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A TWO-PHASE INSTRUMENT SELECTION SYSTEM FOR LARGE VOLUME METROLOGY BASED ON INTUITIONISTIC FUZZY SETS WITH TOPSIS METHOD

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ABSTRACT

Instrument selection is deemed as a compulsory and critical process in automated inspection planning for large volume metrology applications. The process identifies the capable and suitable metrology devices with respect to the desired measurement tasks. Most research efforts in the past have focused on the probe selection for coordinate measuring machines (CMMs). However, increasing demand for accurate measurement in large scale and complex assembly and fabrication industries, such as aerospace and power generation makes these industries to invest in different measurement systems and technologies. The increasing number of systems with different capabilities create difficulties in selecting the most competent Large Volume Metrology Instrument (LVMI) for a given measurement task. Research in this area is sketchy due to having vast candidates of qualified instruments and at the same time the complexly of understanding their real capabilities. This paper proposes a two-phased approach to select the capable LVMIs and rank the LVMIs according to the pre-defined Measurability Characteristics (MCs). Intuitionistic fuzzy sets combined with TOPSIS method is employed to solve this vague and conflicting multi-criteria problem. A numerical case study is given to demonstrate the effectiveness of the system.

KEYWORDS

Inspection process planning; Measurability characteristics; Large volume metrology; TOPSIS methods; Measurement

1. INTRODUCTION

In recent years Large Volume Metrology (LVM) has been rapidly advancing and widely applied in high value manufacturing industries such as aerospace, automotive and power generation, (Estler et al, 2002; Peggs et al, 2009). New development of LVM systems, their application techniques and performance evaluation methods paved the way for enhancing product performance and quality with reduced cost. Many efforts have been made to integrate measurement throughout manufacturing processes in order to maximize the benefits of the latest technologies (Maropoulos et al, 2007 and 2008). As a result, metrology is not only considered as a quality control manner but also an active element in the early design stages.

Inspection process planning (IPP) has been demonstrated as an effective process to take metrology into account from the beginning of manufacturing processes (Li et al, 2004; Zhao et al, 2009). Inspection plan is created along with product design, before the commence of any production activity.

