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Change of Maintenance Strategy for Effective Maintenance

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***Abstract*—This study examines how modification in maintenance strategy affects the efficiency of maintenance. As a case study, DTDC company has been selected for the study. The study compares and evaluates four maintenance strategies; predictive maintenance, condition-based maintenance, preventive maintenance and remedial maintenance. Furthermore, XGBoost, Random Forest and Decision Tree models will be implemented for a training dataset which we have retrieved from open source. ROC graphs of all the models will be compared to each other to find out the most accurate ML model. By analyzing the value of ROC, the best performing Machine Learning model is XGBoost Classifier.**

***Index Terms*— Maintenance, Maintenance strategy, Machine Learning, Preventive Maintenance, Predictive Maintenance.**

I. Introduction

Maintenance has been needed for as long as man has used machines to varying degrees. From being only needed in the event of a breakdown, various maintenance strategies have been developed to prevent breakdowns through preventive maintenance. As technology develops, so do maintenance strategies, and today they use, among other things, Artificial Intelligence (AI) for analysis and to predict breakdowns. Despite this, many companies still use maintenance strategies from the turn of the century. Currently, there are several different strategies that are considered to increase operational reliability through various activities.
DTDC has been active for many years and was for a long time the only private company for letter handling. Since the 1990s, many letters sent to the company have been sorted in sorting machines.
With this as starting point, this study shall investigate whether a change in maintenance strategy for letter sorting machines can increase the efficiency of maintenance for DTDC and to investigate whether Machine Learning (ML) can prove to be a useful tool in predicting wear and tears so that the company can formulate a more comprehensive maintenance strategy. This must be done through a current situation analysis and literature studies which are then compared and suggestions on which maintenance strategies can be applied are then drawn up. Efficiency will be measured from a cost, resource, and availability perspective.
Section II provides maintenance strategies. Section III includes implementation. The results of the work in this research are explained in section IV. Lastly, the conclusion is stated in section V.

II. Maintenance Strategies

A maintenance strategy is defined as the methodology chosen to achieve the maintenance goals. There are

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different ways and approaches to perform maintenance to reach the already set goals. Digitization brings with it a development of maintenance strategies where the computer's role becomes increasingly important. This work has chosen to look at four maintenance strategies that DTDC has set as the most interesting for them [12]. These strategies are also those that Fortum has included in its digitization journey [15] and that are mentioned in [18]. The strategies are predictive maintenance, condition-based maintenance, preventive maintenance and remedial maintenance and are the major development steps for maintenance where each step utilizes new technology or a higher degree of digitization [6].

Figure 1. Maintenance Strategies

A. Predictive Maintenance

Preventive maintenance (PM) is carried out before a breakdown to minimize downtime. It can then be carried out at a scheduled time when the machine is not in operation, in a maintenance window. The maintenance can be scheduled after

- Operating time or number of units produced
- Calendar time

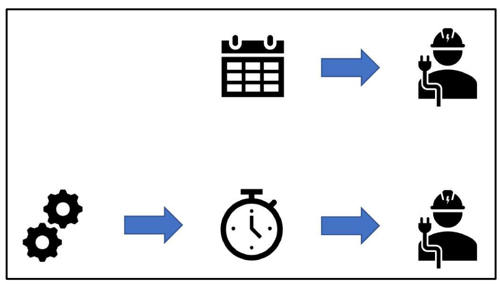

Figure 2: Preventive maintenance. At the top of calendar time, where the calendar controls when a technician is needed, at the bottom of operating time, where the machine's running time is logged and when the time interval is reached, the technician performs maintenance

For operating time/number, this means that maintenance is controlled by how long the machine runs, for example that maintenance is needed every 100 hours that the machine runs or after 10,000 letters.

B. Condition-based Maintenance

Condition-based maintenance (CBM) demonstrates the need for maintenance before it has arisen through measurement or reading and comparison against given control limits [13]. With the increased use of computers, this maintenance strategy has increased in use [1].

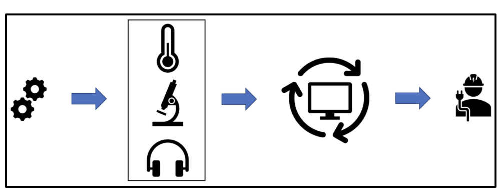

Figure 3: Condition-based maintenance. Sensors and measuring devices collect values from the machine that go to a computer for comparison against control limits. When a control limit is exceeded, information is sent to technicians for action

The strategy involves reading, measuring, or sensing a component and comparing the value against set values in the form of control limits. If the component wears/wears continuously, the interval can be set so that maintenance can be planned before a breakdown of the component without disturbing the operation of the machine. Based on operating statistics, the limits can be set so that they are correct [16]. There are gains in condition checking even on components with a fast failure curve. This is to simplify troubleshooting and prevent any subsequent errors that may occur [11].

