INTERVAL-VALUED INTUITIONISTIC FUZZY TOPSIS-BASED MODEL FOR TROUBLESHOOTING MARINE DIESEL ENGINE AUXILIARY SYSTEM

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SUMMARY

In this paper, we present an interval-valued Intuitionistic Fuzzy TOPSIS model, which is based on an improved score function for detecting failure in a marine diesel engine auxiliary system, using groups of experts' opinions to detect the root cause of failure in the engine system and the area most affected by failures in the diesel engine. The improved score function has been used for the computation of the separation measures from the intuitionistic fuzzy positive ideal solution (IFPIS) and intuitionistic fuzzy negative ideal solution (IFNIS) of alternatives while the criteria weight have been determined using an intuitionistic fuzzy entropy. The study is aimed at providing an alternative method for the identification and analysis of failure modes in engine systems. The results from the study show that although detection of failures in Engines is quite difficult to identify due to the dependency of the engine systems on each other, however using intuitionistic fuzzy multi-criteria decision-making method the faults/failure can easily be diagnosed.

ABBREVIATIONS

FTA	Fault Tree Analysis
FMEA	Failure Mode and Effect Analysis
IVIFS	Interval-valued Intuitionistic Fuzzy set
IVIFSs	Interval-valued Intuitionistic Fuzzy sets
IFE	Intuitionistic Fuzzy entropy
TOPSIS	Technique for Order Preference by Similarity to the Ideal Solution

1. INTRODUCTION

The main aim of every maintenance strategy is to prevent the high cost of productions and maintenance risks due to faults in rotating machines and systems (Zuber & Bajri 2016). Since many of the modern machines and equipment are required to run under increased turbulent conditions and in some cases under high uncertainty (Kettunen 2006). It is important, therefore, that the health of the machines and systems are regularly monitored, checked and troubleshoot for failure. According to Zuber & Bajri (2016), the implementation of condition-based maintenance strategy for monitoring the health of machines and systems requires the acquisition and trending of the physical parameter that is found to be sensitive to the machine degradation and failure.

In identifying the physical parameters and failure in machines systems, several different failure detection measures such as pressure, heating, and flow rate sensors, vibration analysis, noise measurement, motor current signature analysis, wear particle analysis, ultrasound measurements devices and infrared thermography are available and rottenly used to detect and monitor failure in machines and systems. However according to Balin et al. (2014), even if the values and warning indicators from the failure detection measures are taken into account, detection of the exact failed component(s) or system(s) in the machines is still quite difficult to determine, due to the dependency of the machine systems on each other.

Other analytical methods for identifying and evaluating potential machine failure include the Fault Tree Analysis (FTA) method and the Failure Mode and Effect Analysis (FMEA) method. Also, in applying these methods, so many drawbacks have been reported in the literature which includes; the difficulty to precisely and accurately determines the probability of failure event when using the FMEA technique (Mohammadi and Tavakolan 2013; Xie 2013). The fuzziness and hesitation of the experts' subjective assessments which are not accounted for in the FMEA and FTA technique (Zhao et al. 2016) and the limitation of the methods when it comes to design errors, human factors implications, flawed requirements and component interaction accidents (Keizer et al. 2005; Liu et al. 2014; Martínez 2015).

In handling these issues, several alternative methods and approaches have been presented by different authors in the literature. Among them we can mention, Sharma et al. (2005), who integrated fuzzy logic and expert database to evaluate hydraulic system safety and reliability while conducting failure mode and effect analysis (FMEA). Zuber & Bajri (2016), propose an artificial neural network and vibration analysis for automated roller element bearings faults identification, where the vibration features were used as the inputs for the controlled artificial neural network. Shaghaghi and Rezaie (2012) applied a generalized mixture operator to evaluate and aggregate risk priorities of failure modes in an LGS gas type circuit breaker. An expert failure detection system was employed by Cebi et al. (2009) to assist shipboard personnel in predicting and overcoming failures in operational ship auxiliary machinery via a PROLOG programming language. They developed corrective action tables to demonstrate what to do in the event of an emergency based on some identified failure types. Kangavari et al. (2015), uses the FMEA technique to examine risks of systems in the petrochemical industry from the concept phase to the system disposal, detecting the failures in the design stage and determining the control measures and corrective actions to reduce their impacts of failures.

