Enhancing Unplanned Maintenance Priorities Using Artificial Neural Networks: Case Study From Oman Oil & Gas Industry

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Abstract

The energy sector is an exciting area of research and study due to the global demand for oil and gas, improving and optimizing related costs and risks, essentially maximizing the business output. Unplanned corrective maintenance can lead to unscheduled downtime if not attended effectively and efficiently. Maintenance can restore system healthiness and avoid catastrophic failures. This paper explores the prioritization of unplanned work orders (WO) for corrective maintenance using an Artificial Neural Network. A case study from Oil and Gas in Oman was investigated to check the actual practice. The paper proposes a new approach to prioritize unplanned maintenance work orders, considering a classification of three correlated features: failure severity, asset criticality, and reliability. The proposed method shows the needs of such correlated of these features. The Artificial Neural Network-based multi-layer perceptrons method is applied; 82.7% of work orders being tested from the case study shows the low probability of less than 50% on initial priority. The investigation reveals the effectiveness of the suggested method to be applied to get more priority insights. We recommend industrial practitioners to use the approach that supports prioritization of recourses and scheduling activities better, saving cost and avoiding system functional failures.

Keywords
Failures, Reliability, Neural Networks, Prioritization, Unplanned Maintenance

1.Introduction

The energy sector is an interesting area of research and study due to the world's demand for oil and gas. Improving and optimizing related costs & risks are essential to maximizing the business output. Physical asset failures are a concern in the Oil & Gas industry. So, many techniques are used today to prevent and predict failures to avoid operation interruption and the risk & cost consequences. The goals of maintenance operations include improving system availability and reliability, reducing unplanned downtime and frequency of failures, and incrementing system operating efficiency (Li and Ni, 2009). Therefore, asset maintenance strategies are essential to avoid functional failure on a system, so understanding failure modes and preventing or predicting failures support avoiding functional system failures. Condition-based maintenance has allowed us to detect partial and potential failures to avoid unplanned downtime by forcing corrective maintenance. However, attend the partial and potential failures is one of the costs associated with keeping operating safely and profitably, where maintenance directly encourages production performance systems (Li and Ni, 2009). Effective and efficient maintenance could support the productivity and profitability of a manufacturing process (Maletič et al., 2014). Maintenance can restore system healthiness and avoid catastrophic failures. Some of the restoration time sometimes becomes longer due to the resource's availability, which increases the chance of a trip due to the potential or partial failure. So, an effective prioritization policy can efficiently utilize the resources and minimize system operation costs by reducing the downtime and frequency of failures while improving the system production (Li and Ni, 2009). Artificial intelligence with big data available today can support being faster and more efficient to keep system reliability high, avoiding total failure by proper actions taken to prevent such function failures from occurring. Razali et al. (2021) has studied the big data analytics concept in predictive maintenance and showed a significant need for big data analytics application for maintenance management.

Both planned and unplanned maintenance is aimed to extend the asset life cycle for more benefit. But unplanned maintenance activities are causing disturbance to planned activities in terms of resources, leading to waiving preventive maintenance tasks. In addition, unplanned maintenance activities must be adequately attended since they may cause catastrophic incidents. Therefore, adequate and efficient planning and scheduling by prioritizing this unplanned maintenance can support higher asset reliability and save costs by avoiding unnecessary urgency. Setting the priorities becomes a concern, and getting a quality WO priority is essential for a planner. In many practices in the field, based on people's experience and severity, a risk assessment conducting to calculate the priority, so based on people understanding of the system functionality, the priority is set up. As a process safety practice, leak prevention, oil spills, equipment monitoring, overpressure, excess temperature, corrosion, metal fatigue, and other similar conditions, which operations are related to productivity and risk management, so it is essential to monitor the process in-depth (Amalia and& Sommeng, 2020). MHM, et al. (2021) used a model of failures raking and sorting in gas compression plants based on total downtime importance grouping by using the risk priority number (RPN), where prioritized associated risk. On the other hand, developing the capability to link failures and maintenance data incidents is critical to allow a deeper understanding of common factors amongst maintenance-related incidents and potential controls to reduce harm to maintainers (Dempsey et al., 2014).