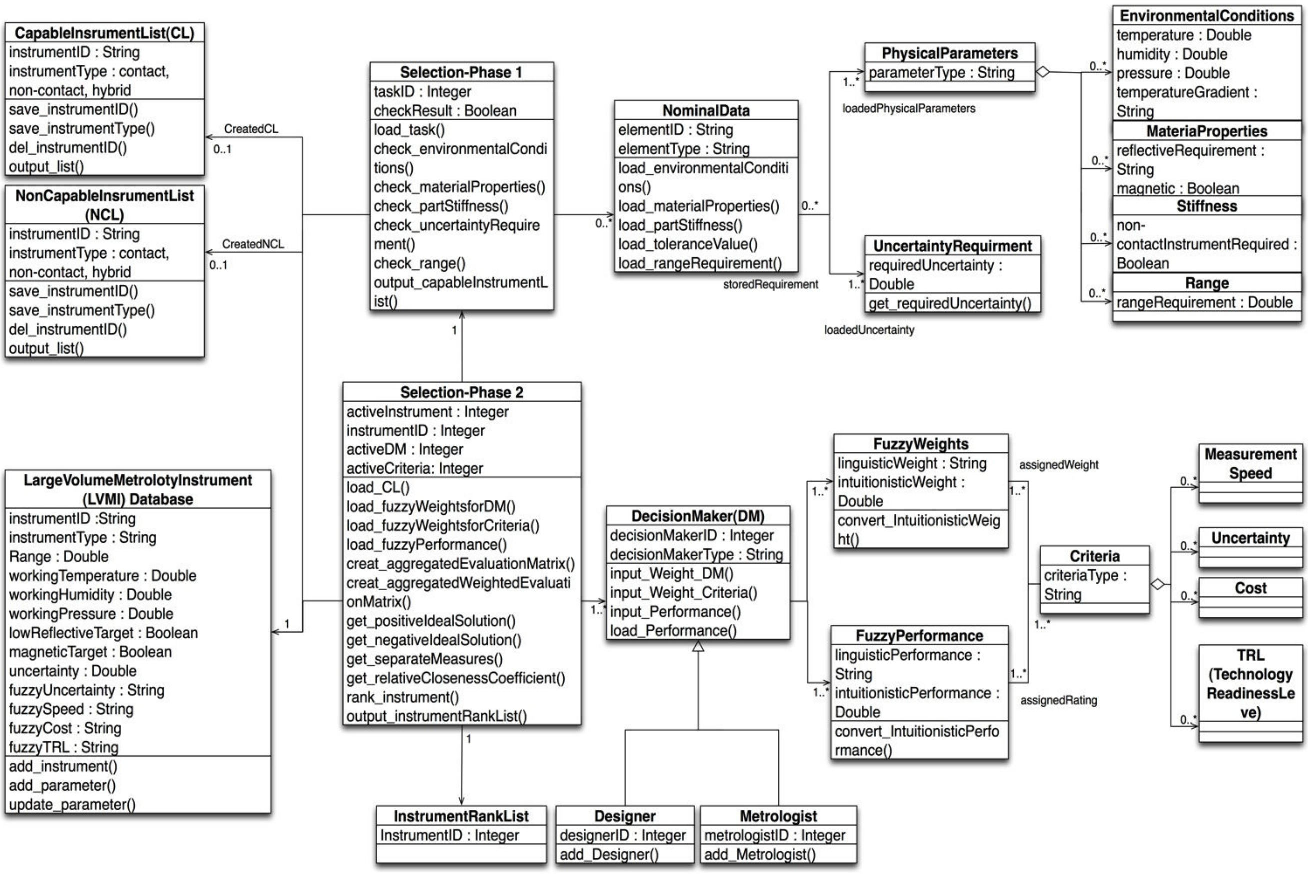

Figure 1 – Structure of the proposed instrument selection system in UML class diagram

This approach can eliminate rework, reducing the possible negative impact engineering change. However research regarding LVM IPP was absent in the literature until Cai et al (2011) proposed the first systematic large volume metrology inspection system. Unlike probe selection in most IPP system for coordinate measuring machines (CMMs), selecting the suitable LVM instrument faces more complexity and vagueness due to the large number of available instruments and uncertain relationships among instrument performance criteria. Previous work (Cai et al, 2008 and 2010; Muelaner et al, 2010) has successfully defined the process of measurability analysis. In this process a variety of criteria are specified with corresponding evaluation methods. Instrument selection is based on the result of measurability analysis although automation is severely limited. However, many task requirements and related importance, which is usually unequal, are ambiguous while defining the criteria. In addition, some parameters of alternative instruments cannot be quantified at this stage without detailed sampling strategy and instrument configuration e.g. inspection time and inspection cost. Vague relationship among criteria also leads to uncertain decision, such as the inherent trade-off relation between cost and uncertainty. In most applications, the selection process involves more than one decision maker (DM) e.g. designers and metrologists. The assigned preference of alternatives may be different due to the unique understanding of the task and unequal knowledge of the instruments. This leads to different assigned weights when the significance of different criteria is evaluated by DMs. It is therefore formulated as a multi-criteria multi-person decision making problem.

Fuzzy set theory (FST) was first introduced by Zadeh (1965), with the objective of denoting vagueness and fuzziness in a set and processing the unquantifiable and incomplete information in decision problems. Fuzzy linguistic models enable the conversion of vague verbal expressions such as ‘extremely’, ‘very’ and ‘medium’ into fuzzy numbers, which allows DMs to estimate the performance of alternatives and make decision based on quantitative data. Atanassov (1986) defined the concept of intuitionistic fuzzy set (IFS) as a generalization of FST, characterized by a membership function and a non-membership function. IFS with technique for order performance by similarity to ideal solution (TOPSIS) have recently attracted great attention in multi-attributes decision-making (MADM) process due to the consideration of both positive-ideal and negative-ideal solution (Karsak, 2002; Bozdag et al, 2003; Chen et al, 2006; Boran et al, 2009; Onut et al, 2009). Precise decision can be made while conflicting criteria are assessed using different weights.

A two-phased instrument selection system is proposed in this paper. System structure is presented using UML class diagram in Figure2. Measurability Characteristics (MCs) are identified and grouped into quantitative and qualitative attributes. Phase-1 enables the filtration of instrument based on crisp requirements of the inspection task. The remaining instruments are assessed in Phase-2 according to qualitative criteria and a rank list of alternatives is given as the result.

2. MEASURABILITY CHARACTERISTICS

It is imperative to clearly identify the requirements of the measurement in order to select the appropriate instrument. Based on the previous work Cai et al (2008, 2010), Muelaner et al (2010), the proposed MCs are categorized into two groups to be assessed in two phases, respectively. For detailed definitions of MCs consult the above literature.

2.1 Crisp Measurability Characteristics

Crisp MCs are defined as $C_{ci,}$ which can be precisely assessed based on the following criteria:

(a) the environmental conditions under which the inspection task will be carried out for instance the temperature, altitude and humidity must meet the instrument specified capabilities ;

(b) the inspection range or the distance of measurement points from the instrument ;

(c) the material properties of the target product. For example magnetic targets can not be applied to aluminium or plastics and transparent or reflective surfaces cannot be scanned efficiently by some laser based measurement systems

(d) the stiffness of the product, e.g. only non-contact system can be deployed on product with high flexibility due to undesired surface movements ;

(e) the uncertainty requirement of the inspection, e.g. the uncertainty of the selected instrument should be confined by decision rules (BSISO 12453-1; 1999ASME B89.7.3.1).

