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RISK MAINTENANCE STRATEGY IN BLADE MANUFACTURING INDUSTRY MACHINERIES - BY USING APPLICATIONS OF TOPSIS METHOD

Poovanna Vivek Dev S
Department of Mechanical Engineering, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai,Tamilnadu,India, vivekdev46@gmail.com

Sachin Salunkhe
Department of Mechanical Engineering, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai,Tamilnadu,India, drsalunkhesachin@veltech.edu.in

Risk Maintenance Strategy in Blade Manufacturing Industry Machineries - by using applications of Topsis Method

Poovanna Vivek Dev S*[1], Sachin Salunkhe [1]

[1] * Department of Mechanical Engineering, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai,Tamilnadu,India

(Corresponding to – vivekdev46@gmail.com)

ABSTRACT

Regarding the capital and operating expenses of windmill turbines, blades are amongst the most vital parts. Those blades are made using conventional manufacturing methods such as deep groove machine, CNC Machine, foam slicing machine, glass layer machine, glass layer winding machine, balsa angle cutting machine, etc. In this research, TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) method is used to sort the machining methods that need to be handled very carefully according to risk and hazard in blade production. This research objective is to find the windmill blade design data, various production processes and its hazards, risks etc. with the help of previous research papers. Through these results, using the TOPSIS method, a priority number can be given to all the production processes and the safety windmill blade production processes that need more attention can be identified.

Keyword-. Windmill blade, production processes, risk and hazard, safety priority

1. INTRODUCTION

Blade manufacturing refers to the process of producing blades used in various applications such as turbines, windmills, aircraft engines, and other industrial equipment. Blades are critical components that must be made to exacting standards in order to perform their intended function [1-5]. The blade manufacturing process typically involves several steps, including:

Design and engineering: The first step in the blade manufacturing process is to design and engineer the blade. This involves using computer-aided design (CAD) software to create a 3D model of the blade and analyze its performance characteristics.

Materials selection: Once the design is complete, the appropriate materials must be selected for the blade. These materials may include composite materials, metals, or other materials, depending on the specific application.

Blade manufacturing: The blade is then manufactured using various techniques, such as moulding, casting, or machining. In the case of composite materials, the manufacturing process may involve laying up layers of the material and then curing them in an oven.

Finishing: Once the blade is manufactured, it is finished to the required specifications. This may involve sanding, painting, or other finishing techniques to ensure the blade is smooth and free from imperfections.

Testing: Finally, the blade is tested to ensure it meets the required performance standards. This may involve subjecting the blade to various stress tests, such as fatigue testing or vibration testing, to ensure it can withstand the expected operating conditions.

Blade manufacturing is a complex process that requires specialized knowledge and expertise. The quality of the blade can have a significant impact on its performance and longevity, and as such, blade manufacturers must take great care to ensure that each blade is manufactured to the highest standards.

One of the most widely used sources of energy for producing electricity today is wind. This source has become one of the most popular energy sources due to significant cost reductions as well as environmental benefits that are in line with global policies aiming for carbon neutrality [6-12]. Two well-known policies that support the use of renewable energy are those of the EU, which aims to increase the use of renewable energy to 27% of total energy generation by 2030 and reduce greenhouse gas emissions by 80% to 95% by the year 2050, and the United States, which has a target of 20% wind-generated electricity. Additionally, the rate of development of China's wind-generated electricity increased by 27% between 2016 and 2017 [13,37-50].

2. Literature Review

An Perkin et al. identified the following selection criteria [14]: rotor diameter, generator size, hub height, pitch angle range, and revolutions per minute (RPM) range.

Genetic algorithms (GAs) were used to develop a method. The computational complexity brought on by the use of GA was the study's main problem. Using system reliability indices, Nemes and Munteanu [15] compared nine different wind turbine models.

Chowdhury et al. [16] used particle swarm optimisation (PSO) to solve the problem, using the energy production capacity as the only criterion. Only one kind of turbine was considered during the optimisation process. Furthermore, PSO was a poor choice due to the algorithm's high temporal complexity.

In order to create a probabilistic model that is solely focused on turbine reliability, Firuzabad and Dobakhshari [17] selected a selection pool of five different turbine types.

The Weibull distribution-based approach of Bencherif et al.[10] singled out the capacity factor as the only criterion for decision-making. The suggested tactic was studied using 24 different turbine types.

When Montoya et al. [18] modified GA, they used two decision criteria: power output and variance in daily power output. While Chowdhury et al. [12] examined 121 different turbine types using the cost of energy as the decision criterion, one of their shortcomings was the complexity of the algorithm they proposed.

Bekele and Ramayya [19] considered blade design as a deciding factor before using GA to optimise the blade form in accordance with site requirements. The study's design approach, which involved creating a new turbine from scratch for each distinct site rather than using existing turbines from various manufacturers, had a serious flaw.

