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RESEARCH ARTICLE

A DEMATEL Approach Based on Fuzzy Sets for Evaluating Critical Factors of Gas Turbine in Marine Engineering

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Abstract
In power production, gas turbines are commonly used components that generate high amount of energy depending on size and weight. They function as integral parts of helicopters, aircrafts, trains, ships, electrical generators, and tanks. Notably, many researchers are focusing on the design, operation, and maintenance of gas turbines. The focal point of this paper is a DEMATEL approach based on fuzzy sets, with the attempt to use these fuzzy sets explicitly. Using this approach, the cause–effect diagram of gas turbine failures expressed in the literature is generated and aimed to create a perspective for operators. The results of the study show that, "connecting shaft has been broken between turbine and gear box" selected the most important cause factor and "sufficient pressure fuel does not come for fuel pump" is selected the most important effect factor, according to the experts.

Keywords DEMATEL method · Fuzzy sets · Marine engineering · Gas turbine · Failure

1 Introduction

The gas turbine is defined as a type of internal combustion engine that ensures the conversion of natural gas or other liquid fuels into mechanical energy. The gas turbine allows a mixture of air and fuel to reach an extremely high temperature, triggering the turbine blades to rotate. A generator is powered by the rotating turbine for the conversion of energy into electricity. Put differently, hot gases are given off from burning of the air–fuel mixture in gas turbines, which causes power generation. The generated power is used in different areas. Researchers argue about gas turbine technology and enhanced maintenance practices.

Article Highlights
- It is aimed to identify the cause and effect diagram of 14 critical failures in gas turbine with the help of the fuzzy DEMATEL method.
- The fuzzy DEMATEL method employed for evaluating the critical factors by taking the experts opinions.
- The results show that the cause and effect diagram of these factors can be useful for ship owners, ship's safety inspectors, managers, and ocean environmentalists.

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The fundamentals of turbine engine multiple-fault diagnosis were examined by Urban (1975), discussing the parameter selection and measurement requirements of gas turbine engines. Merrington et al. (1990) applied analytical redundancy methods to gas turbine engine transient data to extract the desired fault information. They stated that the proposed method produces better results compared with traditional methods. Stamatis et al. (1990) introduced a new method in relation to the simulation of gas turbine performance, with the possibility of adapting to engine properties. The efficiency of the proposed method was proven by an industrial gas turbine application. Diakunchak (1992) analyzed the most significant factors that affect the industrial gas turbine engine performance deterioration. He proposed preventive measures against the detection and monitoring of performance deterioration. Simani et al. (1998) established neural network detection faults, which were modeled by step functions in control sensors. Brotherton et al. (2000) proposed an alternative solution about automatic detection, classification, and prediction of potential critical component failures in gas turbine engines. Roemer et al. established a real-time monitoring system for gas turbine engines to detect and estimate engine faults. They sought for reduced operation and maintenance costs of critical engine components (Roemer and Kacprzynski 2000). Zedda and Singh (2002) suggested a diagnostic system for the performance analysis of gas turbine engine components and sensors. They used the genetic algorithm in the nonlinear steadystate performance model of engines. Orsagh et al. (2003) understood that diagnostic systems for gas turbine engine components play a critical role in the enhancement of aircraft engine reliability and maintainability. They suggested diagnostic algorithms for predicting and detecting bearing and gear failures. Simani (2005) introduced a model-based procedure for finding and isolating faults of a gas turbine system. He investigated his proposed method using a single-shaft industrial gas turbine model. Lu et al. (2014) advanced an integrated approach based on a nonlinear on-board model for gas turbine engine-sensor fault diagnostics. Tayarani-Bathaie et al. worked on the neural network-based fault detection and isolation of gas turbine engines. They displayed the advantages, capabilities, and performance of their proposed fault diagnosis scheme (Tayarani-Bathaie et al. 2014). Perera et al. (2015) investigated the process failures in gas turbine engines on offshore platforms. They utilized maximum likelihood estimation to calculate the model parameters and summarized the system behavior under failure intensity.

In this context, this paper discusses the gas turbine failures expressed in the literature using the fuzzy DEMATEL approach from a cause–effect perspective. The paper is organized as follows to fulfill this purpose. Section 2 presents the research methodology of the proposed approach and literature review. The application and findings are explained in the third section. The final part summarizes the conclusion and contributions of this study.

2 Fuzzy DEMATEL Approach

In this section, the theoretical background of the proposed approach is given first. Then, the application stages of this approach to a problem are provided in detail.

2.1 Fuzzy Sets

Introduced in 1965 by Zadeh (1965), fuzzy logic is a robust tool that deals with the vagueness, ambiguity, and uncertainty of human judgment and assessment during the decision-making process. In reality, decision-making problems are imprecise, such that goals, constraints, and possible actions are hardly known (Zadeh 1965). Rather than the combination of numerous experiences, opinions, ideas, and motivations of an individual or group decision maker, we should convert the linguistic terms into fuzzy numbers, of which fuzzy numbers in practice have necessarily aroused problems in group decision-making. A triangular fuzzy number is interpreted as a triplet $\tilde{A}=(l, m, u)$, in which l, m, and u are the lower, medium, and upper numbers of the fuzzy, respectively, which can be defined as crisp and real numbers ($x \leq y \leq z$). Figure 1 shows triangular fuzzy number obtained within this scope. The membership function of a triangular fuzzy number is described as below:

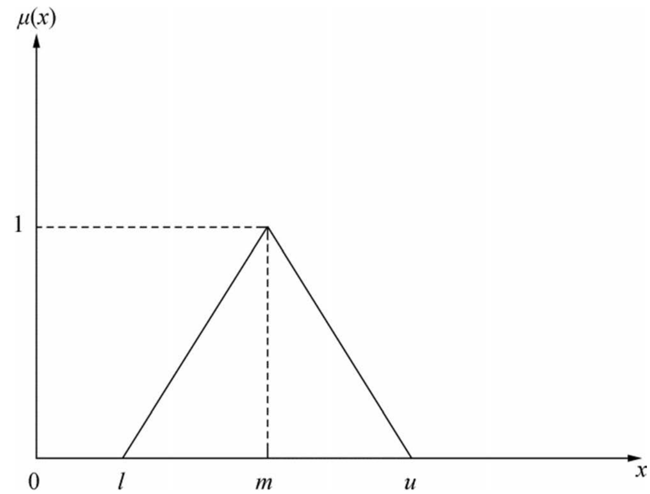

Figure 1 Triangular fuzzy numbers

$$\mu_{\tilde{A}} = \begin{cases} 0 & x < l \\ (x-l)/(m-l) & l \leq x \leq m \\ (u-x)/(u-m) & m \leq x \leq u \\ 0 & x \geq u \end{cases} \tag{1}$$

