Assessing cloud manufacturing applications using an optimally rectified FAHP approach

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Abstract
Cloud Manufacturing (CMfg) is a new manufacturing paradigm that promises to reduce costs, improve data analysis, increase efficiency and flexibility, and provide manufacturers with closer partnerships. However, most past CMfg research has focused on either the information technology infrastructure or the planning and scheduling of a hypothetical CMfg system. In addition, the cost effectiveness of a CMfg application has rarely been assessed. As a result, a manufacturer is not sure whether to adopt a CMfg application or not. To address this issue, an optimally rectified fuzzy analytical hierarchy process (OR-FAHP) approach is proposed in this study to assess a CMfg application. The OR-FAHP approach solves the inconsistency problem of the conventional FAHP method, a well-known technology assessment technique, to make the analysis results more trustable. The OR-FAHP approach has been applied to assess and compare 10 CMfg applications.

Keywords
Cloud manufacturing · Rectification · Fuzzy analytic hierarchy process · Inconsistency

Abbreviations

| Abbreviation | Description                          |
|--------------|--------------------------------------|
| 3D           | Three dimensional                    |
| CF           | Critical factor                      |
| CI           | Consistency index                    |
| CMfg         | Cloud manufacturing                  |
| COG          | Center-of-gravity                    |
| CR           | Consistency ratio                    |
| DM           | Decision maker                       |
| FAHP         | Fuzzy analytical hierarchy process    |
| FGM          | Fuzzy geometric mean                 |
| FNLP         | Fuzzy nonlinear programming          |
| FWA          | Fuzzy weighted average               |
| IT           | Information technology               |
| KKT          | Karush–Kuhn–Tucker                   |
| NLP          | Nonlinear programming                |
| OR           | Optimally rectified                  |
| PP           | Polynomial programming               |
| RI           | Random consistency index             |
| TFN          | Triangular fuzzy number              |

Introduction
Cloud manufacturing (CMfg) is a manufacturing model for enabling ubiquitous, convenient, and real-time access to a shared pool of configurable manufacturing resources through the Internet [1]. CMfg aims to provision and release manufacturing resources rapidly with minimal management efforts or service provider interaction [2]. In the view of Fisher et al. [3], CMfg is able to show the most sustainable and robust manufacturing route, which highlights the importance of cross-organizational collaboration to CMfg. According to Chen [4], the benefits of CMfg reside in the following respects: cost savings, efficiency, additional data analysis capabilities, flexibility, and closer partner relationships.

Tao et al. [5] classified CMfg technologies into eight categories: underlying support, resource access, resource perception and processing, resource virtualization, resource servitization, service management, demand management, transaction management, user business management, and
Various CMfg models have been proposed and applied to different stages of the manufacturing life cycle [6]. For example, a CMfg model was proposed by Laili et al. [7] for the product design stage, so that product designs and design knowledge could be easily shared online. In the production planning stage, Chen and Lin [8] established a CMfg system for distributing production simulation tasks among several cloud-based simulation services. To facilitate the mass production of a product, sensors and adapters were adopted to convert manufacturing resources into cloud resources [5], so that manufacturing resources could be shared to support factories without enough capacities. Among manufacturing resources, three-dimensional (3D) printers are especially easy to be put on clouds. Chen and Lin [9] used this feature to establish an agile and ubiquitous additive manufacturing system that distributed an order among several 3D printing facilities and arranged the transportation plan to pick up the printed pieces, which was the application of CMfg to both mass production and logistics.

The scheduling of jobs in a CMfg system is a challenging task, because jobs are usually distributed in multiple facilities [7]. Laili et al. [7] proposed an energy-adaptive immune genetic algorithm to schedule jobs in a CMfg system for facilitating collaborative product design. Liu et al. [10] considered a multi-task scheduling problem under a CMfg environment, which was a very challenging topic since multiple tasks were to be sequenced across multiple factories. The computational complexity was doubled. To address this topic, they applied production simulation to create promising schedules instead of formulating an optimization model to find out the best schedule. Chen and Wang [11] proposed a branch-and-bound algorithm to minimize the cycle time for delivering a job in a 3D-printing-based CMfg system. A recent literature review on CMfg refers to Ghomi et al. [12].

Although CMfg has been a hot research topic since its emergence, it still faces the following difficulties before being widely applied in practice:

1. Most existing CMfg studies were of experimental natures or only the illustration of conceptual ideas. The information technology (IT) infrastructure and the planning or scheduling of a hypothetical CMfg system are the focuses of most past CMfg studies.

