.3% in the final overall efficiency assessment. This amounts to assigning the self-evaluated efficiencies in Table 5. By Theorem 1, we obtain the weights for cross-efficiency in column 3 of Table 6. The DM`s optimism level is measured as $orness(W) = \left(1/(n-1)\right)\sum_{i=1}^{n}(n-i)w_i = 0.9090$ .The weighted average cross-efficiency values of the 12 suppliers are computed by $\overline{\theta}_i = \sum_{k=1}^{n} w_k \vartheta_{ik}$ for $i=1,\ldots,n$, and the results are presented in the third column of Table 7, from which it is seen that there are two suppliers with the best efficiency of one and cannot be distinguished. In order to select the best supplier, the DM needs to either lower his/her optimism level or apply other decision aiding methodologies.

Suppose the DM reduces his/her optimism level from 0.9090 to 0.8. By Theorem 2, the weights for aggregation are computed, see column 4 of Table 6. The resultant weighted average cross-efficiency values of the 12 suppliers are provided in the fourth column of Table 7, from which it is seen that supplier 3 is the only one with the best overall efficiency and is thus selected as the best robot. For a neutral optimism level best supplier is 0. According to

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Theorem 3, OWA weights have duality property and the weights are in column 6 to 8.

Table 6. OWA Operator Weights for Cross-efficiency Aggregation

Rank	$\alpha = 1$	$\alpha = 0.909$	$\alpha = 0.8$	$\alpha = 0.5$	$\alpha = 0.2$	$\alpha = 0.091$	$\alpha = 0$
1	1	0.4	0.2310	0.0833	0	0	0
2	0	0.3	0.20103	0.0833	0	0	0
3	0	0.2	0.17106	0.0833	0	0	0
4	0	0.1	0.14109	0.0833	0	0	0
5	0	0	0.11112	0.0833	0.02121		0
6	0	0	0.08115	0.0833	0.05118	0	0
7	0	0	0.05118	0.0833	0.08115	0	0
8	0	0	0.02121	0.0833	0.11112	0	0
9	0	0	0	0.0833	0.14109	0.1	0
10	0	0	0	0.0833	0.17106	0.2	0
11	0	0	0	0.0833	0.20103	0.3	0
12	0	0	0	0.0833	0.2310	0.4	1

Table 7. Aggregation of Neutral Cross-efficiencies of 12 Supplier by OWA Operator Weights

Supplier	$\alpha = 1$	$\alpha = 0.909$	$\alpha = 0.8$	$\alpha = 0.5$	$\alpha = 0.2$	$\alpha = 0.091$	$\alpha = 0$
1	1.0000	0.9891	0.9913	0.9392	0.8717	0.7998	0.7677
2	0.9275	0.9274	0.9295	0.8142	0.6786	0.5628	0.3561
3	1.0000	1.0000	1.0000	0.8293	0.6219	0.4669	0.3251
4	0.5425	0.5424	0.5414	0.4581	0.3588	0.2783	0.1461
5	0.7495	0.6666	0.7032	0.6244	0.5083	0.3938	0.2621
6	1.0000	0.9897	0.9765	0.8031	0.5981	0.4275	0.3291
7	0.4388	0.4233	0.4121	0.3084	0.1990	0.1364	0.1191
8	0.3348	0.3262	0.3211	0.2496	0.1724	0.1244	0.0951
9	0.3919	0.3530	0.3165	0.2342	0.1547	0.1063	0.0691
10	0.2689	0.2503	0.2338	0.1828	0.1305	0.0946	0.0501
11	1.0000	1.0000	0.9998	0.9614	0.9097	0.8392	0.7387
12	0.3043	0.3041	0.3048	0.2569	0.1968	0.1436	0.0500

For a optimistic DM, supplier 11 and for extremely optimistic DM, supplier 1 is the best. Obviously, the best selection of suppliers is not fixed. It varies with the DM`s optimism level or subjective preference.

5. Conclusions

Considering the fact, one of the most important processes performed in enterprises today is the evaluation, selection and continuous measurement of suppliers, in this paper a aggregation cross-efficiency by OWA method was introduced for supplier selection which allows the DM's optimism level towards the best relative efficiencies or subjective preferences on different efficiencies to be taken into consideration in the final overall efficiency assessment. We have discussed various subjective preferences of the DM and derived corresponding weight formulations. We have also provided an illustrative example. Our demonstration

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reveals that the best selection of suppliers is not fixed. The selection varies with the DM's optimism level. Therefore, it is very essential that the DM's subjective preference or optimism level should be taken into consideration in the final overall efficiency assessment and particularly in the final selection of the best DMU. It is a flexible manner evaluation and selection suppliers.

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