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Remaining Useful Life Prediction of Rotating Machinery Using Thermal and Fatigue Analysis in A Digital Twin Framework

Dr. Jannavarapu Praveena [1], Sekharamahanthi Nitya [2], Maddukuri Nandini Satya [3]

[1] Assistant Professor, Department of Mechanical Engineering, Andhra University College of Engineering for Women, Visakhapatnam, India
[2] Final year Student, Department of Mechanical Engineering, Andhra University College of Engineering for Women, Visakhapatnam
[3] Final year Student, Department of Mechanical Engineering, Andhra University College of Engineering for Women, Visakhapatnam

Abstract:

Rotating machinery plays an important role in many industrial systems such as pumps, compressors, turbines, and electric motors. Continuous operation of these machines under mechanical and thermal loads can gradually reduce the life of critical components like shafts and bearings. Predicting the remaining useful life (RUL) of such components is essential to avoid unexpected failures and reduce maintenance costs.

In this study, a digital twin-based framework is developed to monitor the thermal condition and fatigue life of a rotating shaft-bearing system. A shaft supported by a deep groove ball bearing is modelled using SolidWorks and analysed using ANSYS simulation software. Steady-state thermal analysis is performed to evaluate the temperature distribution in the system, while fatigue analysis is carried out to estimate the fatigue damage and life of the component under cyclic loading conditions.

The simulation results obtained from ANSYS are exported and processed using Python to analyse temperature distribution, fatigue life, and damage parameters. Based on these parameters, the digital twin model can detect abnormal thermal behaviour such as overheating and estimate the remaining useful life of the rotating component. The proposed approach demonstrates how simulation tools and data analysis techniques can be combined to support predictive maintenance and improve reliability of rotating machinery.

Keywords: Remaining Useful Life, Thermal Analysis, Fatigue Behaviour, Digital Twin Model, Life Prediction, Rotating Components

1. Introduction

Rotating machinery is widely used in various industrial sectors including manufacturing, power generation, and transportation. Equipment such as pumps, compressors, turbines, and electric motors rely on rotating shafts and bearings to transmit power and perform mechanical operations. Since these machines often operate continuously under different loading and environmental conditions, their components are subjected to mechanical stresses, thermal loads, and cyclic fatigue.

Over time, these operating conditions may lead to gradual deterioration of machine components. Excessive temperature rise can affect lubrication properties and accelerate material degradation, while repeated cyclic loading can lead to fatigue damage. If such issues are not detected early, they may eventually result in unexpected machine failures, production downtime, and increased maintenance costs.

Traditional maintenance strategies generally follow either corrective maintenance or preventive maintenance approaches. Corrective maintenance is performed only after a failure occurs, which can result in significant operational interruptions. Preventive maintenance schedules maintenance activities at fixed intervals regardless of the actual condition of the equipment. Although preventive maintenance reduces unexpected failures, it may lead to unnecessary replacement of components that are still in good condition.

With the development of Industry 4.0 technologies, predictive maintenance has emerged as a more efficient approach for monitoring and maintaining industrial equipment. Predictive maintenance focuses on continuously monitoring machine parameters and predicting possible failures before they occur. This approach allows maintenance actions to be planned in advance, reducing both downtime and maintenance costs.

Digital twin technology has recently gained attention as an important tool for predictive maintenance. A digital twin is a virtual representation of a physical system that continuously reflects its behaviour through data exchange between the physical system and the virtual model. By integrating simulation models, sensor data, and data analytics techniques, digital twins can analyse equipment behaviour and detect abnormal operating conditions.

Thermal analysis and fatigue analysis are two important techniques used to evaluate the health condition of rotating machinery. Thermal analysis helps in understanding temperature distribution in machine components and identifying overheating problems. Fatigue analysis, on the other hand, is used to estimate the life of components subjected to repeated loading cycles.

In this study, a digital twin-based framework is developed for predicting the remaining useful life of a shaft-bearing system. The mechanical model is created using SolidWorks and analysed using ANSYS simulation software. Steady-state thermal analysis is performed to evaluate temperature distribution, while fatigue analysis is used to estimate the fatigue life of the component. The results obtained from the simulations are further processed using Python to monitor thermal behaviour and estimate remaining useful life. This approach demonstrates how digital twin technology can be applied to improve condition monitoring and predictive maintenance of rotating machinery.