C. Preventive Maintenance

Predictive maintenance (PDM) is a strategy that is based on detecting the errors before they occur by collecting data from sensors, production statistics and history, analyzing and predicting the condition of the components. However, a combination of analytics, mathematics and sensors allows machines to be fixed before they fail [2]. It is like condition-based maintenance to the extent that it looks at the current condition, but instead of only matching against a set control limit, values are analyzed and compared with previous values, events, and current operation to be able to warn of future breakdowns. Predictive maintenance answers the questions about what will happen before it happens [8].

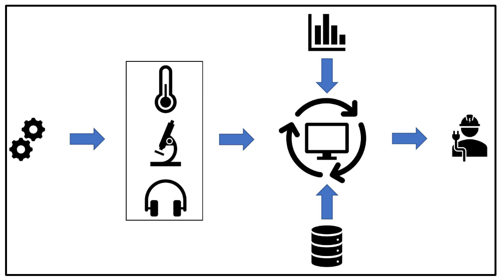

Figure 4: Predictive maintenance. Sensors and measuring instruments collect data from the machine which, together with operating statistics and history, is analyzed and a prediction of maintenance effort is produced

The goal is for accessibility to increase by anticipating all emergency breakdowns and having the opportunity to remedy them before breakdowns occur [2]. A goal of predictive maintenance is to eliminate errors through continuous improvement and to analyze root causes [13].

D. Remedial Maintenance

Remedial or Corrective maintenance (CM) is emergency maintenance that is carried out after a breakdown. It is done only after a breakdown has occurred and therefore stops the use of the machine [16]. This is how maintenance was done at the beginning of industrialization [18] and it is still popular even today [9]. After the breakdown, the machine is examined and diagnosed if the fault can be settled. Spare parts thus need to be in large stock to prevent longer machine downtime [7]. Errors that are not acute but are still discovered can be scheduled for times when production is not using the machine and are called deferred remedial maintenance [14].

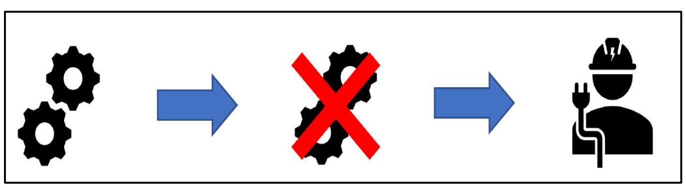

Figure 5: Remedial maintenance. The machine breaks down and a technician is called

Basically, this strategy has very low costs, but they increase with each stop [1]. It also has no initial start-up cost [9]. Weeks can go by without an error, or several errors can occur on the same day. Maintenance costs can skyrocket [3]. Depending on the nature of the error, it can also be difficult to find the source of the error, and without analysis, the root cause can be missed. The spare parts stock must also be large as all kinds of breakdowns must be able to be solved [9].
As it is difficult to prevent all faults on a machine, remedial maintenance is often used as a complement to other strategies for sudden faults [9].

III. Implementation

A. Implementation in ML

1. Dependent and Independent Variables

We describe and offer a synthetic dataset that, to the best of our knowledge and expertise, accurately represents real predictive maintenance data seen in industry. Ten thousand data points are included in the dataset, which is organized into rows with six features per column.

- A product ID that includes a serial number unique to each version and the letters L, M, or H for low (50% of all products), medium (30%), and high (20%) product quality variants.
- Air temperature [K], which was produced by a random walk procedure and then normalized to a 2 K standard deviation at a temperature of about 300 K
- Process temperature [K], which is the air temperature + 10 K plus the result of a random walk process standardized to a 1 K standard deviation.
- rotational speed [rpm] determined with a 2860 W power and a normally distributed noise layer on top of it
- torque [Nm] There are no negative values, and the torque values are generally dispersed about 40 Nm with a σ = 10 Nm.
- tool wear [min], define variations in quality H/M/L increases the employed tool's wear time by 5/3/2 minutes, and a label that reads & "machine failure" denoting if the machine has malfunctioned in this specific datapoint.

XGBoost, Random Forest and Decision Tree models will be implemented for a training dataset which we have retrieved from open source. ROC graphs for binary classification of all the models will be compared to each other to find out the most accurate ML model.