Figure 1 shows the lower, medium, and upper values for the membership function of triangular fuzzy numbers. For any two triangular fuzzy numbers $\widetilde{A}_1 = (l_1, m_1, u_1)$ and $\widetilde{A}_2 = (l_2, m_2, u_2)$, the mathematical calculation can be defined as follows:

The addition operation between the triangular fuzzy numbers is as follows:

$$\widetilde{A}_1 + \widetilde{A}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{2}$$

The subtraction operation between the triangular fuzzy numbers is given by the following:

$$\widetilde{A}_1 - \widetilde{A}_2 = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \tag{3}$$

The multiplication operation between the triangular fuzzy numbers is as follows:

$$\widetilde{A}_1 \, x \, \widetilde{A}_2 = (l_1 x l_2, m_1 \mathrm{x} \mathrm{m}_2, u_1 x u_2) \tag{4}$$

The arithmetic operation for the triangular fuzzy numbers, where k is a constant and positive, is computed using the following equations:

$$kx\widetilde{A}_1 = (kxl_1, kxm_1, kxu_1), (k > 0) \tag{5}$$

$$\frac{\widetilde{A}_1}{k} = \left(\frac{l_1}{k}, \frac{m_1}{k}, \frac{u_1}{k}\right), (k > 0) \tag{6}$$

2.2 Fuzzy DEMATEL

The DEMATEL method was suggested at the Battelle Memorial Institute of Geneva Research Center as a tool enabling the understanding and resolution of real-world problems (Gabus and Fontela 1972; Gul et al. 2014; Gölcük and Baykasoğlu 2016). This method seeks to reveal the direct and indirect relation between criteria, causal, and effect dimensions. Nevertheless, a common assumption indicates that human perceptions (linguistic assessments) on decision criteria are evaluated on a subjective basis. Human perception can be uncertain, and human(s) may be unwilling or cannot determine the exact numerical values to depict the preferences in many real-world cases (Lin 2013; Celik et al. 2015; Celik and Akyuz 2016). Although it a useful technique to evaluate problems and make decisions, fuzzy logic reveals the linguistic assessment in a rational manner (Onat and Celik 2017; Soner et al. 2017). Fuzzy logic, a robust tool, overcomes the vagueness, ambiguity, and uncertainty of human perception and assessment in the decision-making process, as suggested in 1965 by Lotfi A. Zadeh. Various decision-making problems include imprecision given that goals, constraints, and possible actions are unknown in real-world decision-making problems (Zadeh 1965). Therefore, the conversion of linguistic terms into fuzzy numbers in decision-making problems is preferred (Gul et al. 2016). The relationship between the causes and effects of criteria in an intelligible structural model of the system can be converted by the FDEMATEL method, which has been successfully implemented in many fields (Gölcük and Baykasoğlu 2016). The FDEMATEL method has gained popularity because of its specifically realistic feature while visualizing the structure of complicated causal relationships with digraphs (Akyuz and Celik 2015). Table 1 describes the equivalent relationship between the linguistic terms and triangular fuzzy numbers.

The main steps of the method are as below (Hsu et al. 2007; Wu and Lee 2007; Liou et al. 2008):

Step 1. Selecting a number of experts who are knowledgeable and experienced about the problem to obtain consistent judgments.

Table 1 Corresponding relationship between linguistic terms and fuzzy numbers

Linguistic terms	Triangular fuzzy numbers
No influence (No)	(0, 0, 0.25)
Very low influence (VL)	(0, 0.25, 0.5)
Low influence (L)	(0,25, 0.5, 0.75)
High influence (H)	(0.5, 0.75, 1)
Very high influence (VH)	(0.75, 1, 1)

Step 2. Determining error, constructing the fuzzy scale, and applying a linguistic variable with five scales (No, VL, L, H, and VH) with respect to the linguistic terms and triangular fuzzy numbers.

Step 3. Obtaining evaluation of each decision maker from the groups: The pairwise comparison is performed with regard to linguistics variables. The transformation of fuzzy assessments into defuzzified and aggregated crisp values is required. Finally, the construction of initial direct-relation fuzzy matrix ($\widetilde{\boldsymbol{E}}$) of group decision makers is completed. Variable $\widetilde{\boldsymbol{e}}_{ij}$ is the fuzzy evaluation of the ith failure to jth failure and can be signified by $\widetilde{e}_{ij}=\left(l_{ij},m_{ij},u_{ij}\right)$. Here, $\boldsymbol{l}_{ij}$, $\boldsymbol{m}_{ij}$, and $\boldsymbol{u}_{ij}$ represent the lower, middle, and upper values of the fuzzy numbers, respectively.

$$\widetilde{\boldsymbol{E}} = \begin{bmatrix} 0 & \cdots & \widetilde{E}_{1n} \\ \vdots & \ddots & \vdots \\ \widetilde{E}_{n1} & \cdots & 0 \end{bmatrix} \tag{7}$$

$$\widetilde{e}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right) \tag{8}$$

Step 4. Calculating the normalized direct-relation fuzzy matrix. When the construction of the initial direct-relation matrix is achieved, normalization is implemented. Variables $\widetilde{\beta}_i$ and γ are first considered triangular fuzzy numbers to achieve this goal. The respective calculations are presented below:

$$\widetilde{\beta}_i = \sum\widetilde{\boldsymbol{e}}_{ij} = \left(\sum_{\boldsymbol{j=1}}^{\boldsymbol{n}} \boldsymbol{l}_{ij}, \sum_{\boldsymbol{j=1}}^{\boldsymbol{n}} m_{ij}, \sum_{\boldsymbol{j=1}}^{\boldsymbol{n}} u_{ij}\right) \tag{9}$$

$$\gamma = \max\left(\sum_{\boldsymbol{j=1}}^{\boldsymbol{n}} u_{ij}\right) \tag{10}$$

Subsequently, the linear scale transformation is performed to convert errors into comparable scales. The normalized direct-relation fuzzy matrix ($\widetilde{\boldsymbol{F}}$) of group decision makers can be indicated as follows:

$$\widetilde{\boldsymbol{F}}= \begin{bmatrix} \widetilde{\widetilde{F}}_{11} & \dots & \widetilde{F}_{1\boldsymbol{n}} \\ \vdots & \ddots & \vdots \\ \widetilde{F}_{n1} & \dots & \widetilde{F}_{nn} \end{bmatrix} \tag{11}$$

where $\widetilde{f}_{ij}=\frac{\widetilde{e_{ij}}}{\gamma}=\left(\frac{\widetilde{e_{ij}}}{\gamma},\frac{\widetilde{e_{ij}}}{\gamma},\frac{\widetilde{e_{ij}}}{\gamma}\right)$.

