EVALUATION OF THE ROOT CAUSE OF FAILURE IN A CRAWLER CRANE MACHINE USING HYBRID MCDM MODEL

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SUMMARY

A real-life case study has been presented in this paper, where a crawler crane machine is investigated for the root cause of failure, using an expert opinion-based technique which comprises of an integrated model which is based on an Intuitionistic Fuzzy TOPSIS model Exponential related function, and the intuitionistic entropy model. The main contribution and advantages of the proposed approach are in the use of a subjective and objective model for the computation of the criteria weight, which allows for complete assessment of the actual performance and value of each of the criteria. The application of the exponential-related function, which represent the aggregated effect of the positive and negative evaluations in the performance ratings of the alternatives based on the intuitionistic fuzzy set (IFS) data used. And finally, the method ranks all alternatives using the exponential-related function matrix, which accounts for the expert's attitudinal character, which a strong influencing factor in subjective assessments like the one used in some of the root cause of failure/reliability analysis.

1. INTRODUCTION

With the increasing development of related and service industries such as in the construction, chemical, maritime, energy, and aerospace industry, where modern and heavy-duty mobile and crawler crane machines are used. Reliability and safety of the machines have continued to be in high demand, due to its frequent operational requirements, the greater lifting capacity required in these industries, the increasing deadweight, and sometimes the limited working space.
Major accidents and mechanical reliability related issues have made headlines in the marine and service industry recently, like the many cases of heavyweight falling off crane machines, and the tipping-over of the mobile machines. The life casualty and economic loss that normally results from this kind of accident have resulted in more and more interest and concern by researcher and practitioners on the working of the different components making up the machine system. According to the recent crane accident statistic data, which has shown an increase from the year 2006 to 2015 (Fumian, 2013; Marsh & Fosbroke, 2015), the accidents of mobile and crawler crane machines account for about 22.4% of the total number of incidents. Hence, the need for more studies on the reliability of the components making up the machines with the view to building appropriate reliability knowledge that may be useful, in the event of future design change.

Although, some few works have been done recently on overhead and gantry cranes, mobile and crawler crane machines, on accident analysis, risk prediction, safety evaluation during operation and in the remanufacturing of the machine components (Jeng et al., 2010; Lim et al., 2004; Singhose et al., 2008). Others include the metallurgical failure analysis for finding the root cause of failure in a mobile crane turret bolt by Alam, et al, (2018). Kamarul, et al, (2016), used a questionnaire survey-based approach to identify safe practices for the implementation of crane machines in the construction industry, with the purpose of reducing industrial hazards. Balin, et al, (2016), presents a hybrid model which is based on the fuzzy AHP and fuzzy TOPSIS for the selection of components most affected by failure in a gas turbine system. Milazzo & Ancione, (2016), used a survey-based method to analyze and investigate cranes operational safety by analyzing hundreds of worldwide data records over a five-year period.

In these studies, only very few attentions have been given to the identification of the root cause of failure in the components making up the machines, as well as in the identification of components parts that need design change or modification. In responds to this, in this paper, a real-life case study has been conducted on a crawler crane machine for the identification of the root cause of failure using an expert opinion-based technique which comprises of an integrated model which is based on an Intuitionistic Fuzzy TOPSIS model, Exponential related function and intuitionistic entropy model.

One of the main objective/reason for applying the integrated model in this study is to validate the application of the model for a real-life case study. Secondly, to show that the model can overcome the drawbacks of the traditional TOPSIS method where subjective information of attributes, their weights and the attitudinal character of experts (DMs) cannot be simultaneously evaluated. As well as to show the handling of uncertainty related information of failure data and modeling which is a major drawback in conventional reliability analysis methods that uses probability.

The main contribution and advantages of the proposed approach lie in the use of a subjective and objective model for the computation of the criteria weight, which allows for complete assessment of the actual performance and value of each of the criteria. The application of the exponential-related function, which represent the aggregated effect of the positive and negative evaluations in the performance ratings of the alternatives based on the intuitionistic fuzzy set (IFS) data used. And finally, the method ranks all alternatives using the exponential-related function matrix, thereby accounting for the experts (DMs) attitudinal character which a strong influencing factor in subjective assessments like the root cause of failure/reliability.

The rest of the paper is organized as follows; in section 2, the concept of the root cause of failure in the crawler crane is presented. This is followed by the methodology in Section 3 for the evaluation of the root cause of failure which includes; the concept of the IFS, the intuitionistic fuzzy entropy, the exponential-related function and the algorithm of the model which also includes an Intuitionistic Fuzzy TOPSIS model. In section 4, a case study is presented. While some come conclusions are presented in section 5.

2. ROOT CAUSE OF FAILURE IN A CRAWLER CRANE MACHINE

In evaluating the Root Cause of Failure in a Crawler Crane Machine, for convinces; only the operational parts of the cranes have been considered. In figure 1 and Table 2 and 3 below, the operational parts and the failure modes for five (5) of the components in the crawler crane machine have been presented. The components have been evaluated using the multiple risk factors (i.e. Chance of failure (O), Non-detection of Failures (D), Severity (S), and Economic cost (EC)) originally reported in (Sachdeva et al., 2009).