2. XGBoost

For XGBoost , the obtained ROC graph is presented. In the following ROC graph for binary classification, x-axis is taken as false-positive rate, and the y-axis is taken as true positive rate. The obtained value for XGB Classifier is 0.98. The associated training dataset and the code can be seen from GitHub link: https://github.com/pranav-singh-rathore/Maintenance-strategy

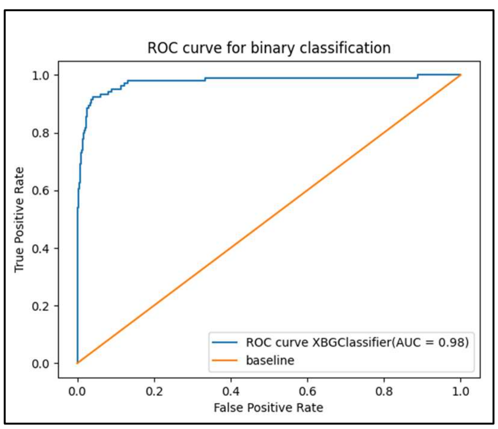

Figure 6: ROC graph for XGBoost

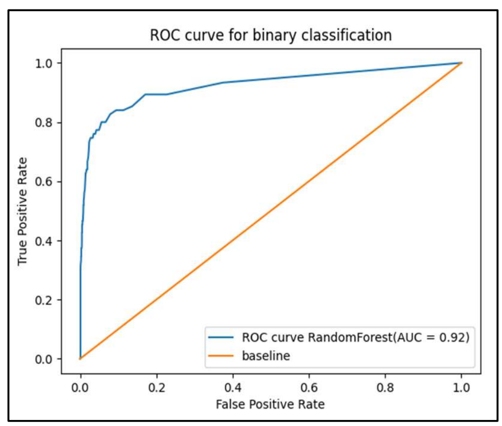

Figure 7: ROC graph for Random Forest

3. Random Forest

For Random Forest , the obtained ROC graph is presented. In the following ROC graph for binary classification, x-axis is taken as false-positive rate, and the y-axis is taken as true positive rate. The obtained value for Random Forest is 0.92.

4. Decision Tree

For Decision Tree , the obtained ROC graph is presented. In the following ROC graph for binary classification, x-axis is taken as false-positive rate, and the y-axis is taken as true positive rate. The obtained value for Random Forest is 0.71.

IV. RESULTS

This paper assesses how the four strategies would affect DTDC in terms of finances, human resources, and machine availability. Comparison is made against the current maintenance strategy in DTDC [17]. At the end,

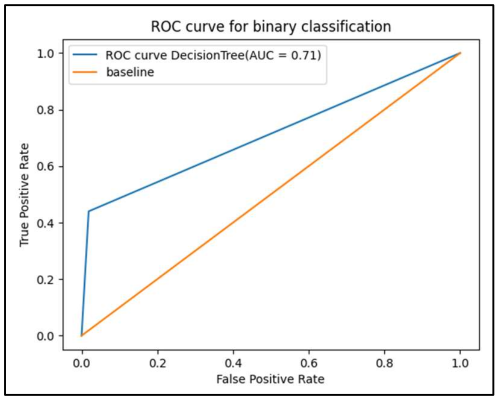

Figure 8: ROC graph for Decision Tree

the results are summarized in a matrix for greater clarity. In comparison, it is assumed that remedial maintenance is still used as a strategy for sudden faults during operation.

A. Predictive Maintenance

In the case of an introduction of predictive maintenance, this means that all planned maintenance is carried out after analysis of operating information and ongoing use. It can also be introduced partially as a complement to another strategy, for example preventive maintenance. Here, both the complete introduction and as a supplement are examined. Predictive maintenance is the only researched strategy that includes root cause analysis and continuous improvement, trying to find the reason why failures occur and thus prevent future failures. The data collected today is deemed to be sufficient to predict errors. During introduction, current data is used, and as breakdowns occur, a need for more sensors and measurements can be discovered, which can then be decided upon.

1. Economy

Predictive maintenance would reduce spare parts consumption as replacements only take place when the system predicts that a replacement is needed and uses a larger part of the components' lifespan. The stock of spare parts could also be reduced as the system warns in time so that there is time to order home new spare parts before the replacement.

Quality is also positively affected as the relationship between quality, driving style and wear and tear can be analyzed and measures put in place before major deteriorations in quality occur.

2. Resources

Since the maintenance is done according to predicted need, it would mean reduced maintenance compared to today, since maintenance is only done when there is a need for it instead of, for example, every month. The need for technicians would be reduced when the planned maintenance would be limited to needs after measured and analyzed [5].