2.2 Fuzzy Measurability Characteristics

Criteria with vagueness are defined as C_{fi}:

(a) the uncertainty capability of the chosen instrument;

(b) overall cost of deploying the instrument which includes recurring cost e.g. purchasing the system and mandatory training, and non-recurring cost e.g. maintenance, depreciation;

(c) measurement speed;

(d) Technology Readiness Level (TRL) of the instrument.

It is uncertainly beneficial to define those fuzzy MCs due to the incomplete information at this early planning stage and conflicting relationship among them. For instance, uncertainty performance of most instruments is related to the measuring distance to the target, which is unknown without the detailed configuration and topological plan of a specific instrument. Measurement speed and cost can only be determined when both sampling strategy and system setup are available. In addition to that, a non-linear trade-off relationship exists between cost and uncertainty resulting in ambiguous decision. An attempt to use more accurate instrument has a potentially higher cost.

Table 1 Example of crisp MCs

Inspection ID		**1**
Crisp MCs		**Details**
Environmental conditions	Temperature	25°
	Altitude	500 m
	Humidity	35%
Stiffness limitation		contact& non-contact
Material property		magnet applicable
Uncertainty requirement		0.2 mm
Range		14m

3. PHASE 1: INSTRUMENT FILTRATION

Figure 2 shows the algorithm of Phase 1 using UML activity diagram. The following steps detail the algorithm of instrument filtration.

Step 1 Retrieving inspection requirements.

In this step, inspection features extracted from design are retrieved individually with associated parameters. The task identification process is detailed in Cai et al (2011). Crisp MCs are then obtained accordingly and set as criteria $C_{ci\ for}$ later evaluation. Table 1 shows an example of interpreted crisp MCs.

Step 2Filtering the instruments.

A capable instrument list (CPL) and an incapable instrument list (IIL) are created to temporarily store the result, facilitating the filtration process. Instruments located in the large volume metrology instrument database are activated sequentially with associated specification I_{si}. The data structure of the database shown in Figure 1 and Table 2 are given as