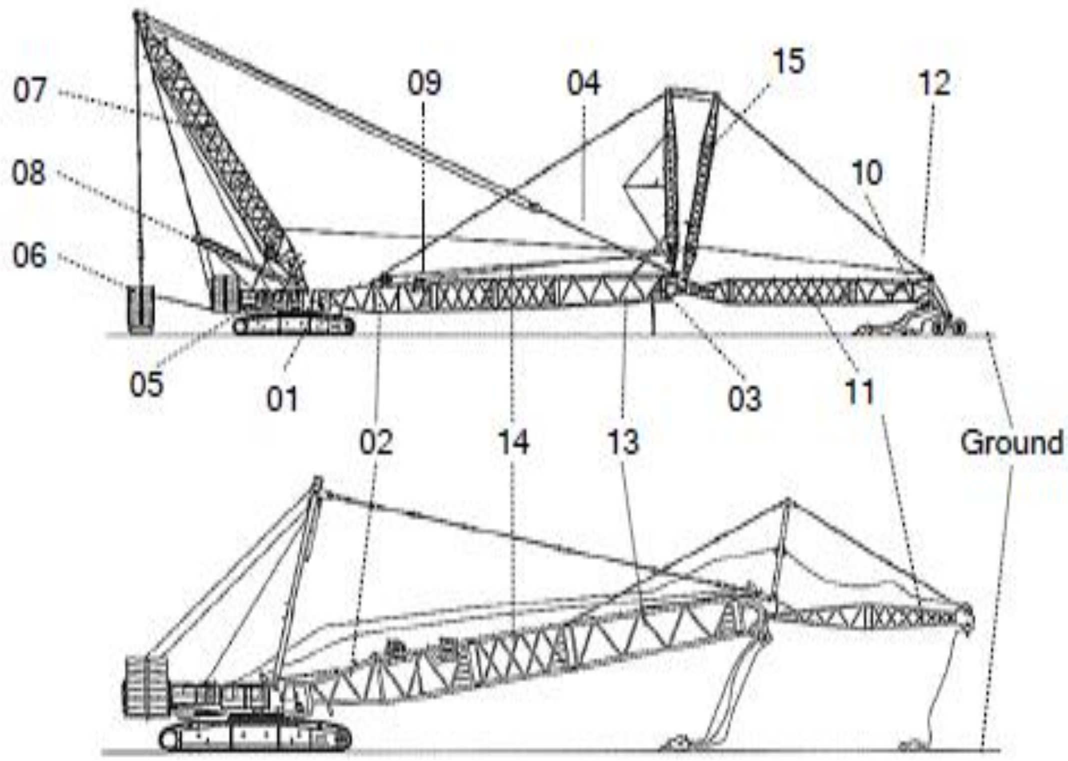

Figure 1: The considered operational parts of the crawler cranes machine

Table 2: The machine's components of the operational parts

01	02	03	04	05
Slewing gear	Main boom base (MBB)	Main boom tip	Load limits device	Hydraulic system of super-lift
06	07	08	09	10
Super-lift counterweight	Super-lift mast	Jib lubbing device of super-lift	Luffing jib boom	Luffing jib tip
11	12	13	14	15
Luffing jib lubbing device	Loading limit of jib lubbing device	Fixed Jib	Jib insert	Cantilever mast

Table 3: Failure modes of each of the components

Components	Failure modes (M)
01	M1 Swing brake valve unable to lock; M2 Slewing gear slow motion; M3 Slewing gear abnormal pressure; M4 Slewing bearing shaking
02	M5 MBB fracture; M6 Anchor bolt looseness; M7 MBB vibration; M8 Anchor bolt breakage
03	M9 Tip distortion; M10 Poor lubrication; M11 Tip blockage; M12 Tip stuck
04	M13 Weight sensor failure; M14 No display of amplifier Circuits; M15 Actuator damage
05	M16 Hydraulic shock; M17 Pressure due to an overload of hydraulic; M18 High-pressure ball valve spun off; M19 Pressure reducing valve stuck; M20 HS leakage

3. PRELIMINARIES

In this section, the concept of the intuitionistic fuzzy set as described by Atanassov, (1986), The intuitionistic fuzzy entropy and the exponential-related function proposed in (Aikhuele & Turan, 2017b, 2017c) are presented.