2. The cost effectiveness of a CMfg system has rarely been assessed.

3. Compared to the manufacturing (or managerial) aspect, the IT aspect of CMfg was much more emphasized. However, many problems in a factory involve managerial issues that cannot be addressed by merely adopting new IT technologies.

For these reasons, a systematic procedure for evaluating a CMfg application is needed so that factory managers can choose from several alternatives for investment. However, this issue has not been fully explored in the past. In contrast, only a few references considered the selection of machines or resources for specific CMfg applications [13, 14]. The motivation of this research is to fill this gap.

An optimally rectified fuzzy analytical hierarchy process (FAHP) (OR-FAHP) approach is proposed in this study. In the proposed methodology, FAHP [15, 16] is applied to rank the priorities of criteria for assessing the performance of a CMfg application. However, to address the inconsistency of the pairwise comparisons made by a decision maker (DM), the proposed methodology rectifies the fuzzy judgment matrix of the DM, thereby enhancing the reliability of the assessment results.

The OR-FAHP approach has been applied to assess 10 CMfg applications to illustrate its applicability. An existing method was also applied to assess these CMfg applications to make a comparison. The differences between the proposed methodology and some existing methods are summarized in Table 1.

The contribution of this study lies in the following aspects:

1. A systematic procedure has been established to evaluate and compare CMfg applications, and the results can better guide the investment of a factory on CMfg applications.

2. A new mechanism is established to rectify a fuzzy judgment matrix to improve its consistency.

The remainder of this paper is organized as follows. Section Proposed methodology introduces the OR-FAHP approach. Ten CMfg applications were assessed using the proposed methodology to illustrate its applicability, as

| Method                | CMfg stages   | Cost-effectiveness | Results optimized? |
|-----------------------|---------------|--------------------|--------------------|
| Laili et al. [7]      | Product design| Not evaluated      | Yes                |
| Tao et al. [5]        | All           | Not evaluated      | No                 |
| Chen and Lin [8]      | Mass production| Not evaluated    | Yes                |
| Liu et al. [17]       | Mass production| Not evaluated    | Yes                |
| The proposed methodology | All          | Evaluated         | Yes                |
detailed in Sect. Assessing ten CMfg applications. Finally, Sect. Conclusions concludes this paper and provides some directions for future research.

**Proposed methodology**

**Procedure**

The OR-FAHP approach is composed of the following steps (see Fig. 1):

1. Compare the relative priority of each criterion for assessing a CMfg application over that of another.
2. Evaluate the fuzzy consistency of the pairwise comparison results.
3. If the fuzzy consistency is high enough, proceed to Step 7; otherwise, go to Step 4.
4. Formulate the fuzzy nonlinear programming (FNLP) model for optimizing the fuzzy consistency.
5. Convert the FNLP model into an equivalent PP problem to be solved.
6. Modify the fuzzy judgment matrix.
7. Derive the fuzzy priority of each criterion using alpha-cut operations.
8. Apply the fuzzy weighted average (FWA) method to assess each CMfg application.
9. Choose the most preferable CMfg application.

In rectifying a fuzzy judgment matrix, the proposed methodology is different from some existing methods, as compared in Table 2.

**FNLP model for rectifying a fuzzy judgment matrix**

In FAHP, a fuzzy judgment matrix is constructed by a DM as:

\[
\hat{A}_{n \times n} = [\hat{a}_{ij}]
\]  

(1)

where

\[
\hat{a}_{ij} = \begin{cases} 
1 & \text{if } i = j \\
\frac{1}{\hat{a}_{ji}} & \text{otherwise}
\end{cases}
\]  

(2)

\(\hat{a}_{ij}\) is the pairwise comparison result representing the relative priority of criterion \(i\) over criterion \(j\), \(1 \leq i, j \leq n\). Basically, \(0 \leq \hat{a}_{ij} \leq 9\). \(\hat{a}_{ij}\) is a positive comparison if \(\hat{a}_{ij} \geq 1\), and can be represented by linguistic terms such as “as important as,” “weakly more important than,” “strongly more important than,” “very strongly more important than,” and “absolutely more important than.” These linguistic terms can be mapped to the following triangular fuzzy numbers (TFNs) \([22–24]\):

- \(L_1\): “As important as” = (1, 1, 3).
- \(L_2\): “Weakly more important than” = (1, 3, 5).