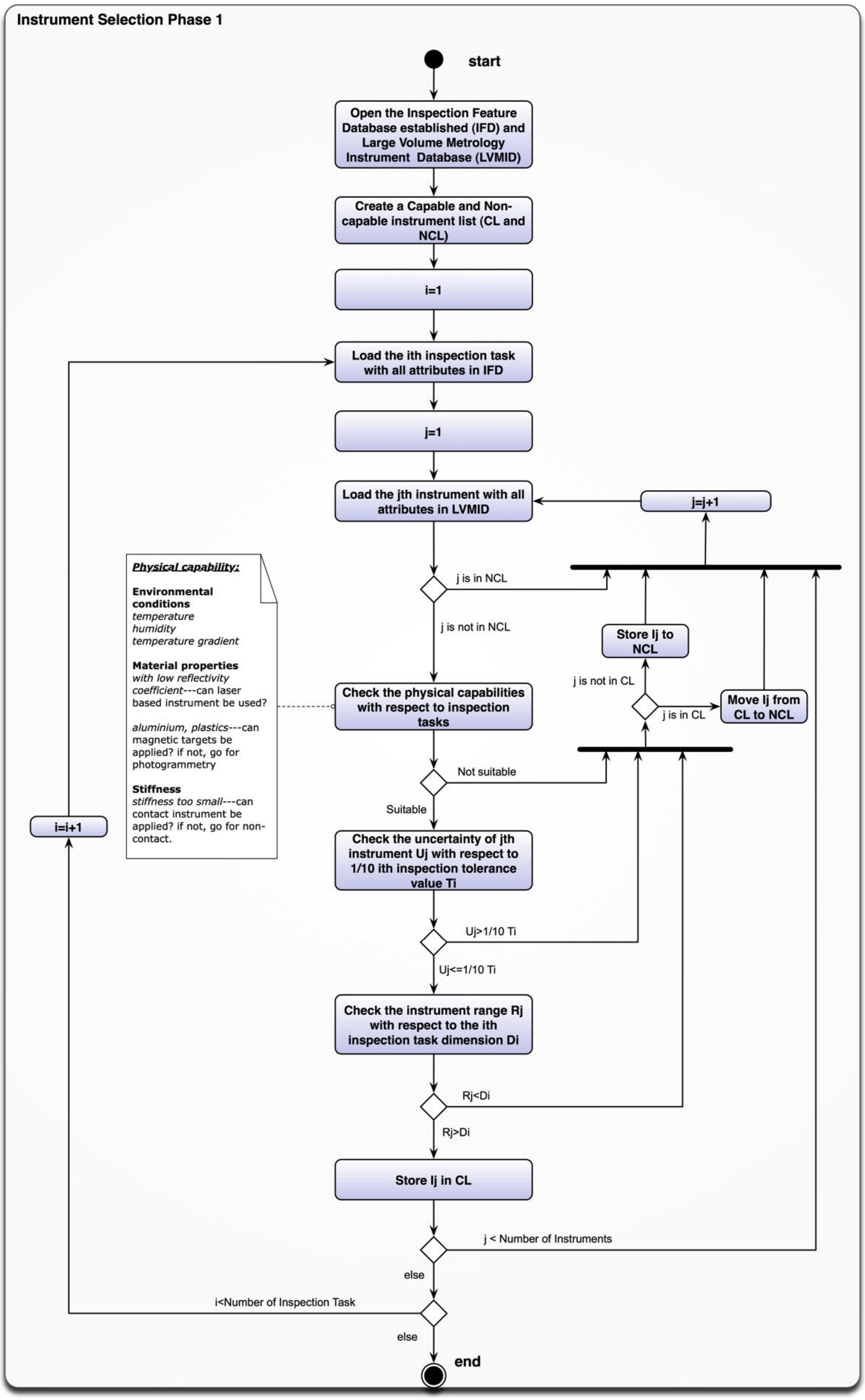

Figure 2 UML activity diagram of Phase 1

an example of FARO Laser Tracker. Comparisons are then carried out between C_{ci} and I_{si} in such order: stiffness of the product, environmental conditions, material properties, uncertainty requirement and inspection range. By assessing the more obvious criteria first the sequence ensures that minimum comparing loops are employed. Once unsatisfied criterion is detected, I_i is removed from CIL to IIL and the rest of C_{ci} are cancelled to save computational power.

Table 2 Stored data of FARO Laser Tracker

Instrument ID	1
Instrument Type	Laser Tracker
Maximum Operating Temperature	50°
Minimum Operating Temperature	-15°
Maximum Operating Altitude	2450 m
Minimum Operating Attitude	-700 m
Maximum Acceptable Humidity	95% non-condensing
Minimum Acceptable Humidity	0
Low reflective target	no
Magnetic target	yes
Range	55 m
Uncertainty	ADM: 16μm + 0.8μm/m Interferometer: 4μm + 0.8μm/m

The output of Phase 1 is a list with all capable instruments with respect to inspection tasks and it is passed to the next stage for further selection.

4.PHASE 2: FUZZY INSTRUMENT SELECTION

4.1 INTUITIONISTIC FUZZY SETS

Zadeh (1965) defined a fuzzy set A as:

$$A = \{\langle x, \mu_A(x)\rangle | x \in X\} \quad (1)$$

where $\mu_A(x): X \rightarrow [0,1]$ is the membership function indicating the degree that element x belongs to the set A. The closer the value of $\mu_A(x)$ is to 1, the more x belongs to A.

Intuitionistic fuzzy set A can be written as:

$$A = \{\langle x, \mu_A(x), v_A(x)\rangle | x \in X\} \quad (2)$$

where $\mu_A(x): X \rightarrow [0,1]$ is the membership function and $v_A(x): X \rightarrow [0,1]$is the non-membership function with the condition that

$$0 \leq \mu_A(x) + v_A(x) \leq 1 \quad (3)$$

Another unique parameter $\pi_A(x)$ known as the intuitionistic fuzzy index is defined as:

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x) \quad (4)$$

The multiplication operator of two IFSs A and B in a finite set X is defined as

$$A \otimes B = \{\mu_A(x) \cdot \mu_B(x), v_A(x) + v_B(x) - v_A(x) \cdot v_B(x) | x \in X\} \quad (5)$$

4.2 IFSs INSTRUMENT SELECTION

Boran et al (2009) and Onut et al (2009) proposed similar approaches to solve the MADM supplier selection problem using TOPSIS. IFSs were utilized to select the appropriate supplier by aggregating individual opinions of DMs for weighting the importance of both criteria and alternatives (Boran et al, 2009). Their research results demonstrated the effectiveness of the approach. A similar method is adopted in this work. The following steps detail the algorithm and process of applying IFSs to instrument selection.

Step 1 Modelling the MADM problem.

(a) Let the capable alternative instruments stored in CIL from Phase 1 be a finite set $I = \{I_1, I_2, \dots, I_n\}$.

(b) Let the fuzzy MCs be a finite criteria set $C = \{C_1, C_2, \dots, C_m\}$, which includes instrument uncertainty, overall cost, inspection speed and TRL.

(c) Let $D = \{D_1, D_2, \dots, D_l\}$ be the decision maker set including both designers and metrologists in the decision making process.

(d) Let $P^{(k)} = (p_{ij}^{(k)})_{m\times n}$ denote the $m \times n$ decision matrix of kth decision maker, where p_{ij} is the performance rating of alternative instrument I_i with respect to criterion C_j.

(e) Alternative instruments are linguistically rated by DMs using terms defined in Table 3. The importance of DMs is evaluated using the linguistic term in Table 4, where the typical converged IFNs are also given.