He et al. (2015) presented a Fuzzy TOPSIS and Rough set based approach for identifying the most critical product infant failures which are a step towards improving the product quality. Liu et al. (2011) applied the fuzzy evidential reasoning (FER) approach with grey theory as an alternative method to the FMEA method and for solving the diversity and expertise issues in the FMEA team assessment. While Alarcin et al. (2014) presented an integrated Fuzzy AHP and TOPSIS methods, for failure detection in an auxiliary system and marine diesel engine using a group of expert's opinions. By assessing the expert's group's opinions, the system most influenced by failures was determined.

As a follow up, in this study, we are proposing a hybrid model by integrating an Interval-valued Intuitionistic Fuzzy TOPSIS model (IVIF-TOPSIS), which is based on an Improved Score Function with Intuitionistic Fuzzy entropy (IFE) method for detecting failure in a marine diesel engine auxiliary system, using group of experts' opinions to detect the root cause of failure in the system and to identify the most affected system in the marine engine. In this regard, the failure in the engine is identified and prioritized, according to the systems in which the failures primarily arise. In this approach, the IFE method is employed to determine the influential weights for the criteria while the Intuitionistic Fuzzy TOPSIS model is used to detect the root cause of the failure.

The choice of using intuitionistic fuzzy set in this study is based on the fact that, it is more capable than the traditional fuzzy sets at handling vagueness and uncertain information in practice (Datta et al. 2013) as well as its ability to model fuzziness and hesitation of the experts' subjective assessments. Also, integrating the IFE method with the IVIF-TOPSIS model which is based on an improved score function based separation method, provides a whole new approach to solving multi-criteria decision-making problem.

The intuitionistic fuzzy set (IFS) which was introduced by Atanassov (1983) is characterized by a membership function and a non-membership function. The benefits of its applications have been addressed in (Xu and Liao 2015; Xu et al. 2013).

The rest of this paper is organized as follows. In section 2 we introduce the Interval-valued Intuitionistic Fuzzy set (IVIFS), the Improved Score Function and the concepts of the IFE method. The IVIF-TOPSIS algorithm which is based on the Improved Score Function is presented in section 3. In Section 4 a numerical case is presented to illustrate the proposed methodology. Finally, the conclusion is presented in section 5.

2. PRELIMINARIES

In this section, we present the fundamental definitions and concepts of the IVIFS as described by Ye (2009), the improved score function by Bai (2013) and the IFE method presented by Ye (2010).

2.1 INTERVAL-VALUED INTUITIONISTIC FUZZY SET (IVIFS)

Definition 1: Let $D[0,1]$ be the set of all closed subintervals of the interval [0, 1] and let $X(\neq \emptyset)$ be a given set. An IVIFS A in X is expressed as (Ye 2009);

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

where $\mu_A: X \to D[0,1]$, $v_A: X \to D[0,1]$ with the condition $0 \le sup\ \mu_A(x) + sup\ v_A(x) \le 1, \forall x \in X$.

The intervals $\mu_A(x)$ and $v_A(x)$ denote, respectively, the degree of membership and non-membership of the element x to the set A. Thus, for each $x \in X$ *the* intervals $\mu_A(x)$ and $v_A(x)$ are closed and their lower and upper end points are denoted by $\mu_{AL}(x), \mu_{AU}(x), v_{AL}(x)$ and $v_{Au}(x)$respectively. We can denote the set as;

$$A = \{\langle x, [\mu_{AL}(x), \mu_{AU}(x)],\ [v_{AL}(x), v_{AU}(x)]\rangle \,|x \in X\}, \quad (2)$$

Where, $0 \le \mu_{AU}(x) + v_{AU}(x) \le 1$, $\mu_{AL}(x) \ge 0$, $v_{AL}(x) \ge 0$

For each element x, we can compute the unknown degree (hesitancy degree) of an intuitionistic fuzzy interval of $x \in X$ in A which is defined as follows:

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x) = [1 - \mu_{AL}(x) - \mu_{AU}(x), 1 - \mu_{AL}(x) - v_{AL}(x)] \quad (3)$$

However, if $\mu_A(x) = \mu_{AL}(x) = \mu_{AU}(x)$ and $v_A(x) = v_{AL}(x) = v_{AU}(x)$, then the given IVIFS A is reduced to an ordinary IFS. For convenience, the IVIFS is expressed as $A = ([a,b],[c,d])$.