![Fig. 1 Procedure of the OR-FAHP approach](image-url)
Table 2 Differences between the proposed methodology and some existing methods in rectifying a fuzzy judgment matrix

| Method                  | Way to enhance consistency   | Subjective or objective | Method type          | Optimality of the solution |
|-------------------------|------------------------------|-------------------------|----------------------|----------------------------|
| Saaty [18]              | Modify the pairwise comparison results | Subjective               | Subjective modification | Non-optimal                |
| Girsang et al. [19]     | Rectifying the judgment matrix | Objective               | Ant colony optimization | Maybe non-optimal          |
| Abadi and Widyarto [20] | Excluding inconsistent results | Subjective               | Subjective judgment  | Non-optimal                |
| Girsang et al. [21]     | Rectifying the judgment matrix | Objective               | Ant colony optimization | Maybe non-optimal          |
| The proposed methodology| Rectifying the judgment matrix | Objective               | Polynomial programming | Optimal                    |

\[ \tilde{L}_3: \text{“Strongly more important than”} = (3, 5, 7). \]
\[ \tilde{L}_4: \text{“Very strongly more important than”} = (5, 7, 9). \]
\[ \tilde{L}_5: \text{“Absolutely more important than”} = (7, 9, 9). \]

If the relative priority is between two successive linguistic terms, TFNs such as \((1, 2, 4), (2, 4, 6), (4, 6, 8), \) and \((6, 8, 9)\) are applicable. Obviously,

\[ a_{ij1} = \max(a_{ij2} - 2, 1) \quad (3) \]
\[ a_{ij3} = \min(a_{ij2} + 2, 9) \quad (4) \]

The fuzzy eigenvalue and eigenvector of \( \tilde{A} \), indicated respectively with \( \tilde{\lambda} \) and \( \tilde{x} \), satisfy

\[ \det(\tilde{A}(-\tilde{\lambda})I) = 0 \quad (5) \]

and

\[ (\tilde{A}(-\tilde{\lambda})I) \times \tilde{x} = 0 \quad (6) \]

where \((-)\) and \((\times)\) denote fuzzy subtraction and multiplication, respectively. The fuzzy maximal eigenvalue and the fuzzy priority of each criterion are derived respectively as

\[ \hat{\lambda}_{\max} = \max_i \hat{\lambda}_i \quad (7) \]
\[ \hat{w}_i = \frac{\hat{x}_i}{\sum_{j=1}^{n} \hat{x}_j} \quad (8) \]

Based on \( \hat{\lambda}_{\max} \), the fuzzy consistency of the pairwise comparison results is evaluated as:

\[ \text{Fuzzy consistency index} \]
\[ \tilde{C}I = \frac{\hat{\lambda}_{\max} - n}{n - 1} \quad (9) \]

\[ \text{Fuzzy consistency ratio} \]
\[ \tilde{C}R = \frac{\tilde{C}I}{RI} \quad (10) \]

where \( RI \) is the random consistency index (Satty, 1980). The pairwise comparison results are inconsistent if \( \tilde{C}I > 0.1 \sim 0.3 \) or \( \tilde{C}R > 0.1 \sim 0.3 \), depending on the matrix size [25–27].

The results of a FAHP analysis are trustable only when the fuzzy consistency of the pairwise comparison results is sufficiently high. Otherwise, an optimally rectifying mechanism is proposed in this study to modify the pairwise comparison results on behalf of the DM, so as to enhance the trustability of the FAHP analysis. The optimally rectifying mechanism makes a minor adjustment to the fuzzy judgment matrix as

\[ \hat{\tilde{A}}' = \tilde{A} + \Delta \tilde{A} \]

namely,

\[ \hat{a}_{ij}' = \hat{a}_{ij} + \Delta \hat{a}_{ij} \forall \hat{a}_{ij} \geq 1; \ i, j \in [1, n]; i \neq j \quad (12) \]

so that the \( \tilde{C}R \) is improved:

\[ \tilde{C}R(\hat{\tilde{A}}') \leq \tilde{C}R(\hat{\tilde{A}}) \quad (13) \]

\( \hat{\tilde{A}}' \) still meets the basic requirements for a fuzzy judgment matrix:

\[ 1 \leq \hat{a}_{ij}' \leq 9\hat{a}_{ij} \geq 1; \ i, j \in [1, n]; i \neq j \quad (14) \]

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\[ \tilde{a}_{ij} = 1; \ i \in [1, \ n] \]  
(15)

\[ \tilde{a}_{ij} = \frac{1}{\tilde{d}_{ji}} \forall \tilde{a}_{ij} \leq 1; \ i, \ j \in [1, \ n]; \ i \neq j \]  
(16)

In addition, \( \tilde{C}R(\tilde{A}') \) is to be optimized by the optimally rectifying mechanism,

Min \( \tilde{Z}_1 = \tilde{C}I(\tilde{A}') \)  
(17)

To assure that the adjustment is minor,

\[ \Delta \tilde{a}_{ij} \sim N(0, \ \sigma^2)\forall \tilde{a}_{ij} \geq 1; \ i, \ j \in [1, \ n]; \ i \neq j \]  
(18)

Theoretically, \( 3\sigma \) is the possibly maximal adjustment. Therefore, it is suggested to assign a value of less than \( 1/3 \) to \( \sigma \).

