International Journal of Scientific and Management Research
Volume 8 Issue 1 (January) 2025
ISSN: 2581-6888
Page: 99-120

Optimizing Maintenance Cost in A Multi Component Environment

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DOI - http://doi.org/10.37502/IJSMR.2025.8105

Abstract

This research presents a cost-centric approach to maintenance scheduling in multi-component systems, aimed at minimizing expenses while optimizing operational efficiency. By integrating predictive analytics and optimization techniques, we conduct a comprehensive analysis of production loss costs for diverse maintenance sequences, employing genetic algorithms to identify the most cost-effective strategy. Through rigorous exploratory data analysis, we refine our model and demonstrate its efficacy in achieving significant cost savings. A comparative case study showcases substantial reductions in maintenance expenses compared to traditional methods like RUL based scheduling, underscoring the potential of our approach in enhancing cost management and operational performance in industrial contexts. This study contributes valuable insights to the field of maintenance optimization and offers practical implications for industry practitioners seeking to improve cost-effectiveness and operational efficiency in multi-component systems.

Keywords: Maintenance scheduling, Cost optimization, multi-component systems, Predictive analytics, Optimization techniques, Genetic algorithms, Exploratory data analysis.

1. Introduction

The In the midst of the revolutionary wave known as Industry 4.0, where the landscape of manufacturing and production is undergoing transformative shifts propelled by digitalization and automation, the intricacies of managing system complexities and associated maintenance costs have surged to the forefront of industrial concerns.

The financial stakes in maintenance management are significant, with estimates suggesting that maintenance expenses can consume a substantial portion, ranging from 15% to a staggering 40%, of total production costs (Dunn, 1987; Lofsten, 2000). This puts considerable pressure on industries to maintain cost-efficiency while meeting the increasing demands of modern operations. Every \$1 of deferred maintenance could potentially quadruple to \$4 in capital renewal costs later on [1]. Moreover, allowing equipment to reach the point of failure could result in costs up to 10 times higher compared to implementing a regular maintenance program. Predictive maintenance emerges as a highly cost-effective strategy, offering savings of approximately 8% to 12% over preventive maintenance, and potentially up to 40% over reactive maintenance, according to the U.S. Department of Energy. Adding to the financial strain, the manufacturing sector of the country incurs approximately \$1.5 billion per year in costs due to unplanned maintenance downtime. Furthermore, the average unplanned downtime for a machine in Bangladesh is 20 [2] hours per year.

However, a recent study has found that implementing a comprehensive maintenance program could reduce costs by up to 50%. System failures in complex environments lead to extensive economic losses from penalties, shutdowns, and opportunistic expenses, highlighting the need for effective maintenance planning. Neglecting strategic maintenance to cut costs jeopardizes routine schedules and asset longevity, impacting industry competitiveness in dynamic markets.

Technological advancements, particularly the adoption of sensors and data collection devices, have revolutionized maintenance practices. Data analytics now allows industries to predict and plan maintenance with precision. Central to this is Remaining Useful Life (RUL) prognostics, which aims to anticipate failures and optimize maintenance deployment. Despite its promise, challenges remain in ensuring RUL reliability and integrating it into maintenance frameworks, especially in complex multi-component systems.

Unplanned equipment downtime significantly threatens productivity and profitability, making optimizing maintenance strategies critical. Developing effective maintenance strategies requires understanding the factors influencing maintenance costs in multi-component environments. The high costs of running equipment to failure underscore the need for proactive maintenance approaches. Industries must navigate escalating maintenance costs and system complexities, making effective maintenance strategies imperative. By embracing data-driven methodologies and innovative technologies, industries can optimize maintenance costs, enhance system reliability, and ensure operational efficiency in a dynamic landscape.

Optimizing maintenance costs in industry is complex, involving unplanned maintenance, aging infrastructure, and inadequate predictive systems. Challenges include resource management, technological integration, regulatory compliance, cost control, and workforce shortages. Leveraging predictive maintenance and innovative solutions can improve processes, reduce costs, and enhance efficiency.

Effective maintenance strategies are crucial for reducing downtime and costs in industrial production. Scheduled and predictive maintenance are common, with research showing that task grouping can lower costs and downtime. However, the best grouping techniques remain uncertain, and important factors are often overlooked. Our study aims to identify key factors in task grouping for predictive maintenance to lower costs and reduce downtime. This research is valuable for industries reliant on machinery and automation, aiming to enhance efficiency and effectiveness by improving maintenance strategies.

2. Literature Review

2.1 Factors affecting maintenance costs

At the dawn of the new century, as Industry 4.0 gained momentum, System complexity and maintenance expenses have grown quickly, and the associated maintenance planning tasks have become very time-sensitive. The consequences of a breakdown in a complicated system are not limited to enormous maintenance expenses; they also include economic losses from opportunistic costs, penalty costs, and the cost of scheduled and unexpected shutdowns [3][4][5][6]. To reduce the maintenance cost, downtime, and failure risks for such systems, determining and executing the most effective maintenance approach becomes increasingly challenging.

One of the most significant challenges industries faces is the optimization of maintenance downtime-related costs, as unplanned equipment downtime can harm productivity, profitability, and overall competitiveness. In order to develop an optimal maintenance plan for these systems, it is crucial to comprehensively grasp the many aspects that impact maintenance expenses and their interrelationships within a multi-component setting.

Maintenance-related downtime in complex multi-component systems poses a significant challenge in industrial settings, necessitating optimal maintenance policies that minimize downtime and related costs. A comprehensive investigation into maintenance strategies and innovative approaches is crucial for enhancing system reliability, availability, and operational efficiency.

Alrabghi and Tiwari introduce a novel approach for optimizing maintenance strategies using discrete event simulation (DES) [7]. This method models the complex interactions between maintenance strategies and system assets, demonstrating a significant contribution to the optimization of maintenance systems. This research is among the first to use DES for such purposes, providing valuable insights into the application of DES in maintenance optimization.

Shi and Zeng present a dynamic, opportunistic condition-based maintenance strategy for multi-component systems [8]. Their strategy relies on real-time predictions of the remaining useful life (RUL) of components, considering stochastic dependence. Using a state space-based model, sequential Kalman filtering, and the expectation maximization (EM) algorithm for parameter estimation, their method is validated through numerical examples and case studies, showcasing its effectiveness in real-time RUL prediction.