Step 5. Calculating total-relation fuzzy matrix. Subsequent to establishing the normalized direct-relation fuzzy matrix, a total-relation fuzzy matrix is calculated by ensuring $\lim_{\omega\to\infty} F^{\omega}=0$. Then, the crisp case of the total-relation fuzzy matrix is obtained as follows.

$$\widetilde{\boldsymbol{T}} = \lim_{\omega\to\infty}\left(\widetilde{F} + \widetilde{F}^2 + \ldots + \widetilde{F}^{\omega}\right) \tag{12}$$

$$\widetilde{\boldsymbol{T}} = \begin{bmatrix} \widetilde{t}_{11} & \ldots & \widetilde{t}_{1n} \\ \vdots & \ddots & \vdots \\ \widetilde{t}_{n1} & \ldots & \widetilde{t}_{nn} \end{bmatrix} \tag{13}$$

where $\widetilde{t}_{ij} = \left(l''_{ij}, m''_{ij}, u''_{ij}\right)$

$$\text{Matrix } \left[l''_{ij}\right] = F_l\, x\, (I - F_l)^{-1} \tag{14}$$

$$\text{Matrix } \left[m''_{ij}\right] = F_m\, x\, (I - F_m)^{-1} \tag{15}$$

$$\text{Matrix } \left[u''_{ij}\right] = F_u\, x\, (I - F_u)^{-1} \tag{16}$$

Step 6. Analyzing the structural model. First, matrix $\widetilde{\boldsymbol{T}}$ is calculated. Then, $\widetilde{r}_i + \widetilde{c}_j$ and $\widetilde{r}_i - \widetilde{c}_j$ are obtained. In the formula, $\widetilde{r}_i$ and $\widetilde{c}_j$ are substituted for the sum of the rows and columns of matrix $\widetilde{\boldsymbol{T}}$, respectively. The expression $\widetilde{r}_i + \widetilde{c}_j$ stands for the importance of factor i, whereas $\widetilde{r}_i - \widetilde{c}_j$ points out the net effect of factor i.

Step 7. Defuzzifying $\widetilde{r}_i + \widetilde{c}_j$ and $\widetilde{r}_i - \widetilde{c}_j$. The expressions $\widetilde{r}_i + \widetilde{c}_j$ + and $\widetilde{r}_i - \widetilde{c}_j$ are defuzzified by using the center of area defuzzification technique introduced by Ross to determine the best non-fuzzy performance value (Ross 1995). For a convex fuzzy number $\widetilde{\delta}$, a real number z^* corresponding to its center of area can be calculated as below (Gumus et al. 2013):

$$z^* = \frac{\int \mu_{\widetilde{\delta}}(z) z \mathrm{d}z}{\int \mu_{\widetilde{\delta}}(z) \mathrm{d}z} \tag{17}$$

The best non-fuzzy performance (BNP) value of a fuzzy number $\widetilde{G} = \left(l_{ij}\ , m_{ij}\ , u_{ij}\right)$ can be found with following formula:

$$\mathrm{BNP}_{ij} = \frac{u_{ij} - l_{ij} + m_{ij} - l_{ij}}{3} + l_{ij} \tag{18}$$

Step 8. Depicting the cause–effect relation diagram. In the final step, the cause-and-effect relation diagram is highlighted by mapping the dataset of $r_i + c_j$ and $r_i - c_j$.

3 Application of the Proposed Approach

Used in shore, off shore, air and watercrafts, and power plants, gas turbine systems are internal combustion engines that need high-quality material, manufacturing sensitivity, and qualified labor. Within this respect, gas turbines are supposed to operate efficiently. Thus, minimization of failures, which adversely influences the gas turbine system over time, is vital. These failures have to be transferred to the production cycle of the gas turbine. This condition can contribute to the manufacturers during the process of production in gas turbines.

In this paper, the failures that affect gas turbine systems are examined and evaluated through an academic point of view, focusing on the way in which these failures are distributed and affected by gas turbine components in combination with the experiences of experts and literature review. In this way, it is tried to create and develop a certain view for the gas turbine in the ship engine industry.

In the evaluation, the main dimensions of the criteria have been verified as a consequence of a comprehensive research and consultation by three experts, including a professor of Naval Architecture and Marine Engineering. The experts have attempted to rank the criteria dimensions in terms of their accuracy, sufficiency, and significance with a view to validating the content of these criteria for gas turbine failure evaluation. Failures in gas turbines have stemmed from former reports, maintenance logbooks, and acquired data, which have been combined with the personnel's experiences. This study presents gas turbine components, considering the various realistic events. Table 2 lists the failures considered in this study (Balin et al. 2016a, b).