Maintenance task prioritization is critical and essential for short-term analysis to reduce unnecessary or improper maintenance activities, mainly when maintenance resources are limited (Li and Ni, 2009). The existing methods for maintenance priority are often through heuristic methods or experience, which can cause unplanned downtime and production losses (Li and Ni, 2009). Moradi and Shadrokh (2019) worked on a case study using a heuristic algorithm as a priority rule for choosing activities in the schedule for a system. Li and Ni (2009) studied a short-term decision support system for maintenance task prioritization based on the system operating conditions. Yang et al. (2007) learned maintenance priority in general by presenting a metric for quantitatively measuring the different maintenance priorities effects; then, a search algorithm obtained maintenance work-order priorities. Their results effectively utilize real-time production data in maintenance scheduling, leading to a production benefit. On the other hand, Alabdulkarim et al. (2014) studied a discrete event simulation model to support maintenance operations decision-makers in selecting the appropriate asset monitoring level for operations. Their unique approach provided numerical evidence proving that a higher asset monitoring level does not always give higher asset availability.

Zangenehmadar et al. (2020) presented in their work a near-optimized budget model that supports scheduling plans for maintenance; their optimization procedure results in a solution alternative that decision-makers could use for their operational requirements. Regarding resources, a personnel scheduling problem is studied by Özder et al. (2020), which focused on fair and balanced job distribution according to the personnel qualifications analyzed using an Artificial Neural Network (ANN). Turan et al. (2020) modeled a maintenance system where repairable is kept on inventory to serve assets to prevent downtime and increase availability. They take optimal values of the repairable spare parts stocks and workforce capacity. They concurrently explore the best maintenance scheduling rule that reduces inventory holding and backorder costs related to the asset's downtime. Jagtap et al. (2020) suggested that critical subsystems are on higher priority from a maintenance perspective, so they developed optimized system availability parameters using the particle swarm optimization method.

The issue of multiclass and imbalanced class outputs is addressed by Buabeng et al. (2021) to improve predictive maintenance; hence a multiclass fault classifier based on clustering and optimized multi-layer perceptron was proposed. The energy industry is moving forward to use advanced technology related to Maintenance 4.0, and digital transformation is one area where industrial practitioners invest in to be efficient and more effective. Technological advancements are reshaping the industry toward digitalized manufacturing regardless of the importance of top-class maintenance (Lundgren et al., 2021). Big data analytics using neural network methods is part of this digital transformation, supporting traditional maintenance development.

This paper investigates a real case study and suggests approach to prioritize better unplanned WOs based on three factors using an artificial neural networks (ANN) technique to support practitioners to better plan and avoid catastrophic failures and reduce cost. The ANN is based on multi-layer perceptrons (MLP). This paper consists of three more sections alongside this introduction. The following section explains the methodology used in the research, including case study investigation and selected ANN algorithm. Section 3 shows the results and discussion of the case study. The last section concludes the study with main recommendations and future research directions.

2. Methodology

The research explored a case study, starting with obtaining a dataset from a real case to analyze the nature of unplanned corrective maintenance priorities and record the observations for other analytics, and understand the practice and affected factors at the level of implantations. The observations are used to develop the proposed approach to set up WOs priorities. A set of classifications has been identified based on three factors/features (asset reliability, asset criticality, & failure severity) to estimate WO probability to being in a classified priority.
The following steps have been applied in the study:

1. Identify features (reliability, criticality & failure severity) from a historical selected dataset
2. Preprocessing includes data cleaning and completion
3. Identify the classification problem and the goal of the output as a prediction of WO priority
4. Identify target output with quantification as a value from 0 to 1
5. Prepare algorithm of the multi-layer neural networks using TensorFlow and Keras, where the transform relation between the input and output.
6. Encoding process carried out for the binarization of the features.
7. Use Rectified Linear Unit (ReLU) as an activation function.
8. Map the production of multiple neurons into probability in a network classifier, Adam is used.
9. Measure model precision or accuracy in the training process using cross-entropy loss
10. Use probability value to prioritize and suggest new priority for each WO
11. Compare random WO's priorities between original and proposed priority to verify the proposed approach.

The nature of priorities in the case study is presented in Table 1. The explored dataset used in the study contains 1567 corrective maintenance WOs for one Year in one plant. We have considered only the re-prioritization of priority levels 2 to 7, excluding priority 1 for emergency jobs (within one day) due to the nature of the job. The three features considered in this study are the input layer for MLP and are shown in Table 2. As per the asset classifications, asset criticality is essential in process safety and production with high criticality (1) and low criticality (3). The equipment criticality plays a vital role in maintenance, and it directs the different maintenance sub-functions towards targeting the top critical equipment (Bouchaala and Noureddine, 2020). Asset reliability is the standard calculated reliability considered a constant failure rate for the asset belongs the WO. The failure severity is either functional failure (0) or potential.