Table 1 Influencing Factors

Reference No	**Publishing Year**	**Setup Cost**	**Cost of Spare parts**	**Cost of Production**	**Penalty Cost**	**Component Inspection**	**Planned Shutdown**	**Unplanned Shutdown**	**Cost of Efficiency Loss**	**Opportunistic Cost**	**Labor Cost**	**Action Cost**	**Admin Break**	**Unavailability Cost**	**Predictive**	**Corrective**
[3]	2008								✓						✓	✓
[4]	2015	✓	✓			✓	✓	✓						✓	✓	✓
[5]	2016		✓											✓	✓	✓
[6]	2016	✓	✓	✓	✓										✓	
[7]	2017									✓					✓	✓
[8]	2017		✓		✓	✓									✓	
[9]	2018														✓	✓
[10]	2018		✓	✓	✓						✓				✓	✓
[11]	2019		✓	✓		✓					✓				✓	✓
[12]	2020		✓	✓		✓				✓	✓		✓		✓	✓
[13]	2020		✓								✓			✓	✓	
[14]	2020		✓				✓									
[15]	2020		✓	✓		✓					✓				✓	✓
[16]	2020	✓	✓			✓				✓	✓				✓	✓
[17]	2021		✓		✓	✓						✓		✓		
[18]	2021		✓	✓							✓					
[19]	2022	✓		✓		✓			✓						✓	✓

[20]	2023		✓								✓			✓		
[21]	2023			✓		✓	✓								✓	✓
Our Study		✓	✓	✓							✓	✓				

Research on the optimization of maintenance task scheduling and vessel routing for offshore wind farms addresses the joint scheduling of maintenance tasks and vessel routing. This study contributes to the field by highlighting the challenges and opportunities in this area, offering valuable insights for optimizing maintenance strategies in offshore wind farms [9].

The impact of intelligent wireless sensor networks on predictive maintenance costs is explored, discussing the economic benefits of maintenance policies, the role of intelligent sensors, and cost optimization. This study likely offers insights into the cost-effectiveness and reliability improvements associated with intelligent wireless sensor networks for predictive maintenance [10].

A study focusing on predictive maintenance (PdM) for small and medium-sized enterprise (SME) CNC machine shops proposes a cost-effective PdM system architecture aimed at predicting cost savings. This research emphasizes the value of PdM for SMEs, predicting positive impacts on maintenance costs and performance, and addressing the minimal representation of SMEs in the literature [11].

Oyarbide-Zubillaga et al. propose a hybrid approach that combines DES with multi-objective evolutionary algorithms (MOEAs) for optimizing preventive maintenance (PM) in manufacturing systems [12]. This methodology allows for considering multiple conflicting objectives, providing a robust framework for enhancing system performance and reliability.

Yuriy and Vayenas integrate DES with a genetic algorithm (GA)-based reliability assessment model for mine equipment systems [13]. This hybrid approach enables realistic system simulations and reliability assessments, identifying optimal strategies to enhance productivity and minimize downtime in mining operations.

Golbasi and Turan develop a DES algorithm for optimizing multi-scenario maintenance policies in industrial systems, combining DES with optimization to minimize downtime and maintenance costs while maximizing system reliability [14].

Petkov, Wu, and Powell conduct a cost-benefit analysis of condition monitoring (CM) in the DEMO remote maintenance system [15]. Their study informs decision-makers about CM's economic viability, aiding strategic planning and resource allocation.

Kamel et al. use genetic algorithms for preventive maintenance scheduling optimization, proposing a mathematical model optimized with a GA to minimize costs and downtime while maximizing reliability [16]. This study offers a potent tool for enhancing maintenance strategies.

Louhichi, Sallak, and Pelletan focus on optimizing maintenance costs for mechanical bearing systems, providing insights and a framework to enhance maintenance strategies and optimize costs in similar systems [17].

Fan et al. propose a group maintenance optimization approach for subsea Xmas trees, addressing stochastic dependencies to improve maintenance strategies in offshore environments [18].

Özgür-Ünlüakın et al. explore cost-effective fault diagnosis in multi-component dynamic systems under corrective maintenance, proposing a method tailored to these systems and enhancing fault diagnosis strategies [19].

A study in aviation maintenance proposes prescriptive strategies using DES for post-prognostics decision-making, offering a comprehensive tool for optimizing maintenance strategies [20].

Hatsey and Birkie explore total cost optimization of submersible irrigation pump maintenance through simulation, enhancing maintenance strategies in the irrigation sector [21].

Gong et al. [20] examine dynamic preventive maintenance optimization for subway vehicle traction systems, considering different stages of system operation to enhance maintenance strategies [22].

A study investigates component maintenance strategies and risk analysis under random shock effects, providing insights for optimizing maintenance strategies [23]

Mwanza, Telukdarie, and Igusa [24] focus on optimizing maintenance workflows in healthcare facilities using a multi-scenario DES and simulation annealing approach, enhancing maintenance strategies and ensuring reliability of critical medical equipment.

Addressing maintenance optimization for complex multi-component systems will lead to substantial cost savings and improved productivity across various industrial sectors.

2.2 Genetic algorithm in maintenance

Predictive maintenance (PdM) is rapidly transforming the landscape of industrial maintenance strategies, focusing on the prediction of equipment failures before they occur to prevent costly downtime and maintenance expenses. This literature review synthesizes recent advancements in the field, highlighting key studies that leverage machine learning (ML), deep learning (DL), and optimization algorithms to enhance predictive maintenance systems within various industries.

Chui, Gupta, and Vasant (2021) developed a genetic algorithm optimized RNN-LSTM model specifically tailored for predicting the remaining useful life (RUL) of turbofan engines[25]. Their work demonstrates how combining genetic algorithms with recurrent neural networks can refine prediction accuracy and adaptively tune the model parameters for specific maintenance scenarios. The authors presented a hybrid predictive maintenance model that integrates clustering, Synthetic Minority Over-sampling Technique (SMOTE), and Multi-Layer Perceptron (MLP) neural networks optimized with a Grey Wolf algorithm[26]. This model effectively addresses the challenges of imbalanced data, enhancing the predictive accuracy for maintenance needs in diverse industrial applications.