Table 3 describes the linguistic assessment of the three marine experts' decisions. For instance, in comparison with C12, C11 is regarded as low (L), low (L), and high (H) by three experts. (Table 3; row 1 and column 2). All evaluations in terms of critical factors are assessed in the same manner in Table 3. Then, the initial direct-fuzzy matrix is constructed by dint of linguistic variables presented in Table 1. Table 4 demonstrates the aggregated fuzzy initial direct matrix. The aggregation of the row 1 (C1) and column 2 (C2) is acquired through the following step:

$$e_{C1,C2} = \frac{(0.25, 0.5, 0.75) + (0.25, 0.5, 0.75) + (0.5, 0.75, 1)}{3}$$

$$e_{C1,C2} = \frac{(1, 1.75, 2.5)}{3} = (0.33, 0.58, 0.83)$$

The normalized matrix is constructed as follows:

$$\widetilde{\beta}_{C1,C2} = \frac{(0.33, 0.58, 0.83)}{10.50}$$

$$\widetilde{\beta}_{C1,C2} = (0.03, 0.06, 0.08)$$

Table 2 List of critical factors

Symbol	Critical factors
C11	Electronic speed regulator failure
C12	Starter motor coupling failure
C13	Connecting shaft has been broken between turbine and gear box
C21	Sufficient pressure fuel does not come for fuel pump
C22	The oil pressure switch failure
C23	The fuel solenoid valve failure
C31	Blocked the outlet of air pressure regulator
C32	Load control valve failure
C33	Pressure regulator filter clogged
C41	Temperature control unit failure
C42	Problems in automatic control air supply lines
C43	Fuel atomizer filter clogged
C51	Eccentricity of shafts
C52	Low oiling pressure

After obtaining the normalized matrix, the total-relation matrix for C1 and C2 is obtained using Eqs. (12)–(16) and calculated as follows:

$$\widetilde{t}_{C1,C2} = (0.03, 0.09, 0.34)$$

Then, the fuzzy values of $\widetilde{r}_{\mathrm{C11}}$ is calculated as follows:

$$\widetilde{r}_{C11} = (0.31, 1.02, 4.5)$$

After obtaining all values of $\widetilde{r}_i$, $\widetilde{c}_j$, $\widetilde{r}_i + \widetilde{c}_j$, and $\widetilde{r}_i – \widetilde{c}_j$, the defuzzification procedure is applied. For example, the defuzzified value of $\widetilde{r}_i$ for C11 is calculated as follows:

$$\widetilde{r}_{C11} = \frac{(4.50–0.31 + 1.02–0.31)}{3} + 0.31 = 1.94$$

All calculations are implemented in the same manner.

Similarly, all calculations are performed to gain the initial direct-fuzzy matrix. Following the initial direct-fuzzy matrix, the normalized direct-relation fuzzy matrix is calculated by using Eqs. (3)–(5). Table 5 shows the normalized initial direct-relation fuzzy matrix. Next, the total-relation fuzzy matrix is calculated by using Eqs. (6)–(10), which are given in Table 6. The fuzzy values of $\widetilde{r}_i$, $\widetilde{c}_j, \widetilde{r}_i + \widetilde{c}_j$, and $\widetilde{r}_i – \widetilde{c}_j$ are calculated (Table 7). Afterward, the defuzzification process

Table 3 Linguistic evaluation of the three marine experts

Criteria	C11	C12	C13	C41	C42	C43	C51	C52
C11	(No, No, No)	(L, L, H)	(No, No, No)	(VL, VL, VL)	(VL, VL, VL)	(VL, VL, VL)	(L, L, L)	(No, No, No)
C12	(H, VH, VH)	(No, No, No)	(VL, VL, VL)	(VL, L, L)	(L, L, L)	(VL, VL, VL)	(No, No, No)	(VL, VL, L)
C13	(VL, VL, VL)	(VL, VL, VL)	(No, No, No)	(VL, VL, L)	(VL, VL, VL)	(L, L, L)	(VH, VH, VH)	(VL, L, VL)
C21	(VL, L, L)	(L, L, L)	(No, No, No)	(VL, L, L)	(H, H, H)	(VH, VH, VH)	(No, No, No)	(VL, VL, VL)
C22	(VL, VL, VL)	(VL, VL, VL)	(No, No, No)	(VL, VL, VL)	(VL, VL, VL)	(H, H, H)	(No, No, No)	(VH, VH, VH)
C23	(L, L, L)	(L, L, H)	(No, No, VL)	(L, L, L)	(L, L, L)	(VH, VH, VH)	(No, VL, VL)	(H, H, H)
C31	(VL, VL, VL)	(L, L, L)	(No, No, No)	(VL, VL, VL)	(VH, VH, VH)	(H, H, H)	(No, No, No)	(VL, VL, L)
C32	(VL, L, L)	(VL, VL, VL)	(No, VL, VL)	(L, L, L)	(VL, VL, L)	(L, L, L)	(No, No, VL)	(L, L, L)
C33	(L, H, H)	(VL, VL, VL)	(No, No, No)	(VL, VL, VL)	(H, H, H)	(L, L, H)	(No, No, No)	(VL, VL, VL)
C41	(VL, VL, VL)	(VL, L, H)	(No, VL, VL)	(No, No, No)	(VL, VL, VL)	(L, L, L)	(No, No, No)	(L, VL, VL)
C42	(L, L, L)	(VL, VL, VL)	(No, No, No)	(VL, VL, VL)	(No, No, No)	(H, H, H)	(No, No, No)	(VL, VL, VL)
C43	(VL, VL, VL)	(VL, L, L)	(No, No, VL)	(VL, VL, L)	(L, VL, L)	(No, No, No)	(No, No, No)	(L, L, L)
C51	(VL, VL, VL)	(VL, VL, VL)	(VH, VH, VH)	(VL, VL, VL)	(No, No, VL)	(No, No, VL)	(No, No, No)	(No, No, No)
C52	(L, H, H)	(VL, VL, VL)	(L, L, VL)	(VL, VL, VL)	(VL, VL, VL)	(L, L, L)	(No, No, No)	(No, No, No)