However, we have designed 18 classes (3x3x2) matrix, with six target outputs of priorities. For series systems, in most cases, higher maintenance priority should be given to unreliable components (Lin and Pozzi 2021). Also, an optimal maintenance priority decision model was developed by Roh et al. (2021), where the frequency of failures is used. The severity of functional failure is also considered. Table 3 shows the 18 classes with desired output priority.

Table 1: WO Priority Ranking

PRIORITY RANKING	DESCRIPTION (TIME TO BE DONE)
1	Emergency - 1 Day
2	Urgent - 1 Week
3	Priority 3 – 2 Weeks
4	Priority 4 – 4 Weeks
5	Priority 5 - 8 Weeks
6	Priority 6 - 6 Months
7	Priority 7 - 1 Year

Table 2: The Three Features Classes

ASSET CRITICALITY	1	2	3
ASSET RELIABILITY	Low <70%	Medium 70-90%	High >90%
FAILURE SEVERITY	Functional (0)	Potential (1)	

Table 3: WO Priority Classes

CLASS	ASSET CRITICALITY	ASSET RELIABILITY	FAILURE SEVERITY	WO PRIORITY
1	1	Low <70%	F (Functional)	2
2	1	Low <70%	P (Potential)	2
3	1	Medium 70-90%	F	2
4	1	Medium 70-90%	P	3
5	1	High >90%	F	2
6	1	High >90%	P	3
7	2	Low <70%	F	2
8	2	Low <70%	P	3
9	2	Medium 70-90%	F	2
10	2	Medium 70-90%	P	4
11	2	High >90%	F	3
12	2	High >90%	P	4
13	3	Low <70%	F	3
14	3	Low <70%	P	5
15	3	Medium 70-90%	F	4
16	3	Medium 70-90%	P	6
17	3	High >90%	F	5
18	3	High >90%	P	7

The following Figure 1 shows a summary of the algorithm being used to test the classifications.

```
Start
    > Read csv Dataset
    >In the original dataset "Priority" indicates the target
    >Dataset segregation 10/20/70 for training, testing and validation
    > Numeric features
    > Select columns to use and encode features
    > Train, batch
    > Validate batch
    > Test batch
    > Keras layer, activation functions and optimizer
    > Loss and accuracy measure
    > Graph model layers
    > Model Fit and loss, accuracy Measure
    > Saving model
End

Start
    > Reloaded model
    > Loading Real dataset with features
    > Loop reading input & results
    > Writing Results to csv file
End
```

Figure 1: ANN Algorithm

3. Results and Discussion

3.1 Real Case Observations

The corrective maintenance WOs in the case study have been studied and investigated to understand the observations. The priorities of WOs in the case study were set up by operation when they observed a failure at the plant from different condition-based techniques. The user uses Computerized Maintenance Management System (CMMS) to raise a maintenance notification with a priority ranking based on a risk assessment. The approval process was then converted to a WO for further processing and planning/scheduling. The maintenance people received their tasks weekly after scheduling to attend the job.

The data shows that the relationship between work orders priority and the three features (asset criticality, failure severity, and asset reliability) are random and not classified, as shown in Figure 2. For example, WO no.23 with priority 5 has functional failure severity, with asset criticality 5 and reliability of 100%, but WO no.37 with priority 2 has functional failure severity, with asset criticality 3 and reliability of 100%. Therefore, the priority ranking does not consider the three features, but the user-raising, job experience, and self-ranking are used. This observation led to further investigation, with the actual job attended (in days) and closure of the WO, confirming that scheduling and priority are not homogeneous in real. Figure 3 presents the actual WO ages in days and the priority. WO no. 55 has a priority of 3, but the job started and was done within more than 100 days when supposed to be done within two weeks considering uncontrolled measure for sure. In Figure 4, real case WOs priorities (4, 5 & 7) show different ages in days considering the starting day of the activities are not according to the priorities.