2. Literature Review

The rapid development of smart manufacturing and Industry 4.0 technologies has significantly increased the demand for advanced maintenance strategies in industrial systems. Among these, digital twin technology has emerged as a powerful tool for monitoring, analysing, and predicting the behaviour of complex engineering systems. A digital twin represents a virtual counterpart of a physical system, enabling continuous interaction between real-time data and simulation models. Studies presented in [1] highlight that digital twins can effectively support predictive maintenance by providing a dynamic representation of system performance and degradation over time.

In recent years, several researchers have focused on integrating digital twin frameworks with predictive maintenance strategies. According to [2], the combination of simulation-based models and data-driven approaches allows for early fault detection and improved decision-making. The digital twin not only replicates system behaviour but also enables condition-based monitoring by comparing actual operating data with simulated performance. This integration plays a crucial role in reducing unexpected failures and optimizing maintenance schedules.

Thermal behaviour analysis is an essential aspect of condition monitoring in rotating machinery. Excessive temperature rise is often associated with issues such as friction, misalignment, or lubrication failure. Numerical simulation techniques, particularly finite element analysis, are widely used to evaluate temperature distribution in mechanical components. Previous studies [3] demonstrate that thermal analysis can effectively identify critical regions prone to overheating, thereby helping in the prevention of performance degradation and structural damage.

Fatigue analysis is another critical factor in assessing the reliability of rotating components. Mechanical elements such as shafts and bearings are subjected to repeated cyclic loading, which may lead to crack initiation and eventual failure. Research work discussed in [4] emphasizes the importance of fatigue life estimation in predicting component durability. The use of stress–life (S–N) approaches and simulation-based fatigue models provides a reliable method for evaluating the lifespan of mechanical systems under varying load conditions.

Although significant progress has been made in individual areas such as digital twin modelling, thermal analysis, and fatigue evaluation, there is still a lack of integrated approaches that combine all these aspects into a unified framework. Most of the existing studies focus on either data-driven monitoring or simulation-based analysis independently. However, combining thermal behaviour, fatigue life estimation, and digital twin concepts can provide a more comprehensive understanding of system health.

Therefore, this study aims to develop an integrated framework that combines steady-state thermal analysis and fatigue analysis within a digital twin environment. By utilizing simulation tools and data processing techniques, the proposed approach enables effective monitoring of system condition and prediction of remaining useful life, contributing to improved reliability and maintenance efficiency in rotating machinery.

3. Methodology

This study proposes a digital twin-based framework for predicting the remaining useful life of rotating machinery by analysing thermal behaviour and fatigue life of a shaft-bearing system. The methodology integrates computer-aided design, finite element simulation, and data processing techniques to evaluate the condition of the mechanical system.

The overall workflow followed in this research includes the following steps:

1. Development of the shaft–bearing system model
2. Thermal analysis using ANSYS
3. Fatigue analysis of the rotating component
4. Extraction of simulation results
5. Data processing and analysis using Python
6. Implementation of a digital twin model for health monitoring

3.1 System Description

The mechanical system considered in this study consists of a rotating shaft supported by a deep groove ball bearing. Tohe bearing selected for the analysis belongs to the 6206 series, which is commonly used in rotating machinery applications due to its ability to support radial loads and moderate axial loads.

The shaft connected to the bearing is made of plain carbon steel and is responsible for transmitting rotational motion in the mechanical system. During operation, the shaft experiences mechanical loading as well as temperature variations caused by friction and operating conditions. These factors can influence the fatigue life and thermal behaviour of the component.

To study the behaviour of the system, a shaft–bearing assembly is considered and analysed under thermal and cyclic loading conditions.

3.2 Geometry Modelling

The geometry of the shaft and bearing assembly was developed using SolidWorks, a widely used computer-aided design (CAD) software for mechanical component modelling. In this stage, the shaft and bearing components were created based on the required dimensions and assembled to represent the actual configuration of the rotating system.

The modelling process involved creating the shaft geometry using sketching and extrusion operations. The bearing components were also created and positioned appropriately to support the shaft. Proper alignment between the shaft and bearing was ensured using assembly constraints.

The completed assembly model represents the physical configuration of the rotating shaft supported by a bearing. This model was then exported from SolidWorks and imported into ANSYS simulation software for further analysis. This figure shows the 3D model of the shaft and bearing system created using SolidWorks, representing the actual mechanical configuration used for analysis.