Table 3 Linguistic Performance and IFNs

Linguistic Performance Evaluation	IFNs
Extremely good (EG)/extremely high (EH)	(1.00,0.00)
Very good (VG)/very high (VH)	(0.80,0.10)
Good (G)/high (H)	(0.70,0.20)
Fair (F)/medium (M)	(0.50,0.40)
Bad (B)/low (L)	(0.25,0.60)

Table 4 Linguistic Importance and IFNs

Linguistic Importance	IFNs
Very Important	(0.90,0.10)
Important	(0.75,0.20)
Medium	(0.50,0.45)
Unimportant	(0.35,0.60)
Very Unimportant	(0.10,0.90)

Step 2 Assigning linguistic importance to designers and metrologists, and calculating the corresponding weights.

Let $W_{D_k} = [\mu_k, v_k, \pi_k]$ be the intuitionistic fuzzy rating of kth decision maker using linguistic term and the weight of kth decision maker is calculated as:

$$\omega_k = \frac{\left(\frac{\mu_k}{\mu_k+\nu_k}\right)}{\sum_{k=1}^{l}\left(\mu_k+\pi_k\left(\frac{\mu_k}{\mu_k+\nu_k}\right)\right)} \quad (6)$$

where $0 \le \omega_k \le 1$ and $\sum_{k=1}^{l}\omega_k = 1$.

Step 3 Aggregating the decision matrix with respect to the individual performance rating of decision makers.

Having fused individual opinion $P^{(k)}$ from all weighted DMs, group opinion is aggregated as the intuitionistic fuzzy decision matrix. IFWA operator is utilized in the aggregation process proposed by Xu (2007a and 2007b).

$$p_{ij} = IFWA_{\omega}\left(p_{ij}^{(1)}, p_{ij}^{(2)}, \ldots, p_{ij}^{(l)}\right) = [1 - \prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\omega_k}, \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\omega_k}, \prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\omega_k} - \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\omega_k}] \quad (7)$$

The matrix is then written as

$$P = \begin{bmatrix} p_{11}p_{12} & \cdots & p_{1m} \\ p_{21}p_{22} & \cdots & p_{2m} \\ \vdots\ \ \vdots & \ddots & \vdots \\ p_{n1}p_{n2} & \cdots & p_{nm} \end{bmatrix} \quad (8)$$

where $p_{ij} = (\mu_{I_i}(x_j), \nu_{I_i}(x_j), \pi_{I_i}(x_j))$.

Step 4 Assigning linguistic importance to the criteria and calculating the corresponding weights.

The system allows decision makers to assign different weights to each criterion, which is a key advantage for emphasizing the vague relation existing among criteria, e.g. uncertainty, inspection speed and cost.

It is assumed that the *k*th decision maker weights the *j*th criterion with an intuitionistic number $w_j{}^{(k)} = [\mu_j^{(k)}, \nu_j^{(k)}, \pi_j^{(k)}]$. The overall weight of the *j*th criterion is calculated using IFWA operator:

$$w_j = IFWA_{\lambda}\left(w_j^{(1)}, w_j^{(2)}, \ldots, w_j^{(l)}\right) = [1 - \prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\omega_k}, \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\omega_k}, \prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\omega_k} - \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\omega_k}] \quad (9)$$

and the weight matrix is then formed as

$$W = [w_1, w_2, \ldots, w_j] \quad (10)$$

where $w_j = (\mu_j, \nu_j, \pi_j)$.

Step 5 Creating the weighted decision matrix by aggregating *P* and *W*.

P and *W* are multiplied using Eq.5 resulting in the weighted intuitionistic fuzzy decision matrix:

$$P \otimes W = \{\langle x, \mu_{I_i}(x)\cdot\mu_W(x), \nu_{I_i}(x)+\nu_W(x)-\nu_{I_i}(x)\cdot\nu_W(x)\rangle \mid x \in X\} \quad (11)$$

The matrix is then written as

$$P' = \begin{bmatrix} r'_{11}r'_{12} & \cdots & r'_{1m} \\ r'_{21}r'_{22} & \cdots & r'_{2m} \\ \vdots\ \ \vdots & \ddots & \vdots \\ r'_{n1}r'_{n2} & \cdots & r'_{nm} \end{bmatrix} \quad (12)$$

and

$$\pi_{I_iW}(x_j) = 1 - \mu_{I_i}(x)\cdot\mu_W(x) - \nu_{I_i}(x) - \nu_W(x) + \nu_{I_i}(x)\cdot\nu_W(x) \quad (13)$$

where $p'_{ij} = (\mu_{I_iW}(x_j), \nu_{I_iW}(x_j), \pi_{I_iW}(x_j))$.

Step 6 Calculating the separation distance of each alternative to positive-ideal solution and negative-ideal solution.