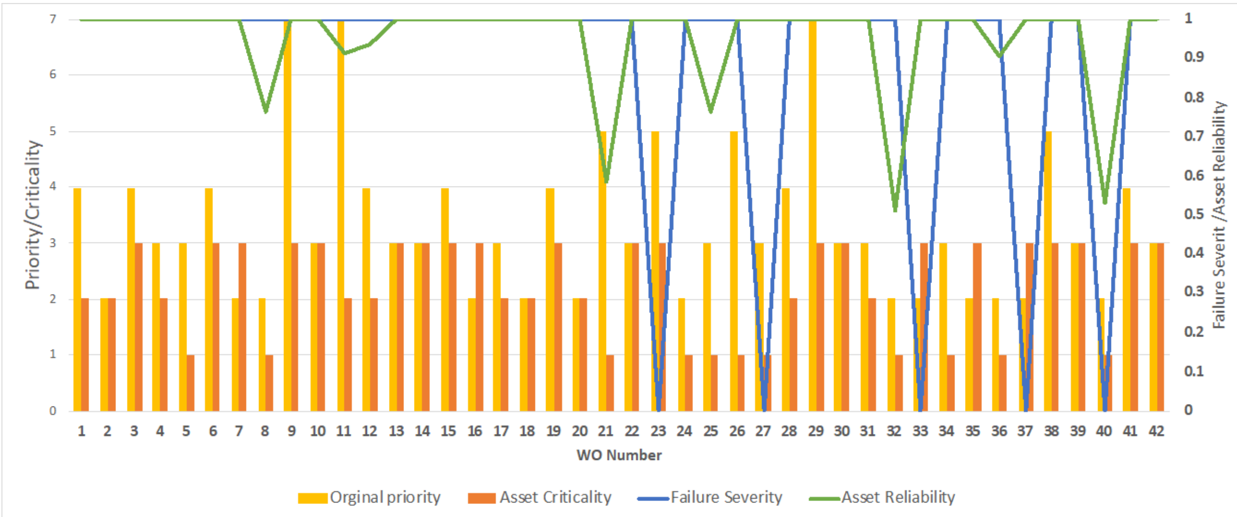

Figure 2: Real Case WO Priorities with Features

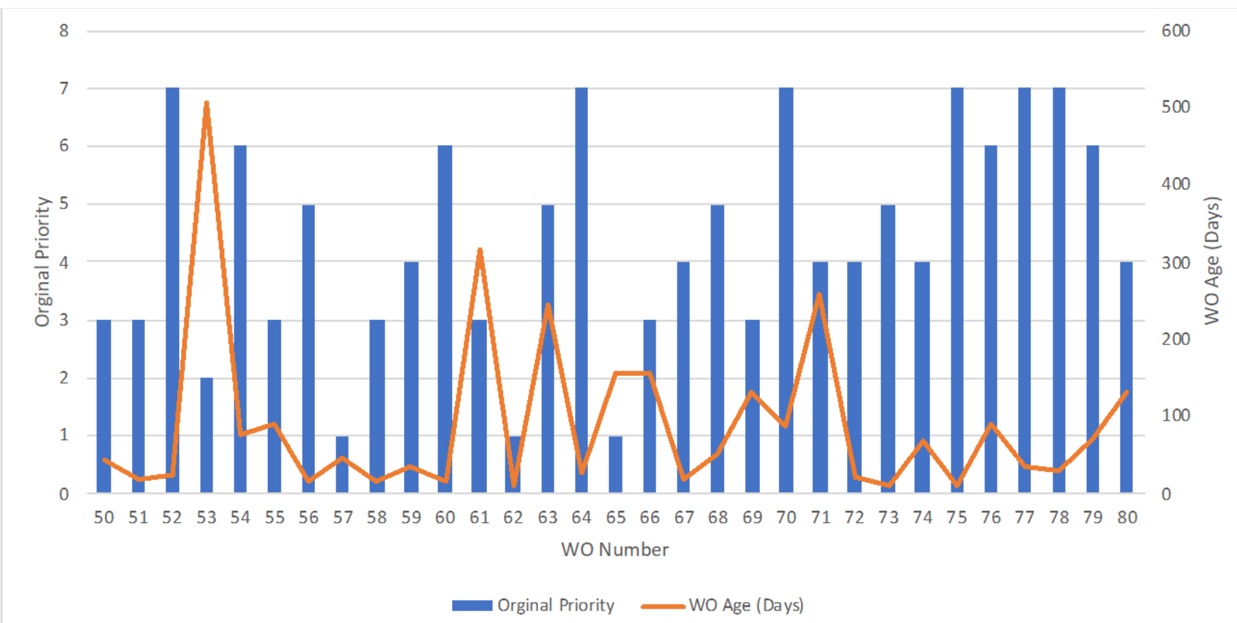

Figure 3: Real Case WOs Priorities with Actual Age in Days

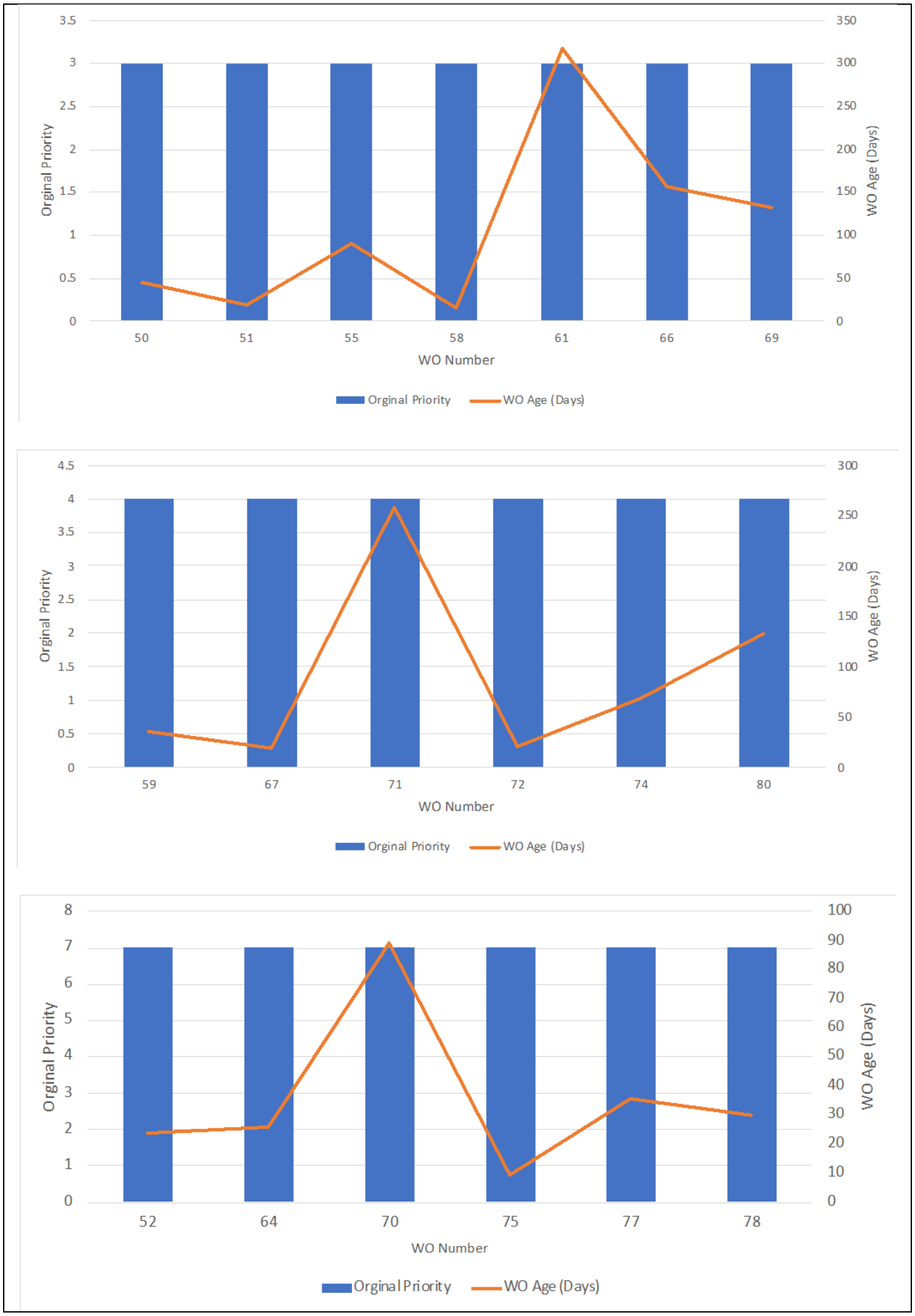

Figure 4: Real Case WOs Priorities (4, 5 & 7) with Actual Age in Days

3.2 The Classification Results using ANN

We applied the same data set to obtain a new priority as per the design classifications. The results show that most of the 1567 WOs, 82.2%, are changed to lower or higher priority, as shown in Table 4. This majority leads the practitioners to look after the practical approach, which is currently not considering the three features under study.