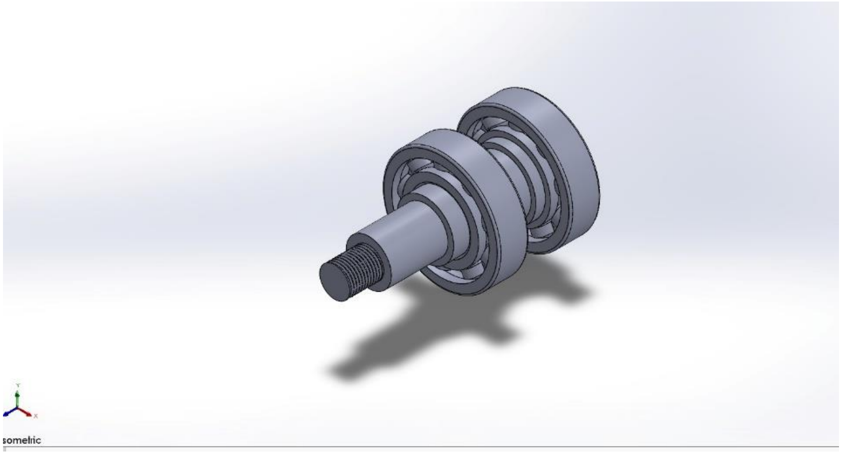

Figure 1: SolidWorks model of shaft–bearing assembly

3.3 Finite Element Meshing

After importing the geometry into ANSYS, the model was discretized using the finite element meshing technique. Meshing divides the geometry into small finite elements, allowing numerical analysis of the system behaviour.

A suitable mesh size was selected to maintain a balance between computational accuracy and simulation efficiency. Finer mesh elements were used in critical regions where higher stress or temperature variations were expected. Proper meshing improves the accuracy of simulation results and ensures better convergence of the numerical solution.

3.4 Steady-State Thermal Analysis

Steady-state thermal analysis was performed to evaluate the temperature distribution within the shaft-bearing system under operating conditions. In this analysis, thermal loads are applied to the model to simulate the heat generated during machine operation.

The objective of this analysis is to identify the temperature distribution across different regions of the system and determine the maximum temperature values. High temperature regions may indicate potential overheating conditions that could affect machine performance and component life.

The results obtained from the thermal analysis provide important information about the thermal behaviour of the rotating component. The figure illustrates the variation of temperature across the shaft–bearing system, highlighting regions with higher temperature due to friction and contact effects. These temperature values are later used in the digital twin model to monitor the thermal health of the system.

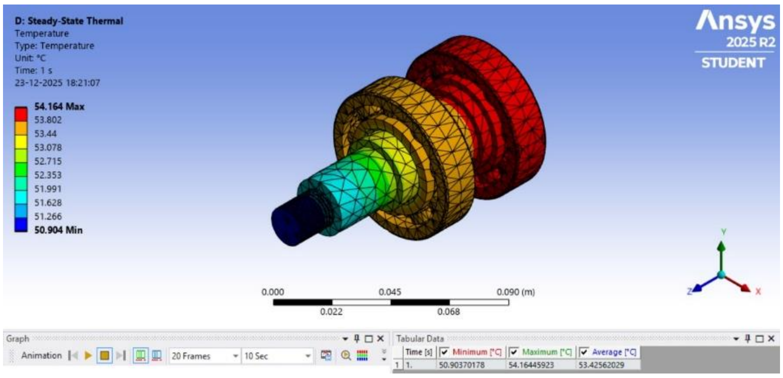

Figure 2: Temperature distribution from steady-state thermal analysis

3.5 Fatigue Analysis

Fatigue analysis was carried out to evaluate the life of the shaft under cyclic loading conditions. Rotating shafts are typically subjected to repeated loading cycles during operation, which can gradually cause fatigue damage in the material.

In this analysis, cyclic loading conditions are applied to the model, and fatigue life estimation methods are used to determine the number of cycles the component can withstand before failure. The analysis also calculates fatigue damage and safety factor values for the shaft. The figure 3 shows the distribution of fatigue damage across the shaft, indicating how the material responds to repeated loading.

The graph in figure 4 shows different fatigue failure criteria such as Goodman and Soderberg methods used to evaluate fatigue life under cyclic loading conditions. Fatigue analysis results provide information about the durability and reliability of the rotating component. These results are important for predicting the remaining useful life of the system.