In the following will make comparisons between two Interval-Valued Intuitionistic sets (IVIFSs), by introducing the improve score function.

2.2 THE IMPROVED SCORE FUNCTION

In order to make comparisons between two IVIFSs, metric methods have been introduced by several researchers including Ye (2009) and Li (2010), however, in this study, we will be concerned only with the improved score function originally proposed by Bai (2013), for the ranking, and the representation of the aggregated effect of positive and negative evaluations in the performance ratings of the alternatives based on IVIFS data. The computation formula for the improved score function is given as;

$$I(A) = \frac{a+a(1-a-c)+b+b(1-b-d)}{2}, \text{ where } I(A) \in [0,1] \quad (4)$$

When $a = b$ and $c = d$, the IVIFS will degenerate to the IFS while the improved score function of IVIFS will degenerate to the score function of IFS proposed by Ye (2009).

2.3 THE INTUITIONISTIC FUZZY ENTROPY

Following the operations of the IFS, let us consider an intuitionistic fuzzy set A in the universe of discourse $X = \{x_1, x_2, x_3, \dots, x_n\}$.The intuitionistic fuzzy set A is transformed into a fuzzy set to structure an entropy measure of the intuitionistic fuzzy set by means of $\mu_{\bar{A}}(x_i) = (\mu_A(x_i) + 1 - v_A(x_i))/2$. Based on the definition of fuzzy information entropy Ye (2010) proposes the intuitionistic fuzzy entropy as follows;

$$E(A) = \frac{1}{n}\sum_{i=1}^{n}\{\{Sin\frac{\pi*[1+\mu_A(x_i)-v_A(x_i)]}{4} + Sin\frac{\pi*[1-\mu_A(x_i)+v_A(x_i)]}{4} - 1\} * \frac{1}{\sqrt{2}-1}\} \quad (5)$$

When the criteria weights are completely unknown, we can use the intuitionistic fuzzy entropy to determine the weights. The criteria weight is given as;

$$W_j = \frac{1-H_j}{n-\sum_{j=0}^{n} H_j} \quad (6)$$

where $W_j \in [0,1], \sum_{j=1}^{n} W_j = 1, H_j = \frac{1}{m}E(A_j)$ and

$0 \leq H_j \leq 1$ for $(j = 1, 2, 3, \dots, n)$.

It is important to note here that, in using the intuitionistic fuzzy entropy for the interval-valued intuitionistic fuzzy values which is in the form $([a, b], [c, d])$. The second part of the interval-valued intuitionistic fuzzy values $[c, d]$ is assume to be equal to zero, (i.e. $c = 0$ and $d = 0$). Hence, only the first part is applied for the evaluation. This proposed new approach has been tested and proven to rank correctly as shown in the hypothetical example below.

3. ALGORITHM FOR THE IVIF-TOPSIS MODEL AND THE IFE METHOD

TOPSIS which was originally proposed by Hwang and Yoon (1981), has remained one of the most widely used MCDM methods with so many papers published on its applications (Tan 2011; Park et al. 2011; Behzadian et al. 2012; Bulgurcu 2012; Jadidi, Hong, and Firouzi 2008; Pakpour et al. 2013; Soufi et al. 2015; Yang and Wu 2008; Ghazanfari, Rouhani, and Jafari 2014; Zhu et al. 2012; Chou et al. 2012).