Helgason [14] used their recommended methodology to assess various Icelandic sites while assuming 47 different turbine designs and using the lowest cost of electricity as the deciding factor. Dong et al. [15] modified a number of nature-inspired algorithms, such as GA, PSO, and differential evolution (DE), using matching index, turbine cost index, and the integrated matching index in order to select the best turbine.

Shirgholami et al. [16] established over 30 selection criteria for selecting a turbine; however, it was also noted that only a portion of these criteria could be used in the selection process. The following criteria were selected based on the characteristics of the potential site. They chose an AHP-based approach.

Bagocius et al. [17] proposed a turbine selection method for offshore wind farms based on the WASPAS method while taking five selection parameters into consideration. These criteria included the nominal power of the wind turbine, the maximum power output allowed in the area, the annual amount of energy produced there, investments, and CO2 emissions.

However, only four distinct turbine types were considered. Khan and Rehman [18,19] recommended using fuzzy logic with hub height, zero output percentage, and rated output as the deciding factors when selecting a turbine.

3. Methodology

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method is a decision-making technique that can be used to calculate the Risk Priority Number (RPN) in blade manufacturing processes. The TOPSIS method compares a set of alternatives based on their distance from ideal and negative-ideal solutions. The alternative with the shortest distance from the ideal solution and the longest distance from the negative-ideal solution is selected as the preferred alternative[20-26].

Here are the procedures for calculating RPN using the TOPSIS method:

- Identify the potential hazards: Identify all the potential hazards in blade manufacturing processes that need to be assessed. This can be done through a hazard analysis or a risk assessment.
- Determine the criteria: Determine the criteria that will be used to assess each potential hazard. This can include severity, frequency, detectability, and other relevant factors.
- Assign weights: Assign weights to each criterion based on its relative importance. The weights should add up to 1.

Rate each potential hazard: Rate each potential hazard on each criterion using a scale of 1 to 10, with 10 being the highest score. This can be done by a team of experts or by using available data.

- Normalize the ratings: Normalize the ratings by dividing each score by the sum of scores for that criterion.
- Multiply normalized scores by weights: Multiply each normalized score by the corresponding weight.
- Determine ideal and negative-ideal solutions: Calculate the ideal and negative-ideal solutions for each criterion by selecting the highest and lowest normalized scores, respectively.
- Calculate the distance from the ideal and negative-ideal solutions: Calculate the distance of each potential hazard from the ideal and negative-ideal solutions using the Euclidean distance formula.
- Calculate the relative closeness to ideal and negative-ideal solutions: Calculate the relative closeness of each potential hazard to the ideal and negative-ideal solutions by dividing the distance to the negative-ideal solution by the sum of the distances to the ideal and negative-ideal solutions.
- Rank the potential hazards: Rank the potential hazards based on their relative closeness to the ideal and negative-ideal solutions. The hazard with the highest rank is the one with the highest RPN and should be prioritized for risk management measures.

Overall, the TOPSIS method can provide a comprehensive and objective approach to prioritizing potential hazards in blade manufacturing processes, and can help organizations to identify and manage risks more effectively[27-36].