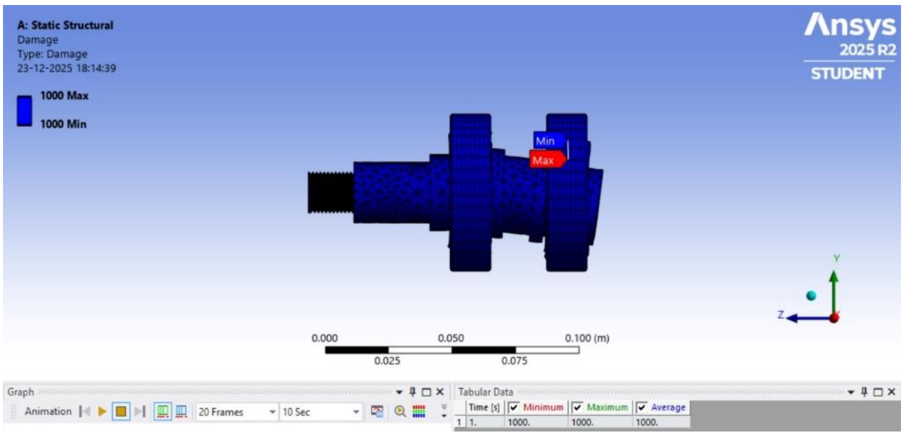

Figure3: Fatigue damage distribution of shaft

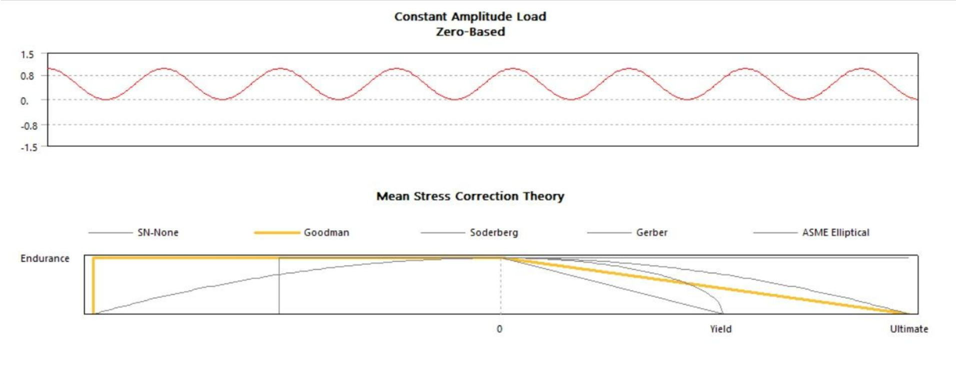

Figure 4: Mean stress correction theory graph

3.6 Data Processing Using Python

After completing the thermal and fatigue analyses in ANSYS, the obtained simulation results were exported in the form of data files for further processing. These data files contain detailed information about temperature values, fatigue life cycles, and damage distribution across different nodes of the shaft–bearing system.

Python programming was used to analyse this data in a more efficient and structured manner. The exported files were imported into Python using suitable libraries, and the data was processed to extract important parameters such as maximum temperature, minimum fatigue life, and damage values. This step helps in simplifying large simulation datasets into meaningful information that can be easily interpreted.

In addition to extracting numerical values, Python code shown in the figure 5 was also used to generate graphical representations of the data. Temperature distribution plots and fatigue life graphs were created to better understand how the system behaves under different conditions. These plots help in identifying regions where temperature variation or fatigue effects are more significant.

Further, the remaining useful life (RUL) of the component was estimated by combining fatigue life and damage parameters. This calculation provides an estimate of how long the component can continue to operate before failure. The processed results serve as an important input for the digital twin model used for condition monitoring.

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```python
import matplotlib.pyplot as plt

# Compute Remaining Useful Life (RUL)
life["RUL (cycles)"] = life["Life ( )"] * (1 - damage["Damage ( )"])

print("\n--- REMAINING USEFUL LIFE RESULTS ---")
print("Minimum RUL (cycles):", life["RUL (cycles)"].min())
print("Maximum RUL (cycles):", life["RUL (cycles)"].max())