In this study, the TOPSIS model has been introduced in the intuitionistic fuzzy environment and the improved score function discussed above applied as an intuitionistic aggregation operator and for the calculation of the intuitionistic fuzzy positive ideal solutions (IFPIS) and the intuitionistic fuzzy negative ideal solutions (IFNIS). The application of the integrated IVIF-TOPSIS model and the IFE method has been expressed concisely in the following steps:

Step 1. Suppose the cross-functional team responsible for the assessment of the failure modes in the machine system has equal weight and of equal status (Professors). With their opinion construct the intuitionistic fuzzy decision matrix $A_{nxm}(a_{ij})$ of the alternatives (A_i) with respect to the criteria (C_i) using the Intuitionistic Fuzzy Numbers for approximating linguistic variable as shown in Table 1.

$$\boldsymbol{D_{mxn}(x_{ij})} = \begin{bmatrix} ([\boldsymbol{a_{11}}, \boldsymbol{b_{11}}], [\boldsymbol{c_{11}}, \boldsymbol{d_{11}}]) & \dots & \cdots & ([\boldsymbol{a_{1n}}, \boldsymbol{b_{1n}}], [\boldsymbol{c_{1n}}, \boldsymbol{d_{1n}}]) \\ ([\boldsymbol{a_{21}}, \boldsymbol{b_{21}}], [\boldsymbol{c_{21}}, \boldsymbol{d_{21}}]) & \dots & \cdots & ([\boldsymbol{a_{2n}}, \boldsymbol{b_{2n}}], [\boldsymbol{c_{2n}}, \boldsymbol{d_{2n}}]) \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ ([\boldsymbol{a_{m1}}, \boldsymbol{b_{m1}}], [\boldsymbol{c_{m1}}, \boldsymbol{d_{m1}}]) & \dots & \cdots & ([\boldsymbol{a_{mn}}, \boldsymbol{b_{mn}}], [\boldsymbol{c_{mn}}, \boldsymbol{d_{mn}}]) \end{bmatrix} \quad (7)$$

Table 1. Intuitionistic Fuzzy Numbers for approximating the linguistic variable

Linguistic terms	Interval-valued intuitionistic fuzzy Number
Very low (VL)	([0.1, 0.3], [0.25, 0.4])
Low (L)	([0.2, 0.55], [0.3, 0.55])
Medium (M)	([0.3, 0.6], [0.45, 0.65])
High (H)	([0.5, 0.7], [0.6, 0.7])
Excellent (EX)	([0.6, 0.9], [0.75, 1.0])

Step 2. Convert the intuitionistic fuzzy decision matrix $A_{nxm}(a_{ij})$ to the improved score function matrix $I(a_{ij})_{nxm}$ to aggregate the intuitionistic fuzzy decision of the cross-functional team (Professors).

$$I(a_{ij})_{nxm} = \begin{bmatrix} \boldsymbol{I_{11}(x_{11})} & \boldsymbol{I_{12}(x_{12})} & \dots & \boldsymbol{I_{1n}(x_{1n})} \\ \boldsymbol{I_{22}(x_{22})} & \boldsymbol{I_{22}(x_{22})} & \cdots & \boldsymbol{I_{2n}(x_{2n})} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{I_{m1}(x_{m1})} & \boldsymbol{I_{m2}(x_{m2})} & \cdots & \boldsymbol{I_{mn}(x_{mn})} \end{bmatrix} \quad (8)$$

Step 3. Determine the weight of each of the evaluating criteria w_j using the concept of the IFE method described in section 2.3.

Step 4. Define the IFPIS (A^+) and IFNIS (A^-) for the score function-based matrix;

$A^+ = (\mu_j, v_j)$, $A^- = (\mu_j, v_j)$, in this study the IFPIS (A^+) and IFNIS (A^-) is given as;

$$A^+ = (1, 1), \quad j = 1, \dots, n \quad (9)$$

$$A^- = (0,0), \quad j = 1, \dots, n \quad (10)$$

Step 5. Compute the improved score function-based separation measures $(d^+{}_i(A^+,\ A_i)$ and $(d^-{}_i(A^-,\ A_i)$ for each alternative from the IFPIS and IFNIS using the equation (11) and (12);

$$d^-{}_i(A^-,\ A_i) = \sqrt{\sum_{i=1}^{n}\left[w_j\ (1 - \left(I(a_{ij})_{nxm}\right)\right]^2} \qquad (11)$$

Similarly,

$$d^-{}_i(A^-,\ A_i) = \sqrt{\sum_{i=1}^{n}\left[w_j\ I(a_{ij})_{nxm}\right]^2} \qquad (12)$$

Step 7. Compute the relative closeness coefficient, (CC_i), which is defined to rank all possible alternatives with respect to the positive ideal solution A^+. The general formula is given as;

$$CC_i = \frac{d^-{}_i(A^-,A_i)}{d^-{}_i(A^-,A_i) + d^+{}_i(A^+,A_i)} \qquad (13)$$

where $CC_i\ (i = 1,2,..n)$ is the relative closeness coefficient of A_i with respect to the positive ideal solution A^+ and $0 \leq CC_i \leq 1$. Hence, the alternatives are ranked according to the descending order.