Table 4 Fuzzy direct influence matrix

Criteria	C11	C12	C13	C41	C42	C43	C51	C52
C11	(0, 0, 0.25)	(0.33, 0.58, 0.83)	(0, 0, 0.25)	(0, 0.25, 0.5)	(0, 0.25, 0.5)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0, 0, 0.25)
C12	(0.67, 0.92, 1)	(0, 0, 0.25)	(0, 0.25, 0.5)	(0.17, 0.42, 0.67)	(0.25, 0.5, 0.75)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0.08, 0.33, 0.58)
C13	(0, 0.25, 0.5)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0.08, 0.33, 0.58)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0.75, 1, 1)	(0.08, 0.33, 0.58)
C21	(0.17, 0.42, 0.67)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	(0.17, 0.42, 0.67)	(0.5, 0.75, 1)	(0.75, 1, 1)	(0, 0, 0.25)	(0, 0.25, 0.5)
C22	(0, 0.25, 0.5)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0, 0.25, 0.5)	(0, 0.25, 0.5)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0.75, 1, 1)
C23	(0.25, 0.5, 0.75)	(0.33, 0.58, 0.83)	(0, 0.08, 0.33)	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0.75, 1, 1)	(0, 0.17, 0.42)	(0.5, 0.75, 1)
C31	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	(0, 0.25, 0.5)	(0.75, 1, 1)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0.08, 0.33, 0.58)
C32	(0.17, 0.42, 0.67)	(0, 0.25, 0.5)	(0, 0.17, 0.42)	(0.25, 0.5, 0.75)	(0.08, 0.33, 0.58)	(0.25, 0.5, 0.75)	(0, 0.08, 0.33)	(0.25, 0.5, 0.75)
C33	(0.42, 0.67, 0.92)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0, 0.25, 0.5)	(0.5, 0.75, 1)	(0.33, 0.58, 0.83)	(0, 0, 0.25)	(0, 0.25, 0.5)
C41	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0, 0.17, 0.42)	(0, 0, 0.25)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	(0.08, 0.33, 0.58)
C42	(0.25, 0.5, 0.75)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0, 0.25, 0.5)
C43	(0, 0.25, 0.5)	(0.17, 0.42, 0.67)	(0, 0.08, 0.33)	(0.08, 0.33, 0.58)	(0.17, 0.42, 0.67)	(0, 0, 0.25)	(0, 0, 0.25)	(0.25, 0.5, 0.75)
C51	(0, 0.25, 0.5)	(0, 0.25, 0.5)	(0.75, 1, 1)	(0, 0.25, 0.5)	(0, 0.08, 0.33)	(0, 0.08, 0.33)	(0, 0, 0.25)	(0, 0, 0.25)
C52	(0.42, 0.67, 0.92)	(0, 0.25, 0.5)	(0.17, 0.42, 0.67)	(0, 0.25, 0.5)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	(0, 0, 0.25)

Table 5 Normalized initial direct-relation fuzzy matrix

C11	C12	C13	C41	C42	C43	C51	C52
(0, 0, 0.02)	(0.03, 0.06, 0.08)	(0, 0, 0.02)	(0, 0.02, 0.05)	(0, 0.02, 0.05)	(0, 0.02, 0.05)	(0.02, 0.05, 0.07)	(0, 0, 0.02)
(0.06, 0.09, 0.1)	(0, 0, 0.02)	(0, 0.02, 0.05)	(0.02, 0.04, 0.06)	(0.02, 0.05, 0.07)	(0, 0.02, 0.05)	(0, 0, 0.02)	(0.01, 0.03, 0.06)
(0, 0.02, 0.05)	(0, 0.02, 0.05)	(0, 0, 0.02)	(0.01, 0.03, 0.06)	(0, 0.02, 0.05)	(0.02, 0.05, 0.07)	(0.07, 0.1, 0.1)	(0.01, 0.03, 0.06)
(0.02, 0.04, 0.06)	(0.02, 0.05, 0.07)	(0, 0, 0.02)	(0.02, 0.04, 0.06)	(0.05, 0.07, 0.1)	(0.07, 0.1, 0.1)	(0, 0, 0.02)	(0, 0.02, 0.05)
(0, 0.02, 0.05)	(0, 0.02, 0.05)	(0, 0, 0.02)	(0, 0.02, 0.05)	(0, 0.02, 0.05)	(0.05, 0.07, 0.1)	(0, 0, 0.02)	(0.07, 0.1, 0.1)
(0.02, 0.05, 0.07)	(0.03, 0.06, 0.08)	(0, 0.01, 0.03)	(0.02, 0.05, 0.07)	(0.02, 0.05, 0.07)	(0.07, 0.1, 0.1)	(0, 0.02, 0.04)	(0.05, 0.07, 0.1)
(0, 0.02, 0.05)	(0.02, 0.05, 0.07)	(0, 0, 0.02)	(0, 0.02, 0.05)	(0.07, 0.1, 0.1)	(0.05, 0.07, 0.1)	(0, 0, 0.02)	(0.01, 0.03, 0.06)
(0.02, 0.04, 0.06)	(0, 0.02, 0.05)	(0, 0.02, 0.04)	(0.02, 0.05, 0.07)	(0.01, 0.03, 0.06)	(0.02, 0.05, 0.07)	(0, 0.01, 0.03)	(0.02, 0.05, 0.07)
(0.04, 0.06, 0.09)	(0, 0.02, 0.05)	(0, 0, 0.02)	(0, 0.02, 0.05)	(0.05, 0.07, 0.1)	(0.03, 0.06, 0.08)	(0, 0, 0.02)	(0, 0.02, 0.05)
(0, 0.02, 0.05)	(0.02, 0.05, 0.07)	(0, 0.02, 0.04)	(0, 0, 0.02)	(0, 0.02, 0.05)	(0.02, 0.05, 0.07)	(0, 0, 0.02)	(0.01, 0.03, 0.06)
(0.02, 0.05, 0.07)	(0, 0.02, 0.05)	(0, 0, 0.02)	(0, 0.02, 0.05)	(0, 0, 0.02)	(0.05, 0.07, 0.1)	(0, 0, 0.02)	(0, 0.02, 0.05)
(0, 0.02, 0.05)	(0.02, 0.04, 0.06)	(0, 0.01, 0.03)	(0.01, 0.03, 0.06)	(0.02, 0.04, 0.06)	(0, 0, 0.02)	(0, 0, 0.02)	(0.02, 0.05, 0.07)
(0, 0.02, 0.05)	(0, 0.02, 0.05)	(0.07, 0.1, 0.1)	(0, 0.02, 0.05)	(0, 0.01, 0.03)	(0, 0.01, 0.03)	(0, 0, 0.02)	(0, 0, 0.02)
(0.04, 0.06, 0.09)	(0, 0.02, 0.05)	(0.02, 0.04, 0.06)	(0, 0.02, 0.05)	(0, 0.02, 0.05)	(0.02, 0.05, 0.07)	(0, 0, 0.02)	(0, 0, 0.02)