3.1 INTUITIONISTIC FUZZY SET

Definition 1: If the IFS A in $X = \{x\}$ is defined fully in the form $A = \{\langle x, \mu_A(x), v_A(x), \pi_A(x)\rangle \mid x \in X\}$, where $\mu_A : X \rightarrow [0,1]$, $v_A : X \rightarrow [0,1]$ and $\pi_A : X \rightarrow [0,1]$. The different relations and operations for the IFS are shown in eq. (1) to (4).

$$A.B = \{\langle x, \mu_A(x).\mu_B(x), v_A(x) + v_B(x) - v_A(x).v_B(x)\rangle \mid x \in X\} \quad (1)$$

$$A + B = \{\langle x, \mu_A(x) + \mu_B(x) - \mu_A(x).\mu_B(x), v_A(x).v_B(x)\rangle \mid x \in X\} \quad (2)$$

$$\lambda A = \{\langle x, 1 - (1 - \mu_A(x))^\lambda, (v_A(x))^\lambda\rangle \mid x \in X\}, \ \ \lambda > 0. \quad (3)$$

$$A^\lambda = \{\langle x, (\mu_A(x))^\lambda, 1 - (1 - v_A(x))^\lambda\rangle \mid x \in X\}, \ \ \lambda > 0 \quad (4)$$

In the following, we make comparisons between two IFS, by introducing the Exponential-related function which is a metric method, derived from the traditional exponential score function and accuracy functions.

3.2 EXPONENTIAL-RELATED FUNCTION

Definition 2: (Aikhuele & Turan, 2017)

Let $A = (\mu, v)$ be the intuitionistic fuzzy number. The new exponential-related function ER of the intuitionistic fuzzy number can be defined as,

$$ER(A) = e^{\left(\frac{1-\lambda(\mu^2 - v^2)}{3}\right)}, \text{where } E \quad R(A) \in [1/e, e] \quad (5)$$

where λ is the flexibility and adjustability parameter and has the range value $\lambda \in [-0.9, 0.9]$. If $0.1 < \lambda \leq 0.9$, then the DMs is said to be risk-averse. If $\lambda = 0$, the DM is risk neutral and finally, if $-0.1 < \lambda \leq -0.9$, then the DM is considered to be risk-seeking.

3.3 THE INTUITIONISTIC FUZZY ENTROPY (IFE)

Definition 3: (Aikhuele & Turan, 2017c; Liu & Ren, 2014)

Let 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, Liu & Ren, (2014) proposes the intuitionistic fuzzy entropy as follows;

$$E(A) = \frac{1}{n}\sum_{i=1}^{n} \text{Cot}\left(\frac{\pi}{4} + \frac{|\mu^2{}_A(x_i) - v^2{}_A(x_i)|}{4}\pi\right) \quad (6)$$

Such that, when the criteria weights are completely unknown, the IFE can be used to determine the weights. Where the criteria weight is given as;

$$W_j = \frac{1-H_j}{n-\sum_{j=0}^{n} H_j} \quad (7)$$

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 $(j = 1, 2, 3, \ldots, n)$.

Algorithm of the proposed integrated Model for root cause of failure evaluation

In this section, the algorithm for the integrated model which comprises of the Intuitionistic Fuzzy TOPSIS model, Exponential related function, and the intuitionistic entropy model is presented using a stepwise based procedure.

Step 1: A group of Decision Makers (DMs) with weight vector $\lambda = (\lambda_1, \lambda_2, \lambda_3, .., \lambda_l)^T$ are engaged, and their preferences/judgments which are given using linguistic variables as shown in Table 1 below, are aggregate using Intuitionistic Fuzzy Weighted Geometric (IFWG) operator (Xu & Yager, 2006) after they have been converted to intuitionistic fuzzy number (IFNs). The aggregated DMs individual assessment matrices $D^k (k = 1,2,3, \ldots, l)$ is described in this study a the comprehensive group assessment matrix $(R_{mxn}(x_{ij}))$;

$$IFWG\ (d_1 d_2 d_3, \ldots, d_n) = \left(\prod_{i=1}^{n} (\mu_{ij})^{w_j}, 1 - \prod_{i=1}^{n} (1 - v_{ij})^{w_j}\right) \quad (8)$$

$$R_{mxn}(a_{ij}) = \begin{bmatrix} (\mu_{11}, v_{11}) & (\mu_{12}, v_{12}) & \cdots & (\mu_{1n}, v_{1n}) \\ (\mu_{21}, v_{21}) & (\mu_{22}, v_{22}) & \cdots & (\mu_{2n}, v_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ (\mu_{m1}, v_{m1}) & (\mu_{m2}, v_{m2}) & \cdots & (\mu_{mn}, v_{mn}) \end{bmatrix} \quad (9)$$

Table 1: Fuzzy numbers for approximating the linguistic variable

Linguistic terms	Intuitionistic fuzzy number
Extremely Low (EL)	(0.00, 0.05)
Very Low (VL)	(0.05, 0.10)
Low (L)	(0.10, 0.20)
Medium (M)	(0.30, 0.40)
Good (G)	(0.50, 0.50)
Very Good (VG)	(0.50, 0.60)
High (H)	(0.70, 0.80)
Very High (VH)	(0.80, 0.90)
Extremely High (EH)	(0.90, 0.90)

Step 2: Determine the weight of each of the evaluating criteria w_j using the IFE method.