Finally, the following FNLP model is formulated to rectify the fuzzy judgment matrix, so as to optimize the fuzzy consistency:

(Model FNLP)

Min \( \tilde{Z}_1 = \tilde{C}R(\tilde{A}') \)  
(19)

subject to

\[ \tilde{C}R(\tilde{A}') \leq \tilde{C}R(\tilde{A}) \]  
(20)

\[ 1 \leq \tilde{a}_{ij}' \leq 9\forall \tilde{a}_{ij} \geq 1; \ i, \ j \in [1, \ n]; \ i \neq j \]  
(21)

\[ \tilde{a}_{ij}' = \tilde{a}_{ij} (+) \Delta \tilde{a}_{ij} \forall \tilde{a}_{ij} \geq 1; \ i, \ j \in [1, \ n]; \ i \neq j \]  
(22)

\[ \tilde{a}_{ij}' = 1; \ i \in [1, \ n] \]  
(23)

\[ \tilde{a}_{ij}' = \frac{1}{\tilde{d}_{ji}} \forall \tilde{a}_{ij} \geq 1; \ i, \ j \in [1, \ n]; \ i \neq j \]  
(24)

\[ \Delta \tilde{a}_{ij} \sim N(0, \ \sigma^2)\forall \tilde{a}_{ij} \geq 1; \ i, \ j \in [1, \ n]; \ i \neq j \]  
(25)

Model FNLP needs to be converted into a more tractable form to be easily solved.

**PP model**

First, according to Eqs. (1) and (2), \( a_{ij}' \) and \( a_{ij}'' \) can be derived from \( a_{ij}''' \). Therefore, only the value of \( a_{ij}''' \) needs to be determined, turning the problem into a crisp nonlinear programming (NLP) one:

(Model NLP)

Min \( Z_2 = CR(A') \)  
(26)

subject to

\[ CR(A') \leq CR(A) \]  
(27)

\[ 1 \leq a_{ij}' \leq 9\forall a_{ij} \geq 1; \ i, \ j \in [1, \ n]; \ i \neq j \]  
(28)

\[ a_{ij}' = a_{ij} + \Delta a_{ij} \forall a_{ij} \geq 1; \ i, \ j \in [1, \ n]; \ i \neq j \]  
(29)

\[ a_{ij}' = 1; \ i \in [1, \ n] \]  
(30)

\[ a_{ij}' = \frac{1}{a_{ij}'} \forall a_{ij} \geq 1; \ i, \ j \in [1, \ n]; \ i \neq j \]  
(31)

\[ \Delta a_{ij} \sim N(0, \ \sigma^2)\forall a_{ij} \geq 1; \ i, \ j \in [1, \ n]; \ i \neq j \]  
(32)

Subsequently, \( CR(A') \) can be approximated as

\[ CR(A') = \frac{1}{n} \sum_{i=1}^{n} \frac{\sum_{j=1}^{n} (a_{ij}' w_{ij}'^2)}{w_{ij}'} - n \]  
(33)

where

\[ w_{ij}' = \frac{\sqrt{\prod_{j=1}^{n} a_{ij}''}}{\sum_{i=1}^{n} \sqrt[2]{\prod_{j=1}^{n} a_{ij}''}} \]  
(34)

according to the geometric mean method [22]. Introducing a new variable \( u_i \) into (33) as

\[ u_i = \frac{\sum_{j=1}^{n} (a_{ij}'' w_{ij}'^2)}{w_{ij}'} \]  
(35)

or

\[ u_i w_{ij}'^2 = \sum_{j=1}^{n} (a_{ij}'' w_{ij}'^2) \]  
(36)

Equation (33) becomes

\[ CR(A') = \frac{1}{n} \sum_{i=1}^{n} u_i - n \]  
(37)

Subsequently, introducing a new variable \( v_i \) into (34) as

\[ v_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}''} \]  
(38)

or

\[ v_i^n = \prod_{j=1}^{n} a_{ij}'' \]  
(39)
Equation (34) becomes

\[ w'_{i2} = \frac{v_i}{\sum_{i=1}^{n} v_i} \]  

