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A Weighted Rough Set Based Fuzzy Axiomatic Design Approach for the Selection of AM Processes

Informative title: *A novel approach for AM processes selection*

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Abstract

Additive manufacturing (AM) or 3D printing, as an enabling technology for mass customisation or personalization, has been developed rapidly in recent years. Various design tools, materials, machines and service bureaus can be found in the market. Clearly, the choices are abundant, but users can be easily confused as to which AM process they should use. This paper first reviews the existing multi-attribute decision-making methods for AM process selection and assesses their suitability with regards to two aspects, *preference rating flexibility* and *performance evaluation objectivity*. We propose that an approach that is capable of handling incomplete attribute information and objective assessment within inherent data has advantages over other approaches. Based on this proposition, this paper proposes a weighted preference graph method for personalized preference evaluation, and a rough set based fuzzy axiomatic design approach for performance evaluation and the selection of appropriate AM processes. An example based on the previous research work of AM machine selection is given to validate its robustness for the priori articulation of AM process selection decision support.

Keywords: rough set, fuzzy axiomatic design, preference graph, multi-attribute decision making, relative importance rating, additive manufacturing

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Nomenclature

AD	Axiomatic Design
AHP	Analytic Hierarchy Process
AM	Additive Manufacturing
ASTM	American Society for Testing and Materials
CAD	Computer-Aided Design
DSP	Decision Support Problem
DNP	DEMATEL based Network Process
FR	Functional Requirement
FSE	Fuzzy Synthetic Evaluation
GRA	Grey Relational Analysis
GT&MA	Graph Theory and Matrix Approach
MADM	Multi-Attribute Decision Making
MOORA	Multi-Objective Optimization on the basis of Ratio Analysis
PG	Preference Graph
PROMETHEE	Preference Ranking Organisation Method for Enrichment Evaluations
RIR	Relative Importance Rating
SMART	Simple Multi Attribute Rating Technique
STL	STereoLithography
TFN	Triangular Fuzzy Number
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TRN	Triangular Rough Number
U-sDSP	Utility-based Selection Decision Support Problem

1. Introduction

Additive manufacturing (AM), also known as 3D printing, creates physical objects from a geometrical representation by successive addition of material [1]. This prevailing fabrication process, first became available in 1987, generally begins with a STereoLithography (STL) file that describes a 3D model created by a Computer-Aided Design (CAD) system. Its flourish is attributed to the unique capabilities of this process such as complex geometry production, integrated assemblies and elimination of many conventional manufacturing constraints [2]. Besides, it potentially provides huge benefits in terms of reducing manufacturing costs, shorten product development time span and improved quality of end products [3]. It has been claimed that AM technologies can reduce up to 70% of cost and decrease the time-to-market by 90% [4]. Since its emergence, AM has been exploited in various manufacturing areas, such as automotive, aerospace, electronics industries, and domains such as medicine, education, architecture, cartography, toys and entertainment.

According to American Society for Testing and Materials (ASTM) Standard F2792 [5], AM technologies can be classified into seven groups: binder jetting, directed energy deposition, material extrusion, material jetting, powder bed fusion, sheet lamination and vat photo-polymerization. Nowadays, more than one thousand industrial AM machines and materials have been identified in the market [6]. Each machine, material and system has its own strengths and limitations [7]. It is unable for an end user to keep track of all the available choices nor to be aware of the process capabilities of each system. Also, due to the variety of each product's complexity, the manufacturability of each AM process should be evaluated properly beforehand [8,9]. Nevertheless, due to the lack of experience and knowledge, users frequently face the problem to select the most appropriate AM process to meet their specific requirements [3]. Therefore, an intelligent selection tool becomes critical for the end user to select a proper machine or technology that is adequate for his own needs.

Aiming to provide an effective tool for AM process selection, this work proposes a novel weighted, rough set based fuzzy axiomatic design (AD) approach. The paper is organized as follows: Section 2 gives a comprehensive review of the existing multi-attribute decision making (MADM) methods for AM process selection based on two aspects: preference rating and performance evaluation. Section 3 proposes a novel method for AM process selection. Weighted preference graph (PG) method is introduced for personalized preference rating, and rough set based fuzzy AD method is proposed for performance evaluation and the final customer-centric decision making. Section 4 outlines the procedures of the proposed AM process selection. To validate the method, Section 5 gives an illustrative example based on previous works. Conclusions and future work are given in Section 6.

2. Review of MADM methods for AM process selection

Table 1 gives an overview of some existing research on MADM methods for AM process selection. The typical approach, preference evaluation, performance evaluation and output of each work are summarised respectively. We assume that for all the MADM ranking methods, preference evaluation and performance evaluation are the most critical factors in selecting the most appropriate AM process, which are therefore reviewed and compared in the following part.

2.1 Performance evaluation

Performance evaluation stands for collecting and assessing the capability information about AM processes. In order to determine the performance, deterministic values are required in MADM methods [7], which is quite challenging. Since the performance is influenced by various factors such as materials, parameters, the condition of the machine, etc. Also, for some qualitative attributes such as cost and build time, the inherent vagueness and uncertainty make quantitative evaluation difficult to achieve [3]. In this case, fuzzy set theory has been widely adopted to convert the qualitative evaluation into deterministic values (Table 1). Grey set theory has also been proposed [10]. However, fuzzy arithmetic operation has its own limitations. First, it may result in the enlargement of its fuzzy intervals [11,12], and accordingly affects the decision-making analysis. Secondly, the membership function selection is challenging for the performance of a fuzzy system, as it is usually determined based on engineers' experience and intuition subjectively [13]. Unlike fuzzy set theory which defines a set by a partial membership without clear boundary, the rough set theory utilizes the boundary region of a set to express vagueness [14,12]. Also, there is no need for it to require any external or additional subjective information to analyse data [15,14], which gives its objectivity. Moreover, rough set theory is suitable for small-sized data set which statistical methods are not available [16,12].

