

Article

A Pre-aggregation Fuzzy Collaborative Intelligence-based Fuzzy Analytic Hierarchy Process Approach for Selecting Alternative Suppliers amid the COVID-19 Pandemic

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Abstract: In the existing group decision-making fuzzy analytic hierarchy process (FAHP) methods, the consensus among experts has rarely been fully reached. To fill this gap, in this study, a pre-aggregation fuzzy collaborative intelligence (FCI)-based FAHP approach is proposed. In the proposed pre-aggregation FCI-based FAHP approach, fuzzy intersection is applied to aggregate experts' pairwise comparison results if these pairwise comparison results overlap. The aggregation result is a matrix of polygonal fuzzy numbers. Subsequently, alpha-cut operations are applied to derive the fuzzy priorities of criteria from the aggregation result. The pre-aggregation FCI-based FAHP approach has been applied to select suitable alternative suppliers for a wafer foundry in Taiwan amid the COVID-19 pandemic. The experimental results revealed that the pre-aggregation FCI-based FAHP approach significantly reduced the uncertainty inherent in the decision-making process by deriving fuzzy priorities with very narrow ranges.

Keywords: group decision-making; fuzzy analytic hierarchy process; consensus; wafer foundry; COVID-19 pandemic

1. Introduction

Analytic hierarchy process (AHP), proposed by Saaty [1], is a popular multiple-criteria decision-making method. AHP is based on pairwise comparisons made by an expert. However, pairwise comparisons are subjective and the expert is sometimes not sure of the results. To address this issue, various fuzzy AHP (FAHP) methods, such as fuzzy geometric mean (FGM) [2], fuzzy extent analysis (FEA) [3], and alpha-cut operations (ACO) [4], have been proposed by expressing pairwise comparison results with fuzzy sets. The types of fuzzy sets adopted in these methods include ordinary fuzzy sets [5], intuitionistic fuzzy sets [6], interval type-2 fuzzy sets [7], hesitant fuzzy sets [8], etc.

Multiple experts are usually involved in a FAHP problem to avoid personal bias and omissions, which turns the FAHP problem into a group decision-making FAHP problem [9]. Sometimes the pairwise comparison results by experts are aggregated before they derived the fuzzy priorities of criteria, i.e., the pre-aggregation way [5,10-12]. There are also studies in which the fuzzy priorities of criteria derived by experts are aggregated instead, i.e., the post-aggregation way [13-16], is to aggregate the fuzzy priorities of criteria derived by experts. The pre-aggregation way eliminates the

necessity for each expert to derive the fuzzy priorities of criteria individually, while the post-aggregation way is easier to calculate. This study follows the pre-aggregation way.

The existing pre-aggregation FAHP methods are subject to the following problems:

- (1) Experts' judgment are usually aggregated without checking whether they have reached a consensus [5].
- (2) Most past studies aggregated experts' judgments using FGM [5,11], which may lead to unreasonable and unacceptable results [17].
- (3) A few studies measured the distance between any two experts' judgments to check the existence of a consensus [10]. However, distance-based measures increase the uncertainty of the fuzzy group decision-making process, because a suitable distance function needs to be chosen, and a threshold for two judgments' distance has to be established.

Fuzzy collaborative intelligence (FCI) methods [18-19] adopt fuzzy intersection (FI) as the aggregator and can solve these problems naturally [20]. However, FCI methods have only been applied to post-aggregation problems [15-16] because the calculation is easier. To fill this gap, in this study, a pre-aggregation FCI-based FAHP approach is proposed.

In the proposed pre-aggregation FCI-based FAHP approach, FI is applied to aggregate experts' pairwise comparison results. If all FI outcomes are non-empty sets, then there is a consensus among experts; otherwise, experts need to modify their pairwise comparison results. Subsequently, considering the special shapes of FI outcomes, alpha-cut operations (ACO) [21] are applied to derive the fuzzy priorities of criteria from the aggregation result.

The difference between the proposed methodology and some existing pre-aggregation group decision-making FAHP methods are listed in Table 1. The proposed methodology has been applied to an alternative supplier selection problem amid the COVID-19 pandemic.

Table 1. Differences between the proposed methodology and some existing group decision-making FAHP methods.

Method	Consensus Measure	Level of Consensus	Aggregation Method	Method for Deriving Fuzzy Priorities	Acceptability of Results
Zheng et al. [5]	No	Unknown	Discussion	FGM	Unknown
Wang et al. [11]	No	Low	FGM	FEA	Low ~ High
Gao et al. [10]	Distance between judgments	Moderate	FGM	FGM	Moderate ~ High
Chen [12]	No	Low	FGM	FGM	Low ~ High
The proposed methodology	FI result	High	FI	ACO	High

The remainder of this paper is organized as follows. Section 2 reviews the existing methods for measuring the consensus among experts in an FAHP application. Section 3 introduces the pre-aggregation FCI-based FAHP approach. Section 4 reports the results of applying the pre-aggregation FCI-based FAHP approach to select suitable alternative suppliers for a wafer foundry in Taiwan amid the COVID-19 pandemic. Some existing methods were also applied to this case for comparison. Section 5 concludes this study and puts forth some potential topics for future research.

2. Existing Consensus Measures in Group Decision-making FAHP

Most past FAHP studies did not check the existence of a consensus among experts, but directly aggregated the pairwise comparison results done by experts or the fuzzy priorities of criteria derived by them [15], which may lead to unacceptable results [17]. There are two time points at which the consensus among experts can be measured: before deriving the fuzzy priorities of criteria (i.e., the

pre-aggregation way), and after deriving the fuzzy priorities of criteria (i.e., the post-aggregation way) [22].