(40)

or

\[ w'_{i2} \sum_{i=1}^{n} v_i = v_i \]  

(41)

To approximate the distribution in Eq. (32), the mean value and range of the distribution are specified as

\[ E(\Delta a_{ij2}) = 0 \]  

(42)

\[ -3\sigma \leq \Delta a_{ij2} \leq 3\sigma \]  

(43)

Equation (42) is equivalent to the following equation:

\[ \frac{\sum_{a_{ij2} \geq 1} \Delta a_{ij2}}{\sum_{a_{ij2} \geq 1} 1} = 0 \]  

(44)

which is slightly relaxed to allow for greater flexibility:

\[ -\xi \leq \frac{\sum_{a_{ij2} \geq 1} \Delta a_{ij2}}{\sum_{a_{ij2} \geq 1} 1} \leq \xi \]  

(45)

Finally, the following PP problem is to be solved instead:

\( \text{(Model PP)} \)

Min \( Z_3 \)

s.t.

\[ Z_3 = \frac{1}{n} \sum_{i=1}^{n} u_i - n \]  

(46)

\[ Z_3 \leq CR(A) \]  

(47)

\[ u_i w'_{i2} = \sum_{j=1}^{n} (a'_{i j2} w'_{j2}); \ i = 1 \sim n \]  

(48)

\[ w'_{i2} \sum_{i=1}^{n} v_i = v_i; \ i = 1 \sim n \]  

(49)

\[ v'_i = \prod_{j=1}^{n} a'_{i j2}; \ i = 1 \sim n \]  

(50)

\[ a'_{i j2} = a_{i j2} + \Delta a_{ij2} \bar{a}_{ij2} \geq 1; \ i, j = 1, n; \ i \neq j \]  

(51)

The Karush–Kuhn–Tucker (KKT) conditions of Model PP are polynomials that can be easily solved using existing optimization packages [28]. In addition, if \( \Delta a_{ij} \) takes on integer values (i.e., \(-2, -1, 0, 1, \) and \(2\)), the feasible solutions to Model PP become enumerable. The number of feasible solutions is \( 5^n \).

After obtaining the optimal solution to the PP model,

\[ a'_{i j1} = \max(a'_{i j2} - 2, 1) \]  

(52)

\[ a'_{i j3} = \min(a'_{i j2} + 2, 9) \]  

(53)

Finally, FWA was applied to assess each CMfg application by considering all the criteria:

\[ \tilde{s}_k = \frac{\sum_{i=1}^{n} \tilde{u}_i(x) \tilde{s}_{ki}}{\sum_{i=1}^{n} \tilde{u}_i} \]  

(54)

where \( \tilde{s}_{ki} \) is the performance of the \( k \)-th CMfg application by considering the \( i \)-th criterion. Since the divisor of Eq. (61) is the same for all CMfg applications, it can be ignored.

### Assessing ten CMfg applications

The proposed methodology was applied to assess 10 CMfg applications. According to the survey by Oliveira et al. [29], the relative advantage (CF1), technology readiness (CF2), firm size (CF3), and cost savings (CF4) are factors critical to the adoption of CMfg technologies. For this reason, the priorities of the four critical factors were to be determined. After a series of pairwise comparisons, the following fuzzy
judgment matrix was constructed:

\[
\begin{bmatrix}
1 & 1/(1, 2, 4) & 1/(1, 3, 5) & 1/(3, 5, 7) \\
(1, 2, 4) & 1 & (1, 3, 5) & 1/(5, 7, 9) \\
(1, 3, 5) & 1/(1, 3, 5) & 1 & 1/(3, 5) \\
(3, 5, 7) & 5, 7, 9 & 1/(3, 5) & 1
\end{bmatrix}
\]

The consistency of the pairwise comparisons was evaluated as

\[
\tilde{C}(\tilde{\mathbf{A}}) = (0, 0.162, 6.079)
\]

\[
\tilde{C}(\tilde{\mathbf{A}}) = (0, 0.180, 6.754)
\]

which showed some inconsistency. As a result, the judgment matrix needed to be rectified. Lingo was adopted to build and optimize the Model PP of this problem on a PC with i7-7700 CPU 3.6 GHz and 8 GB RAM, as shown Fig. 2. \(\xi\) and \(\sigma\) were set to 0.2 and 1/3, respectively. A branch-and-bound algorithm was applied to solve the PP problem. The execution time was less than 1 s. The optimal solution was

\[
\mathbf{A}' = \begin{bmatrix}
1 & 1/2 & 1/2 & 1/6 \\
2 & 1 & 2 & 1/6 \\
2 & 1/2 & 1 & 1/4 \\
6 & 6 & 4 & 1
\end{bmatrix}
\]