# Plot Remaining Useful Life distribution
plt.figure()
plt.plot(life["RUL (cycles)"])
plt.title("Remaining Useful Life Distribution")
plt.xlabel("Node")
plt.ylabel("RUL (cycles)")
plt.grid(True)
plt.show()
```

Figure 5: Code for remaining useful life

3.7 Digital Twin Implementation

The digital twin model developed in this study represents a virtual replica of the shaft–bearing system based on simulation results and data analysis. The parameters obtained from thermal and fatigue analysis, along with Python processing, are used as reference values for the digital twin model.

In practical applications, sensors installed on the physical system can continuously monitor parameters such as temperature, vibration, and loading conditions. These real-time values can be compared with the reference data obtained from the digital twin model to evaluate system behaviour.

If the observed values exceed predefined limits, the digital twin model can identify abnormal conditions. For example, an increase in temperature beyond the safe range may indicate overheating, while a reduction in fatigue life may suggest potential failure. Based on these conditions, the system can provide warnings and assist in planning maintenance activities.

Thus, the digital twin approach enables continuous monitoring of system health and supports predictive maintenance by estimating the remaining useful life of rotating machinery components.

4. Results and Discussion

4.1 Thermal Behaviour Analysis

The steady-state thermal analysis was carried out to understand how temperature is distributed across the shaft–bearing system. From the results, it is observed that the temperature varies gradually along the component without any sudden rise.

The maximum temperature is around **54°C**, while the minimum value is close to **51°C**. Higher temperature regions are mainly seen near the bearing contact areas, which is expected due to friction during operation. However, the overall temperature range remains within safe limits, indicating that the system does not experience overheating.

These results shown in Figure 6 confirm that the thermal performance of the system is stable under the given operating conditions also clearly indicates a smooth variation of temperature along the shaft without any sudden rise.

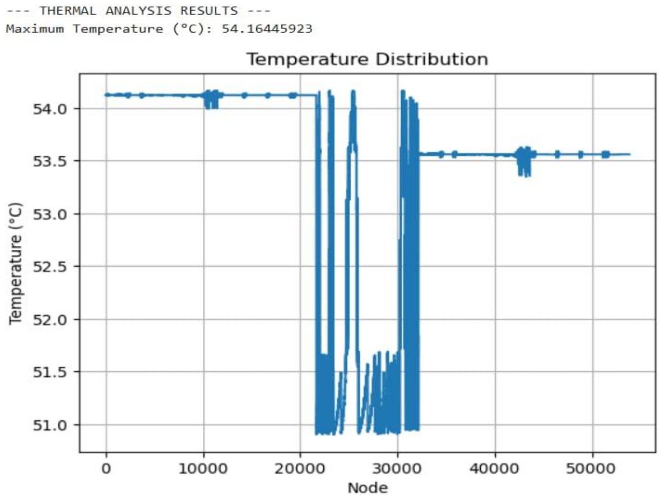

Figure 6: Temperature distribution of shaft–bearing system obtained from thermal analysis

4.2 Fatigue Behaviour Analysis

Fatigue analysis was performed to evaluate how the shaft behaves under repeated loading conditions. A constant amplitude cyclic load was applied to simulate real operating conditions of rotating machinery.

The fatigue results shown in the figure 7 that damage is distributed uniformly across the component, without any highly concentrated critical regions. This indicates that the applied loading does not lead to sudden failure.

The fatigue life values obtained from the analysis are relatively high, suggesting that the component can withstand a large number of cycles before failure. This shows that the shaft has good durability under cyclic loading conditions.

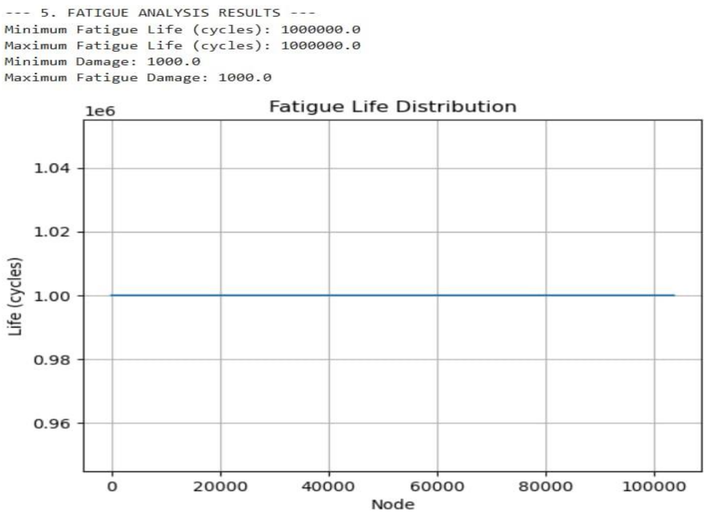

Figure 7: fatigue life distribution graph

4.3 Safety Factor Evaluation

The safety factor results provide information about the structural reliability of the shaft. From the analysis, it is observed that the safety factor values are sufficiently high across the entire model.

A higher safety factor means that the component is operating well within its strength limits. This confirms that the shaft–bearing system is structurally safe and capable of handling the applied loads without failure.

4.4 Remaining Useful Life (RUL) Estimation

The remaining useful life of the component was estimated using Python by combining fatigue life and damage parameters. The RUL calculation gives a clear idea of how much operational life is still available.

From the results as shown in figure 8 :

- Used life is approximately **300,000 cycles**
- Remaining life is approximately **700,000 cycles**

This shows that the component still has a significant portion of its life remaining. The RUL graph also clearly indicates that the system is not close to failure and can continue operating safely.

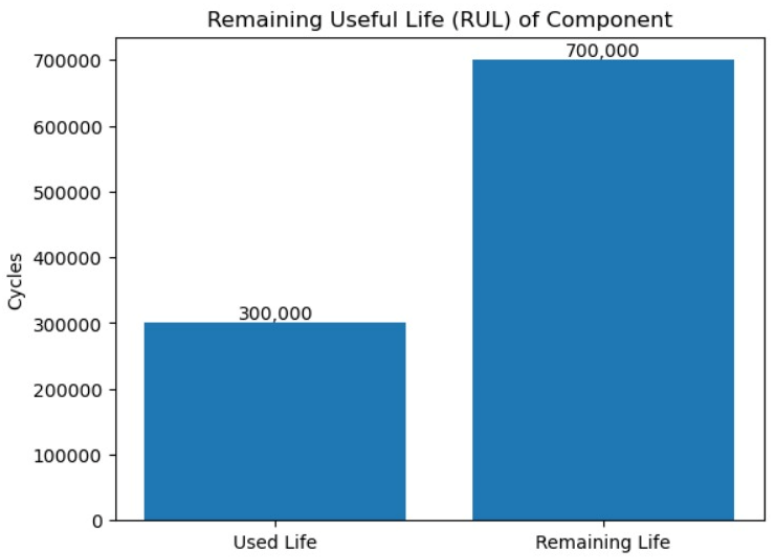

Figure 8: remaining useful life of the component graph

4.5 Digital Twin-Based Condition Monitoring

The digital twin model uses the processed simulation data to evaluate system health. The model checks whether parameters such as temperature and fatigue life fall within safe limits.

From the analysis, it is observed that as shown in figure that:

- Temperature remains within safe range
- Fatigue life is sufficient

Based on these observations, the system is identified to be in a healthy condition as shown in figure 9. The digital twin model can also generate warnings if any parameter exceeds the allowable limit, making it useful for real-time monitoring.