4. APPLICATION OF THE IFE METHOD AND IVIF-TOPSIS MODEL

In this section, we demonstrate the computational process of the IFE method and IVIF-TOPSIS algorithm proposed herein for detecting a failure in a marine diesel engine auxiliary system for case 1 and for the hypothetical example in case 2.

4.1 IMPLEMENTATION

Case 1. Failure in the machine can results in severe damage and significant loss of resources when not detected on time (Demirel et al. 2015). The severity of faults and failure in machines are mostly different. Some of the failures can be so severe that if not detected and repaired or adjusted on time, it can cause more serious accidents as in the case of component failure during operational conditions. Failures in machines are frequently precursors of further breakdown which are mostly discovered only during the machine operation. Criteria to evaluate such probable breakdown/failure, in this case, a marine diesel engine auxiliary system have been investigated and obtained through extended consultation from a group of experts (Three Professors in the department of Manufacturing Engineering). They were asked to rate the relevance, accuracy, and adequacy of the criteria and sub-criteria and to confirm 'content validity' with regards to the operation of the marine diesel engine assessment.

Five probable failures (criteria) in the engine systems (MTU 2012; Alarcin, Balin, and Demirel 2014; Demirel et al. 2015) have been identified and they are consolidated with the experience and opinions of the experts, these criteria and their subs-criteria include;

- Engine turns but does not fire (C_1). This criterion includes the following sub-criteria, Engine cabling (C_{11}), Starter (C_{12}), Engine governor (C_{13}), Fuel system (C_{14}).
- Engine speed not steady (C_2). This criterion includes the following sub-criteria, Engine governor (C_{21}), Fuel system (C_{22}), Fuel injection equipment (C_{23}), and Speed sensor (C_{24}).
- Sudden shut down of the engine during normal operation (C_3). Low-level day tank (C_{31}), Low Oil pressure (C_{32}), and High-Pressure Fuel pump failures (C_{33})
- Black exhaust gas (C_4) Air supply (C_{41}), Fuel injection equipment (C_{42}),
- Increase of the oil level during engine operation (C_5) Cooling water leakage (C_{51}), and Fuel oil leakage (C_{52})

These failures are recognized to have a relationship with different systems in the engine. Hence, the root cause of these failures is determined based on these systems and they categorized as;

- Engine Governor System (A_1),
- Fuel System (A_2),
- Air supply System (A_3),
- Engine Coolant System (A_4).

Using the assessment report from the group of experts on the marine diesel engine, we implement the proposed IFE method and Intuitionistic Fuzzy TOPSIS model. Summary of the implementation is given below.

Step 1: The intuitionistic fuzzy decision matrix is constructed using the intuitionistic fuzzy number in Table 1 to express the ratings of the four systems with respect to each of the criteria and sub-criteria to form the intuitionistic fuzzy decision matrix $A_{nxm}(a_{ij})$ as shown in Table 2.

Step 2: Using the improved score function, the intuitionistic fuzzy decision matrix $A_{nxm}(a_{ij})$ is converted to form the improved score function matrix $I(a_{ij})_{nxm}$as show in the Table 3. Also, by following the implementation procedure for the IFE method, the weights of the criteria and sub-criteria is calculated, the results of the criteria and sub-criteria weights are shown in Table 3.

By using equation (11) and (12), we compute the improved score function-based separation measures $(d^+{}_i(A^+,\ A_i)$ and $(d^-{}_i(A^-,\ A_i)$ $(i = 1,2,3,4)$, the results are as follows;

$(d^+{}_1(A^+,\ A_1) = 0.128$, $(d^-{}_1(A^-,\ A_1) = 0.099$
$(d^+{}_2(A^+,\ A_2) = 0.132$, $(d^-{}_2(A^-,\ A_2) = 0.095$,
$(d^+{}_3(A^+,\ A_3) = 0.130$, $(d^-{}_3(A^-, A_3) = 0.096$,
$(d^+{}_4(A^+, A_4) = 0.131$, $(d^-{}_4(A^-, A_4) = 0.095$.