Table 4: WO Priority Change

TOTAL WO	1563	
WO PRIORITY WITH LOW PROBABILITY	1285	82.2%
WO PRIORITY NOT CHANGED_HIGH PROBABILITY	278	17.8%

Figure 5 shows the MLP layers details, where the test applied for all the dataset WOs. The classification algorithm average loss was 0.6222, and accuracy was calculated with 0.8147.

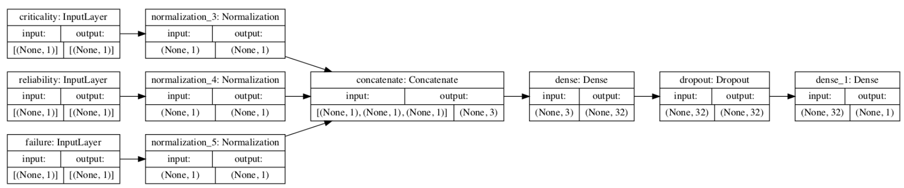

Figure 5: ANN-based MLP Layers

Figure 6 compares sample WOs with a new priority set as per the new approach compared with originals. The new suggested priority by the ANN considers the failure severity, asset criticality, and reliability. Figure 7 presents a sample of WOs that have both priorities compared with the three features.

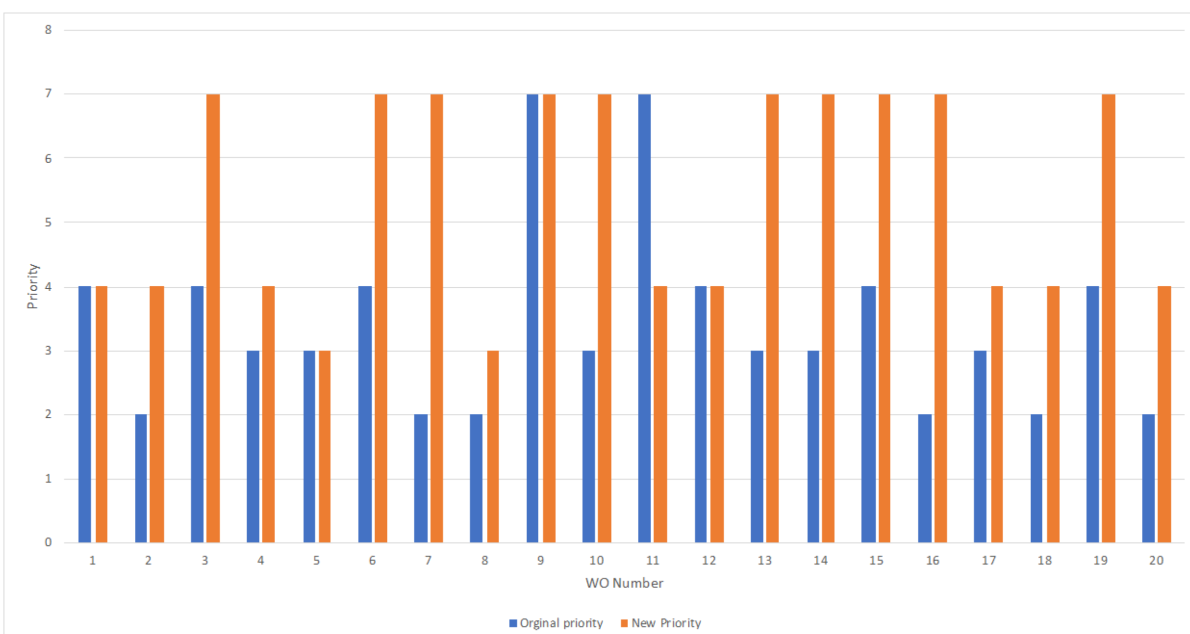

Figure 6: Comparative of Sample WOs With New Set of Priority

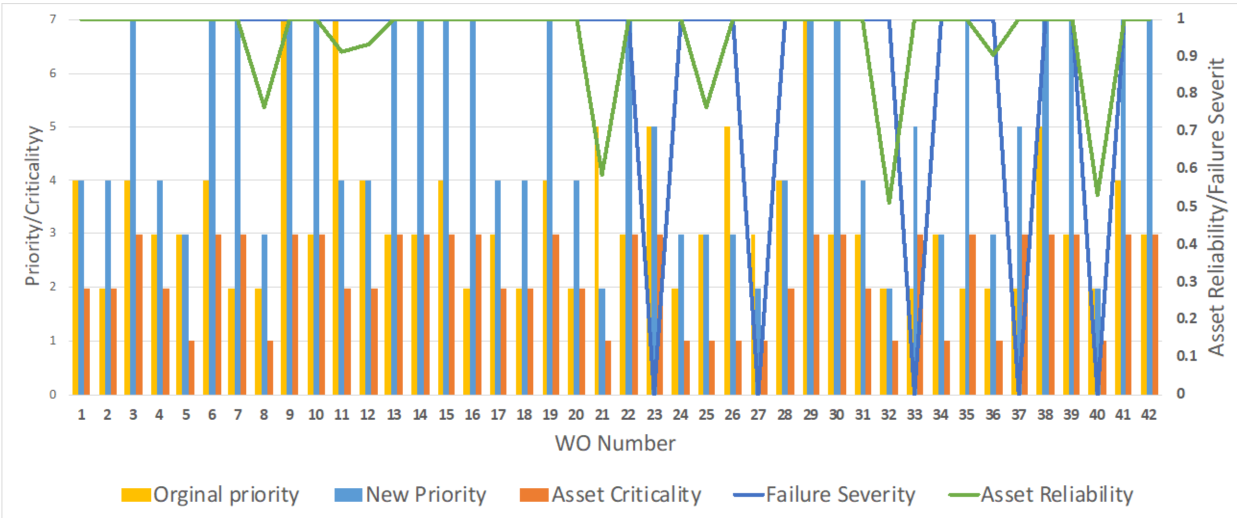

Figure 7: Original and New Priority with Three Features

To validate the results, we have randomly selected some WOs and studied them with the new priorities; Table 5 shows three WOs in detail. The WO with original priority (2, Urgent, one week) was to check and fix a failure on a stack gas flare metering, a lost communication to SCADA, which is not critical and not causing the unsafe condition or impacting production. The actual corrective job was done after 68 days. However, our approach and ANN suggested prioritizing (4, 4 weeks), which is a more accurate priority compared with the attended period. Second, WO with priority (3, 2 weeks) was for gas turbine bearings 2&3 lube oil drain with high alarm temperature, as a potential failure, and the actual job was done within three days. Our approach using ANN suggested a priority (2, 1 week) that reflected real need. The last example is a WO with original priority 7 for a UPS failure, and the job was completed after 41 days due to spare cards not being available. This UPS is critical and should not never be priority 7. Our approach and ANN suggested being a priority (2, 1 week), reflecting more the need to accelerate the asset's return to service.