This study provided an extensive overview of predictive maintenance within the context of Industry 4.0, discussing various models and the inherent challenges of integrating these systems into modern industrial operations. Their work underscores the complexity of deploying predictive maintenance systems that need to be both efficient and scalable across different sectors [27]. Zhai, Kandemir, and Reinhart (2022) explored the integration of predictive maintenance with production scheduling using deep generative prognostic models [28]. This approach not only predicts maintenance needs but also aligns them with production schedules to minimize the impact on operational efficiency.

De Pater, Reijns, and Mitici (2022) discussed an alarm-based predictive maintenance scheduling model for aircraft engines that accounts for imperfect RUL prognostics[29]. Their approach focuses on maximizing safety and reliability by developing maintenance schedules that are sensitive to the uncertainties in RUL predictions. Ren (2021) emphasized optimizing predictive maintenance using machine learning to improve the reliability of various engineering systems[30]. His research highlights how ML models can be trained to identify patterns and predict failures more accurately than traditional methods. Teoh, Gill, and Parlikad (2021) introduced an IoT and fog-computing-based predictive maintenance model that leverages ML for effective asset management in Industry 4.0[31]. Their model processes real-time data at the edge of the network, facilitating quicker response times and reducing the need for data transmission to the cloud.

Nikfar, Bitencourt, and Mykoniatis (2022) proposed a two-phase machine learning approach for predictive maintenance of low voltage industrial motors[32]. This method distinguishes between different phases of the equipment lifecycle, allowing for more targeted and effective maintenance interventions. Khorsheed and Beyca (2021) integrated machine learning with utility theory to create a framework for real-time predictive maintenance in pumping systems[33]. This integration allows for the balancing of maintenance costs against the probability and impact of system failures, optimizing the maintenance schedule in real-time based on changing conditions.

Serradilla, Zugasti, Rodriguez, and Zurutuza (2022) conducted a survey on deep learning models for predictive maintenance, comparing various approaches and discussing their challenges and future prospects[34]. Their study provides a comprehensive look at how deep learning can be utilized to enhance the predictive capabilities of maintenance systems. Paprocka, Kempa, and Skołud (2021) focused on predictive maintenance scheduling with reliability characteristics that depend on the phase of the machine lifecycle[35]. Their optimization approach ensures that maintenance resources are allocated more efficiently, based on the specific needs of each phase. Vincent, Salsabila, Siswanto, and Kuo (2022) developed a two-stage genetic algorithm for coordinating spare parts inventory and planned maintenance under uncertain failure conditions[36]. This approach helps in managing the logistics of spare parts and maintenance activities, reducing the risk of unexpected failures and downtime.

Collectively, these studies illustrate the dynamic nature of predictive maintenance research and its application across various industrial domains. They highlight the critical role of advanced computational techniques in enhancing the predictability and reliability of maintenance operations, ultimately leading to increased operational efficiency and reduced costs. As industries continue to advance towards fully integrated digital systems, predictive maintenance will play an increasingly vital role in ensuring the sustainability and profitability of industrial operations.

2.3 RUL based maintenance

In recent years, the implementation of predictive maintenance strategies powered by advancements in data analytics and machine learning has garnered significant attention in industrial operations. This literature review examines several key studies that contribute to the field of predictive maintenance, particularly focusing on methodologies for calculating and predicting the Remaining Useful Life (RUL) of various components and systems. These studies leverage diverse computational models and innovative algorithms to enhance the reliability and efficiency of maintenance operations.

Aivaliotis et al. (2017) present a novel RUL calculation approach using physical-based simulation models, showcased at the 2017 International Conference on Engineering, Technology and Innovation[37]. Their method emphasizes the use of detailed simulations to predict wear and tear, which can be particularly beneficial for industries requiring precise maintenance schedules to prevent unexpected downtime.

The authors explore RUL prediction in multi-state manufacturing systems, considering functional dependencies among components[38]. Their research highlights the complexities of systems where component states are interdependent accommodate these nuances, thereby improving the overall system reliability. In a similar vein, and they develop predictive maintenance strategies that the authors introduce a dynamic predictive maintenance model for turbofan engines using data-driven probabilistic RUL prognostics[39]. Their work is crucial for the aerospace industry where maintenance decisions have critical safety implications. This approach allows for maintenance scheduling based on probabilistic assessments of component life, which can significantly reduce the risk of failure.

The author proposes a risk-averse framework for RUL estimation that is designed to err on the side of caution, thus ensuring higher safety standards in maintenance practices[40]. Their methodology uses advanced statistical techniques to adjust predictions in favor of scenarios that minimize potential risks, which is vital for high-stakes industries. This study delves into Bayesian deep learning for their prognostic-driven predictive maintenance framework[41]. This method combines the strength of Bayesian statistics with the versatility of deep learning, offering a robust tool for handling the uncertainties inherent in RUL predictions.

The study by Hu and Chen (2020) focused on the predictive maintenance of systems subject to hard failures using the proportional hazards model[42]. This statistical approach models the hazard rate as a function of several covariates, which provides a nuanced understanding of the factors influencing the likelihood of system failure. Lee and Mitici (2023) investigated the application of deep reinforcement learning for predictive aircraft maintenance[43]. By integrating deep learning with probabilistic models of RUL, their research represents a cutting-edge approach to maintenance that can dynamically adapt to new data and evolving conditions in real-time. This study utilized artificial neural networks for the RUL prediction of equipment in production lines[44]. Their study demonstrates the applicability of neural networks in capturing complex non-linear relationships in data, which are often present in industrial settings.

Another significant contribution by de Pater and Mitici (2021) focuses on multi-component systems of repairable[45]. Their predictive maintenance strategy considers RUL prognostics along with constraints such as a limited stock of spare components, addressing a common practical challenge in maintenance management. The authors enhance RUL estimation techniques using a similarity-based prognostic algorithm coupled with an RNN autoencoder[46]. This approach effectively captures the temporal patterns in operational data, improving the accuracy of RUL estimates.

Together, these studies provide a comprehensive overview of current innovations in predictive maintenance strategies. They not only highlight the diverse approaches to RUL estimation and prediction but also underscore the importance of integrating these technologies into practical, real-world maintenance operations. This body of work forms a solid foundation for further research and implementation of predictive maintenance in various industrial sectors, aiming to optimize maintenance schedules, reduce operational costs, and enhance system reliability.