Table 1

Review of MADM methods and their preference evaluation, performance evaluation and output in AM process selection

<table>
<tr><th rowspan="2">Author, year</th><th rowspan="2">Method</th><th colspan="2">Preference evaluation</th><th colspan="2">Performance evaluation</th><th>Output</th></tr>
<tr><th>Input effort</th><th>Weighting approach</th><th>Type of value</th><th>Data source</th><td rowspan="17">Ranking & scores & further information</td></tr>
<tr><td>Mahesh et al. [17]</td><td>Fuzzy logic</td><td rowspan="12">Very low (weighting values or goal values)</td><td>-</td><td>Q1</td><td rowspan="6">B</td></tr>
<tr><td>Zhang et al. [18]</td><td>Knowledge value measuring</td><td>-</td><td rowspan="5">Q1 & Q2</td></tr>
<tr><td>Wang et al. [19]</td><td>GRA</td><td rowspan="12">Direct assignment</td></tr>
<tr><td>Vahdani et al. [20]</td><td>Novel modified TOPSIS</td></tr>
<tr><td>Chakraborty [21]</td><td>MOORA</td></tr>
<tr><td>İç [22]</td><td>TOPSIS</td></tr>
<tr><td>Mahapatra, Panda [10]</td><td>GRA</td><td>Uniform distribution</td><td>E</td></tr>
<tr><td>Khrais et al. [23]</td><td>Fuzzy reasoning</td><td>Q2</td><td>E</td></tr>
<tr><td>Chuk, Thomson [24]</td><td>Weighted criteria evaluation</td><td rowspan="5">Q1</td><td>V</td></tr>
<tr><td>Jones, Campbell [25]</td><td>Weighted rating</td><td>B & V</td></tr>
<tr><td>Roberson et al. [26]</td><td>Proposed ranking system</td><td>B</td></tr>
<tr><td>Ghazy [27]</td><td>SMART</td><td>-</td></tr>
<tr><td>Munguia et al. [28]</td><td>fuzzy inference</td><td rowspan="2">Low (weighting values and goal values)</td><td>V & E</td></tr>
<tr><td>Zhang, Bernard [29]</td><td>Integrated decision-making model</td><td>Q1 & Q2</td><td>-</td></tr>
<tr><td>Byun, Lee [7]</td><td>Modified TOPSIS</td><td rowspan="2">Slightly low (Pairwise comparisons of weighting)</td><td rowspan="2">Pairwise comparison</td><td>Q1 & Q2</td><td>B</td></tr>
<tr><td>Lan* et al. [30]</td><td>FSE</td><td>Q1 & Q2</td><td>E</td></tr>
</table>

Armillotta [31]	AHP			Q2	V & E	
Lokesh, Jain [32]	AHP			Q2	E	
Rao, Padmanabhan [33]	GT&MA			Q1 & Q2	B	
Wilson, Rosen [34]	Selection DSP &interval analysis	Medium (Pairwise comparisons of weighting and lottery)		Q1	-	
Liao et al. [35]	DNP & VIKOR	Slightly high (Pairwise comparisons of weighting and interdependencies)		Q2	E	
Venkata Rao, Patel [36]	Improved PROMETHEE	High (Pairwise comparisons of weighting and indifference thresholds, preference curve shape and parameters)		Q1 & Q2	B	
Fernandez et al. [37]	U-sDSP	Very high (lowest and highest acceptable values, monotonicity and curvature of the preference curve for each attribute, weighting values and goal values)	Direct assignment	Uniform distribution	-	

*Note: Q1 stands for *Quantitative data*; Q2 stands for *Qualitative data*; E stands for *Expert and engineer experience*; B stands for *Benchmarking*; V stands for *Vendor's documents.*

2.2 Preference evaluation

For preference evaluation, the major task is to guide the user to decide on the relative importance of different attributes. Two kinds of methods have been widely used: *direct assignment* and *pairwise comparison* (Table 1). In *direct assignment*, a user can directly evaluate the relative importance of one attribute over the others in a certain scale [22]. The process is quite simple and straightforward but it can be hard for users to choose the proper values. They tend to rate almost every attribute as important [38,39] with the highest possible scores. Also, since the priority rank is somewhat dependable on the type of scales used, there is low robustness in the variation of cardinal scale values [39]. To make the weighting process more reasonable for the user, the *pairwise comparison* method is adopted. However, users need to provide a comparison for every pair of attributes, which require too much elaborate information from them and sometimes beyond their knowledge capability. It will probably result in inconsistency among the comparisons. Therefore, it is unrealistic to undertake this method with many AM attributes by expecting users to provide much repetitious information accurately [40,41].

3. Weighted rough set based fuzzy AD method

Based on the above review, two important criteria in evaluating the most appropriate AM process selection have been derived:

1) Objectivity of imprecise performance evaluation. That is, the performance evaluation process should involve less human or designers subjective interpretation.
2) Flexibility and usability of preference evaluation. The preference evaluation process should be flexible enough (e.g. vague expression or incomplete user information) and user friendly to match with real life situations.

Aiming to improve the existing methods by emphasizing these two criteria, this section proposes two methods to deal with performance evaluation and preference evaluation, respectively.

3.1 Rough set based fuzzy AD method for performance evaluation

3.1.1 Basic notion of fuzzy AD

AD was first proposed by Suh [42] to guide engineering designs. It can be applied to all design activities by the provided systematic design framework with methodology. The most important concept of AD is the existence of two axioms [42]:

"The Independence Axiom: Maintain the independence of functional requirements (FRs).

The Information Axiom: Minimize the information content."

For the *Information Axiom*, it states that among each design solution that satisfies the *Independence Axiom*, the one with smallest amount of information is the best [43].

In fuzzy cases, according to Kulak and Kahraman [44], the vague data can be linguistic terms, fuzzy sets, or fuzzy numbers. The linguistic terms need to be transformed into fuzzy numbers first and crisp values are assigned to them subsequently for further evaluation. For the vague information, they can be well defined by the triangular fuzzy numbers (TFNs), as shown in Fig. 1, and thus, the information content is calculated as [45,44]:

$$I_i = \log_2\left(\frac{TFN\ \ of\ \ System\ \ Design}{Common\ \ Area}\right) \tag{1}$$

where I_i stands for the information content of the i^{th} attribute. "TFN of system design" is the system design capability range by TFNs ratings; "TFN of design range" stands for the designer's evaluation range of the *FRs* by TFNs ratings; their overlapping area is where the acceptable solution exists, known as the "common area"; and the "degree of membership function" indicates the probabilities of achieving the *FRs*.