Table 5: Three Real WO Example Details

ORIGINAL PRIORITY	CLASSIFIED PRIORITY	PROBABILITY	ACTUAL JOB CLOSED AFTER (DAYS)	TYPE OF ASSET	FAILURE
2 (ONE WEEK)	4 (Eight Week)	55.5%	68 days	Meter	Flowmeter Reading is zero at SCADA
3 (TWO WEEK)	2(One Week)	74.8%	3 days	Gas Turbine	drain Temp Hi, BC_AN_RT327 alarm, NG BRG.2&3 drain Temp Hi
7 (ONE YEAR)	2(One Week)	54.6%	41 days	UPS	The charger of UPS-2 does not function due to INCA Card failure

5. Conclusion

The unplanned corrective maintenance due to failures are causing distributing the planned maintenance activities, so prioritizing them in terms of failure severity and related assets criticality & reliability are essential to minimize the impact on system reliability, plant & people safety, and cost. The proposed approach shows the needs of such correlated WOs and the three features. The ANN-based MLP applied with 82.7% of WOs being tested from the case study demonstrates the low probability of users' chosen priority. The use of ANN to support maintenance management can support practitioners apart of digital transformation to be more effective in making decisions.

In conclusion, the investigation research shows the effectiveness of the suggested method. The application of our approach will support getting more insights on the priority of WOs in terms of three tested factors: Asset reliability, criticality, and failure severity. It also prioritizes recourses and scheduling activities better, saving cost and avoiding functional system failures. We recommend industrial practitioners apply the approach. For the future, we advise considering more factors and features to expand the coloration. We also suggest looking after solutions to automate the process in the industry, starting from data digitizing and including ANN in industrial digital platforms. In addition, we are planning to extend the study for proper scheduling, including preventive and predictive maintenance work orders priorities, series system reliability, budget, geographical and logistic features.

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