or

\[
\tilde{\mathbf{A}}' = \begin{bmatrix}
1 & 1/(1, 2, 4) & 1/(1, 2, 4) & 1/(4, 6, 8) \\
(1, 2, 4) & 1 & (1, 2, 4) & 1/(4, 6, 8) \\
(1, 2, 4) & 1/(1, 2, 4) & 1 & 1/(2, 4, 6) \\
(4, 6, 8) & (4, 6, 8) & (2, 4, 6) & 1
\end{bmatrix}
\]

giving \(Z^* = CR(\mathbf{A}') = 0.053\). The consistency of the fuzzy judgment matrix has been significantly enhanced after rectification. In addition, the pairwise comparison results were inconsistent before rectification, but became consistent after rectification. The cores of the fuzzy priorities of criteria determined using the proposed methodology were 0.080, 0.165, 0.127, and 0.628, respectively.

Subsequently, the value of \(\sigma\) was changed to 1/6. In this way, the rectified judgment matrix would be closer to the original one. The optimization result was

\[
\mathbf{A}' = \begin{bmatrix}
1 & 1/2.3 & 1/2.5 & 1/5.5 \\
2.3 & 1 & 2.5 & 1/6.5 \\
2.5 & 1/2.5 & 1 & 1/3.5 \\
5.5 & 6.5 & 3.5 & 1
\end{bmatrix}
\]

giving \(Z^* = CR(\mathbf{A}') = 0.109\). The consistency was still considerably better than that of the original fuzzy judgment matrix, which revealed that even a very minor adjustment was helpful to the improvement of consistency.

A parametric analysis was also conducted to analyze the effect of \(\xi\) on the consistency that could be achieved. When the value of \(\xi\) increased, the rectifying flexibility became higher. Five values of \(\xi\), from 0.1 to 0.5, have been tried. The results are summarized in Fig. 3. As expected, the CR that could be achieved improved with the increase in the value of
$\xi$, and converged to about 0.048, which implied the limit of the proposed methodology.

The optimally rectified fuzzy judgment matrix was constructed according to Eqs. (59) and (60) as

$$
\tilde{A}' = \begin{bmatrix}
1 & 1/(1, 2, 4) & 1/(1, 2, 4) & 1/(4, 6, 8) \\
1/(1, 2, 4) & 1 & 1/(1, 2, 4) & 1/(4, 6, 8) \\
(4, 6, 8) & (4, 6, 8) & (2, 4, 6) & 1
\end{bmatrix}
$$

The fuzzy maximal eigenvalue and the fuzzy priorities of the critical factors were derived using alpha-cut operations, and then were approximated with TFNs as.

$$
\tilde{\lambda}^*_{\text{max}} = (4.010, 4.143, 5.150),
\tilde{w}_1^* = (0.043, 0.080, 0.151),
\tilde{w}_2^* = (0.095, 0.165, 0.288),
\tilde{w}_3^* = (0.066, 0.127, 0.257),
\tilde{w}_4^* = (0.461, 0.628, 0.708).
$$

Ten CMfg applications were evaluated. The contents of the CMfg applications are shown in Table 3. The most recent (after 2017) and most widely cited (according to Google Scholar) references are provided to support each CMfg application. The performances of the CMfg applications by considering the critical factors have been evaluated according to the rules depicted in Table 4 [29, 30].

The evaluation results are summarized in Table 5.

FWA was applied to derive the overall performance of each CMfg application by considering all the critical factors. The results are shown in Table 6.

The overall performance of each CMfg application was defuzzified using the center-of-gravity (COG) method. The results are summarized in Table 7.

The most preferable CMfg was “migrating management information systems to cloud-based services”, followed by “3D-printing-based ubiquitous manufacturing” and “capacity sharing via business-to-business electronic commerce system”. In contrast, the least preferable CMfg application was “cloud-based environment for customer-oriented product design”. It was noted that such results were dependent on the DM’s subjective judgment.

For comparison, the existing rectifying fuzzy geometric mean (FGM)-FWA method was also applied to the collected data, which rectified the fuzzy judgment matrix by adjusting the most influential element [53, 54]. As a result, the fuzzy judgment matrix changed to

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

giving $CR(\tilde{A}') = (0, 0.119, 0.6108)$, which was less consistent than that rectified using the proposed methodology.