Step 3: Using the exponential related function ER (i.e. equation (5)), the comprehensive group assessment matrix $R_{mxn}(x_{ij})$ is convert to form the exponential related matrix $ERM_{mxn}\left(ER_{ij}\left(a_{ij}\right)\right)$ which represents the aggregated effect of the positive and negative evaluations in the performance ratings of the alternatives based on the intuitionistic fuzzy set (IFS) data;

$$ERM_{mxn}\left(E_{ij}\left(a_{ij}\right)\right) = \begin{bmatrix} ER_{11}(x_{11}) & ER_{12}(x_{12}) & \cdots & ER_{1n}(x_{1n}) \\ ER_{22}(x_{22}) & ER_{22}(x_{22}) & \cdots & ER_{2n}(x_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ ER_{m1}(x_{m1}) & ER_{m2}(x_{m2}) & \cdots & ER_{mn}(x_{mn}) \end{bmatrix} \quad (10)$$

Step 4: Define the IFPIS $A^+ = (\mu_j, v_j)$ and IFNIS $A^- = (\mu_j, v_j)$ for the alternatives i.e.

$A^+ = \{\langle C_j, [1,1]\rangle \,|C_j \in C\}$, $A^- = \{\langle C_j, [0,0]\rangle \,|C_j \in C\}$, $j = 1,2,3, \ldots., n$.

Step 5: Compute the exponential-related function-based separation measures in intuitionistic fuzzy environment $(d^+{}_i(A^+, A_i)$ and $(d^-{}_i(A^-, A_i)$ for each alternative for the IFPIS and IFNIS.

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

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

where w_j is the weight of the criteria.

Step 6: 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;

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

where $CC_i\ (i = 1,2,..n)$ is the relative closeness coefficient of A_i with respect to the positive ideal solution A+ and $0 \leq CC_i \leq 1$.

Step 7: Rank the alternatives in the descending order.

4. THE COMPUTATION OF THE ROOT CAUSE OF FAILURE IN A CRAWLER CRANE MACHINE

In this case, following the methodological approach adopted in this study, a group of thirty-three (33) experts with basic and expert knowledge on the workings of crawler crane machines were invited to give their preference and expert ratings on the failure modes with respect to the multiple risk factors. After careful analysis of their response, the failure modes and multiple risk factors were screened and five (5) of the expert's ratings that appeared to be more reasonable were adopted for the evaluation of the crawler crane machine and. Based on their level of experience and expertise in terms of education (i.e. Secondary School graduate, Higher diploma graduate, B.Eng., M.Sc., and PhD), they were assigned the weight vector $\gamma = \{0.10;\ 0.15; 0.20; 0.15, 0.25\}^T$ respectively. This is in line with previous literature on reliability assessment, like Liu et al., (2014) who used five (5) experts opinions for the reliability assessment of thin film transistor liquid crystal display (TFT-LCD) product. Song et al., (2013) used four (4) experts' opinions for reliability assessment of reheat valve system in nuclear steam turbine. Aikhuele, et al., (2016), Aikhuele, et al., (2017) and Liu, et al., (2014), used five (5) experts' opinions for troubleshooting marine diesel engine and for the reliability assessment of horizontal directional drilling (HDD) machine. Liu et al., (2015) used four (4) experts' opinions for the reliability assessment thin film transistor liquid crystal display (TFT-LCD) product. Aikhuele & Turan, (2017a) and Kutlu & Ekmekçioğlu, (2012) uses three (3) experts' opinions for the reliability assessment of manufacturing facility and. Alarcin et al., (2014) uses three (3) experts' opinions for troubleshooting auxiliary systems of ship main engines.

Using the computational algorithm of the integrated model, the linguistic evaluations of the failure modes with respect to the multiple risk factors by the experts (DMs) is presented in Table 1 Appendix 1. Thereafter, using Equation (5) after the linguistic have been converted to IFNs, the DMs judgments are aggregated to form the comprehensive group assessment matrix $\boldsymbol{R}_{\boldsymbol{20x5}}(\boldsymbol{a}_{\boldsymbol{ij}})$ as shown in Table 4.