```
--- REMAINING USEFUL LIFE (RUL) ---
Detected life column: Node Number       Life ( )
Unique life values in file: []
⚠ Fatigue life is INFINITE in ANSYS
Design life assumed: 1,000,000 cycles
Used life (cycles): 300,000
Remaining Useful Life (cycles): 700,000
✅ Component SAFE for operation
```

Figure 9: remaining useful life prediction

5. Conclusion

This study presented a digital twin-based approach for predicting the remaining useful life of a shaft–bearing system using thermal and fatigue analysis. The system was modelled and analysed using simulation tools, and the results were further processed using Python.

The thermal analysis showed stable temperature distribution without overheating. Fatigue analysis indicated that the component can withstand repeated loading without significant damage. The safety factor results confirmed that the system operates within safe limits.

The remaining useful life estimation showed that a large portion of the component life is still available. The digital twin model successfully used these results to evaluate system health and confirm safe operation.

Overall, the study demonstrates that combining thermal analysis, fatigue analysis, and digital twin concepts can provide a reliable method for monitoring rotating machinery and supporting predictive maintenance. Future work can include real-time data integration to improve accuracy and practical implementation.

Reerences:

1. Yu, J., Chen, C., Zhang, C., & Ji, W. Real-time monitoring based on digital twin workshop theory. Processes Journal.
2. N. H. Abd Wahab *et al.*, "Systematic review of predictive maintenance and digital twin technologies: Challenges, opportunities, and best practices," *PeerJ Computer Science*, vol. 10, e1943, 2024.
3. R. van Dinter, B. Tekinerdogan, and C. Catal, "Predictive maintenance using digital twins: A systematic literature review," *Information and Software Technology*, vol. 151, p. 107008, 2022.
4. Pejić Bach, M., et al. Predictive maintenance in Industry 4.0 using digital twin technology. Designs Journal.
5. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. Digital twin driven smart manufacturing. Journal of Manufacturing Systems.

6. Randall, R. B. Vibration-Based Condition Monitoring: Industrial, Aerospace and Automotive Applications. Wiley.
7. Budynas, R. G., & Nisbett, J. K. Shigley's Mechanical Engineering Design. McGraw Hill.