Criteria such as uncertainty, TRL and speed denoted by C_B are beneficial while rating the alternative instruments. By contrast, the overall cost is considered as cost criterion denoted by C_C. The intuitionistic fuzzy positive-ideal solution I^* and negative-ideal solution I^- are defined as:

$$I^* = (\mu_{I^*W}(x_j), \nu_{I^*W}(x_j)) \quad (14)$$

$$I^- = (\mu_{I^-W}(x_j), \nu_{I^-W}(x_j)) \quad (15)$$

where

$$\mu_{I^*W}(x_j) = (max\ \mu_{I_iW}(x_j) | j \in C_B), (min\ \mu_{I_iW}(x_j) | j \in C_C)$$
$$\nu_{I^*W}(x_j) = (min\ \nu_{I_iW}(x_j) | j \in C_B), (max\ \nu_{I_iW}(x_j) | j \in C_C)$$
$$\mu_{I^-W}(x_j) = (min\ \mu_{I_iW}(x_j) | j \in C_B), (max\ \mu_{I_iW}(x_j) | j \in C_C)$$
$$\nu_{I^-W}(x_j) = (max\ \nu_{I_iW}(x_j) | j \in C_B), (min\ \nu_{I_iW}(x_j) | j \in C_C)$$

Normalized Euclidean distance is adopted in this paper to measure the separation between alternatives and positive-ideal solution I^* and negative-ideal solution I^- as D_i^* and D_i^-:

$$D_i^* = p'_{ij} - I^* = \sqrt{\frac{1}{2n}\sum_{j=1}^{n}\begin{bmatrix}(\mu_{I_iW}(x_j) - \mu_{I^*W}(x_j))^2 + (\nu_{I_iW}(x_j) - \nu_{I^*W}(x_j))^2 \\ +(\pi_{I_iW}(x_j) - \pi_{I^*W}(x_j))^2\end{bmatrix}} \quad (16)$$

and

$$D_i^- = p'_{ij} - I^- =$$

$$\sqrt{\frac{1}{2n}\sum_{j=1}^{n}\begin{bmatrix}(\mu_{I_iW}(x_j)-\mu_{I^-W}(x_j))^2+(\nu_{I_iW}(x_j)-\nu_{I^-W}(x_j))^2\\+(\pi_{I_iW}(x_j)-\pi_{I^-W}(x_j))^2\end{bmatrix}} \quad (17)$$

Step 7 Ranking the alternative instruments based on the relative closeness coefficient.

All instruments are then scored with the relative closeness coefficient RC_i with respect to the positive-ideal solution:

$$RC_i = \frac{D_i^-}{D_i^- + D_i^*} \quad (18)$$

The candidates are then ranked according to the value of RC_i. Higher score indicates more suitability of the corresponding alternative instrument.

The algorithm of Phase 2 is shown in Figure 3 and the most suitable instrument is highlighted as the result of instrument selection process.

5. NUMERICAL CASE STUDY

An instrument is required for an inspection task and the crisp MCs is shown in Table 1. Available instruments stored in database include 2 laser trackers, 2 laser scanners, laser radar, iGPS and photogrammetry system. The filtration process is implemented as follows:

(a) photogrammetry system is removed from CIL due to insufficient range coverage.

(b) laser scanners and iGPS are filtered out due to unsatisfied uncertainty requirement.

Under this circumstance, 2 laser trackers and laser radar have remained from Phase 1, as the alternative instruments:

I_1: Laser Tracker 1
I_2: Laser Tracker 2
I_3: Laser Radar

One designer (DM_1) and two metrologists (DM_2 and DM_3) are involved in the performance evaluation process based on the four fuzzy MCs：

C_1: Instrument uncertainty
C_2: Overall cost
C_3: Inspection Speed
C_4: TRL

The process of fuzzy instrument selection is consisted of the following steps:

Step 1 Assigning linguistic importance to DMs and calculating the corresponding weights.

Each DM is assigned with a linguistic importance term shown in Table 6. This process is based on the degree of knowledge possessed by DMs regarding specific inspection task and instrument. Corresponding weights are obtained using Eq.6.

Step 2 Aggregating the decision matrix with respect to the individual performance rating of decision maker.

The performance rating from each DM is shown in Table 7.

Table 6 DMs importance and corresponding weights

	DM_1	DM_2	DM_3
Linguistic importance	Important	Very important	Medium
Weight	0.356	0.406	0.238

Table 7 Performance rating of alternatives

Criteria	Instrument	DM_1	DM_2	DM_3
C_1 uncertainty	I_1	EG	EG	VG
	I_2	VG	G	VG
	I_3	G	G	F
C_2 cost	I_1	VH	VH	H
	I_2	M	H	M
	I_3	EH	EH	EH
C_3 speed	I_1	VG	F	F
	I_2	G	G	F
	I_3	VG	EG	VG
C_4 TRL	I_1	VG	EG	VG
	I_2	G	VG	G
	I_3	F	G	B

The linguistic ratings are then converted to IFNs using Table 3. The intuitionistic fuzzy decision matrix is calculated according to Eq.7:

$$P = \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & C_3 & C_4 \end{array} \\ \begin{bmatrix} (1.000,0.000,1.000) & (0.780,0.118,0.662) & (0.639,0.244,0.395) & (1.000,0.000,1.000) \\ (0.764,0.133,0.632) & (0.594,0.302,0.292) & (0.594,0.302,0.292) & (0.746,0.151,0.595) \\ (0.661,0.236,0.426) & (1.000,0.000,1.000) & (1.000,0.000,1.000) & (0.553,0.332,0.220) \end{bmatrix} \end{array} \begin{array}{c} \\ I_1 \\ I_2 \\ I_3 \end{array}$$