Table 4: The comprehensive group assessment matrix for the Crawler Crane Machine

Failure Modes	Occurrence O	Severity S	Detection D	Economic cost EC
M1	(0.204, 0.215)	(0.376, 0.509)	(0.000, 0.185)	(0.178, 0.173)
M2	(0.400, 0.600)	(0.765, 0.754)	(0.737, 0.778)	(0.835, 0.849)
M3	(0.000, 0.240)	(0.704, 0.691)	(0.543, 0.568)	(0.615, 0.494)
M4	(0.000, 0.606)	(0.000, 0.361)	(0.211, 0.211)	(0.113, 0.333)
M5	(0.339, 0.315)	(0.638, 0.588)	(0.291, 0.527)	(0.481, 0.467)
M6	(0.000, 0.210)	(0.638, 0.588)	(0.708, 0.717)	(0.770, 0.762)
M7	(0.363, 0.491)	(0.398, 0.403)	(0.000, 0.477)	(0.000, 0.425)
M8	(0.000, 0.456)	(0.833, 0.820)	(0.000, 0.416)	(0.000, 0.236)
M9	(0.226, 0.229)	(0.595, 0.445)	(0.770, 0.762)	(0.747, 0.771)
M10	(0.000, 0.238)	(0.000, 0.486)	(0.368, 0.398)	(0.678, 0.691)
M11	(0.226, 0.229)	(0.312, 0.330)	(0.339, 0.346)	(0.000, 0.238)
M12	(0.288, 0.282)	(0.246, 0.197)	(0.000, 0.474)	(0.302, 0.459)
M13	(0.660, 0.786)	(0.752, 0.778)	(0.791, 0.793)	(0.727, 0.762)
M14	(0.000, 0.408)	(0.678, 0.691)	(0.703, 0.691)	(0.577, 0.676)
M15	(0.278, 0.345)	(0.000, 0.220)	(0.226, 0.229)	0.209, 0.247)
M16	(0.266, 0.264)	(0.266, 0.264)	(0.433, 0.504)	(0.438, 0.541)
M17	(0.312, 0.330)	(0.752, 0.778)	(0.669, 0.641)	(0.312, 0.367)
M18	(0.807, 0.807)	(0.791, 0.793)	(0.718, 0.711)	(0.815, 0.666)
M19	(0.427, 0.531)	(0.552, 0.662)	(0.638, 0.564)	(0.623, 0.587)
M20	(0.413, 0.573)	(0.703, 0.745)	(0.718, 0.711)	(0.655, 0.640)

With the exponential related function ER, the comprehensive group assessment matrix is converted to form the exponential-related matrix which represents the aggregated effect of the positive and negative evaluations in the performance ratings of the alternatives based on the intuitionistic fuzzy set (IFS) data. Here, the attitudinal character of the DMs is introduced. In this case, for convenience, two different risk attitudes that the DMs may pose during the decision-making process have been considered, that is when the risk attitudes of the DMs is $\lambda = 0.1$ indicating that the DMs were risk-averse, and when $\lambda = -0.1$ which indicate that DMs were risk-seeking. The introduction of the attitudinal parameter $\boldsymbol{\lambda}$ is expected to allow for flexibility and a more complete view and representation of the attitudinal character of the DMs which is a strong influencing factor in the decision-making as it relates to the evaluation of the machine's reliability.

Using the Intuitionistic Fuzzy Entropy, the weight of the multiple risk factors was calculated from the comprehensive group assessment matrix and the result is given by the weight vector $\omega = \{0.305, 0.221, 0.222, 0.252\}^T$ respectively. By following step 4-6 in the algorithm of the integrated model, the exponential related function-based separation measures $(d^+{}_i(A^+, A_i)$ and $(d^-{}_i(A^-, A_i)$ $(i = 1,2,\ldots,4)$ is calculated, follow by the relative closeness coefficient CC_i, $(i = 1,2,\ldots,4)$ to the ideal solution using equation (13). Then, the relative closeness coefficients of the risk options are then ranked in the descending order. The final ranking results are shown in Table 5 for the two different DMs risk attitudes.

Table 5: The relative closeness coefficients for the failure modes ranking for the Crawler Crane Machine

Failure Modes	$\boldsymbol{\lambda = 0.1}$				$\boldsymbol{\lambda = -0.1}$			
	$d^+{}_i$	$d^-{}_i$	CC_i	Rank	$d^+{}_i$	$d^-{}_i$	CC_i	Rank
M1	0.2004	0.7051	0.7787	8	0.1989	0.7036	0.7796	11
M2	0.2017	0.7064	0.7779	15	0.1976	0.7023	0.7804	5
M3	0.1994	0.7041	0.7793	3	0.1999	0.7046	0.7790	18
M4	0.2040	0.7087	0.7765	20	0.1954	0.7000	0.7818	1
M5	0.2001	0.7047	0.7789	5	0.1993	0.7040	0.7794	14
M6	0.1998	0.7044	0.7791	4	0.1996	0.7042	0.7792	17
M7	0.2027	0.7074	0.7773	19	0.1966	0.7013	0.7810	2
M8	0.2025	0.7071	0.7774	18	0.1969	0.7015	0.7809	3
M9	0.1991	0.7038	0.7795	2	0.2002	0.7049	0.7788	19
M10	0.2014	0.7061	0.7780	14	0.1979	0.7026	0.7802	7
M11	0.2001	0.7047	0.7789	5	0.1992	0.7039	0.7794	14
M12	0.2013	0.7059	0.7782	12	0.1981	0.7028	0.7801	8
M13	0.2017	0.7064	0.7779	15	0.1976	0.7023	0.7804	5
M14	0.2018	0.7065	0.7778	17	0.1975	0.7022	0.7805	4
M15	0.2003	0.7050	0.7787	8	0.1990	0.7036	0.7796	11
M16	0.2005	0.7052	0.7786	10	0.1988	0.7035	0.7797	10
M17	0.2000	0.7047	0.7789	5	0.1993	0.7040	0.7793	16
M18	0.1984	0.7030	0.7799	1	0.2010	0.7057	0.7783	20
M19	0.2005	0.7051	0.7786	10	0.1989	0.7035	0.7796	11
M20	0.2011	0.7058	0.7782	12	0.1982	0.7029	0.7800	9