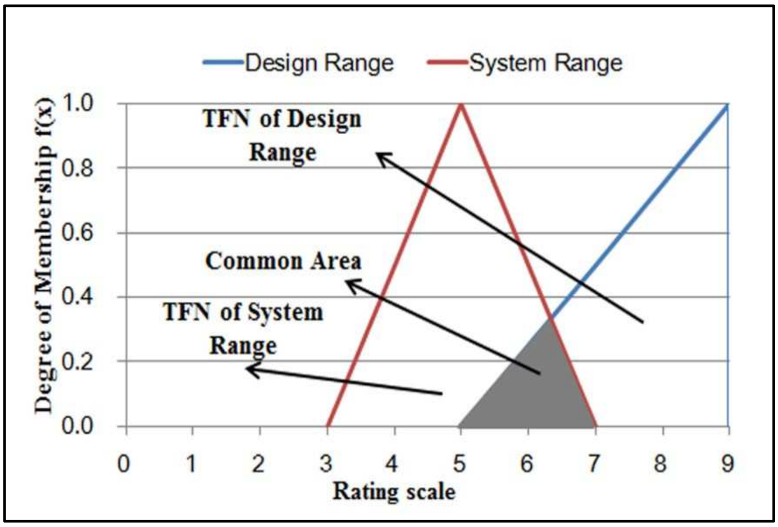

Fig.1. TFN based fuzzy AD method (derived from [46]).

Though fuzzy AD method has been widely used in various engineering field, such as: advanced manufacturing systems' comparison [44], transportation companies' evaluation [45], and shipyards' selection [47], nevertheless, the selection of fuzzy membership functions in all existing case studies are determined by designers subjectively [46].

3.1.2 Triangular Rough Numbers

Due to the subjective selection of fuzzy membership functions, the boundary intervals of fuzzy set based method will be enlarged correspondingly, and thus affects the final decision of selecting the proper AM process. Aiming to solve this problem, this paper proposes a triangular rough number (TRN) based approach. It takes advantages of rough set based method, i.e. rough number method to enhance the MADM of AM processes selection.

Definition. Assume there is a set of *n* classes of users' perceptions *M*, $P = (M_1, M_2, \ldots, M_n)$ ordered in a sequence of $M_1 < M_2 < \ldots < M_n$. *U* is the universe consisting of all the objects and *Y* is an arbitrary object of *U*, then for any class $M_j \in P, 1 \leq j \leq n$, the lower and upper approximation of M_j [11,12] are defined as:

Lower approximation:

$$\underline{Apr}\left(M_j\right) = \cup\left\{Y \in U / P\left(Y\right) \leq C_j\right\}; \tag{2}$$

Upper approximation:

$$\overline{Apr}\left(M_j\right) = \cup\left\{Y \in U / P\left(Y\right) \geq M_j\right\}; \tag{3}$$

Thus, the vagueness of user perception M_j can be represented by a rough number defined by its lower and upper limits.

Lower limit:

$$\underline{Lim}\left(M_j\right) = \in\frac{1}{N_L}\sum P\left(Y\right) | Y \quad \underline{Apr}\left(M_j\right); \tag{4}$$

Upper limit:

$$\overline{Lim}\left(M_j\right) = \in\frac{1}{N_U}\sum P\left(Y\right) | Y \quad \overline{Apr}\left(M_j\right); \tag{5}$$

where N_L and N_U are the count of objects included in the lower and upper approximation of user perception M_j, respectively.

Hence, the membership function of user perception M_j can be represented by its lower limit (p_j = 0), M_j itself (p_i = 1) and its upper limit (p_j = 0) [46] in a proposed TRN set, which defined as:

$$TRNs\left(C_j\right) = \left(\underline{Lim}\left(C_j\right), \quad C_j, \quad \overline{Lim}\left(C_j\right)\right) \tag{6}$$

Users' vague assessments on the attributes being considered in AM processes selection are first transformed into crisp numbers by 1-9 rating scale, as shown in Table 2. Then, they are calculated into rough numbers based on Eq. (2) to (5). The membership functions are determined by the crisp numbers (the numbers predefined in a rating scale) and their resultant rough numbers based on Eq. (6), other than designer's subjective selection [46]. For example, designer's vague evaluation of attribute *Build time* from A, B, C, D machine is *low (3), slightly low (4), high (7), medium (5), respectively*. Then, based on Eq. (2) to (6), the TRNs of each machine are: TRN_A *(3, 3, 4.75)*, TRN_B *(3.5, 4, 5.33)*, TRN_C *(4.75, 7, 7)*, TRN_D *(4, 5, 6)*. As TRNs are defined by its inherent data other than designers' subjective interpretations, the proposed method fares better than TFNs based method by processing linguistic assessments more objectively.

Table 2

The ratings of attributes on major AM systems [7]

	A	R	S	E	C	B
SLA3500	120	6.5	65	5	VH	M
SLS2500	150	12.5	40	8.5	VH	M
FDM8000	125	21	30	10	H	VH
LOM1015	185	20	25	10	SH	SL
Quadra	95	3.5	30	6	VH	SL
Z402	600	15.5	5	1	VVL	VL

*Note: A: accuracy (μm), R: surface roughness (μm), S: tensile strength (MPa), E: elongation ($\%$), C: cost of the part, B: build time of the part.

3.1.3 TRNs based fuzzy AD method

In order to determine the most appropriate AM process for users' expectation, the Information Axiom is utilized to calculate the information content of each attribute based on users' acceptable values (system range) and the performance evaluation (design range) (Fig. 2).