Finally, the relative closeness coefficient $CC_i, (i = 1,2,3,4)$ to the ideal solution are calculated using equation (13), the results is given as;

$CC_1 = 0.436$, $CC_2 = 0.418$, $CC_3 = 0.425$ and $CC_4 = 0.420$,

Therefore, the ranking orders for the four systems are in the form (descending order) $A_1 > A_3 > A_4 > A_2$, obviously, from the evaluation, the Engine Governor System A_1 is the most affected area in engine considering the assessment given by the experts.

The significant of the ranking result as it relates to the different failure modes is that it would help and give the Chief Engineer more information on how to make a more efficient decision about the engine.

Table 2. Intuitionistic fuzzy decision matrix

	Governor System (A_1)	Fuel System (A_2)	Air supply System (A_3)	Coolant System (A_4)
C_1	([0.20, 0.48], [0.33, 0.53])	([0.40, 0.65], [0.50, 0.65])	([0.30, 0.53], [0.43, 0.58])	([0.20, 0.48], [0.33, 0.53])
C_{11}	([0.37, 0.57], [0.48, 0.6])	([0.47, 0.80], [0.65, 0.88])	([0.43, 0.72], [0.55, 0.70])	([0.20, 0.48], [0.33, 0.53])
C_{12}	([0.43, 0.67], [0.55, 0.85])	([0.27, 0.58], [0.4, 0.60])	([0.17, 0.47]. [0.28, 0.75])	([0.20, 0.48], [0.33, 0.63])
C_{13}	([0.33, 0.62],[0.45, 0.68])	([0.37, 0.63], [0.50, 0.62])	([0.33, 0.62], [0.45, 0.78])	([0.23, 0.57], [0.35, 0.53])
C_{14}	([0.30, 0.53], [0.43, 0.63])	([0.53, 0.77], [0.65, 0.68])	([0.30, 0.58], [0.43, 0.50])	([0.37, 0.63], [0.50, 0.58])
C_2	([0.27, 0.52], [0.38, 0.58])	([0.53, 0.77], [0.65, 0.90])	([0.23, 0.57], [0.63, 0.35])	([0.43, 0.67], [0.55, 0.67])
C_{21}	([0.43, 0.72], [0.55, 0.55])	([0.43, 0.70], [0.58, 0.65])	([0.37, 0.63], [0.58, 0.50])	([0.33, 0.62], [0.45, 0.67])
C_{22}	([0.37, 0.57], [0.48, 0.78)	([0.37, 0.57], [0.48, 0.88])	([0.17, 0.40], [0.32, 0.67])	([0.23, 0.50], [0.38, 0.63])
C_{23}	([0.30, 0.58], [0.43, 0.6])	([0.47, 0.78], [0.60, 0.60])	([0.20, 0.55], [0.30, 0.48])	([0.40, 0.65], [0.50, 0.57])
C_{24}	([0.33, 0.62], [0.45, 0.65])	([0.37, 0.57], [0.48, 0.85])	([0.30, 0.60], [0.45, 0.55])	([0.47, 0.73], [0.60, 0.65])
C_3	(0.30, 0.58], [0.43, 0.63])	([0.10, 0.30], [0.25, 0.60])	([0.23, 0.43], [0.37, 0.65])	([0.43, 0.67], [0.55, 0.78])
C_{31}	(0.40, 0.65], [0.50, 0.58])	([0.27, 0.58], [0.40, 0.68])	([0.33, 0.62], [0.45, 0.60])	([0.37, 0.68], [0.50, 0.73])
C_{32}	([0.43, 0.72], [0.55, 0.55])	([0.43, 0.67], [0.55, 0.67])	([0.37, 0.57], [0.48, 0.78])	([0.30, 0.53], [0.43, 0.63])
C_{33}	([0.37, 0.57], [0.48, 0.78])	([0.40, 0.65], [0.50, 0.58])	([0.33, 0.62], [0.45, 0.60])	([0.37, 0.63], [0.50, 0.62])
C_4	([0.20, 0.48], [0.33, 0.53])	([0.43, 0.67], [0.55, 0.67])	([0.40, 0.65], [0.50, 0.58])	([0.20, 0.48], [0.33, 0.53])
C_{41}	([0.33, 0.62], [0.45, 0.60])	([0.43, 0.72], [0.55, 0.55])	([0.43, 0.67], [0.55, 0.67])	([0.40, 0.65], [0.50, 0.58])
C_{42}	([0.43, 0.67], [0.55, 0.67])	([0.30, 0.53], [0.43, 0.63])	([0.37, 0.63], [0.50, 0.62])	([0.37, 0.57], [0.48, 0.78])
C_5	([0.43, 0.72], [0.55, 0.55])	([0.20, 0.48], [0.33, 0.53])	([0.33, 0.62], [0.45, 0.60])	([0.30, 0.53], [0.43, 0.63])
C_{51}	([0.30, 0.53], [0.43, 0.63])	([0.37, 0.57], [0.48, 0.78])	([0.20, 0.48], [0.33, 0.53])	(0.30, 0.53], [0.43, 0.63])
C_{52}	([0.65, 0.50], [0.65, 0.30])	([0.72, 0.55], [0.70, 0.20])	([0.37, 0.60], [0.50, 0.58])	([0.20, 0.48], [0.33, 0.53])