Table 6: The different ranking order for the alternatives under the different attitudinal scenario

λ	Ranking order	Best alternative (RCF)
0.1	M18>M9>M3>M6>M5=M11=M17>M1=M15>M16=M19>M12=M20>M10>M2=M13>M14 >M8 >M7>M4	M18
0.3	M18>M9>M3>M6>M5=M11=M17>M1=M15>M16=M19>M12=M20>M10>M2=M13>M14 >M8 >M7>M4	M18
0.4	M18>M9>M3>M6>M5=M11=M17>M1=M15>M16=M19>M12=M20>M10>M2=M13>M14 >M8 >M7>M4	M18
0.5	M18>M9>M3>M6>M5=M11=M17>M1=M15>M16=M19>M12=M20>M10>M2=M13>M14 >M8 >M7>M4	M18
0.7	M18>M9>M3>M6>M5=M11=M17>M1=M15>M16=M19>M12=M20>M10>M2=M13>M14 >M8 >M7>M4	M18
0.9	M18>M9>M3>M6>M5=M11=M17>M1=M15>M16=M19>M12=M20>M10>M2=M13>M14 >M8 >M7>M4	M18
0.0	M18=M9=M3=M6=M5=M11=M17=M1=M15=M16=M19>M12=M20=M10=M2=M13=M14 =M8 =M7=M4	Indifferent
-0.1	M4>M7>M8>M14>M13=M2>M10>M12>M20>M16>M1=M15=M19>M5=M11>M17>M6 >M8 >M9>M18	M4
-0.3	M4>M7>M8>M14>M13=M2>M10>M12>M20>M16>M1=M15=M19>M5=M11>M17>M6 >M8 >M9>M18	M4
-0.4	M4>M7>M8>M14>M13=M2>M10>M12>M20>M16>M1=M15=M19>M5=M11>M17>M6 >M8 >M9>M18	M4
-0.5	M4>M7>M8>M14>M13=M2>M10>M12>M20>M16>M1=M15=M19>M5=M11>M17>M6 >M8 >M9>M18	M4
-0.7	M4>M7>M8>M14>M13=M2>M10>M12>M20>M16>M1=M15=M19>M5=M11>M17>M6 >M8 >M9>M18	M4
-0.9	M4>M7>M8>M14>M13=M2>M10>M12>M20>M16>M1=M15=M19>M5=M11>M17>M6 >M8 >M9>M18	M4

Finally, in Table 6, the different ranking order for the alternatives under the different attitudinal scenario that the DMs might put on during the product reliability assessment is given.

4.1 DISCUSSION OF THE RESULT

Examination of the results for the Root Cause of Failure in the Crawler Crane Machine highlights a number of interesting observations. Firstly, it has shown to fulfill one of the important needs and objectives of this study that is to validate the application of the defined and developed methods in real-life case studies. Secondly, it has shown to overcome the drawbacks of the traditional TOPSIS method that cannot consider simultaneously the subjective information of attributes, their weights and the attitudinal character of DMs. As well as in the handling of uncertainty information of failure data and modeling which is a major drawback in conventional reliability analysis methods that uses probability.

The ranking results has provided a more complete view of the reliability of the Crawler Crane Machine as it relates to the assessment of the root cause of failure, by looking at them from various scenario depending on the interest of the DMs (i.e. the risk-averse, risk neutral and risk-prone attitudes of the DMs) as well as how it better fit the machine. Hence, the author believes the proposed method for product reliability in this study has provided a better and novel alternative to existing reliability methods. Finally, in the event of any design change, from the analysis of the Crawler Crane Machine presented in this studied, the designer and product development team will have to look more closely at the Cantilever mast and Slewing gear in the machine and the Cooling and Hydraulic system for the truck with the view to building more reliability features into these parts and the corresponding components.

5. CONCLUSION

In this paper, a real-life case study has been presented, where a crawler crane machine is investigated for the identification of the root cause of failure, using an expert opinion based technique which comprises of an integrated model which is based on an Intuitionistic Fuzzy TOPSIS model, Exponential related function and the intuitionistic entropy model originally proposed in (Aikhuele & Turan, 2017b, 2017c).

The main contribution and advantages of the proposed approach lie in the use of a subjective and objective model for the computation of the criteria weight, which allows for complete assessment of the actual performance and value of each of the criteria. The application of the exponential-related function, which represent the aggregated effect of the positive and negative evaluations in the performance ratings of the alternatives based on the intuitionistic fuzzy set (IFS) data used. And finally, the method ranks all alternatives using the exponential-related function matrix, thereby accounting for the experts (DMs) attitudinal character which a strong influencing factor in subjective assessments like the root cause of failure/reliability.

Despite the encouraging results from the proposed model and the study, there are a number of areas in the model that can be improved by further research.