The fuzzy priorities of critical factors were derived as.

$$
\tilde{w}_1^* = (0.040, 0.080, 0.201),
\tilde{w}_2^* = (0.082, 0.163, 0.329),
\tilde{w}_3^* = (0.070, 0.158, 0.345),
\tilde{w}_4^* = (0.354, 0.600, 0.759).
$$

The overall performance of each CMfg application was evaluated using FWA, and then defuzzified using COG. The results are summarized in Table 8. The most suitable CMfg
### Table 4 Rules for evaluating the performances of a CMfg application

| Critical factor     | Evaluation rule                                                                 |
|---------------------|----------------------------------------------------------------------------------|
| Relative advantage  | \( \hat{x}_{k_1}(x_{k_1}) = \begin{cases} 
(0, 0, 1.6) & 0 \leq x_{k_1} \leq 1/7 \\
(0, 0, 1.6) & 1/7 \leq x_{k_1} \leq 2/7 \\
(0, 1.6, 3.3) & 2/7 \leq x_{k_1} \leq 3/7 \\
(1.6, 3.3, 5) & 3/7 \leq x_{k_1} \leq 4/7 \\
(3.3, 5, 6.7) & 4/7 \leq x_{k_1} \leq 5/7 \\
(5, 6.7, 8.4) & 5/7 \leq x_{k_1} \leq 6/7 \\
(8.4, 10, 10) & 6/7 \leq x_{k_1} \leq 1 \\
\end{cases} \) |
|                     | where \( x_{k_1} = 1/5 \) (the percentage of business operation management improvement + the percentage of operation quality improvement + the percentage of specific task efficiency improvement + the percentage of increased business + the percentage of productivity improvement) |
| Technology readiness| \( \hat{x}_{k_2}(x_{k_2}) = \begin{cases} 
(0, 0, 1.6) & 0 \leq x_{k_2} \leq 1/7 \\
(0, 0, 1.6) & 1/7 \leq x_{k_2} \leq 2/7 \\
(0, 1.6, 3.3) & 2/7 \leq x_{k_2} \leq 3/7 \\
(1.6, 3.3, 5) & 3/7 \leq x_{k_2} \leq 4/7 \\
(3.3, 5, 6.7) & 4/7 \leq x_{k_2} \leq 5/7 \\
(5, 6.7, 8.4) & 5/7 \leq x_{k_2} \leq 6/7 \\
(8.4, 10, 10) & 6/7 \leq x_{k_2} \leq 1 \\
\end{cases} \) |
|                     | where \( x_{k_2} = 1/3 \) (the percentage of employees who have Internet access + the percentage of employees who can apply ITs related to the CMfg application + the percentage of employees who are familiar with the CMfg application) |
| Firm size           | \( \hat{x}_{k_3}(x_{k_3}) = \begin{cases} 
(0, 0, 1.6) & 0 \leq x_{k_3} \leq 1/7 \\
(0, 0, 1.6) & 1/7 \leq x_{k_3} \leq 2/7 \\
(0, 1.6, 3.3) & 2/7 \leq x_{k_3} \leq 3/7 \\
(1.6, 3.3, 5) & 3/7 \leq x_{k_3} \leq 4/7 \\
(3.3, 5, 6.7) & 4/7 \leq x_{k_3} \leq 5/7 \\
(5, 6.7, 8.4) & 5/7 \leq x_{k_3} \leq 6/7 \\
(8.4, 10, 10) & 6/7 \leq x_{k_3} \leq 1 \\
\end{cases} \) |
|                     | where \( x_{k_3} = 1/2 \) (the percentage of employees supported by the CMfg application + the percentage of business operations supported by the CMfg application) |

### Table 4 (continued)

| Critical factor     | Evaluation rule                                                                 |
|---------------------|----------------------------------------------------------------------------------|
| Cost savings        | \( \hat{x}_{k_4}(x_{k_4}) = \begin{cases} 
(0, 0, 1.6) & 0 \leq x_{k_4} \leq 1/7 \\
(0, 0, 1.6) & 1/7 \leq x_{k_4} \leq 2/7 \\
(0, 1.6, 3.3) & 2/7 \leq x_{k_4} \leq 3/7 \\
(1.6, 3.3, 5) & 3/7 \leq x_{k_4} \leq 4/7 \\
(3.3, 5, 6.7) & 4/7 \leq x_{k_4} \leq 5/7 \\
(5, 6.7, 8.4) & 5/7 \leq x_{k_4} \leq 6/7 \\
(8.4, 10, 10) & 6/7 \leq x_{k_4} \leq 1 \\
\end{cases} \) |
|                     | where \( x_{k_4} = 1/3 \) (the possibility that the benefits of the CMfg application are greater than the costs + the percentage of energy and environmental cost reduction + the maintenance cost of the CMfg application as a percentage of the investment) |