In the pre-aggregation way, a consensus exists if the distance between the fuzzy judgment matrixes of any two experts is smaller than a threshold $\tilde{\xi}$ [10],

$$\tilde{d}(\tilde{\mathbf{A}}(k), \tilde{\mathbf{A}}(l)) = \sqrt{\sum_{i=1}^n \sum_{j=1}^n (\tilde{a}_{ij}(k) - \tilde{a}_{ij}(l))^2} \leq \tilde{\xi} \quad \forall k \neq l \quad (1)$$

where $\tilde{d}()$ is the fuzzy distance function; $\tilde{\mathbf{A}}(k) = [\tilde{a}_{ij}(k)]$ is the fuzzy judgment matrix of expert k ; $\tilde{a}_{ij}(k)$ indicates the relative priority of criterion i over criterion j compared by expert k ; $k = 1 \sim K$. A similar condition is to request the distance from the fuzzy judgment matrix of each expert to the average of all experts' fuzzy judgment matrixes to be smaller than the threshold:

$$\tilde{d}(\tilde{\mathbf{A}}(k), \tilde{\mathbf{A}}(all)) \leq \tilde{\xi} \quad \forall k \quad (2)$$

where $\tilde{\mathbf{A}}(all) = [\tilde{a}_{ij}(all)]$ is the average (or geometric mean) of all experts' fuzzy judgment matrixes:

$$\tilde{a}_{ij}(all) = \frac{\sum_{k=1}^K \tilde{a}_{ij}(k)}{K} \quad \text{or} \quad \sqrt[K]{\prod_{k=1}^K \tilde{a}_{ij}(k)} \quad (3)$$

In the post-aggregation way, a consensus exists if the distance between the fuzzy priorities derived by any two experts is smaller than a threshold $\tilde{\zeta}$,

$$\tilde{d}(\tilde{\mathbf{w}}(k), \tilde{\mathbf{w}}(l)) = \sqrt{\sum_{i=1}^n (\tilde{w}_i(k) - \tilde{w}_i(l))^2} \leq \tilde{\zeta} \quad \forall k \neq l \quad (4)$$

where $\tilde{\mathbf{w}}(k)$ is the fuzzy priorities of criteria derived by expert k . A similar condition is to request or the distance from the fuzzy priorities derived by each expert to the average of fuzzy priorities derived by all experts to be smaller than the threshold:

$$\tilde{d}(\tilde{\mathbf{w}}(k), \tilde{\mathbf{w}}(all)) \leq \tilde{\zeta} \quad \forall k \quad (5)$$

where $\tilde{\mathbf{w}}(all) = [\tilde{w}_i(all)]$ is the average of fuzzy priorities derived by all experts:

$$\tilde{w}_i(all) = \frac{\sum_{k=1}^K \tilde{w}_i(k)}{K} \quad (6)$$

Distance-based criteria are subject to the following problems:

- (1) The formula for calculating the distance between two fuzzy judgment matrixes (or fuzzy priorities) is not easy to calculate.
- (2) There are other methods to measure the distance between two fuzzy judgment matrixes (or fuzzy priorities). However, there is no absolute rule for choosing the most suitable method.
- (3) The value of the threshold $\tilde{\xi}$ (or $\tilde{\zeta}$) is subjectively determined, which adds to the uncertainty of the decision-making process.

From the viewpoint of fuzzy collaborative intelligence, if experts' fuzzy judgment matrixes overlap, i.e., the FI of these fuzzy judgment matrixes is not an empty set, then there is a consensus among them [20]:

$$FI(\{\tilde{a}_{ij}(k)\}) \neq \emptyset \quad \forall i, j, k \quad (7)$$

As an alternative, if the fuzzy priorities derived by experts overlap, then there is a consensus among them:

$$FI(\{\tilde{w}_i(k)\}) \neq \emptyset \quad \forall i, k \quad (8)$$

Most past studies [23-24] checked the existence of a consensus among experts in the post-aggregation way using Criterion (8) to simplify the calculation. To fill this gap, in this study, the existence of a consensus among experts is checked in the pre-aggregation way using Criterion (7).

3. Methodology

3.1. Anterior Aggregation

The fuzzy judgement matrix of expert k is denoted by $\tilde{\mathbf{A}}(k)=[\tilde{a}_{ij}(k)]$. FI [20] is applied to aggregate all experts' fuzzy judgment matrixes into a consolidated fuzzy judgment matrix $\tilde{\mathbf{A}}(all)=[\tilde{a}_{ij}(all)]$:

$$\tilde{\mathbf{A}}(all) = FI(\{\tilde{\mathbf{A}}(k)\}) \quad (9)$$

or

$$\tilde{a}_{ij}(all) = FI(\{\tilde{a}_{ij}(k)\}) \quad (10)$$

with the following membership function:

$$\mu_{\tilde{a}_{ij}(all)}(x) = \min_k (\mu_{\tilde{a}_{ij}(k)}(x)) \quad (11)$$

If $\tilde{a}_{ij}(all)$ is an empty set for any i and j , then experts lack a consensus and need to modify their pairwise comparison results.

Without loss of generality, all fuzzy parameters and variables in the proposed methodology are given in or approximated with triangular fuzzy numbers (TFNs). For example,

$$\tilde{a}_{ij}(k) = (a_{ij1}(k), a_{ij2}(k), a_{ij3}(k)) \quad (12)$$

The following theorem holds.