Assignment of weight to the DMs can be improved by developing a new objective approach, instead of the subjective approach adopted in this study.

In using the group of DMs opinion or judgment to facilitate the evaluation of the root cause of failure, it is often meaningless when most of the DMs provide incorrect information. As the model cannot detect the presence of incorrect information, in the future, a linguistic scale can be developed that will allow the DMs, to not only give judgment or assessment to alternatives with respect to the attributes but also state the confidence they have in their assessment or judgment.

6. REFERENCE

1. AIKHUELE, D. O., SOROOSHIAN, S., ANSAH, R. H., & TURAN, F. M. (2017). *Application of intuitionistic fuzzy topsis model for troubleshooting an offshore patrol boat engine*. Polish Maritime Research, 24(94), 68–76.
2. AIKHUELE, D. O., & TURAN, F. M. (2017a). *A modified exponential score function for troubleshooting an improved locally made Offshore Patrol Boat engine*. Journal of Marine Engineering & Technology, in press, 1–7. https://doi.org/10.1080/20464177.2017.1286841
3. AIKHUELE, D. O., & TURAN, F. M. (2017b). *An intuitionistic fuzzy multi-criteria decision-making method based on an exponential-related function.* International Journal of Fuzzy System Applications, 6(4), 33–48.
4. AIKHUELE, D. O., & TURAN, F. M. (2017c). *Extended TOPSIS model for solving multi-attribute decision making problems in engineering*. Decision Science Letters, 6, 365–376. https://doi.org/10.5267/j.dsl.2017.2.002
5. AIKHUELE, D. O., TURAN, F. M., ODOFIN, S. M., & ANSAH, R. H. (2016). *Interval-valued intuitionistic fuzzy TOPSIS-based model for troubleshooting marine diesel engine auxiliary system*. International Journal of Maritime Engineering-Part A, 159, 1–8. https://doi.org/10.3940/rina.ijme.2016.a1.402
6. ALAM, M. R., HASSAN, S. F., AMIN, M. A., ARIF-UZ-ZAMAN, K., & KARIM, M. A. (2018). *Failure Analysis of a Mobile Crane: A Case Study*. Journal of Failure Analysis and Prevention, 18(3), 545–553.
7. ALARCIN, F., BALIN, A., & DEMIREL, H. (2014). *Fuzzy AHP and Fuzzy TOPSIS integrated hybrid method for auxiliary systems of ship main engines*. Journal of Marine Engineering & Technology, 13(1), 3–11. https://doi.org/10.1080/20464177.2014.11020288
8. ATANASSOV, K. T. (1986). *Intuitionistic fuzzy sets*. Fuzzy Sets and Systems, 20(1), 87–96. https://doi.org/10.1016/S0165-0114(86)80034-3
9. BALIN, A., DEMIREL, H., & ALARCIN, F. (2016). *A novel hybrid MCDM model based on fuzzy AHP and fuzzy TOPSIS for the most affected gas turbine component selection by the failures.* Journal of Marine Engineering & Technology, 15(2), 69–78. https://doi.org/10.1080/20464177.2016.1216252
10. FUMIAN, W. (2013). *Hoisting machinery accident statistics analysis and prevention from 2006 to 2011*. China Special Equipment Safety, 29(2), 49–51.
11. JENG, S.-L., YANG, C.-F., & CHIENG, W.-H. (2010). *Outrigger Force Measure for Mobile Crane Safety Based on Linear Programming Optimization*. Mechanics Based Design of Structures and Machines, 38(2), 145–170. https://doi.org/10.1080/15397730903482702
12. KAMARUL, M., MOHAMAD, A., & MOHAMAD, M. I. (2016). *Crane Failure and Accident in Construction* (Vol. 2).
13. KUTLU, A. C., & EKMEKÇIOĞLU, M. (2012). *Fuzzy failure modes and effects analysis by using fuzzy TOPSIS-based fuzzy AHP*. Expert Systems with Applications, 39(1), 61–67. https://doi.org/10.1016/j.eswa.2011.06.044
14. LIM, T. H., KIM, Y. S., JONG HWAN CHOI, HONG SUN LEE, & SOON YONG YANG. (2004). *Development of tipping-over rate computation system for hydraulic excavator having crane function*. In KORUS 2004, 8th Korea-Russia International Symposium on Science and Technology, pp. 76-79, 2005 (pp. 110–112).
15. LIU, H.-C., LIU, L., & LI, P. (2014). *Failure mode and effects analysis using intuitionistic fuzzy hybrid weighted Euclidean distance operator*. International Journal of Systems Science, 45(10), 2012–2030. https://doi.org/10.1080/00207721.2012.760669
16. LIU, H.-C., LIU, L., & LI, P. (2015). *Failure mode and effects analysis using intuitionistic fuzzy hybrid TOPSIS approach*. Soft Comput, 19, 1085–1098. https://doi.org/10.1007/s00500-014-1321-x
17. LIU, H.-C., YOU, J.-X., LIN, Q.-L., & LI, H. (2014). *Risk assessment in system FMEA combining fuzzy weighted average with fuzzy decision-making trial and evaluation laboratory*. International Journal of Computer Integrated Manufacturing, 28(7), 701–714. https://doi.org/10.1080/0951192X.2014.900865