3. Methodology

We want to minimize the maintenance cost in a multi components system. With this aim, we have read some related research papers. After reading the research papers we have decided to make a model which will minimize the total production loss cost. Actually, the cost for maintenance is varied by the scheduling system. If the maintenance schedule is optimal then it will be cost effective. We have worked on 2 research papers. One of the papers works with the scheduling of maintenance and another one works on calculating the maintenance cost. We want to extend both of the papers. First, we want to measure the RUL of machines. After that we have proposed a mathematical model which will minimize the production loss cost. Using the RUL and other data we will be able to calculate the total production loss cost from our mathematical model. We have used genetic algorithms along with the proposed mathematical model for calculating the optimal schedule of maintenance. After scheming the machines, we will calculate the total cost of maintenance using various factors which are not considered in other papers. After finishing the total cost calculating equation, we will able to finalize the total cost for our model. We have used NASA CMPAS data to explain the methodology properly. We can do sensitivity analysis for differentiating our results from other methods. The proposed process flow chart is given below.

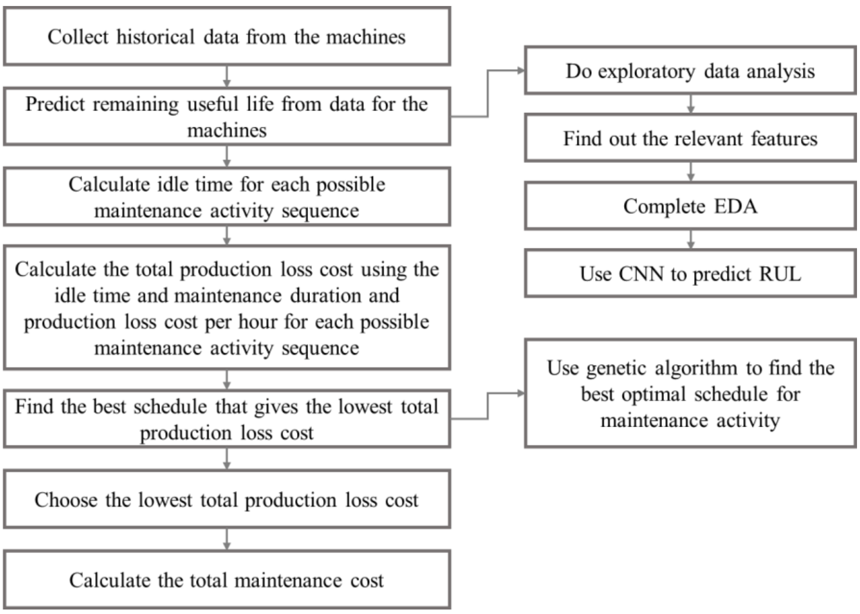


Fig. 1 Methodology Flow Chart

3.1 Mathematical Model Formation

Production loss cost = PLC

Idle time = T

Maintenance duration = MD

Production loss per hour = C

Previous running maintenance task time = t

Remanning useful life = RUL

Here,

The Production Loss Cost, PLC = (Idle time + Maintenance duration) × Production loss per hour;

It can be written as,

PLC = (T+MD) ×C (1)

Idle time will be calculated as,

Idle time, T = max ((Previous running maintenance task time- Remaining useful life),0);

Or, T= max (t - RUL ,0) (2)

Target:

Our target is to minimize PLC (Production Loss Cost)

Required Data:

Remaining useful life (RUL)

Maintenance Duration

Production Loss Per Hour

3.2 Predicting the Remaining Useful Life of Machines

We have managed to find out RUL (Remaining Useful Life) of a machine based on Alarm-based predictive maintenance scheduling for aircraft engines with imperfect Remaining Useful Life prognostics [1].

We are using CMAPSS Jet Engine Simulated Data [2] as a sample to test our model.

This study used CNN Model to find out the Remaining Useful Life. We are testing other models to find out which model gives us the best result with less error.

3.3 Calculation of Remaining Useful Life

We used machine learning algorithms to calculate the Remaining useful life of a Machine. The training data set was collected from CMAPSS Jet Engine Simulated Data [2].

First, we imported the data into kaggle.com then the data was organized for more efficient use.

```
df = pd.read_csv('/kaggle/input/rultrained/RUL_Train_001.csv')
df
```

Fig. 2 Data Imported on Kaggle

	Cycle	OpSet1	OpSet2	OpSet3	SensorMeasure1	SensorMeasure2	SensorMeasure3	SensorMeasure4	SensorMeasure5	SensorMeasure6	...	SensorMeasure13
0	1	-0.0007	-0.0004	100.0	518.67	641.82	1589.70	1400.60	14.62	21.61	...	2388.02
1	2	0.0019	-0.0003	100.0	518.67	642.15	1591.82	1403.14	14.62	21.61	...	2388.07
2	3	-0.0043	0.0003	100.0	518.67	642.35	1587.99	1404.20	14.62	21.61	...	2388.03
3	4	0.0007	0.0000	100.0	518.67	642.35	1582.79	1401.87	14.62	21.61	...	2388.08
4	5	-0.0019	-0.0002	100.0	518.67	642.37	1582.85	1406.22	14.62	21.61	...	2388.04
...	...	...	...	...	...	...	...	...	...	...	...	...
20626	196	-0.0004	-0.0003	100.0	518.67	643.49	1597.98	1428.63	14.62	21.61	...	2388.26
20627	197	-0.0016	-0.0005	100.0	518.67	643.54	1604.50	1433.58	14.62	21.61	...	2388.22
20628	198	0.0004	0.0000	100.0	518.67	643.42	1602.46	1428.18	14.62	21.61	...	2388.24
20629	199	-0.0011	0.0003	100.0	518.67	643.23	1605.26	1426.53	14.62	21.61	...	2388.23
20630	200	-0.0032	-0.0005	100.0	518.67	643.85	1600.38	1432.14	14.62	21.61	...	2388.26

Fig. 3 Imported Data

SensorMeasure15	SensorMeasure16	SensorMeasure17	SensorMeasure18	SensorMeasure19	SensorMeasure20	SensorMeasure21	RUL
8.4195	0.03	392	2388	100.0	39.06	23.4190	191
8.4318	0.03	392	2388	100.0	39.00	23.4236	190
8.4178	0.03	390	2388	100.0	38.95	23.3442	189
8.3682	0.03	392	2388	100.0	38.88	23.3739	188
8.4294	0.03	393	2388	100.0	38.90	23.4044	187
...	...	...	...	...	...	...	...
8.4956	0.03	397	2388	100.0	38.49	22.9735	4
8.5139	0.03	395	2388	100.0	38.30	23.1594	3
8.5646	0.03	398	2388	100.0	38.44	22.9333	2
8.5389	0.03	395	2388	100.0	38.29	23.0640	1
8.5036	0.03	396	2388	100.0	38.37	23.0522	0

Fig. 4 Imported Data (Continued)

Here we can see that there is Cycle time different sensors and finally at the end of the table there is a column of RUL which indicates the Remaining Useful Life of the machine after that cycle. After importing the data, it is time to find out the relevant features. We used a threshold of 0.5 to find the correlation matrix.