Theorem 1. A consensus among all experts exists if $\max_{i \neq j} \left(\max_{k \neq l} \left(\max(a_{ij1}(k), a_{ij1}(l)) - \min(a_{ij3}(k), a_{ij3}(l)) \right) \right) \leq 0$

Proof of Theorem 1. Experts reach an overall consensus regarding the value of \tilde{a}_{ij} if

$$FI(\{\tilde{a}_{ij}(l)\}) \neq \emptyset \quad (13)$$

which means

$$[a_{ij1}(k), a_{ij3}(k)] \cap [a_{ij1}(l), a_{ij3}(l)] \neq \emptyset \quad \forall \quad k \neq l \quad (14)$$

which is equivalent to

$$\max(a_{ij1}(k), a_{ij1}(l)) \leq \min(a_{ij3}(k), a_{ij3}(l)) \quad \forall \quad k \neq l \quad (15)$$

which can be condensed into

$$\max_{k \neq l} \left(\max(a_{ij1}(k), a_{ij1}(l)) - \min(a_{ij3}(k), a_{ij3}(l)) \right) \leq 0 \quad (16)$$

which holds for all i and j . Therefore,

$$\max_{i \neq j} \left(\max_{k \neq l} \left(\max(a_{ij1}(k), a_{ij1}(l)) - \min(a_{ij3}(k), a_{ij3}(l)) \right) \right) \leq 0 \quad (17)$$

Theorem 1 is proved. \square

The FI result of TFNs is a polygonal fuzzy number [20]. As a result, all elements of the fuzzy consolidated judgment matrix are polygonal fuzzy numbers, as illustrated in Figure 1. In addition, since FI works on the membership rather than the value of each element, the multiplicity property still holds:

$$FI(\{\tilde{a}_{ij}(k)\}) = \frac{1}{FI(\{\tilde{a}_{ji}(k)\})} \quad (18)$$




1		$1/\triangle$
$1/\triangle$	1	
	$1/\triangle$	1

Figure 1. A consolidated fuzzy judgment matrix with polygonal fuzzy numbers.

3.2. Deriving the Fuzzy Priorities of Criteria

ACO [24] are applied to derive the fuzzy priorities of criteria. First, fuzzy parameters and variables are represented with their α cuts. For example,

$$a_{ij}(all)(\alpha) = [a_{ij}^L(all)(\alpha), a_{ij}^R(all)(\alpha)] \quad (19)$$

where L and R indicate the left and right α cuts of a fuzzy variable, respectively. Then, an eigen analysis is conducted to derive the values of fuzzy eigenvalue $\tilde{\lambda}(all)$ and fuzzy vector $\tilde{\mathbf{x}}(all)$, in terms of their α cuts, as

$$\det(\mathbf{A}^*(all)(\alpha) - \lambda^\dagger(all)(\alpha)\mathbf{I}) = 0 \quad (20)$$

$$(\mathbf{A}^*(all)(\alpha) - \lambda^\dagger(all)(\alpha)\mathbf{I})\mathbf{x}^\diamond(all)(\alpha) = 0 \quad (21)$$

where $*$, \dagger , and \diamond can be L or R . If α takes 11 possible values (0, 0.1, ..., 1), Equations (20) and (21) need to be solved $10 \cdot 2^{C_2} + 1$ times. The minimal and maximal values of the results are used to construct the α cut of fuzzy eigenvector and eigenvalue [4]:

$$\begin{aligned} x_i(all)(\alpha) &= [x_i^L(all)(\alpha), x_i^R(all)(\alpha)] \\ &= [\min_{\diamond} x_i^\diamond(all)(\alpha), \max_{\diamond} x_i^\diamond(all)(\alpha)] \end{aligned} \quad (22)$$

$$\begin{aligned} \lambda(all)(\alpha) &= [\lambda^L(all)(\alpha), \lambda^R(all)(\alpha)] \\ &= [\min_{\dagger} \lambda^\dagger(all)(\alpha), \max_{\dagger} \lambda^\dagger(all)(\alpha)] \end{aligned} \quad (23)$$

In addition, Equations (20) and (21) involve a number of fuzzy multiplication operations. As a result, if $\tilde{a}_{ij}(all)$ is a TFN, then $\tilde{\lambda}(all)$ and $\tilde{\mathbf{x}}(all)$ will be triangular fuzzy numbers with curved edges [21]. If $\tilde{a}_{ij}(all)$ is a polygonal fuzzy number, then $\tilde{\lambda}(all)$ and $\tilde{\mathbf{x}}(all)$ will be polygonal fuzzy numbers with curved edges.

The fuzzy priorities of criteria $\tilde{\mathbf{w}}(all)$ are obtained by normalizing $\tilde{\mathbf{x}}(all)$ as

$$\tilde{w}_i(all) = \frac{\tilde{x}_i(all)}{\sum_{i=1}^n \tilde{x}_i(all)} \quad (24)$$

In addition, there are n possible values of $\tilde{\lambda}(all)$. The fuzzy maximal eigenvalue is denoted by $\tilde{\lambda}_{\max}(all)$. The consistency of all experts' pairwise comparison results is evaluated in terms of fuzzy consistency ratio $CR(all)$ as

$$CR(all) = \frac{\tilde{\lambda}_{\max}(all) - n}{n - 1} \quad (25)$$

where RI is random consistency index [1]. $CR(all) \geq 0$. $CR(all)$ needs to be less than 0.1, but can be relaxed to less than 0.3 if the problem size is large. Otherwise, experts are asked to modify their pairwise comparison results.