18. LIU, M., & REN, H. (2014). *A New Intuitionistic Fuzzy Entropy and Application in Multi-Attribute Decision Making*. Information, 5(4), 587–601. https://doi.org/10.3390/info5040587
19. MARSH, S. M., & FOSBROKE, D. E. (2015). *Trends of occupational fatalities involving machines*, United States, 1992-2010. American Journal of Industrial Medicine, 58(11), 1160–1173. https://doi.org/10.1002/ajim.22532
20. MILAZZO, M. F., & ANCIONE, G. (2016). *Investigation of crane operation safety by analysing main accident causes*. Risk, Reliability and Safety: Innovating Theory and Practice – Walls, Revie & Bedford (Eds), (September), 74–80.
21. SACHDEVA, A., KUMAR, D., & PRADEEP KUMAR. (2009). *Multi-factor failure mode critically analysis using TOPSIS*. Princessaliceadoptionhome.Org, 9(8), 1–9. Retrieved from http://www.princessaliceadoptionhome.org/2013/08
22. SINGHOSE, W., KIM, D., & KENISON, M. (2008*). Input Shaping Control of Double-Pendulum Bridge Crane Oscillations*. Journal of Dynamic Systems, Measurement, and Control, 130(3), 034504. https://doi.org/10.1115/1.2907363
23. SONG, W., MING, X., WU, Z., & ZHU, B. (2013). *Failure modes and effects analysis using integrated weight-based fuzzy TOPSIS*. International Journal of Computer Integrated Manufacturing, 26(12), 1172–1186. https://doi.org/10.1080/0951192X.2013.785027
24. XU, Z., & YAGER, R. R. (2006). *Some geometric aggregation operators based on intuitionistic fuzzy sets*. International Journal of General Systems, 35(4), 417–433. https://doi.org/10.1080/03081070600574353

Table 1 Appendix 1: The Linguistic evaluations on failure modes by the Experts (Ei)

Failure Modes	Occurrence O					Severity S					Detection D					Economic cost EC				
	E1	E2	E3	E4	E5	E1	E2	E3	E4	E5	E1	E2	E3	E4	E5	E1	E2	E3	E4	E5
M1	L	VL	L	M	L	H	VH	L	M	L	L	M	L	EL	VL	L	L	L	L	L
M2	L	L	L	H	VH	H	H	VG	H	VH	VH	H	VH	VH	VG	H	VH	VH	VH	VH
M3	EL	EL	VL	M	L	VH	EH	H	M	M	L	M	M	VH	VG	H	M	M	M	M
M4	EL	EL	VL	H	VH	M	M	M	EL	VL	L	L	VL	M	L	L	VL	VL	VL	VL
M5	L	L	L	M	M	M	M	M	VH	VG	H	VH	VG	L	VL	L	VG	VL	VG	VG
M6	L	L	L	EL	VL	M	M	M	VH	VG	H	VH	VG	VH	VG	H	VH	VG	VH	H
M7	L	L	L	VH	VG	M	M	VG	M	L	L	EL	L	VH	VG	H	VG	EL	VL	VG
M8	EL	EL	VL	VH	VG	VH	EH	H	H	VH	M	M	VG	EL	M	L	M	EL	VL	L
M9	L	L	L	M	L	M	M	M	M	M	H	VH	VG	VH	H	VH	H	VH	VG	H
M10	L	M	EL	EL	VL	H	VH	M	EL	EL	VL	H	VG	VL	L	M	M	VH	VG	H
M11	L	M	L	L	L	M	M	M	L	L	L	M	M	M	L	VL	EL	M	L	L
M12	L	M	L	M	L	M	L	L	VL	L	EL	EL	VL	L	VH	VG	VH	L	VL	L
M13	L	H	VH	H	VH	H	VH	VH	VG	H	VH	VH	VG	H	VH	VG	VH	VH	VG	H
M14	EL	M	M	M	M	M	M	VH	VG	H	VH	VH	VG	H	M	L	M	VH	VG	H
M15	L	L	VL	VG	VL	EL	VL	M	L	L	L	M	L	L	L	L	L	M	L	L
M16	M	M	L	L	L	M	M	L	L	L	L	L	M	M	H	VH	H	L	L	VG
M17	L	L	M	L	M	H	VH	VH	VG	H	M	M	M	VG	VH	L	L	M	L	VG
M18	VH	VH	H	VH	H	VH	VH	VG	H	VH	M	M	H	VH	H	VH	H	VG	VH	EH
M19	M	VH	VG	M	L	M	L	VG	H	VH	M	M	M	VH	M	VH	M	VG	VG	VG
M20	M	L	M	L	VH	VG	H	VH	VH	VG	M	M	H	VH	H	VH	H	VG	VG	VG