Table 6 Total-relation fuzzy matrix

Criteria	C11	C12	C13	C41	C42	C43	C51	C52
C11	(0.01, 0.04, 0.3)	(0.03, 0.09, 0.34)	(0, 0.01, 0.18)	(0, 0.05, 0.29)	(0.01, 0.07, 0.33)	(0.01, 0.08, 0.37)	(0.02, 0.05, 0.21)	(0, 0.04, 0.28)
C12	(0.07,0.13,0.39)	(0.01, 0.04, 0.31)	(0, 0.03, 0.22)	(0.02, 0.07, 0.32)	(0.03, 0.1, 0.38)	(0.01, 0.09, 0.4)	(0, 0.01, 0.18)	(0.01, 0.07, 0.33)
C13	(0, 0.07, 0.34)	(0, 0.06, 0.33)	(0.01, 0.02, 0.2)	(0.01, 0.06, 0.31)	(0.01, 0.07, 0.35)	(0.03, 0.1, 0.42)	(0.07, 0.1, 0.25)	(0.01, 0.07, 0.33)
C21	(0.02, 0.09, 0.37)	(0.03, 0.09, 0.36)	(0, 0.01, 0.19)	(0.02, 0.07, 0.33)	(0.06, 0.12, 0.41)	(0.08, 0.16, 0.45)	(0, 0.01, 0.18)	(0.01, 0.07, 0.33)
C22	(0.01, 0.07, 0.36)	(0.01, 0.07, 0.34)	(0, 0.01, 0.2)	(0, 0.06, 0.31)	(0.01, 0.08, 0.36)	(0.06, 0.14, 0.46)	(0, 0.01, 0.18)	(0.08, 0.14, 0.38)
C23	(0.03, 0.09, 0.37)	(0.04, 0.1, 0.36)	(0, 0.02, 0.2)	(0.03, 0.08, 0.33)	(0.03, 0.1, 0.38)	(0.08, 0.16, 0.45)	(0, 0.02, 0.2)	(0.05, 0.11, 0.37)
C31	(0.01, 0.07, 0.34)	(0.03, 0.08, 0.34)	(0, 0.01, 0.18)	(0, 0.06, 0.3)	(0.08, 0.14, 0.39)	(0.06, 0.13, 0.43)	(0, 0.01, 0.17)	(0.01, 0.07, 0.32)
C32	(0.02, 0.08, 0.35)	(0, 0.06, 0.32)	(0, 0.03, 0.2)	(0.03, 0.08, 0.32)	(0.02, 0.08, 0.35)	(0.03, 0.1, 0.41)	(0, 0.02, 0.18)	(0.03, 0.08, 0.34)
C33	(0.04, 0.1, 0.38)	(0.01, 0.06, 0.33)	(0, 0.01, 0.19)	(0, 0.06, 0.31)	(0.06, 0.12, 0.4)	(0.04, 0.11, 0.43)	(0, 0.01, 0.18)	(0, 0.06, 0.32)
C41	(0.01, 0.06, 0.33)	(0.03, 0.08, 0.33)	(0, 0.02, 0.2)	(0, 0.03, 0.27)	(0.01, 0.07, 0.33)	(0.03, 0.1, 0.4)	(0, 0.01, 0.17)	(0.01, 0.07, 0.31)
C42	(0.03, 0.09, 0.37)	(0.01, 0.06, 0.33)	(0, 0.01, 0.19)	(0, 0.06, 0.31)	(0.01, 0.06, 0.34)	(0.06, 0.13, 0.45)	(0, 0.01, 0.18)	(0.01, 0.06, 0.32)
C43	(0.01, 0.07, 0.34)	(0.02, 0.08, 0.34)	(0, 0.02, 0.2)	(0.01, 0.07, 0.31)	(0.03, 0.09, 0.37)	(0.02, 0.07, 0.37)	(0, 0.01, 0.18)	(0.03, 0.09, 0.34)
C51	(0, 0.04, 0.25)	(0, 0.04, 0.24)	(0.07, 0.1, 0.21)	(0, 0.04, 0.22)	(0, 0.03, 0.23)	(0, 0.04, 0.27)	(0.01, 0.01, 0.13)	(0, 0.02, 0.21)
C52	(0.04, 0.1, 0.36)	(0, 0.06, 0.31)	(0.02, 0.05, 0.22)	(0, 0.05, 0.29)	(0, 0.07, 0.33)	(0.03, 0.1, 0.4)	(0, 0.01, 0.17)	(0.01, 0.04, 0.28)

Table 7 Fuzzy values of $\widetilde{r}_i, \widetilde{c}_j, \widetilde{r}_i + \widetilde{c}_j$, and $\widetilde{r}_i - \widetilde{c}_j$

Criteria	$\widetilde{r}_i$	$\widetilde{c}_j$	$\widetilde{r}_i + \widetilde{c}_j$	$\widetilde{r}_i - \widetilde{c}_j$
C11	(0.31, 1.02, 4.5)	(0.29, 1.11, 4.86)	(0.61, 2.13, 9.35)	(−4.54, −0.08, 4.2)
C12	(0.35, 1.14, 4.91)	(0.21, 0.98, 4.57)	(0.56, 2.12, 9.48)	(−4.22, 0.17, 4.7)
C13	(0.31, 1.11, 4.86)	(0.1, 0.35, 2.77)	(0.41, 1.46, 7.63)	(−2.46, 0.77, 4.76)
C21	(0.4, 1.17, 4.97)	(0.52, 1.42, 5.66)	(0.92, 2.59, 10.63)	(−5.26, −0.25, 4.45)
C22	(0.41, 1.19, 5)	(0.26, 1.05, 4.65)	(0.68, 2.24, 9.64)	(−4.24, 0.15, 4.73)
C23	(0.39, 1.2, 4.93)	(0.34, 1.17, 4.88)	(0.73, 2.38, 9.81)	(−4.49, 0.03, 4.58)
C31	(0.32, 1.05, 4.66)	(0.57, 1.51, 5.73)	(0.89, 2.56, 10.39)	(−5.41, −0.46, 4.09)
C32	(0.28, 1.04, 4.71)	(0.32, 1.15, 5.01)	(0.6, 2.18, 9.71)	(−4.72, −0.11, 4.39)
C33	(0.34, 1.08, 4.87)	(0.43, 1.29, 5.34)	(0.77, 2.37, 10.21)	(−5, −0.2, 4.44)
C41	(0.25, 0.97, 4.52)	(0.13, 0.84, 4.22)	(0.37, 1.82, 8.73)	(−3.97, 0.13, 4.39)
C42	(0.38, 1.15, 4.92)	(0.35, 1.17, 4.95)	(0.73, 2.32, 9.87)	(−4.56, −0.03, 4.57)
C43	(0.34, 1.1, 4.78)	(0.56, 1.5, 5.72)	(0.91, 2.6, 10.5)	(−5.38, −0.4, 4.22)
C51	(0.09, 0.55, 3.27)	(0.11, 0.28, 2.58)	(0.2, 0.83, 5.85)	(−2.49, 0.27, 3.16)
C52	(0.26, 1, 4.51)	(0.26, 0.98, 4.45)	(0.52, 1.98, 8.96)	(−4.19, 0.02, 4.25)

is applied for conversion of the fuzzy numbers into crisp numbers. Table 8 specifies the crisp values of r_i, c_j, $r_i + c_j$, $r_i - c_j$. The cause–effect relation diagram is constructed with regard to the crisp numbers. The cause-and-effect relationship diagram is designed based on the above outcomes in the last step of the proposed approach.