4. Case Study

4.1. Application of the Proposed Methodology

Supplier selection is a multiple-criteria decision-making problem that has been extensively studied [25-27]. A number of factors are considered critical to the performance of a supplier, such as product quality, price, delivery speed, company reputation, supplier relationship, etc. [15,28]. An alternative supplier is a supplier with which a formal cooperation relationship does not exist. An alternative supplier may not be the best choice in regular supplier selection, but has to be resorted to during the COVID-19 pandemic. For this reason, criteria for choosing an alternative supplier may be different from those for choosing a regular supplier [29]. In addition, amid the COVID-19 pandemic, a manufacturer (including supplier and alternative supplier) has to be robust to the pandemic to ensure its operations [16,30]. Factors critical to the robustness of a manufacturer to the COVID-19 pandemic include pandemic containment performance, pandemic severity, vaccine acquisition speed, demand shrinkage, supplier impact, and infection risk [16].

The COVID-19 pandemic has forced many factories to shut down, resulting in the breakage of related supply chains [31]. To fill the shortage of supply, a manufacturer needs to find alternative suppliers [32]. Therefore, how to choose suitable alternative suppliers amid the COVID-19 pandemic becomes an important problem. A wafer foundry in Taiwan would like to choose suitable alternative suppliers amid the COVID-19 pandemic. Current suppliers of the wafer foundry were mostly located in Taiwan, Netherlands, and USA. Among these regions, Netherlands and USA have been highly impacted by the pandemic [33]. Therefore, looking for alternative suppliers to replace existing suppliers in the two regions became a critical task to the wafer foundry. To fulfill this task, the proposed methodology was applied.

The following factors were considered critical to the performance of an alternative supplier amid the COVID-19 pandemic:

- price,
- delivery speed,
- company reputation,
- pandemic containment performance, and
- pandemic severity.

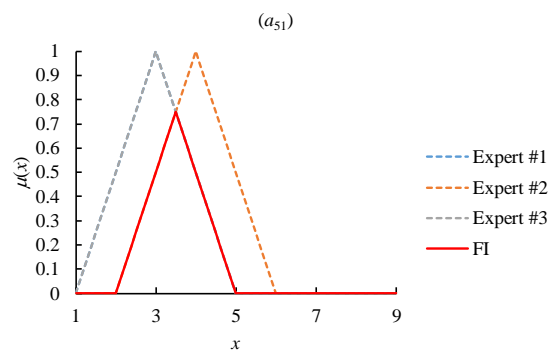
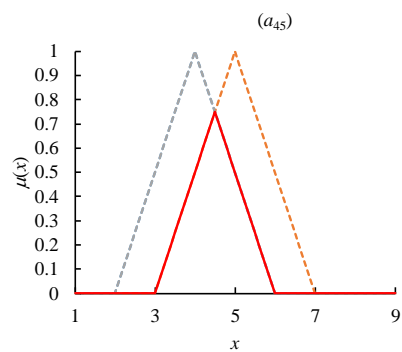
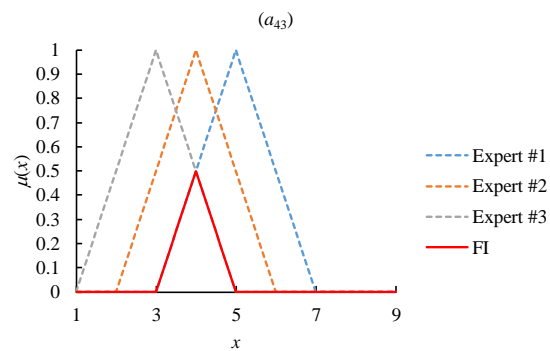
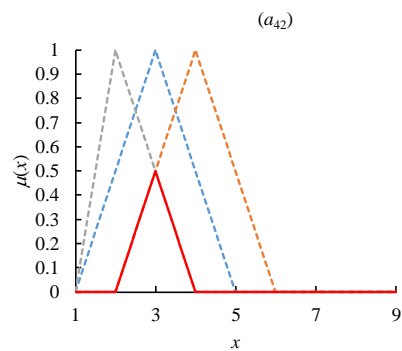
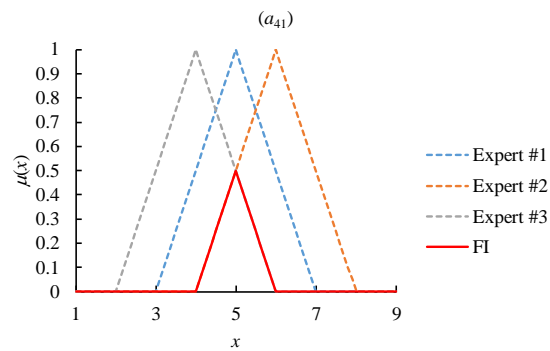
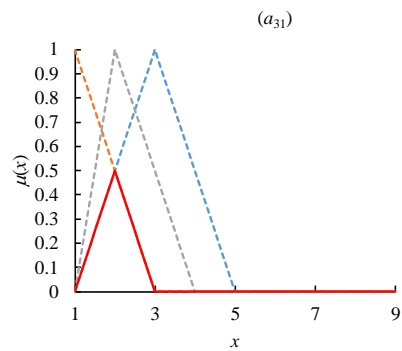
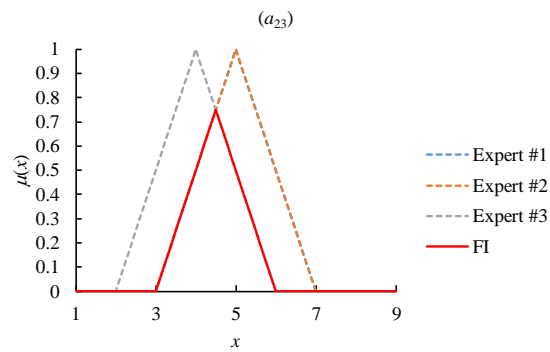
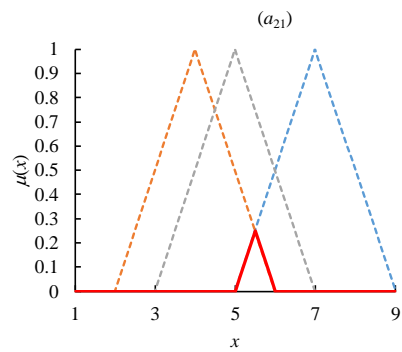
Three experts were involved in the alternative supplier selection process. At first, each expert was requested to compare the relative fuzzy priorities of criteria in pairs. The comparison results are presented below:

$$\tilde{A}(1) = \begin{bmatrix} 1 & - & - & - & - \\ (5, 7, 9) & 1 & (3, 5, 7) & - & - \\ (1, 3, 5) & - & 1 & - & - \\ (3, 5, 7) & (1, 3, 5) & (3, 5, 7) & 1 & (2, 4, 6) \\ (1, 3, 5) & (1, 1, 3) & (1, 1, 3) & - & 1 \end{bmatrix}$$

$$\tilde{A}(2) = \begin{bmatrix} 1 & - & - & - & - \\ (2, 4, 6) & 1 & (3, 5, 7) & - & - \\ (1, 1, 3) & - & 1 & - & - \\ (4, 6, 8) & (2, 4, 6) & (2, 4, 6) & 1 & (3, 5, 7) \\ (2, 4, 6) & (1, 3, 5) & (1, 3, 5) & - & 1 \end{bmatrix}$$

$$\tilde{A}(3) = \begin{bmatrix} 1 & - & - & - & - \\ (3, 5, 7) & 1 & (2, 4, 6) & - & - \\ (1, 2, 4) & - & 1 & - & - \\ (2, 4, 6) & (1, 2, 4) & (1, 3, 5) & 1 & (2, 4, 6) \\ (1, 3, 5) & (1, 2, 4) & (1, 3, 5) & - & 1 \end{bmatrix}$$

Fuzzy intersection was applied to aggregate all experts' pairwise comparison results. The results are shown in Figure 2. Obviously, experts achieved a consensus regarding the value of each relative priority.



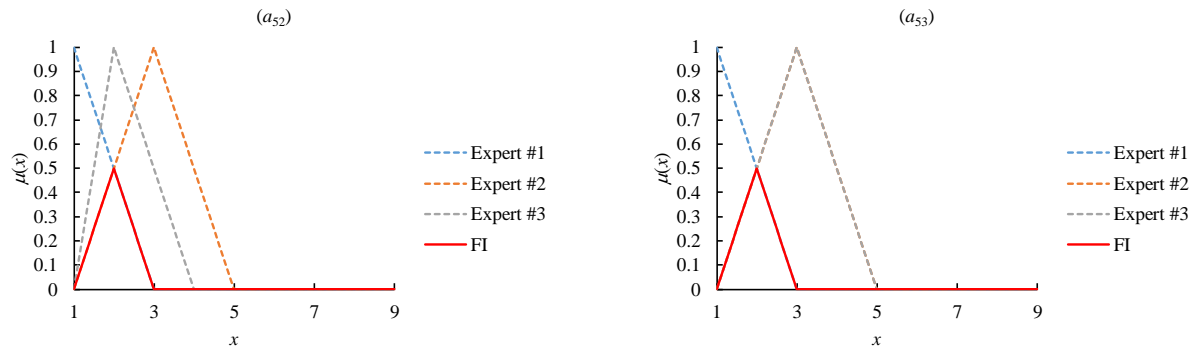


Figure 2. The fuzzy intersection results.

To apply ACO to derive the values of fuzzy priorities, the aggregation result was discretized into α cuts, as shown in Table 2. Obviously, only α cuts when α was less than 0.2 needed to be considered, which significantly shortened the enumeration process. Subsequently, MATLAB 2017 was adopted to implement ACO on a PC with i7-7700 CPU 3.6 GHz and 8 GB RAM. The program code was shown in Figure 3. The execution time was 6.4 seconds. Finally, the derived fuzzy maximal eigenvalue and fuzzy priorities of criteria are shown in Figures 4 and 5, respectively.

Table 2. The α cuts of the aggregation result.