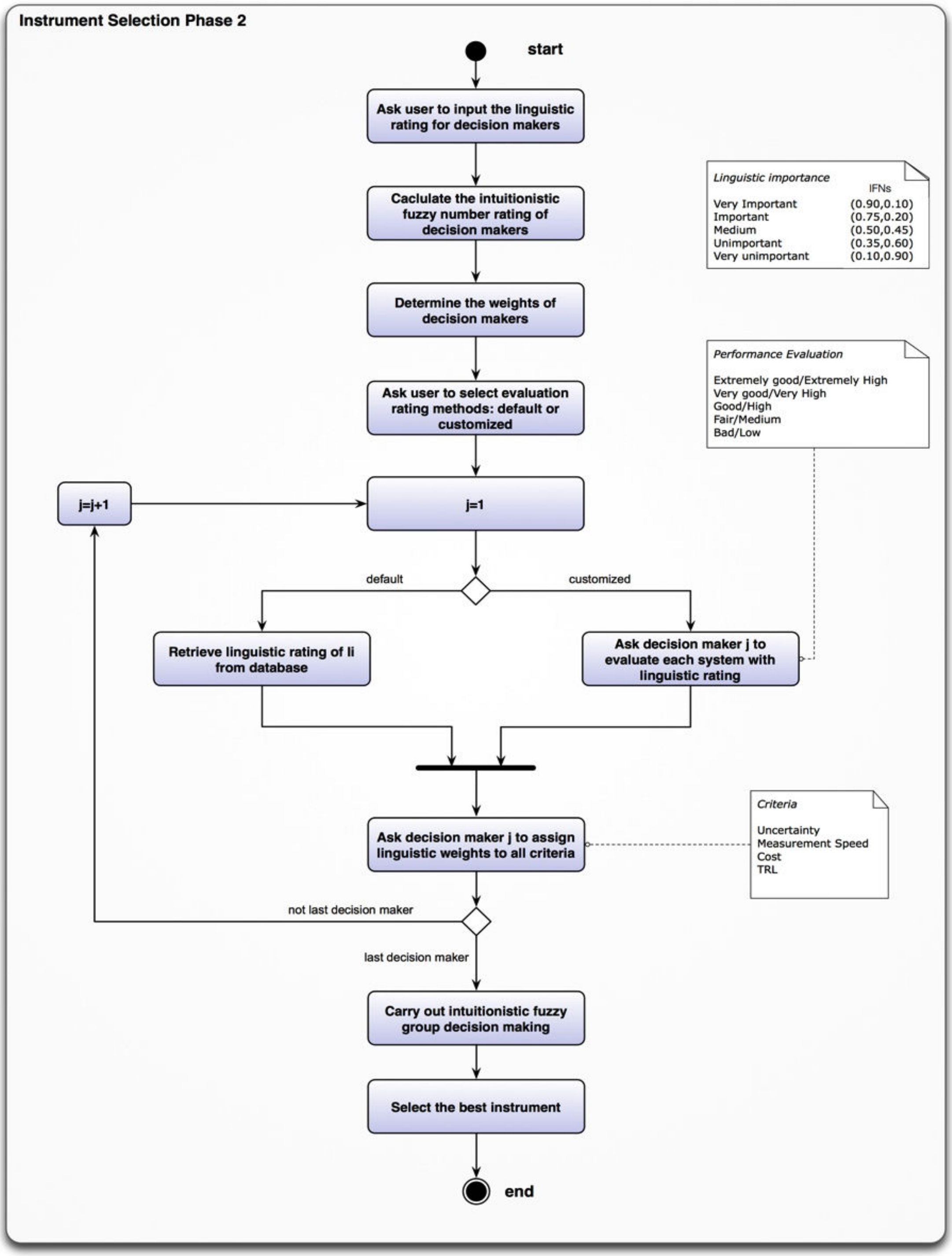

Figure 3 UML activity diagram of Phase 2

Step 3 Calculating the aggregated weight of criteria

The assigned importance by DMs with respect to each criterion is shown in Table 8 with converted corresponding IFNs.

The weight matrix is aggregated using Eq.9 as:

$$W = [w_{C_1}, w_{C_2}, w_{C_3}, w_{C_4}]$$

$$= \begin{bmatrix} (0.861,0.128,0.011) \\ (0.787,0.189,0.023) \\ (0.799,0.170,0.031) \\ (0.576,0.371,0.053) \end{bmatrix}^T$$

Step 4 Creating the weighted decision matrix by aggregating matrices *P* and *W*.