4 Findings

In Figure 2, the cause–effect diagram is constructed based on $r_i + c_j$, $r_i - c_j$. The critical factors that are above the x-axis represent the cause group. If the $r_i - c_j$ is larger than zero, it represents the cause group. On the other hand, if $r_i - c_j$ is smaller than zero, it represents the effect group. According to the distribution around the axis, the effect group falls below, whereas the cause group remains above the x-axis.

Table 8 Crisp values of r_i, c_j, $r_i + c_j$, and $r_i - c_j$

Criteria	r_i	c_j	$r_i + c_j$	$r_i - c_j$
C11	1.94	2.09	4.03	− 0.14
C12	2.13	1.92	4.05	0.22
C13	2.10	1.07	3.17	1.02
C21	2.18	2.53	4.71	− 0.35
C22	2.20	1.99	4.19	0.21
C23	2.17	2.13	4.31	0.04
C31	2.01	2.61	4.62	− 0.59
C32	2.01	2.16	4.17	− 0.15
C33	2.10	2.35	4.45	− 0.25
C41	1.91	1.73	3.64	0.18
C42	2.15	2.16	4.31	− 0.01
C43	2.08	2.60	4.67	− 0.52
C51	1.30	0.99	2.29	0.31
C52	1.92	1.90	3.82	0.03

While evaluating the critical factors of gas turbine of ships, the concentration on the analysis of cause factor that exerts ultimate and enormous impact on the overall system is critical. Figure 2 demonstrates that C13 (connecting shaft has been broken between turbine and gear box) holds the highest $r_i - c_j$ value among all errors in the cause group, which suggests that C13 creates additional impact on the all system. C51 (eccentricity of shafts) achieves the second highest $r_i - c_j$ value, ranking second among all errors. Additionally, C22 (the oil pressure switch failure) possesses the highest r_i (2.20) and $r_i + c_j$ value (4.19) among the causal factors with regard to influential impact degree.

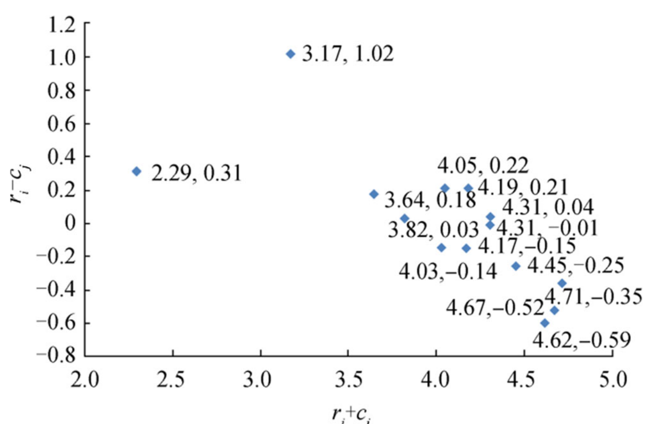

Figure 2 Cause–effect relation diagram

In the entire process, C12 is the fourth most critical factor (starter motor coupling failure) because of its $r_i - c_j$ value (0.21), also ranking fourth place in the process.

Given that other factors only influence the effect factors, the analysis of effect factors (critical factors) that result in serious consequences in gas turbines of ships can be necessary.

In consideration of the cause–effect relation diagram, C21 (sufficient pressure fuel does not come for fuel pump) obtains the highest $r_i + c_j$ value (4.71) in the entire system. The $r_i - c_j$ value (-0.35) of C21 is lower compared with the other factors in the effect group. However, C43 (fuel atomizer filter clogged) reaches the second highest $r_i + c_j$ value (4.67) in the entire system. The lowest value is that of $r_i - c_j$ (-0.52) of C43 in comparison with the other factors in the effect group. Thus, a considerable effect by C43 is monitored on the other factors. Therefore, C43 causes another powerful impact on the other measured factors. Then, originating from C31 (blocks the outlet of air pressure regulator) and C33 (pressure regulator filter clogged), high $r_i + c_j$ values (4.62 and 4.45, respectively) are assessed in the entire system. Their $r_i - c_j$ values are very low $(-0.59$ and $-0.25)$. Thus, they are bound to be affected by the other factors. The remaining factors are of moderate $r_i + c_j$ values as shown in the diagram.

5 Conclusions

Gas turbines have long been used in a wide range of applications in different areas, drawing the attention of researchers in the field of failure detection in gas turbines. In this respect, rapid and consistent reaction of operators to any failure during processing matters is critically important. All failures of gas turbine components in this study have been investigated taking into account the expert's experience and literature review. The fuzzy set-based DEMATEL gives rise to the reduction of maintenance costs and increment of availability of gas turbine components. This approach works towards solutions of the minor problems prior to turning into major ones. Significant maintenance practices providing the basis for relevant future studies are being followed.

Elaborate investigation on failure detection of gas turbine components may be required. Interval type-2 fuzzy sets can cover the proposed hybrid method. In addition, the so-called decision-making approaches, namely, "TOPSIS, VIKOR, Choquet Integral," under a fuzzy environment can be assessed similarly in terms of problems and obtained results. This study is seen as a remarkable reference for maintenance processes for ship engine operators.