α	a_{21}	a_{23}	a_{31}	a_{41}	a_{42}	a_{43}	a_{45}	a_{51}	a_{52}	a_{53}
0	[5, 6]	[3, 6]	[1, 3]	[4, 6]	[2, 4]	[3, 5]	[3, 6]	[2, 5]	[1, 3]	[1, 3]
0.1	[5.2, 5.8]	[3.2, 5.8]	[1.2, 2.8]	[4.2, 5.8]	[2.2, 3.8]	[3.2, 4.8]	[3.2, 5.8]	[2.2, 4.8]	[1.2, 2.8]	[1.2, 2.8]
0.2	[5.4, 5.6]	[3.4, 5.6]	[1.4, 2.6]	[4.4, 5.6]	[2.4, 3.6]	[3.4, 4.6]	[3.4, 5.6]	[2.4, 4.6]	[1.4, 2.6]	[1.4, 2.6]
0.3		[3.6, 5.4]	[1.6, 2.4]	[4.6, 5.4]	[2.6, 3.4]	[3.6, 4.4]	[3.6, 5.4]	[2.6, 4.4]	[1.6, 2.4]	[1.6, 2.4]
0.4		[3.8, 5.2]	[1.8, 2.2]	[4.8, 5.2]	[2.8, 3.2]	[3.8, 4.2]	[3.8, 5.2]	[2.8, 4.2]	[1.8, 2.2]	[1.8, 2.2]
0.5		[4, 5]	[2, 2]	[5, 5]	[3, 3]	[4, 4]	[4, 5]	[3, 4]	[2, 2]	[2, 2]
0.6		[4.2, 4.8]					[4.2, 4.8]	[3.2, 3.8]		
0.7		[4.4, 4.6]					[4.4, 4.6]	[3.4, 3.6]		

```

stime=now      % start time
fl=zeros(6,1)  % fuzzy eigenvalue
fev=zeros(5,6) % alpha cuts of fuzzy eigenvector; alpha = 0, 0.1, 0.2

a21=[5 6;5.2 5.8;5.4 5.6]
...
a53=[1 3;1.2 2.8;1.4 2.6]

for i0=1:3
    alpha0=i0*0.1-0.1    % alpha
    lmin=9999
    lmax=0
    evmin=[9999 9999 9999 9999 9999]
    evmax=[0 0 0 0 0]

    A=zeros(5,5) % crisp pairwise comparison matrix
    A(1,1)=1
    ...
    A(5,5)=1

```



```

for i1=1:2
    for i2=1:2
        for i3=1:2
            for i4=1:2
                for i5=1:2
                    for i6=1:2
                        for i7=1:2
                            for i8=1:2
                                for i9=1:2
                                    for i10=1:2

                                        % build crisp pairwise comparison matrix
                                        A(2,1)=a21(i0,i1)
                                        A(1,2)=1/A(2,1)
                                        ...
                                        A(5,3)=a53(i0,i10)
                                        A(3,5)=1/A(5,3)

                                        % derive the eigenvalue and eigenvector
                                        [E, V] = eig(A)

                                        % update alpha cuts of fuzzy eigenvalue and eigenvector
                                        if V(1,1)<Imin
                                            Imin=V(1,1)
                                        end
                                        if V(1,1)>Imax
                                            Imax=V(1,1)
                                        end

                                        ev=E(:,1)/sum(E(:,1))
                                        for j=1:5
                                            if ev(j)<evmin(j)
                                                evmin(j)=ev(j)
                                            end
                                        end
                                        for j=1:5
                                            if ev(j)>evmax(j)
                                                evmax(j)=ev(j)
                                            end
                                        end

                                    end
                                end
                            end
                        end
                    end
                end
            end
        end
    end
end

% update fuzzy eigenvalue and eigenvector
fl(i0,1)=Imin
fl(7-i0,1)=Imax
for j=1:5
    fev(j,i0)=evmin(j)

```

```

    fev(j,7-i0)=evmax(j)
end
end

etime=now      % end time
(etime-stime)*60*60*24    % elapsed time

```

Figure 3. The MATLAB program code.

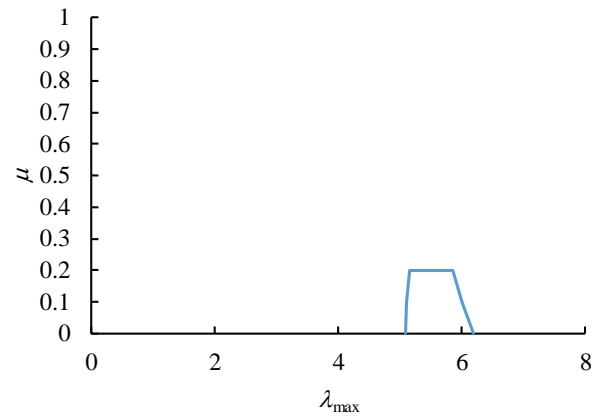
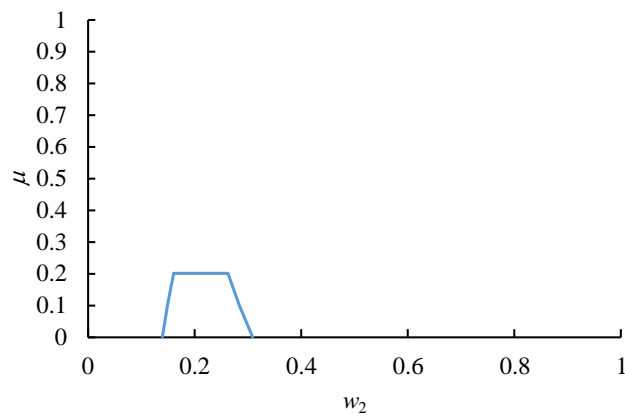
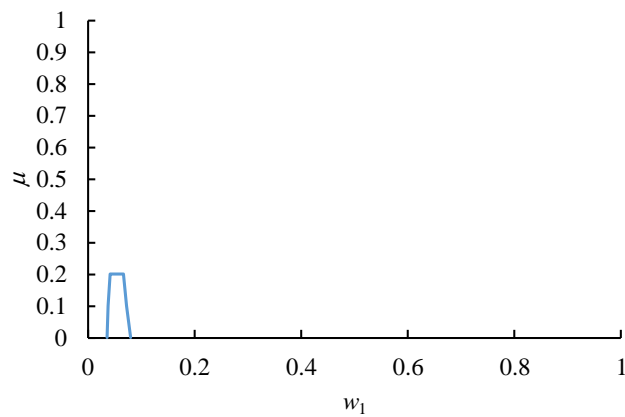


Figure 4. Fuzzy maximal eigenvalue.