With the constructed intuitionistic fuzzy decision matrix *P* and weights matrix *W*, the aggregated weighted decision matrix P' is established using Eq.

$$\begin{array}{cccccc} & C_1 & C_2 & C_3 & C_4 & \\ P' = & \left[\begin{matrix}(0.861,0.128,0.011) \\ (0.658,0.224,0.098) \\ (0.569,0.334,0.097)\end{matrix}\right. & \begin{matrix}(0.614,0.285,0.102) \\ (0.467,0.434,0.099) \\ (0.787,0.189,0.024)\end{matrix} & \begin{matrix}(0.511,0.373,0.117) \\ (0.474,0.421,0.105) \\ (0.799,0.170,0.031)\end{matrix} & \left.\begin{matrix}(0.576,0.371,0.053) \\ (0.429,0.466,0.105) \\ (0.318,0.580,0.102)\end{matrix}\right] & \begin{matrix} I_1 \\ I_2 \\ I_3 \end{matrix}\end{array}$$

Table 8 Assigned importance for all criteria

Criteria	DM_1	DM_2	DM_3
C_1	I (0.75,0.2)	VI (0.90,0.10)	VI (0.90,0.10)
C_2	VI (0.90,0.10)	I (0.75,0.2)	M (0.50,0.45)
C_3	I (0.75,0.2)	I (0.75,0.2)	VI (0.90,0.10)
C_4	M (0.50,0.45)	M (0.50,0.45)	I (0.75,0.2)

Step 5 Calculating the separation distance of each alternative to positive-ideal solution and negative-ideal solution.

In this case, uncertainty, TRL and speed are considered as beneficial criteria and cost is deemed as cost criterion. Therefore, $C_B = [C_1, C_3, C_4]$ and $C_c = [C_2]$. The intuitionistic fuzzy positive-ideal solution$I^*$and negative-ideal solutionI^- are obtained as:

$$I^* = \{(0.861,0.128,0.011), (0.467,0.434,0.099), (0.799,0.170,0.031), (0.576,0.371,0.053)\}$$

$$I^- = \{(0.569,0.334,0.097), (0.787,0.189,0.024), (0.474,0.421,0.105), (0.318,0.580,0.102)\}$$

Normalized Euclidean distance is obtained to measure the separation between alternatives and positive-ideal solution $I^*$and negative-ideal solution I^- using Eq.16 and Eq.17in Table 9.

Table 9 Separation measure and relative closeness coefficient

Instruments	D^*	D^-	***RC***
I_1	0.148	0.192	0.565
I_2	0.183	0.162	0.469
I_3	0.228	0.147	0.393

Step 6 Ranking the alternative instruments based on the relative closeness coefficient.

All instruments are then scored with the relative closeness coefficient $RC_i$with respect to the positive-ideal solution shown in Table 9. The ranking order is $I_1 \succ I_2 \succ I_3$ and I_1 is selected as the most appropriate instrument in the alternatives since it has the highest RC.

With the interest of demonstrating the sensitivity of the decision model, a different importance set is assigned to all criteria shown in Table 10 and the results are given in Table 11.

Table 10 Assigned importance for all criteria-case 2

Criteria	DM_1	DM_2	DM_3
C_1	I (0.75,0.2)	I (0.75,0.2)	I (0.75,0.2)
C_2	VI (0.90,0.10)	I (0.75,0.2)	M (0.50,0.45)
C_3	VI (0.90,0.10)	VI (0.90,0.10)	VI (0.90,0.10)
C_4	M (0.50,0.45)	M (0.50,0.45)	I (0.75,0.2)

Table 11 Separation measure and relative closeness coefficient-case2

Instruments	D^*	D^-	***RC***
I_1	0.168	0.165	0.495
I_2	0.182	0.153	0.456
I_3	0.157	0.178	0.531

The inspection speed is considered more important than in the previous case while less importance is given to inspection uncertainty. This shifting leads to a clearly different decision as $I_3$is ranked first due to its significantly higher rating than $I_1$and I_2in terms of measurement speed. The decision model is successfully aware of this priority change of criteria and reveals the correct selection result.

6. CONCLUSION

The recent developments of inspection process planning methodology demands instrument selection as a mandatory and vital process, which paves the way for subsequent planning activities. Nevertheless, the measurement device selection for large volume metrology (LVM) is rarely studied while most research efforts focusing on the probe selection for coordinate measuring machines. The large and increasing number of available instruments with a variety of assessing criteria presents a barrier to an applicable selection system.

A two-phased LVM instrument selection system using intuitionistic fuzzy sets combined with TOPSIS method is described in this paper. Measurability Characteristics (MCs) are first identified with respect to specific inspection task and grouped into quantitative (crisp) and qualitative (fuzzy) attributes. An instrument filtration procedure is implemented in Phase 1 based on the results of assessing crisp MCs. In the second phase, the remaining instruments are ranked using intuitionistic fuzzy group decision-making method. Vague criteria are appropriately assessed in this early stage by taking advantage of linguistic importance and performance rating.

A numeric case study shows the process of the proposed approach. Furthermore, the sensitivity of the decision model to the variable priority of the criteria has been successfully demonstrated.

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