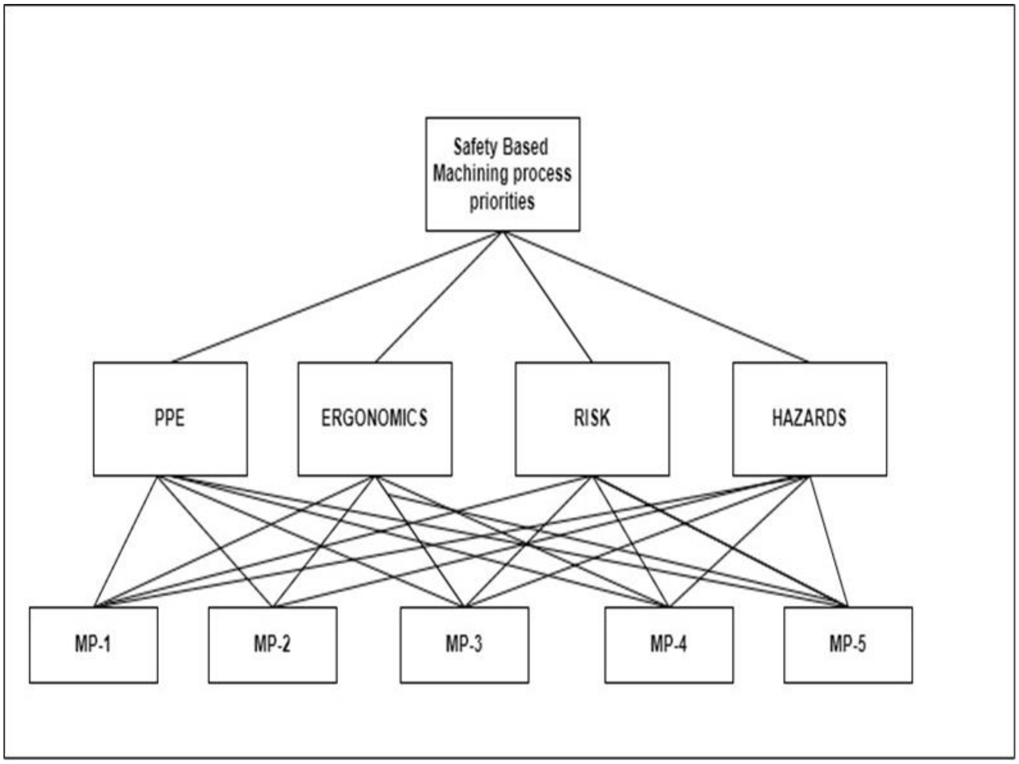

Fig.2 Hierarchy of the objective

Figure 2 express the hierarchy of the research and the steps involved such as define criteria and alternative.

3 RESULT AND DISCUSSION

Lifting and handling heavy windmill blades

- Severity - 8
- Likelihood - 6
- Detectability - 9

2. Working at heights during installation

- Severity - 7
- Likelihood - 8
- Detectability - 6

3. Exposure to hazardous chemicals during the painting process

- Severity - 9
- Likelihood - 4
- Detectability - 7

Normalize the ratings

We will normalize the ratings by dividing each score by the sum of scores for that criterion:

1. Lifting and handling heavy windmill blades

- Severity - 8/24 = 0.33
- Likelihood - 6/18 = 0.33
- Detectability - 9/27 = 0.33

2. Working at heights during installation

- Severity - 7/24 = 0.29

- Likelihood - 8/18 = 0.44

- Detectability - 6/27 = 0.22

3. Exposure to hazardous chemicals during the painting process

- Severity - 9/24 = 0.38

- Likelihood - 4/18 = 0.22

- Detectability - 7/27 = 0.26

Multiply normalized scores by weights

We will multiply each normalized score by the corresponding weight:

1. Lifting and handling heavy windmill blades

- Severity - 0.33 x 0.4 = 0.132

- Likelihood - 0.33 x 0.3 = 0.099

- Detectability - 0.33 x 0.3 = 0.099

2. Working at heights during installation

- Severity - 0.29 x 0.4 = 0.116

- Likelihood - 0.44 x 0.3 = 0.132

- Detectability - 0.22 x 0.3 = 0.066

3. Exposure to hazardous chemicals during the painting process

- Severity - 0.38 x 0.4 = 0.152

- Likelihood - 0.22 x 0.3 = 0.066

- Detectability - 0.26 x 0.3 = 0.078

To use the TOPSIS method, we first need to normalize the ratings for each criterion by dividing each rating by the sum of the ratings for that criterion. This gives us the following normalized ratings:

Option 1:

- Blade sharpness: 0.304

- Durability: 0.360

- Cost: 0.222

Option 2:

- Blade sharpness: 0.348

- Durability: 0.240

- Cost: 0.278

Option 3:

- Blade sharpness: 0.261

- Durability: 0.320

- Cost: 0.333

Option 4:

- Blade sharpness: 0.391

- Durability: 0.080

- Cost: 0.167

Based on the TOPSIS method calculation in the previous question, we can rank the blade manufacturing options based on their distance from the positive ideal solution and the negative ideal solution. The option with the smallest distance to the positive ideal solution is ranked first, and the option with the largest distance to the negative ideal solution is ranked last. Therefore, the ranking of the blade manufacturing options from best to worst is:

1. Option 4

2. Option 2

3. Option 3

4. Option 1

5. CONCLUSION

Safety is of utmost importance in the blade manufacturing industry as it involves working with heavy machinery, rotating cutting tools, and hazardous chemicals. Any lapse in safety can result in serious injuries or fatalities to workers, damage to equipment, and production downtime. Therefore, it is essential to identify and prioritize the machinery that requires more attention from a risk maintenance perspective to ensure the safety of workers and equipment.

The TOPSIS method is a multi-criteria decision-making method that can be used to identify and prioritize the machinery in blade manufacturing processes based on their risk priority. By using this method, the blade manufacturing industry can take a proactive approach to risk management and prioritize their maintenance and inspection activities accordingly.

The TOPSIS method takes into account multiple criteria, such as probability of failure, severity of consequences, and detectability of failure, and assigns weights to each criterion based on their relative importance. It then calculates a risk priority score for each machinery based on these criteria and their weights. The machinery with the highest risk priority score is considered the highest priority for risk maintenances

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