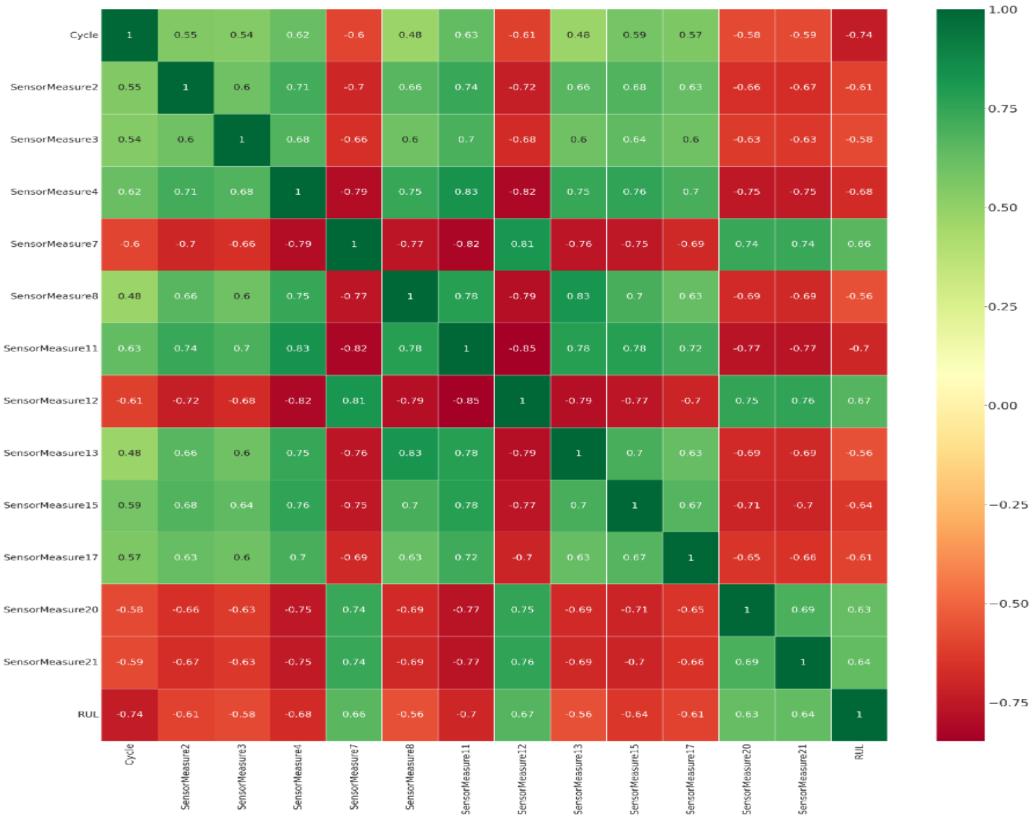


Fig. 2 Correlation Matrix to identify the relevant features

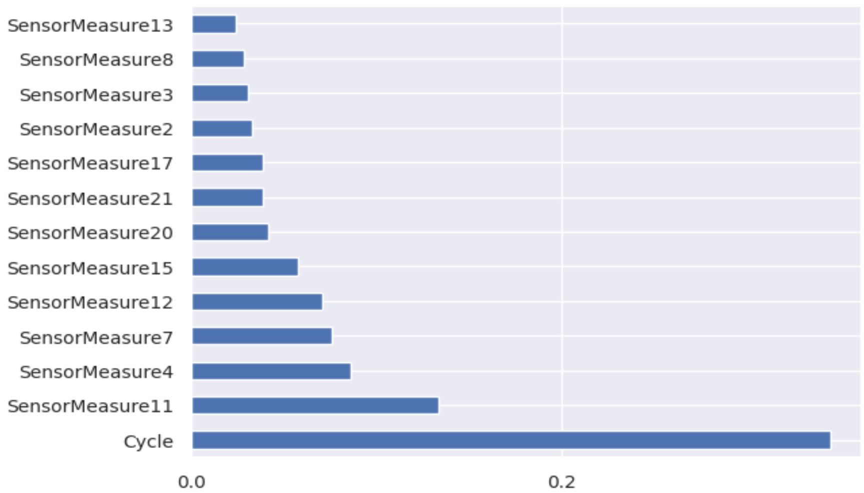


Fig. 3 Feature Importance Matrix

After that we used CNN to find out the RUL same used in our base paper.

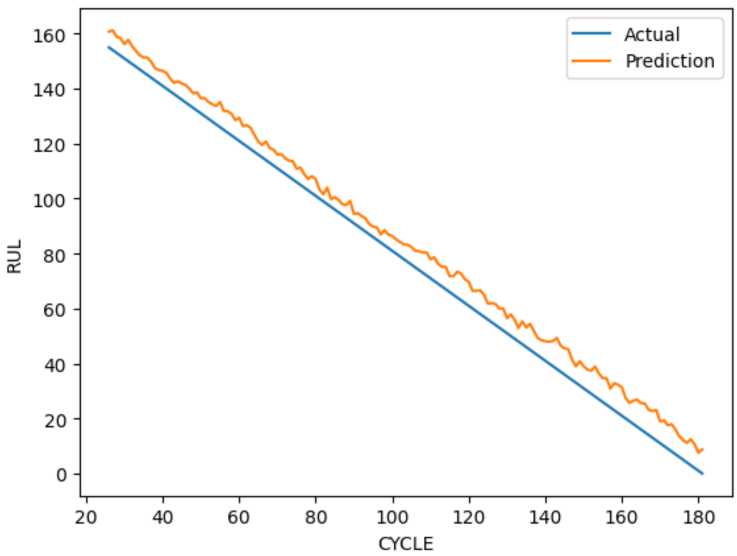
We had four data subsets FD001, FD002, FD003, FD004. We found the RMSE for each of the data subsets. We evaluated the RMSE by using the following equation (3).