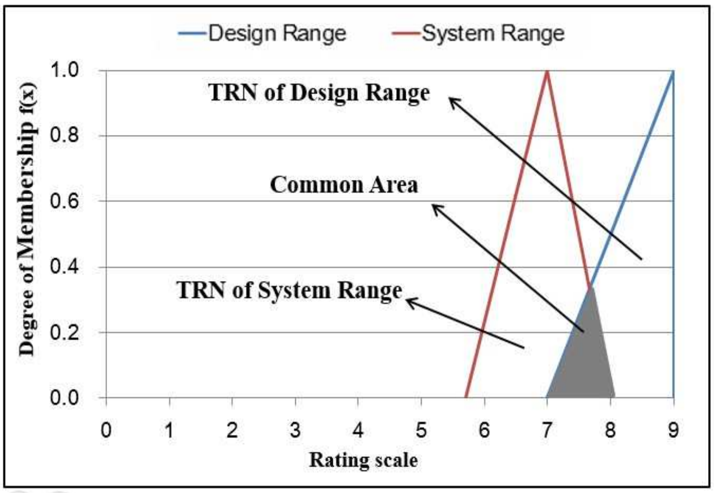

Fig. 2. TRN based fuzzy AD method

In Fig. 2, the horizontal axis represents the rating scale of 1 to 9, and the vertical axis stands for the membership functions of the corresponding AM attributes. Thus, according to Eq. (1), the information content is calculated as:

$$I_i = \log_2\left(\frac{TRNs\ of\ System\ Range}{Common\ Area}\right) \tag{7}$$

The acceptable solution exists in the "common area" where the above ranges overlap. The larger the common area is, the more appropriate AM process is.

3.2 Weighted PG method for preference evaluation

Preference ordering provides a straightforward method in ranking the individual preferences of the AM process attributes. Other than the direct assignment and the pairwise comparison approaches, it represents a good compromise between simplicity and reliability of user's input data, especially when user's prioritizing is doubtful, the preference ordering is definitely more intuitive than that of weights [48]. Moreover, in order to be flexible, preference ordering should include the cases of indifference relationship (i.e. equal importance) among attributes and the possibility of omitting one or more attributes [49].

PG, as one of the preference ordering methods, was first proposed by Nahm and Ishikawa [50], it was utilized to determine the priorities of users' imprecise judgment (or perception) on the importance of requirements. As a group decision-making method, the PG method enables users to make incomplete or partial comparisons between each requirements, thus reduces their input effort. Users only need to specify the preference order that they clearly know initially [41], which is closer to real life cases. Despite its usability and flexibility, however, the determination of preference weights is only by summing up all the dominant numbers based on the ranking positions, which cannot show the relative strong or weak relationship among attributes in actual operation. Besides, the PG method only depicts the dominant relationship among attributes, which did not take indifference relationship into consideration.

In order to adapt PG method into personalized AM process selection more flexibly and accurately, this work enhances the original method by considering each user's preferences as an individual and by taking indifference relationship into consideration. Moreover, Simos' method [51] is adopted and revised in determining the weights of vectors in user's preference ordering.

3.2.1 Definition

Assume that N AM attributes have been identified based on user *M's* requirements, which are denoted as *Attribute 1*, *Attribute 2*, ⋯, *Attribute n*, ⋯, *Attribute N*, respectively. *M* is asked to make a preference ordering among different attributes by defining four cases ($1 \leq i, j \leq N$):

(1) *Attribute j* dominates *Attribute i,* which is represented as a vector from *Attribute i* pointing to *Attribute j* (e.g. the vector in between *Attribute 1 and 2* in Fig. 3).

(2) *Attribute j* is indifference with *Attribute i.* which is represented as an equal set E_k *{i, j}* (e.g. *Attribute 2 and 3* in Fig. 3), which *k* stands for the *kth* equal set.

(3) *Attribute j* is and *Attribute i.* has dominance relationship with other attributes, while no relationship between themselves, which is represented as *incomparable attributes* (e.g. *Attribute 2, 3 and Attribute 4* in Fig. 3).

(4) *Attribute i and attribute j* are omitted, which is represented as a separate set *O {i, j}* (e.g.

Attribute 7 in Fig. 3)

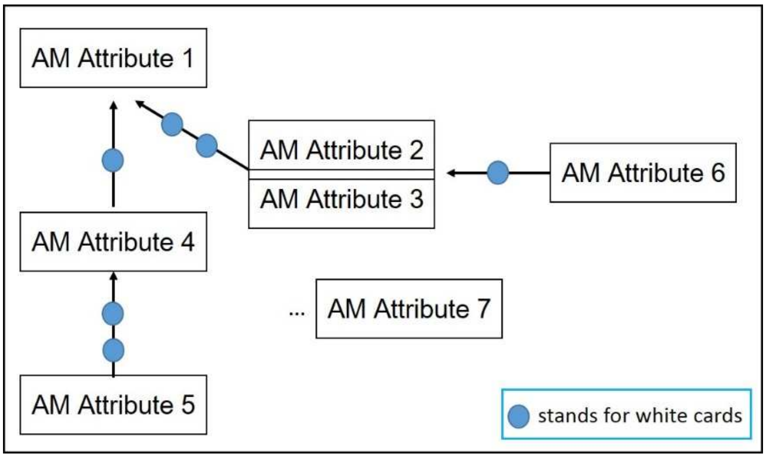

Fig. 3. An example of PG-based preference rating

Thus, the PG expressed by user *M* can be denoted as PG_M in a hierarchical bottom-up manner, from the least important attributes in the lowest level (*Position 1*) up to the most important ones.

Let PG_M be an adjacency matrix for the PG and *K* be a positive integer representing the number of elements in set *O*. Then, the entry pg_{ij} $(i, j= 1, 2,\cdots, n, \cdots, N\text{-}O)$ of PG_M^{N-O} gives the number of *N-O* stage dominances of *i* over *j*, the dominance matrix D_M is given as follows:

$$D_M = PG_M^1 + PG_M^2 + \dots PG_M^n + \dots PG_M^{N-K} \tag{8}$$

The sum of the entries d_i in row *i* of the dominance matrix means the total number of ways that *i* is dominant one, two, …, *N –K* stages [41,52]. The *(N-K-1)* stage dominances are calculated for *PG* in this case. Suppose that Fig. 3 is the *PG* that user *M* presented. It shows, for example, that *M* think *Attribute 1* is more important than *Attribute 2 and Attribute 3, b*ut not knowing the relationship between *Attribute 2 and Attribute 3.* Following this manner, user can intuitively generate *PG* that represent partial orderings of AM attributes regarding the relative importance based on their own preferences, and thus both the PG_M and the dominance matrix D_M is represented as:

$$PG_M = \begin{bmatrix} 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{9}$$

$$D_M = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{matrix} \to 5 \\ \to 1 \\ \to 1 \\ \to 1 \\ \to 0 \\ \to 0 \end{matrix} \tag{10}$$

Thus, $\mathrm{d}_M^1 = 5$, $\mathrm{d}_M^2 = 2$, $\mathrm{d}_M^3 = 0$, $\mathrm{d}_M^4 = 1$, $\mathrm{d}_M^5 = 0$, $\mathrm{d}_M^6 = 0$, which means that *Attribute 1* is the most important attribute which dominated in 5 ways, and accordingly, *Attribute 2* is dominated in 2 ways; *Attribute 3* is dominated in 0 way; *Attribute 4* is dominated in 1 way; *Attribute 5* is dominated in 0 way; *Attribute 6* is dominated in 0 way. If any attribute has no dominance relationship with other attributes, e.g. *Attribute 7,* which is 'not applicable' and will not be taken into further calculation.