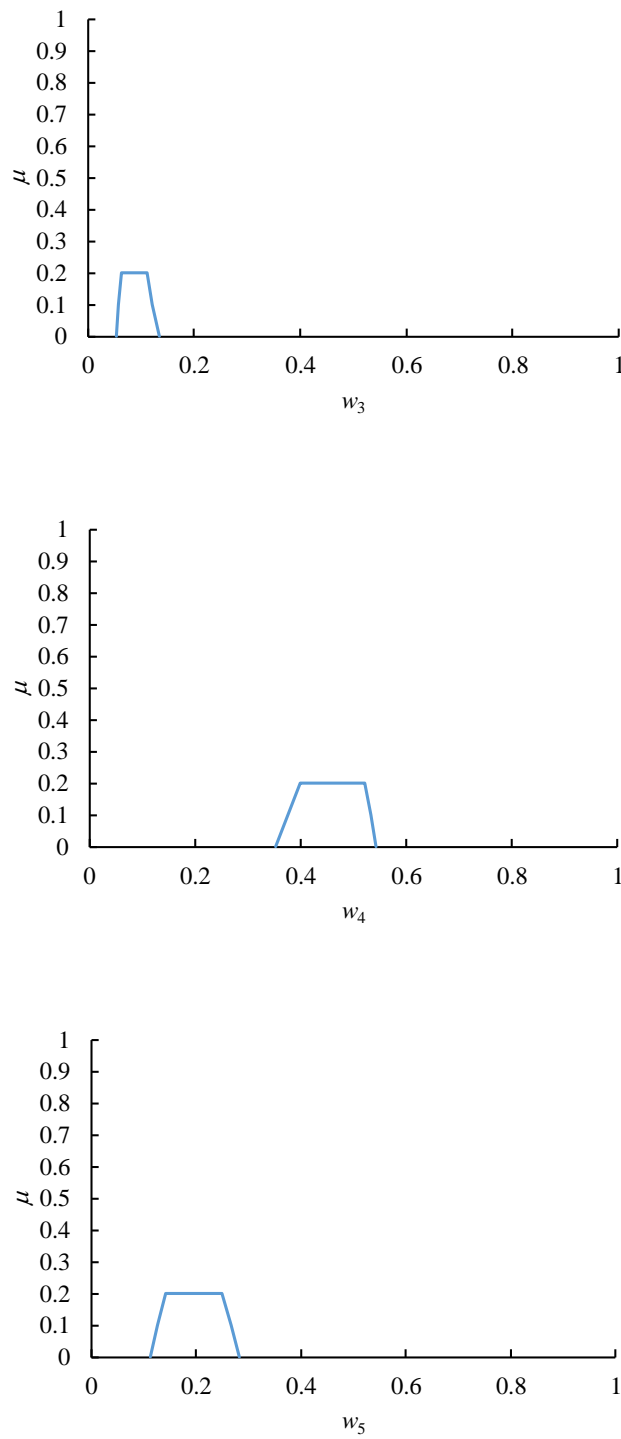


Figure 5. Fuzzy priorities.

4.2. Application of Existing Methods

For comparison, three existing methods were also applied to this case. The first existing method was the pre-aggregation FGM-FGM method, in which FGM was applied to aggregate experts’ fuzzy judgment matrixes and then derive the fuzzy priorities of criteria from the aggregation result. The results are shown in Figure 6.

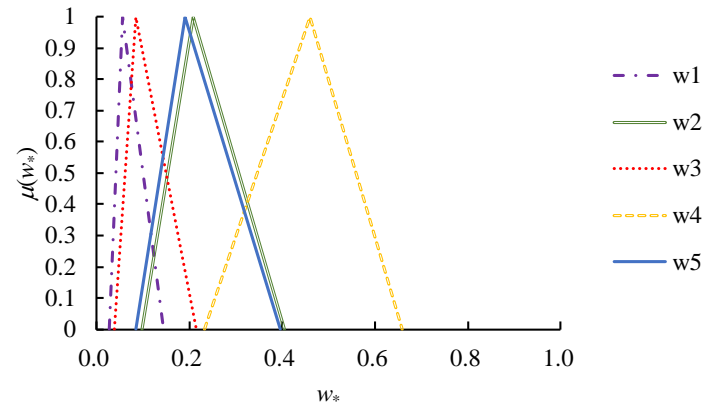


Figure 6. The fuzzy priorities of criteria derived using the FGM-FGM method.

The second existing method was the post-aggregation FGM-fuzzy arithmetic mean (FAM) method, in which each expert derived the fuzzy priorities of criteria using FGM. Then, the fuzzy priorities derived by all experts were aggregated using FAM. The results, shown in Figure 7, were very close to those derived using the FGM-FGM method.

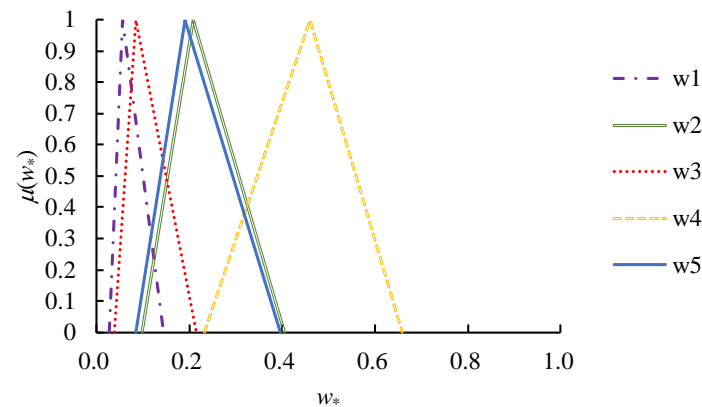


Figure 7. The fuzzy priorities of criteria derived using the FGM-FAM method.