Table 3. Improved score function matrix and criteria weights

	Governor System (A_1)	Fuel System (A_2)	Air supply System (A_3)	Coolant System (A_4)	Weight
C_1	(0.385)	(0.448)	(0.426)	(0.385)	0.044
C_{11}	(0.449)	(0.335)	(0.428)	(0.385)	0.057
C_{12}	(0.380)	(0.417)	(0.315)	(0.361)	0.048
C_{13}	(0.418)	(0.445)	(0.387)	(0.420)	0.055
C_{14}	(0.413)	(0.429)	(0.457)	(0.455)	0.050
C_2	(0.416)	(0.344)	(0.439)	(0.440)	0.054
C_{21}	(0.482)	(0.440)	(0.468)	(0.421)	0.059
C_{22}	(0.398)	(0.370)	(0.314)	(0.377)	0.038
C_{23}	(0.428)	(0.460)	(0.417)	(0.474)	0.058
C_{24}	(0.428)	(0.378)	(0.443)	(0.445)	0.054
C_3	(0.420)	(0.248)	(0.359)	(0.404)	0.038
C_{31}	(0.470)	(0.394)	(0.443)	(0.410)	0.057
C_{32}	(0.482)	(0.440)	(0.398)	(0.413)	0.050
C_{33}	(0.398)	(0.470)	(0.443)	(0.445)	0.051
C_4	(0.385)	(0.440)	(0.470)	(0.385)	0.047
C_{41}	(0.443)	(0.482)	(0.440)	(0.470)	0.058
C_{42}	(0.440)	(0.413)	(0.445)	(0.398)	0.047
C_5	(0.482)	(0.385)	(0.443)	(0.413)	0.051
C_{51}	(0.413)	(0.398)	(0.385)	(0.413)	0.041
C_{52}	(0.528)	(0.553)	(0.455)	(0.385)	0.043

Case 2. Let us consider a practical problem originally presented by Ye (2009), to make a new example for failure detection in marine vessel engine. A marine vessel engine has four systems A_i (i = 1,2, 3,4) and the four systems are evaluated by a team of experts with respect to the following criteria; (1) Severity C_1, (2) Occurrence C_2 and (3) Detection C_3. The intuitionistic fuzzy decision matrix given by the team of experts is shown in Table 4.