### Table 5 Performances of the CMfg applications by considering the critical factors

| CMfg application no. | CF1  | CF2  | CF3  | CF4  |
|----------------------|------|------|------|------|
| 1                    | Low  | Very high | Medium | Medium |
| 2                    | High | Low  | High | High |
| 3                    | Medium | High | Medium | High |
| 4                    | Medium | High | Low  | Medium |
| 5                    | High | Low  | Low  | Very high |
| 6                    | Medium | Low  | Low  | Medium |
| 7                    | Medium | High | High | High |
| 8                    | Medium | High | Medium | Low |
| 9                    | Low  | Low  | Medium | Medium |
| 10                   | High | Medium | Low  | Low  |

### Table 6 Overall performances of the CMfg applications

| CMfg application no. | Overall performance |
|----------------------|---------------------|
| 1                    | (2.376, 5.289, 9.844) |
| 2                    | (2.850, 5.859, 10.325) |
| 3                    | (3.140, 6.348, 11.100) |
| 4                    | (2.138, 4.849, 9.023) |
| 5                    | (3.304, 6.278, 10.147) |
| 6                    | (1.663, 4.007, 7.554) |
| 7                    | (3.252, 6.564, 11.537) |
| 8                    | (0.835, 3.145, 7.489) |
| 9                    | (1.739, 4.167, 7.914) |
| 10                   | (0.529, 2.569, 6.383) |
Table 7 Defuzzification results

| CMfg application no. | Defuzzified overall performance | Rank |
|----------------------|---------------------------------|------|
| 1                    | 5.836                           | 5    |
| 2                    | 6.344                           | 4    |
| 3                    | 6.863                           | 2    |
| 4                    | 5.337                           | 6    |
| 5                    | 6.576                           | 3    |
| 6                    | 4.408                           | 8    |
| 7                    | 7.118                           | 1    |
| 8                    | 3.823                           | 9    |
| 9                    | 4.607                           | 7    |
| 10                   | 3.160                           | 10   |

Table 8 Evaluation results using the rectifying FGM-FWA method

| CMfg application no. | Defuzzified overall performance | Rank |
|----------------------|---------------------------------|------|
| 1                    | 6.192                           | 5    |
| 2                    | 6.744                           | 3    |
| 3                    | 7.210                           | 2    |
| 4                    | 5.593                           | 6    |
| 5                    | 6.718                           | 4    |
| 6                    | 4.621                           | 8    |
| 7                    | 7.534                           | 1    |
| 8                    | 4.311                           | 9    |
| 9                    | 4.905                           | 7    |
| 10                   | 3.522                           | 10   |

application, “migrating management information systems to cloud-based services”, did not change. However, the ranking result was different from that generated using the proposed methodology [55–88].

Conclusions

As a new paradigm of manufacturing, CMfg is expected to bring several benefits to a manufacturer. However, most existing CMfg studies were of experimental natures or only the illustration of conceptual ideas. In addition, the cost effectiveness of a CMfg system has rarely been evaluated. As a result, a manufacturer is not sure whether or how to adopt a CMfg application. To address this issue, the OR-FAHP approach was proposed in this study to assess and compare CMfg applications. The OR-FAHP approach was an extension of the conventional FAHP method by resolving the inconsistency problem. In the proposed methodology, a FNLP model was first formulated to optimize the consistency by rectifying the fuzzy judgment matrix. Compared with existing methods for the same purpose, the OR-FAHP approach was able to ensure the optimality of the solution, which guaranteed the correctness of the decision.

The OR-FAHP approach has been applied to assess and compare 10 CMfg applications. According to the experimental results,

1. The consistency of the pairwise comparison results was considerably enhanced by rectifying the fuzzy judgment matrix.
2. “Migrating management information systems to cloud-based services” and “cloud-based environment for customer-oriented product design” were assessed as the most and least preferable CMfg applications, respectively.

Obviously, the objective of this study, comparing CMfg applications systematically, has been achieved. In addition, the OR-FAHP approach proposed in this study also successfully improved the consistency of the fuzzy judgment matrix by 39% without drastically changing the fuzzy judgment matrix.

Subsequently, the proposed methodology can be extended to deal with cases involving multiple DMs. In addition, the participants of a supply, design, or demand chain should choose CMfg applications that are compatible with those chosen by others. Further, a tailored algorithm can be designed to help solve the PP problem to improve the computational efficiency. These constitute some directions for future research.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical statement This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Not required.

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