$$\text{RMSE} = \sqrt{\left(\frac{1}{n}\sum_{w=1}^{n} {e_w}^2\right)} \quad (3)$$

Table 2. RMSE comparison between Our approach vs Base paper approach

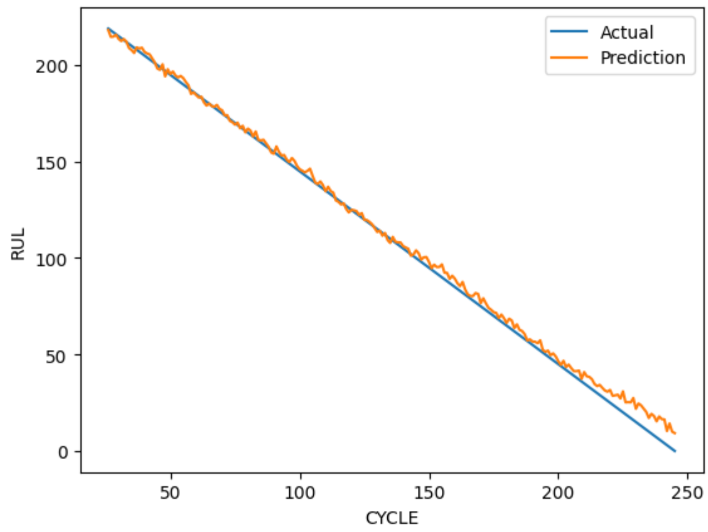
CNN Result Comparison	FD001 RMSE	FD002 RMSE	FD003 RMSE	FD004 RMSE
Our Analysis Result	8.40%	3.86%	13.80%	5.28%
Base Paper Analysis Result	12.62%	22.36%	12.64%	23.31%

Table 2 shows the RMSE for each of the 4 test data subsets of C-MAPSS.



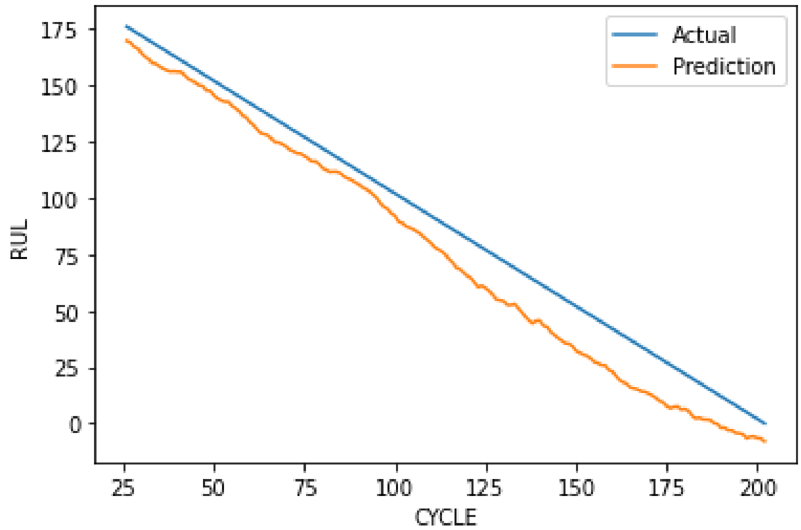
RMSE: 8.40%

Data Set: FD001



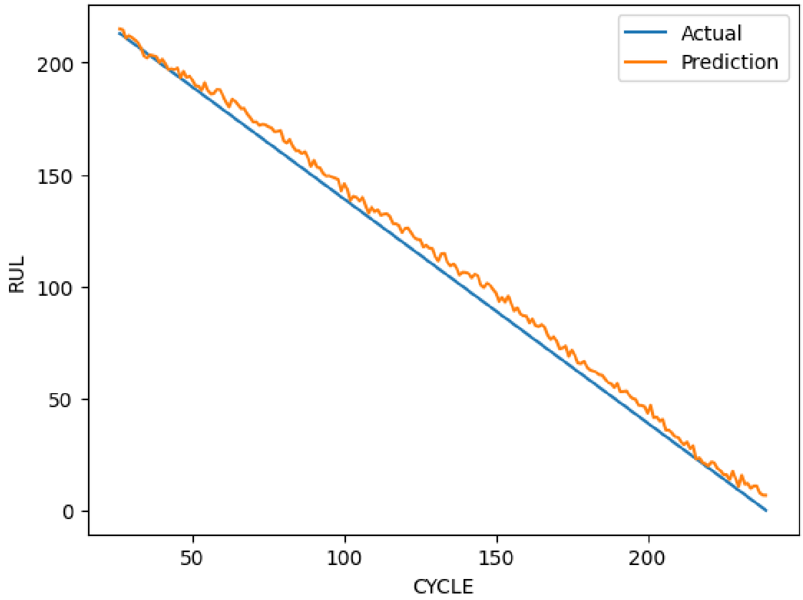
RMSE 3.86%

Data Set: FD002



RMSE 13.80%

Data Set: FD003



RMSE 5.28%

Data Set: FD004

From the above discussion we can say that we have found a significant lower error rate using CNN method. By using CNN model, we will be able to find the RUL for our data.

3.4 Scheduling by Genetic Algorithm

In our study, we utilized a genetic algorithm to identify the most optimized sequence that minimizes total production loss cost, as outlined in our proposed mathematical model detailed in Appendix A. This model serves as the foundation for the genetic algorithm's operation. By applying this advanced computational technique, we systematically explored various sequences, enabling us to determine the one that leads to the least production loss cost. This approach ensures a comprehensive search within the solution space, leveraging the genetic algorithm's strengths in optimization and its ability to handle complex, multi-variable problems. Consequently, the resulting sequence from our model significantly reduces production inefficiencies, demonstrating the efficacy of our proposed method. This section details the application and outcomes of the genetic algorithm, providing a robust framework for minimizing production loss and enhancing overall system efficiency.

3.5 Total Cost Calculation

To determine the total maintenance cost for each machine, the Production Loss Cost, Maintenance Cost, and Setup Cost are aggregated. This comprehensive approach ensures that all relevant factors influencing maintenance expenses are accounted for, facilitating a more accurate assessment of the overall cost implications of maintenance activities.