The next compared existing method was the post-aggregation FGM-FI method. First, FGM was applied by each expert to derive the fuzzy priorities of criteria. Then, FI was applied to aggregate the derived fuzzy priorities. The results are shown in Figure 8. The derived fuzzy priorities approximated TFNs. However, the ranges of the fuzzy priorities derived using the FGM-FI method were narrower than those derived by the previous two methods, showing that the precision was improved. In addition, the highest membership of a fuzzy priority derived using the FGM-FI method was usually lower than 1.

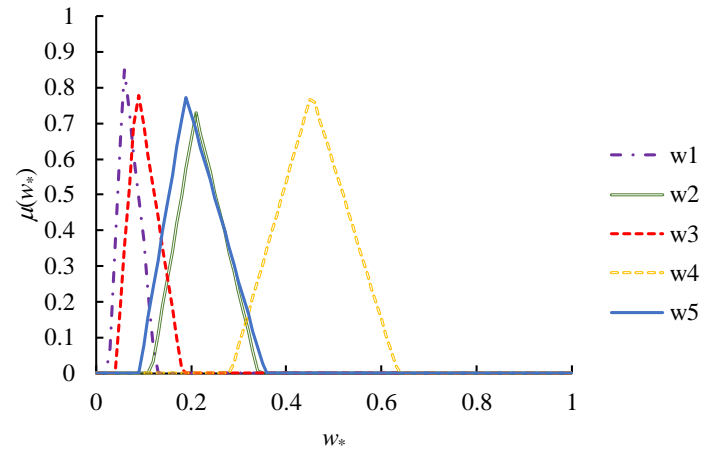


Figure 8. The fuzzy priorities of criteria derived by the post-aggregation FGM-FI method.

4.3. Discussion

According to the experimental results, the following points are discussed:

- (1) Although \tilde{a}_{ij} 's were given in TFNs, the fuzzy maximal eigenvalue and fuzzy priorities derived using the proposed methodology were polygonal fuzzy numbers with curved edges.
- (2) "Pandemic containment performance" was the most critical factor to the performance of an alternative supplier, followed by "delivery speed" and "pandemic severity". In contrast, the least critical factor was "price".
- (3) The fuzzy maximal eigenvalue ranged from 5.08 to 6.20, equivalent to a critical ratio of 0.02 to 0.27. The defuzzified value using the center-of-gravity method [34] was 0.11, showing sufficient consistency.
- (4) By aggregating experts' judgments using the proposed pre-aggregation FCI-based FAHP approach, the uncertainty inherent in the decision-making process has been considerably lessened, which was shown by very narrow fuzzy priorities. For example, the value of \tilde{w}_4 derived using the proposed methodology is compared with those derived using the existing methods in Figure 9. The proposed methodology shrank the width of \tilde{w}_4 by up to 55%.

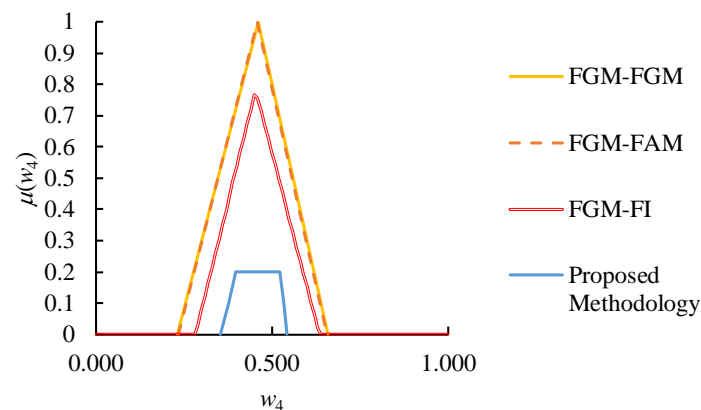


Figure 9. The values of \tilde{w}_4 derived using various methods.

5. Conclusions

In a fuzzy group decision-making method, experts need to reach a consensus for the decision-making result to be acceptable to all of them. However, this requirement has not been fully satisfied by the existing group decision-making FAHP methods. To fill this gap, a pre-aggregation FCI-based FAHP approach is proposed in this study. The pre-aggregation FCI-based FAHP approach satisfies the strictest consensus requirement, i.e., the pairwise comparison results by experts should overlap. In the proposed methodology, first FI is applied to aggregate experts' pairwise comparison results if these pairwise comparison results overlap. The aggregation result is a matrix of polygonal fuzzy numbers. Subsequently, ACO are applied to derive the fuzzy priorities of criteria from the aggregation result.

The pre-aggregation FCI-based FAHP approach has been applied to select suitable alternative suppliers for a wafer foundry in Taiwan amid the COVID-19 pandemic. For elaborating the effectiveness of the pre-aggregation FCI-based FAHP approach, three existing methods were also applied to the same case, so as to make a comparison. Finally, the following conclusions were drawn from the experimental results:

- (1) "Pandemic containment performance" and "delivery speed" were considered as the most critical factors to the performance of an alternative supplier, which was obviously due to the COVID-19 pandemic.
- (2) Compared to the three existing FAHP methods, the pre-aggregation FCI-based FAHP approach significantly reduced the uncertainty inherent in the decision-making process by deriving fuzzy priorities with very narrow ranges.

The proposed methodology can be extended in future studies to deal with cases in which only a partial consensus has been achieved. In other words, some pairwise comparison results overlap, while others do not. Or, the derived fuzzy priorities overlap, but pairwise comparison results do not.

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