3.2.2 Determination of normalized weights

Simos' "card playing" method [51] and its revised method [53] provide a simple and straightforward approach for multi-criteria decision aiding, and it has been successfully utilized in many cases, such as material selection [54], green bridge rating system [55] and etc. Despite their advantages, however, the operation is based on the assumption that all the attributes (or criteria) can be ordered in a preference sequence by a certain amount of subsets. It neglects two situations: 1) some attributes are omitted by the user due to lack of knowledge; 2) the *incomparable attributes* which users cannot determine their dominant relationship. These problems occurred quite often in the AM process selection, as various technologies, materials, parameters, machines and etc. (as illustrated in Section 1) are provided, and users are incapable to manage it. Aiming at this, a novel weighted PG method is proposed based on the previous research.

In a PG case, each vector is performed by adding "white cards", i.e. ranking positions in a bottom-up manner, respectively. The "white card" stands for the difference of user preference between the two attributes, and the more of cards, the greater difference lies. Also, the lowest level is defined as *Position 0*. For example, in Fig. 3, user *M* puts one "white cards" in the vector between *Attribute 2 and 6*. Since *Attribute 6* is in the lowest level of *Position 0, thus, Attribute 2* is in *Position 2* correspondingly. Following this manner, the position of each attribute can be calculated by summing up all the dominant attributes' positions:

$$P_M^i = \sum_{j=1}^{N-K} \left(P_M^j + WC_j + 1 \right), \text{ where } pg_{ij} = 1; \tag{11}$$

where P_M^i represents the *ith* Attribute's ranking position, WC_j stands for the number of *"white card"* in between *Attribute j and i*. The equation satisfies only when there is a vector pointing from *Attribute i* to *Attribute j*. Thus, the ranking position set of *N-K* attributes can be denoted as:

$$P_M = \left[P_{M,}^{1} \quad P_{M,}^{2} \quad \dots \quad P_M^n \quad \dots \quad P_M^{N-K} \right] \tag{12}$$

In order to calculate the normalized weight of each attribute, each ranking position is added by 1, and thus *Attribute i* can be calculated by:

$$W_M^i = \frac{P_M^i + 1}{\sum_{j=1}^{N-K} (P_M^j + 1)} \tag{13}$$

and user *M*'s preference rating can be described as a vector:

$$RIR_M = \left(W_M^1, \quad W_M^2, \quad \dots \quad W_M^{N-K}, \quad \dots \quad 0 \right) \tag{14}$$

Thus, for the above example in Fig. 3, user *M*'s preference ratings are:

$$RIR_M = \left(0.57, \quad 0.14, \quad 0.11, \quad 0.11, \quad 0.04, \quad 0.04, \quad 0 \right) \tag{15}$$

One claim is that the proposed weighted PG method can be utilized as an initial tool for determining the ratings of preference ordering with limited user information, such as omitted attributes, incomparable attributes etc. When the selection process evolves and user's capability grows, other existing methods (e.g. revised Simos' approach or AHP) can enhance or replace it with more accuracy.

4. Procedures of proposed AM process selection method

Fig. 4 depicts the proposed method for AM process selection. It consists of six steps including preference rating, performance evaluation and the final weighted ranking. Each step is described in details as follows:

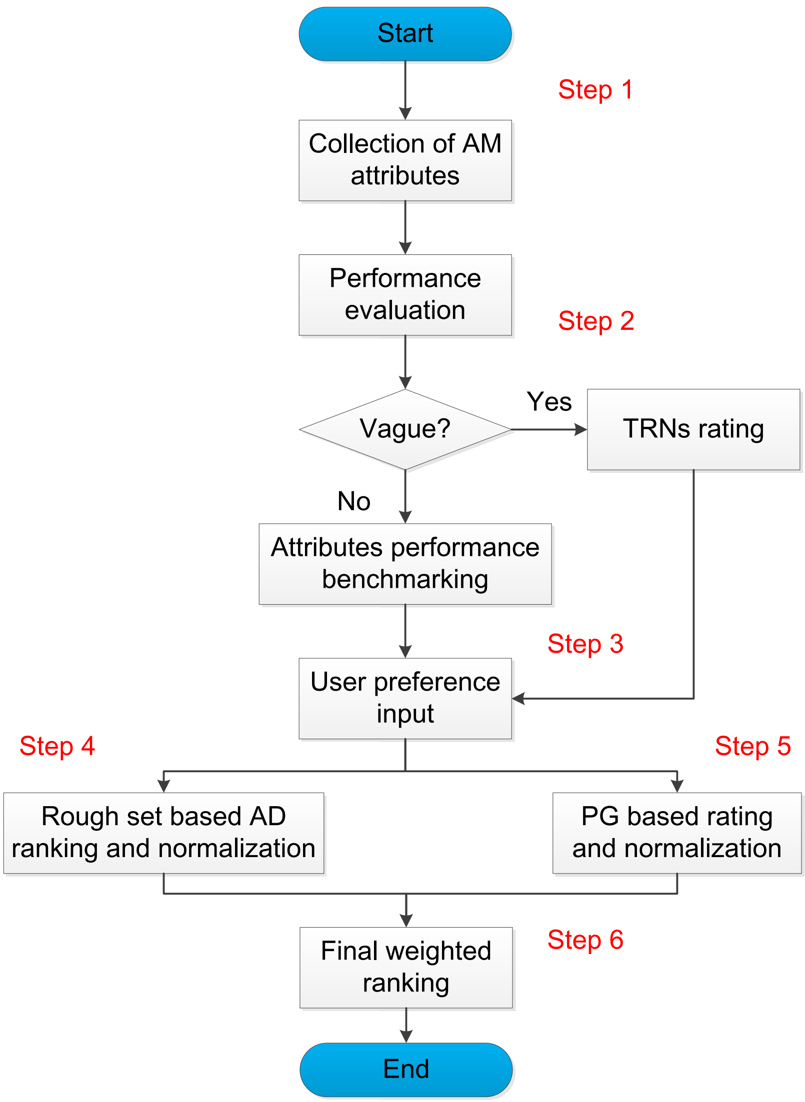

Fig. 4. Flow chart of proposed method for AM process selection

Step 1: Collection of AM performance attributes

The collection of related attributes can be achieved mainly by four ways:

1) *Vendor documents*. Basic information, such as build envelope, layer thickness, resolution, accuracy, materials and so forth is often given in datasheets by the equipment manufacturers.
2) *Expert and engineer experience*. Using questionnaires to collect information from experts and engineers and capture their accumulated process knowledge is a popular approach [3,35,32]. However, most of the information derived from experts and engineers is vague and incomputable and therefore there is a need to translate it into numerical values.
3) *Benchmarking*. Benchmarking plays a significant role in AM process evaluation [56]. The results from testing are more persuasive than otherwise. Data from benchmarking could be more reliable and persuasive, but this approach may be time-consuming and expensive [3].

4) *Mathematical modelling*. Some attributes (e.g. build time and cost) are influenced by assorted factors and contingent on specific cases. Linguistic values can be used to express the comparative performance of each alternative which is in vagueness. Therefore, mathematic models are used to tackle this issue and models need to be comprehensive and accurate enough to reflect the real situation.

Step 2: AM attributes performance evaluation

Precisely describing the performance of AM processes is a big challenge. The performance is influenced by assorted factors including materials, process parameters, post-processing, the condition of the machine, the ambience of the machine, etc. By varying these factors, a different performance can be achieved, e.g. high precision in low speed or high speed with low precision. Furthermore, the performance cannot be well controlled even under the same combination. Some unpredictable factors, such as ambient temperature, nozzle jam in material extrusion processes and particle size of powder materials, have impacts on the performance as well. The heterogeneous properties of printed parts make it more difficult to precisely predict the performance. Therefore, it is reasonable for this work to simplify the evaluation process by assuming no dependency lies in between each AM attribute.

After gathering the information from Step 1, the performance attributes are classified into two categories: *crisp values* from benchmarking or documents, e.g. accuracy, surface roughness, and *vague information* from expert judgement, e.g. cost or build time. For the *crisp values*, they can be directly adopted for the rough set based AD method calculation in further steps. For the *vague information*, they need to transfer into *crisp values* first and correspondingly into the further evaluation processes.

Step 3: User preference input

User preference input can be classified into two categories:

1) *Relative importance rating (RIR)*. Users input their preferences regarding each AM performance attribute, and they are further utilized for PG based rating and normalization to determine the weights.
2) *Acceptable value or goal value*. This is usually optional since users without expert knowledge might not be capable of setting. *Acceptable value* only considers the lowest acceptable level for each attribute and uses that to decide whether a given solution can fulfil users' requirements. In contrast, goal value mainly considers the trade-offs between different attributes and recommends the best marked solution for users while the threshold is usually not taken into account.

Step 4: Rough set based AD ranking and normalization

According to Fig. 2 and Eq. (7), the proposed method has different ways of measurement based on the type of value provided by users.

For *acceptable value* cases, the value set for each performance attribute are regarded as the system range. The ratings of AM performance attributes are represented as the design range. Thus, the information content of each performance attributes is calculated without weighting information. If I_i is infinite, that is no overlapping area between system range and design range, it means the AM process is not acceptable. If I_i is 0, that is system range and design range coincides, it means the corresponding AM attribute can definitely meet user's satisfaction.

For *goal value* cases, the user's value set for each performance attribute are regarded as the design range. Correspondingly, the system range is the evaluation of each attribute. In this case, the proposed method is similar to the distance based methods (e.g. TOPSIS), which the information content stands for the 'distance' between the goal value and attribute performance.

If no value provided by users, it is similar to the goal value approach except that the design range is determined by the benchmarking base. For the vague information, each TRN number $TRN_i = (a, b, c)$ is defuzzified using the centroid method as:

$$\overline{TRN_i} = \frac{1}{3}\left(a+b+c\right) \tag{16}$$

Normalization. For the outcome of Eq. (7), the information content of each attribute needs to be normalized by following equation:

$$\overline{\boldsymbol{I}_i^k} = \frac{\boldsymbol{I}_i^k}{\sum_{i=1}^{N} \boldsymbol{I}_i^k} \tag{17}$$

where $\overline{I_i^k}$ stands for the normalized information content of the i^{th} AM process in the k^{th} *attribute*.

Step 5: PG based rating and normalization

After Step 4, in order to take user's preferences into consideration, the proposed weighted PG method is utilized. User provides his/her partial preference information on the AM attributes that he/she know clearly, e.g. the PG shown in Fig. 3. Then, the PG is transferred into a dominance matrix based on Eq. (8) and Eq. (10), and the normalized preference ratings are calculated by Eqs. (11) to (13).

Step 6: Weighted ranking for best AM process selection

At last, to select the most appropriate or best AM process, based on the previous steps and equations, each normalized weight of AM attribute is multiplied with each performance evaluation result (information content) respectively and the sum of each AM process information content is represented by:

$$\sum I_i^k = \sum_{i=1}^{N} RIR_i^k \times I_i^k \tag{18}$$

where k stands for the k^{th} AM process choice. RIR_i stands for the relative importance rating of i^{th} attribute by user and correspondingly, I_i is the information content of the i^{th} attribute.

5. An illustrative example

As mentioned above, due to the complexity of various attributes performance and the interdependency among them, it is reasonable to simplify the evaluation process by assuming no dependency lies in between each AM attribute. In order to validate our method by comparing other proposed ones, we collected all the attributes being considered in the above AM process selection literature (see Appendix I). This paper selects the example of Byun and Lee [7], as it is a typical case which has been utilized and compared by many other research work [33,57,20,21,19,29,22]. According to Section 4, the procedures are described in six steps.