Let:

- PLC represent the Total Production Loss Cost.
- MC represent the Maintenance Cost.

- SC represent the Setup Cost.
- TC represent the Total Cost.

The total maintenance cost (TC) for each machine can be expressed as the sum of the Production Loss Cost, Maintenance Cost, and Setup Cost:

$$TC=PLC+MC+SC \tag{4}$$

This model allows for the comprehensive evaluation of maintenance expenses, considering both the direct costs associated with maintenance tasks (Maintenance Cost and Setup Cost) as well as the indirect costs resulting from downtime or reduced productivity (Total Production Loss Cost). By aggregating these components, a more accurate assessment of the overall maintenance cost can be obtained.

4. Case Study

This case study explores the efficacy of a novel maintenance scheduling approach that prioritizes total cost considerations over RUL-based strategies. By comparing this innovative approach with a traditional RUL-centric model, we aim to evaluate its effectiveness in achieving cost savings and operational improvements. Through rigorous analysis and comparison of these two methodologies, this study seeks to provide valuable insights into the optimal maintenance scheduling practices for modern industrial systems.

4.1 Design of the Case Study

The design of a case study serves as a pivotal step in comprehending and resolving complex problems while aiming for accurate results. In this particular case study, our primary objective was to conduct a comparative analysis of costs between our proposed maintenance scheduling model and the model utilized in a previous study [5]. To facilitate this analysis, we leveraged the NASA Turbofan Jet engine dataset, comprising data from 100 turbofan engines, amalgamated from FD001, FD002, FD003, and FD004. As outlined in our methodology, we partitioned the dataset into 80% training data and 20% testing data, employing Convolutional Neural Networks (CNN) to derive Remaining Useful Life (RUL) prognostics, a process consistent with the previous research approach.

For our study, we sampled 10 engines from the dataset, each exhibiting an average lifespan of 204 cycles, with a minimum of 110 cycles and a maximum of 430 cycles. Figure 6.1 illustrates the two contrasting approaches utilized in our study and the base paper [4]. In our approach, we initiated by computing the production loss cost utilizing RUL and our proposed mathematical model. This production loss cost calculation was pivotal in gauging the impact of maintenance scheduling decisions on overall production efficiency.

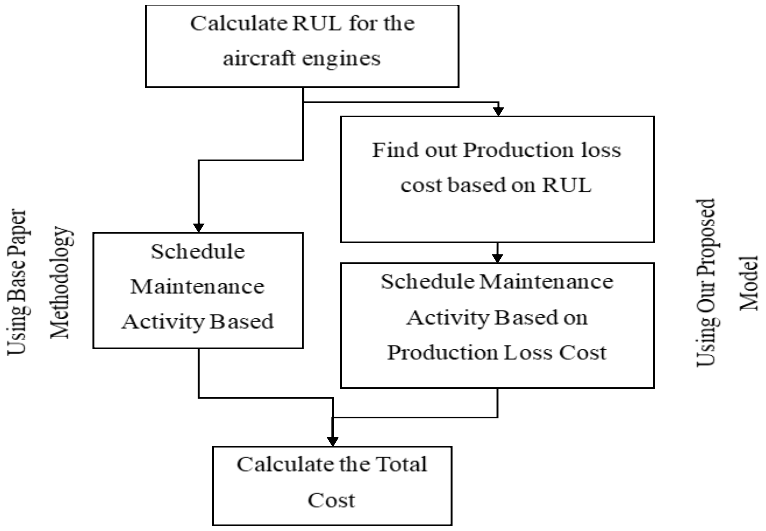
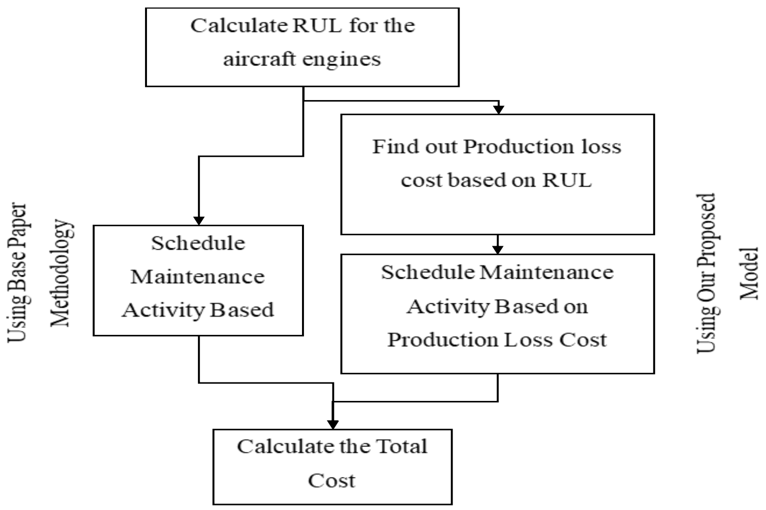


Fig. 7 Process of the case study

Subsequently, employing a genetic algorithm, we determined the optimal sequence for maintenance activities, aiming to minimize the total production loss cost. Conversely, in the base paper's methodology, maintenance scheduling was predicated on the remaining useful life of each machine, prioritizing the repair of machines with imminent failures. Post-scheduling, the total cost was computed to evaluate the efficacy of the maintenance strategy.

Following the computation of total costs using both approaches, a comparative analysis was conducted to discern the strengths and weaknesses of each model. By scrutinizing the cost differentials and performance outcomes, we sought to ascertain the superior model for designing maintenance scheduling protocols. This comparative analysis is instrumental in informing future maintenance strategies and optimizing operational efficiency in industrial settings.



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4.2 Data Analysis and Result Formulation

Following is the randomly sampled data described in section 6.2. Table 6.1 shows RUL, Maintenance Duration and Production Loss Cost is given for each engine and the engines are selected randomly.

Table 3 RMSE comparison between Our approach vs Base paper approach [46]

SL	Engine No	RUL (Days)	Maintenance Duration (Days)	Production Loss Cost (Days)
0	1	36	2.6	4016
1	2	30	3.8	3818
2	10	25	3.3	3485
3	11	42	2.9	3375
4	13	28	3.3	3416
5	14	14	2.4	3075
6	16	2	2.4	4010
7	17	10	3.6	4107
8	18	24	2.5	4173
9	26	38	2.8	4077

After sampling the data, the next task is to schedule using the RUL as instructed in the base paper[47] The following table is sequenced based on the RUL.