Table 4: The intuitionistic fuzzy decision matrix

	C_1	C_2	C_3
A_1	([0.4, 0.5], [0.3, 0.4])	([0.4, 0.6], [0.2, 04])	([0.1, 0.3], [0.5, 0.6])
A_2	([0.6, 0.7], [0.2, 0.3])	([0.6, 0.7], [0.2, 0.3])	([0.4, 0.7], [0.1, 0.2])
A_3	([0.3, 0.6], [0.3, 0.4])	([0.5, 0.6], [0.3, 0.4])	([0.5, 0.6], [0.1, 0.3])
A_4	([0.7, 0.8], [0.1, 0.2])	([0.6, 0.7], [0.1, 0.3])	([0.3, 0.4], [0.1, 0.2])

Using the improved score function just as in case 1, the intuitionistic fuzzy decision matrix $A_{nxm}(a_{ij})$ is converted to form the improved score function matrix $I(a_{ij})_{nxm}$. Also, following the implementation procedure for the IFE method, the weight of the criteria is calculated. The result is given as $W_j = \{0.35, 0.21, 0.44\}$, which appear to be in total agreement with ranking of the criteria in (Ye 2009).

The improved score function-based separation measures for the four systems are calculated using equation (11) and (12), while the relative closeness coefficient CC_i, $(i = 1,2,3,4)$ for the systems are calculated with equation (13). The results of the evaluations are shown in Table 5.

Table 5: The results of the evaluations

	C_1	C_2	C_3	$d^+{}_i$	$d^-{}_i$	CC_i
A_1	0.54	0.58	0.24	0.38	0.25	0.39
A_2	0.71	0.71	0.69	0.18	0.42	0.70
A_3	0.51	0.60	0.68	0.24	0.37	0.61
A_4	0.82	0.74	0.52	0.23	0.40	0.64

Therefore, the ranking orders for the four systems are in the form (descending order) $A_2 > A_4 > A_3 > A_1$, and the system A_1, is concluded as the most affected area of engine considering the assessment given by the experts and the result is in total agreement with ranking result in (Ye 2009).

4.2. DISCUSSION

To further demonstrate the feasibility of the proposed method for failure detection, we have compared the ranking result of hypothetical example with some similar computational approaches including, the entropy weights-based correlation coefficients method by Ye (2010a), the novel accuracy function-based MCDM method by Ye (2009), and finally with the conventional TOPSIS model. The comparison result is shown in Table 6.

Table 6: Comparison of results

A_i	Proposed method	Rank	TOPSIS	Rank	(Ye 2010a)	Rank	(Ye 2009)	Rank
A_1	0.39	4	0.41	4	0.66	4	0.16	4
A_2	0.70	1	0.70	1	0.93	1	0.43	1
A_3	0.61	3	0.60	3	0.84	3	0.31	3
A_4	0.64	2	0.65	2	0.92	2	0.37	2

The advantages of using the proposed intuitionistic fuzzy multi-criteria decision-making method which is based on IVIF-TOPSIS and IFE method over the traditional FMEA methods and the other failure warming devices is that;

- The results from the proposed model for failure detection are more objective and reliable due to the fact that the fuzziness and hesitation of the experts' subjective assessments are well reflected and modeled, unlike the traditional FMEA and other MCDM methods.
- The implementation procedures of the proposed model and approach are quite easy and straightforward as compared to the other Multi-criteria decision-making methods.
- The criteria weights were calculated using an objective weight approach, which makes the overall result more reliable, as compared to the subjective approach in the reviewed literature.

5. CONCLUSIONS

In this paper, we investigated the application of an interval-valued intuitionistic fuzzy TOPSIS model, which is based on an improved score function for detecting failure in a marine diesel engine, in relation to component interaction accidents and failure, using groups of experts' opinions to detect the root cause of failure in the engine, and the area most affected by the failures in the engine systems. The failure in the engine have been determined and prioritized, according to the systems in which the failures primarily arise. In this approach, an intuitionistic fuzzy entropy method has applied to determine the influential weights for the criteria.

To further demonstrate the efficacy of the proposed approach in failure detection, the method has been applied to a hypothetical example in literature where the ranking of the criteria weights and the marine vessel systems (alternatives) appears to be in total agreement with the case example. This goes to show that intuitionistic fuzzy entropy can be applied to determine criteria weight even when an interval-valued intuitionistic fuzzy number is used for the decision matrix.

Finally, we can conclude that this study has been able to provide a better alternative method for the identification and analysis of failures in marine systems (engines).

In the future, we will continue working on the application of the proposed method, specifically for building reliability-related knowledge during the design of complex products and systems, also attempt will be made to quantitatively estimate the weight of the experts which is a weakness in this paper.

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