Step 1 and Step 2: Six attributes - *A1: accuracy (A), A2: surface roughness (R), A3: tensile strength (S), A4: elongation (E), A5: cost of the part (C) and A6: build time (B)* – were identified as the evaluation attributes with 6 machines, i.e.: SLA3500, SLS2500, FDM8000, LOM1015, Quadra and Z402 taken into consideration for AM processes selection. The attributes performance of each machine is given in Table 2, of which *A5 and A6* are vague expression based on experts' experience, e.g. very high (VH), very very low (VVL) and etc.

Step 3: Since no *goal value or accept value* considered, in this case, user only needs to provide their partial preference information on the given attributes. In order to compare with the existing AHP pairwise method [7], the dominance relationship between six attributes is depicted by a PG showing the similarly preferences (Fig. 5). For example, the ranking position of *A6* is 5.

Step 4: For the linguistic terms of *A5 and A6*, they are first assigned with a crisp number in a 1-9 rating scale, as shown in Table 3. It stands for different classes in rough set theory. Then, based on Eqs. (2) to (6), the TRNs for *A5 and A6* are calculated respectively, as shown in Table 4. For example, the vagueness of *cost* attribute in SLA3500 is *very high: (6.3, 8, 8).* As no *goal value or accept value* included, the defuzzification of TRNs are calculated by Eq. (16), as shown in Table 4, e.g. *cost* attribute in SLA3500 is *very high: 7.43.*

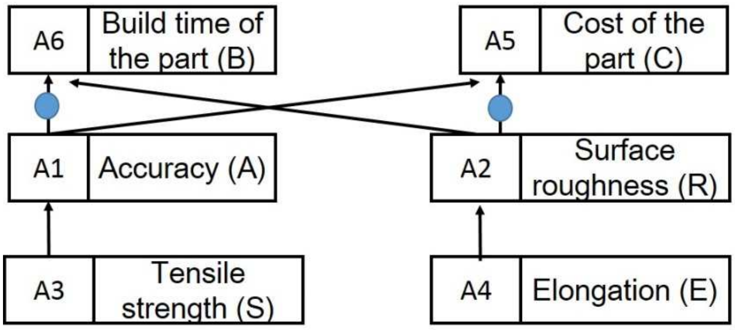

Fig. 5. PG-based preference rating among AM attributes

Table 3

Linguistic variables in 1-9 rating scale

Terms of linguistic variable	Rating scale
Very, very low (VVL)	1
Very low (VL)	2
Low (L)	3
Slightly low (SL)	4
Medium (M)	5
Slightly high (VH)	6
High (H)	7
Very High (VH)	8
Very, very High (VVH)	9

Then, the information content of each attribute can be calculated based on the benchmarking by Eq. (7). The system ranges are represented by each attribute value and the design ranges are determined by the best performance choices' values among each attribute, respectively. For example, the best choice for *A1: accuracy* is Quadra, value 95. Therefore, for *A1* in Z402, the common area, that is the overlapping area of between design range (95) and system range (600) is 95. Thus, the information content of *A1* in Z402 is calculated as:

$$I_i = \log_2\left(\frac{600}{95}\right) = 2.658963 \tag{19}$$

Following this manner, the sum of each AM process information content is given in Table 5 without preference weighting. Then, based on Eq. (17), the normalized information is given in Table 6. Since the one with smallest information content is the best one, therefore, Quadra is the best choice. And the ranking of choices without weights are: Quadra > Z402 > SLA3500 > SLS2500 > LOM1015 > FDM8000.

Step 5: Based on Eq. (8), the dominance matrix of attributes in Fig. 5 are represented as follows:

$$D=\begin{bmatrix}0&0&1&0&0&0\\0&0&0&1&0&0\\0&0&0&0&0&0\\0&0&0&0&0&0\\1&1&1&1&0&0\\1&1&1&1&0&0\end{bmatrix}\begin{matrix}\to 1\\\to 1\\\to 0\\\to 0\\\to 4\\\to 4\end{matrix} \tag{20}$$

Correspondingly, the ranking position and relative importance rating of each AM attribute are calculated by Eqs. (11) to (13), and represented as:

$$P_M=\begin{bmatrix}2, & 2, & 1, & 1, & 6, & 6\end{bmatrix} \tag{21}$$

$$RIR=\begin{pmatrix}0.111 & 0.111 & 0.056 & 0.056 & 0.333 & 0.333\end{pmatrix} \tag{22}$$

Step 6: Based on the information content of each attribute in Table 5, and the calculated *RIR* vector in Step 5, the weighted ranking for AM process selection is derived by Eq. (18), as shown in Table 7. And correspondingly, the rankings of AM processes are: Z402 > Quadra > LOM1015 > SLA3500 > SLS2500 > FDM8000, which Z402 is the most appropriate one.

Compared with the results from Byun and Lee [7] which is ranked as: Z402 > LOM1015 > Quadra > SLA3500 > > SLS2500 > FDM8000. It is found that only the second best choice is different, which does not affect the result of the best AM process selection. The fact of ranking difference is result from the various normalization processes of decision matrix between TOPSIS method and rough set based fuzzy AD method. One can find that TOPSIS is based on the *absolute normalization* mechanism, i.e. the distance (or information content) are normalized by adding all the values of attributes into calculation, as depicted in Eq. (20):

$$\mathrm{r}_i^k=\frac{x_i^k}{\sqrt{\sum_{i=1}^{N}x_i^k}} \tag{22}$$

, where r_i^k stands for the normalized weight of the i^{th} AM process in the k^{th} attribute. Nevertheless, for rough set based fuzzy AD method, it is based on the *relative normalization* mechanism (see Eq. (17)). The normalized information content of each attribute (i.e. system range) of any AM process is determined by comparing with its best attribute (i.e. design range). In other words, AD method treat each best attribute with information content of none (or positive distance of infinite). The author would like to argue that the *relative normalization* mechanism should be more suitable for the AM process selection since it represents the limit of each attributes within the existing selection scope. Moreover, the proposed method shows talents in evaluating the most appropriate AM process with more objectivity and more user input flexibility.