Table 4 Scheduling based on RUL as the base paper[48]

SL	Engine No	RUL (Days)	Maintenance Duration (Days)	Production Loss Cost (USD)
4	13	0	3.3	3416
6	16	2	2.4	4010
7	17	10	3.6	4107
5	14	14	2.4	3075
8	18	24	2.5	4173
2	10	25	3.3	3485
1	2	30	3.8	3818
0	1	36	2.6	4016
9	26	38	2.8	4077
3	11	42	2.9	3375

Now after scheduling is done the total cost is calculated. The following table shows the total cost of maintaining these 10 engines using the base paper model.

Table 5 Cost Calculation using Base Paper Model

SL	Engine No	RUL (Days)	Maintenance Duration (Days)	Production Loss Cost (Days)	Idle Time (Days)	Production Loss Cost (USD)	Maintenance Duration (USD)	Setup Cost (USD)	Total Cost (USD)
4	13	0	3.3	3416	3.3	11272.8	1076028	29011	1,116,311.80
6	16	2	2.4	4010	3.7	14837	803602	79724	898,163.00
7	17	10	3.6	4107	3.6	14785.2	949688	24834	989,307.20
5	14	14	2.4	3075	2.4	7380	1197649	100385	1,305,414.00
8	18	24	2.5	4173	2.5	10432.5	855025	77240	942,697.50
2	10	25	3.3	3485	3.3	11500.5	937157	110357	1,059,014.50
1	2	30	3.8	3818	3.8	14508.4	804455	57003	875,966.40
0	1	36	2.6	4016	2.6	10441.6	1067847	46175	1,124,463.60
9	26	38	2.8	4077	2.8	11415.6	769771	23492	804,678.60
3	11	42	2.9	3375	2.9	9787.5	848394	20170	878,351.50
			Total Production Loss Cost			**160498.4**	**Total Cost**		**10,038,505.40**

In Table 5 we can see the total cost is 10,038,505.40 US Dollars[48]

Now we are going to compare this with our proposed model to understand if our proposed model better than the base paper model.

Table 6 Maintenance Scheduling based on our proposed model [48]

SL	Engine No	RUL (Days)	Maintenance Duration (Days)	Production Loss Cost (USD)	Maintenance Duration (USD)	Setup Cost (USD)	Total Cost (USD)
4	13	0	3.3	11272.8	1076028	29011	1116312
6	16	2	2.4	14837	803602	79724	898163
0	1	36	2.6	10441.6	1067847	46175	1124464
7	17	10	3.6	14785.2	949688	24834	989307
5	14	14	2.4	7380	1197649	100385	1305414
1	2	30	3.8	14508.4	804455	57003	875966
8	18	24	2.5	10432.5	855025	77240	942698
2	10	25	3.3	11500.5	937157	110357	1059015
3	11	42	2.9	9787.5	848394	20170	878352
9	26	38	2.8	11415.6	769771	23492	804679
		Total Production Loss Cost		**116361.1**	**Total Cost**		**9994368**

From Table 6 we can see that the total cost is 9994368.1 US Dollars[47] which is significantly lower than the cost found on the base paper. First RUL is calculated and after that Production loss cost is calculated and based on the production loss cost the maintenance activity is scheduled and finally the total cost is calculated.

5. Result & Discussion

Our research implemented a cost-centric approach to optimize maintenance activities in a multi-component system, focusing on minimizing expenses. By forecasting the Remaining Useful Life (RUL) of system components, we calculated production loss costs for various maintenance sequences. Using genetic algorithms, we identified the optimal maintenance schedule, integrating predictive analytics and optimization techniques. Exploratory data analysis helped refine our model, leading to a robust maintenance strategy.

Our case study demonstrated significant cost savings with our approach, achieving a total cost of 9,994,368.1 USD compared to the base paper model's 10,038,505.40 USD, and a notable 28% reduction in production loss costs from 160,498.40 USD to 116,361.1 USD. This prioritization based on cost implications, rather than RUL, proved effective in better cost management and substantial expense reduction. Our model optimized maintenance duration, minimized production loss costs, improved resource utilization, reduced downtime, and enhanced operational performance.

Our study demonstrates the effectiveness of a cost-centric approach in optimizing maintenance for multi-component systems. By prioritizing tasks based on cost implications instead of solely the Remaining Useful Life (RUL) of components, we achieved significant cost savings and operational efficiency. A key finding was a 28% reduction in production loss costs, underscoring the benefits of a comprehensive cost-based maintenance strategy.

Integrating predictive analytics with optimization techniques, specifically genetic algorithms, allowed us to forecast component failures and determine optimal maintenance schedules. This approach enhanced resource utilization and reduced downtime. Insights from exploratory data analysis refined our model, making it more suited to the system's specific characteristics.

Overall, our research highlights that prioritizing maintenance tasks based on cost, combined with predictive analytics and optimization, can significantly reduce expenses and improve operational performance, offering valuable strategies for industries aiming to enhance cost management and maintenance efficiency.

6. Conclusion

Our research highlights the critical role of cost optimization in maintenance scheduling for multi-component systems. By integrating predictive analytics and optimization techniques, we demonstrated that prioritizing maintenance tasks based on cost implications, rather than traditional metrics like Remaining Useful Life (RUL), leads to significant cost savings and enhanced operational efficiency.

Our case study showed a notable cost reduction, with our optimized maintenance strategy totaling 9,994,368.1 USD, compared to the base paper's 10,038,505.40 USD, representing a 28% savings in production loss costs. This reduction underscores the effectiveness of considering maintenance duration in cost optimization, leading to improved resource utilization and minimized downtime.

The study underscores the importance of a cost-centric approach in maintenance scheduling, offering valuable insights for better cost management and operational performance. These findings provide practical implications for industries aiming to optimize maintenance activities and achieve substantial cost savings.

Future directions for enhancing our maintenance scheduling model include incorporating additional cost factors like energy, labor, and materials for comprehensive cost optimization. Developing a multi-machine maintenance system and integrating strategies for semi-broken machines could enhance efficiency and reduce downtime. Implementing advanced task grouping techniques can optimize resource allocation and improve technician productivity. These avenues aim to further refine maintenance optimization, enhancing operational efficiency and cost-effectiveness in industrial settings.

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