References

Akyuz E, Celik E (2015) A fuzzy DEMATEL method to evaluate critical operational hazards during gas freeing process in crude oil tankers. J Loss Prev Process Ind 38:243–253. https://doi.org/10.1016/j.jlp.2015.10.006

Balin A, Demirel H, Alarcin F (2016a) A novel hybrid MCDM model based on fuzzy AHP and fuzzy TOPSIS for the most affected gas turbine component selection by the failures. J Mar Eng Technol 15(2):69–78. https://doi.org/10.1080/20464177.2016.1216252

Balin A, Demirel H, Alarcin F (2016b) An evaluation approach for eliminating the failure effect in gas turbine using fuzzy multiple criteria. Trans R Inst Nav Arch 158(part a):219–230. https://doi.org/10.3940/rina.ijme.a3.377

Brotherton T, Jahns G, Jacobs J, Wroblewski D (2000) Prognosis of faults in gas turbine engines. Aerospace Conf Proc IEEE 6:163–171. https://doi.org/10.1109/AERO.2000.877892

Celik E, Akyuz E (2016) Application of interval type-2 fuzzy sets DEMATEL methods in maritime transportation: the case of ship collision. Int J Mar Eng 158(A4):359–372. https://doi.org/10.3390/app10113919

Celik E, Gul M, Aydin N, Gumus AT, Guneri AF (2015) A comprehensive review of multi criteria decision making approaches based on interval type-2 fuzzy sets. Knowl-Based Syst 85:329–341. https://doi.org/10.1016/j.knosys.2015.06.004

Diakunchak IS (1992) Performance deterioration in industrial gas turbines. J Eng Gas Turbines Power 114(2):161–168. https://doi.org/10.1115/1.2906565

Gabus A, Fontela E (1972) World problems, an invitation to further thought within the framework of DEMATEL. Battelle Geneva Research Centre, Geneva, pp 1–8

Gölcük İ, Baykasoğlu A (2016) An analysis of DEMATEL approaches for criteria interaction handling within ANP. Expert Syst Appl 46: 346–366. https://doi.org/10.1016/j.eswa.2015.10.041

Gul M, Guneri AF, Derin B (2014) Evaluation of service quality criteria for a private medical center by using SERVQUAL and DEMATEL methods. Sigma 32:240–253

Gul M, Celik E, Aydin N, Gumus AT, Guneri AF (2016) A state of the art literature review of VIKOR and its fuzzy extensions on applications. Appl Soft Comput 46:60–89. https://doi.org/10.1016/j.asoc.2016.04.040

Gumus AT, Yayla AY, Celik E, Yildiz A (2013) A combined fuzzy-AHP and fuzzy-GRA methodology for hydrogen energy storage method selection in Turkey. Energies 6(6):3017–3032. https://doi.org/10.3390/en6063017

Hsu CY, Chen KT, Tzeng GH (2007) FMCDM with fuzzy DEMATEL approach for customers' choice behavior model. Int J Fuzzy Syst 9(4):236–246

Lin RJ (2013) Using fuzzy DEMATEL to evaluate the green supply chain management practices. J Clean Prod 40:32–39. https://doi.org/10.1016/j.jclepro.2011.06.010

Liou JJ, Yen L, Tzeng GH (2008) Building an effective safety management system for airlines. J Air Transp Manag 14(1):20–26. https://doi.org/10.1016/j.jairtraman.2007.10.002

Lu F, Chen Y, Huang J, Zhang D, Liu N (2014) An integrated nonlinear model-based approach to gas turbine engine sensor fault diagnostics. Proc Inst Mech Eng G J Aerospace Eng 228(11):2007–2021. https://doi.org/10.1177/0954410013511596

Merrington G, Kwon OK, Goodwin G, Carlsson B (1990) Fault detection and diagnosis in gas turbines. In: ASME 1990 International Gas Turbine and Aeroengine Congress and Exposition, V005T15A010-V005T15A010. https://doi.org/10.1115/1.2906559

Onat O, Celik E (2017) An integral based fuzzy approach to evaluate waste materials for concrete. Smart Struct Syst 19(3):323–333. https://doi.org/10.12989/sss.2017.19.3.323

Orsagh RF, Sheldon J, Klenke CJ (2003) Prognostics/diagnostics for gas turbine engine bearings. The 2003 International Joint Power Generation Conference, pp 159-167. https://doi.org/10.1115/GT2003-38075

Perera LP, Machado MM, Valland A, Manguinho DA (2015) Modelling of system failures in gas turbine engines on offshore platforms. IFAC Pap OnLine 48(6):194–199. https://doi.org/10.1016/j.ifacol.2015.08.031

Roemer MJ, Kacprzynski GJ (2000) Advanced diagnostics and prognostics for gas turbine engine risk assessment. Aerospace Conf Proc IEEE 6:345–353. https://doi.org/10.1109/AERO.2000.877909

Ross TJ (1995) Fuzzy logic with engineering applications, vol 592. McGraw-Hill, Inc, New York

Simani S (2005) Identification and fault diagnosis of a simulated model of an industrial gas turbine. IEEE Trans Ind Inform 1(3):202–216. https://doi.org/10.1109/TII.2005.844425

Simani S, Fantuzzi C, Spina PR (1998) Application of a neural network in gas turbine control sensor fault detection. IEEE Conf Control Appl Proc 1:182–186. https://doi.org/10.1109/CCA.1998.728322

Soner O, Celik E, Akyuz E (2017) Application of AHP and VIKOR methods in maritime transportation under interval type-2 fuzzy environment. Ocean Eng 129:107–116. https://doi.org/10.1016/j.oceaneng.2016.11.010

Stamatis A, Mathioudakis K, Papailiou KD (1990) Adaptive simulation of gas turbine performance. J Eng Gas Turbines Power 112(2):168–175. https://doi.org/10.1115/1.2906157

Tayarani-Bathaie SS, Vanini ZS, Khorasani K (2014) Dynamic neural network-based fault diagnosis of gas turbine engines. Neurocomputing 125:153–165. https://doi.org/10.1016/j.neucom.2012.06.050

Urban LA (1975) Parameter selection for multiple fault diagnostics of gas turbine engines. J Eng Power 97(2):225–230. https://doi.org/10.1115/1.3445969

Wu WW, Lee YT (2007) Developing global managers' competencies using the fuzzy DEMATEL method. Expert Syst Appl 32(2):499–507. https://doi.org/10.1016/j.eswa.2005.12.005

Zadeh LA (1965) Fuzzy sets. Inf Control 8:338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

Zedda M, Singh R (2002) Gas turbine engine and sensor fault diagnosis using optimization techniques. J Propuls Power 18(5):1019–1025. https://doi.org/10.2514/2.6050