Table 4

Calculation result of TRNs and defuzzified TRNs on major AM systems

	SLA3500	SLS2500	FDM8000	LOM1015	Quadra	Z402
C	(6.3, 8, 8) 7.43	(6.3, 8, 8) 7.43	(4.7, 7, 7.8) 6.5	(3.5, 6, 7.4) 5.63	(6.3, 8, 8) 7.43	(1, 1, 6.3) 2.77
B	(4, 5, 6) 5	(4, 5, 6) 5	(4.7, 8, 8) 6.9	(3.3, 4, 5.2) 4.17	(3.3, 4, 5.2) 4.17	(2, 2, 4.7) 2.9

Table 5

Calculation result of unweight rough set based fuzzy AD information content

	I_A	I_R	I_S	I_E	Ic	I_B	$\sum I$
SLA3500	0.337035	0.893085	3.70044	2.321928	1.423476	0.785875	9.461839
SLS2500	0.658963	1.836501	3	3.087463	1.423476	0.785875	10.79228
FDM8000	0.395929	2.584963	2.584963	3.321928	1.230554	1.250543	11.36888
LOM1015	0.961526	2.514573	2.321928	3.321928	1.023249	0.523994	10.6672
Quadra	0	0	2.584963	2.584963	1.423476	0.523994	7.117396
Z402	2.658963	2.146841	0	0	0	0	4.805804

Table 6

Calculation result of normalized unweight rough set based fuzzy AD information content

	I_A	I_R	I_S	I_E	Ic	I_B	$\sum I$
SLA3500	0.06724	0.089524	0.260736	0.158621	0.218183	0.203054	0.997357
SLS2500	0.131466	0.184093	0.211382	0.210918	0.218183	0.203054	1.159096
FDM8000	0.07899	0.259119	0.182138	0.226935	0.188613	0.323114	1.25891
LOM1015	0.191829	0.252063	0.163605	0.226935	0.156838	0.135389	1.12666
Quadra	0	0	0.182138	0.17659	0.218183	0.135389	0.712301
Z402	0.530475	0.215201	0	0	0	0	0.745677

Table 7

Calculation result of weighted rough set based fuzzy AD information content

	I_A	I_R	I_S	I_E	I_C	I_B	ΣI
SLA3500	0.007464	0.009937	0.014601	0.008883	0.072655	0.067617	0.181157
SLS2500	0.014593	0.020434	0.011837	0.011811	0.072655	0.067617	0.198948
FDM8000	0.008768	0.028762	0.0102	0.012708	0.062808	0.107597	0.230843
LOM1015	0.021293	0.027979	0.009162	0.012708	0.052227	0.045085	0.168454
Quadra	0	0	0.0102	0.009889	0.072655	0.045085	0.137828
Z402	0.058883	0.023887	0	0	0	0	0.08277

6. Conclusion

AM process selection problem has been discussed for years. Many tools and system have been brought up to facilitate the selection, which typically consists of three parts: AM performance evaluation, user preference evaluation and a ranking scheme. This work first analysed the existing MADM methods for AM process selection and evaluates their suitability by two aspects: *preference rating flexibility* and *performance evaluation objectivity.* We assume that an approach dealing with incomplete weighting information and assessing AM attribute performance objectively within inherent data should be advantageous. However, the review shows that:

- *Preference rating* is generally done by pairwise comparison or direct assignment. User often lack of sufficient knowledge and real life cases tend to be more dynamic and complex, which the existing method cannot deal with them accurately.
- *Performance evaluation.* The membership function selection in fuzzy set based cases is usually determined based on engineers' experience and intuition subjectively. This could result in inaccuracy of the best AM process selection.

Based on the above problems, this paper proposed a novel weighted rough set based fuzzy AD approach for AM process selection. In order to handle users' incomplete information in rating, this work proposed the weighted PR method which is more suitable for real life cases with dynamic situations and limited user information. Also, it maintained the rating accuracy by partial pair-wise comparison, and also reduced user input effort. To achieve evaluation objectivity, the proposed rough set based fuzzy AD approach overcomes the subjectivity of designer's interpretation on the fuzzy membership selection by rough numbers and rough boundary intervals instead. Accordingly, a flowchart is given to describe the procedures of the MADM for AM process selection. The case study result shows that the weighted rough set based AD method can perform as well as the previous work. Moreover, it has advantages in processing subjective linguistic assessments since the membership functions are calculated from the inherent data other than predefined by designers subjectively, especially when information is limited.

The proposed priori articulation of preferences process decision support method has its own limitation, as it is suitable for users without much knowledge and experience in AM process selection. In the future, the robustness of the method will be validated with more complicated applications, and a posteriori articulation of preferences approach should be developed to help knowledgeable users explore existing solutions and make their designs more suitable to an AM process.

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Appendix I

Attributes being considered in existing AM process selection

Author, year	**Surface finish**	**Geometric properties**					**Functional properties**				**Production**				
		Resolution/ Minimum feature size	Dimensional accuracy		Build envelope	Complexity	Part function	Mechanical property	Thermal property	Material type	Cost	Time	Quantity	Reliability	Post-processing
			Overall	feature											
Jones, Campbell [25]	√			√	√		√	√			√	√	√		√
Chuk, Thomson [24]	√		√		√			√			√	√			√
Wilson, Rosen [34]		√			√	√		√			√	√			
Fernandez et al. [37]		√	√					√							
Byun, Lee [7] Rao, Padmanabhan [33] Venkata Rao, Patel [36] Chakraborty [21] Vahdani et al. [20] İç [22] Wang et al. [19] Zhang et al. [18]	√		√					√			√	√			
Lan* et al. [30]	√		√		√	√		√	√		√	√			√
Mahesh et al. [17]	√	√		√				√							
Byun, Lee [58]	√		√								√	√			
Armillotta [31]	√		√				√	√			√	√			√
Lokesh, Jain [32]	√				√				√		√	√		√	
Khrais et al. [23]	√		√		√						√	√			√
Munguia et al. [28]	√	√	√		√			√	√	√	√	√			√

Ghazy [27]	√	√	√		√			√	√				√		
Roberson et al. [26]	√										√	√			
Mahapatra, Panda [10]			√					√			√	√			
Zhang, Bernard [29]	√							√			√	√			
Liao et al. [35]														√	