Planning becomes more difficult, just as for maintenance during operating hours and conditions, as it is difficult to predict errors over a longer time horizon. Shorter predictions are available, and maintenance could to some extent be planned for the coming week, depending on the fault development time, and driving schedule [4]. If the service is to be developed itself, technical resources with analytical skills who can control the service, as well as developers, are required [10].

B. Condition-based Maintenance

In the case of an introduction of condition-based maintenance, this means that all planned maintenance is done after measuring conditions. It can also be introduced partially as a complement to another strategy, for example preventive maintenance. Here, both the complete introduction and as a supplement are examined.

1. Economy

The use of spare parts would be reduced as the spare parts would be used throughout their lifetime and replacement would not be necessary before the spare part has sufficient wear to cause impaired function. Fewer controls and given control limits would positively affect the percentage of changes as well. Spare parts stocks could be reduced if delivery times match the control limits that are set so that an ordered spare part can be delivered before the component fails. In the case of a full implementation, more sensors and measurements would be needed to be able to collect operating data to be able to measure before planned maintenance [1].

2. Resources

The resource requirement would be reduced just as with uptime, as the number of maintenance jobs would be reduced when all controls are removed and only actions take place. But the need for resources with analytical ability would increase, where the resources produce control limits and put together connections for condition checks. If the condition checks were to be done manually instead of via sensors, the need for resources would increase significantly [3]. A manual review of collected data and comparison against control limits could be helpful for planning but requires analytical skills and knowledge of how much wear and tear occurs each week [5].

C. Preventive Maintenance

Here it is chosen to look at preventive maintenance on operating time instead of the number of letters entered, which could also be relevant. This is because the supplier specifies operating hours in their documents. This strategy would provide a maintenance that follows the use of the machines where maintenance is done according to how much the various machines are used.

1. Economy

The fact that maintenance is carried out in relation to how much the machine is used primarily affects spare parts costs, as checks and replacements can take place closer to the full life of the components than on calendar time like today. A disadvantage is that it would be difficult to plan maintenance and thus order home spare parts on time, which could lead to an increased need for larger spare parts stocks [15].

2. Resources

The resource requirement for maintenance would be significantly reduced. If the planned maintenance produced today is compared to how it would be done if it were carried out at the supplier's recommended operating time, a reduced need is seen by approximately 671.53 hours in one year (2019), if the maintenance were to be done immediately when the need arose, which is a reduction of 58 % against today. Over several years, the reduction should not be as great, as certain maintenance will only occur the following year, such as, for example, the maintenance that is done after one year. In five years with the same operating time as 2019, the need would decrease by 50%.

TABLE I: DIFFERENCE IN PLANNED MAINTENANCE DURING CALENDAR TIME AND NEED FOR MAINTENANCE DURING OPERATING TIME

Maintenance	Week	1 month	2 months	3 months	6 months	1 year	Total time (h)
Calendar time 218-224	52	12	6	4	2	1	166.28
Total operating time							1163.96
218	30	7	3	2	1	0	90.14
219	28	7	3	2	1	0	88.6
220	22	5	2	1	0	0	51.67
221	22	5	2	1	0	0	51.67
222	20	5	2	1	0	0	50.13
223	24	6	3	2	1	0	80.11
224	24	6	3	2	1	0	80.11
Total							492.43

D. Remedial Maintenance

In the event of a change to remedial maintenance only, all actions are carried out after breakdown. However, certain measures that are not urgent can be postponed and planned for later.

1. Economy

Remedial maintenance could, in the short term, generate a reduced cost as spare parts would only be replaced after a breakdown and thus the entire lifetime of the components would be used. In the longer term, however, there is a large risk that small errors generate large damage before action is taken and entail large costs. Even the cost of purchasing spare parts can increase as it is now possible to repair some spare parts when faults have been discovered earlier. It also means that all spare parts need to be in stock and thus a larger stock balance. The strategy has no initial start-up costs.

2. Resources

The resource management would need to have more on-call resources as all maintenance is basically moved to the evening and night when the machines run the most. The resources currently used for preventive maintenance would not be needed, but overall, the resources are moving towards an increased need. The risk of doing too much maintenance is small as only the maintenance that is needed for the machine to be operational is carried out.

E. Result Analysis of Machine Learning Models

All the three Machine Learning models have been compared for the best performance. This is done by analyzing Area Under Curve (AUC) value. As the value of AUC increases, the model's performance also increases. It provides an aggregate measure of performance across all classification thresholds.

The three Machine Learning models which have been used are Decision Tree, Random Forest and XGBoost Classifier. The obtained AUC values are:

- Decision Tree AUC = 0.72
- XGBoost Classifier AUC = 0.98
- Random Forest AUC = 0.92

By analyzing the values of AUC, the best performing ML model is XGBoost Classifier.

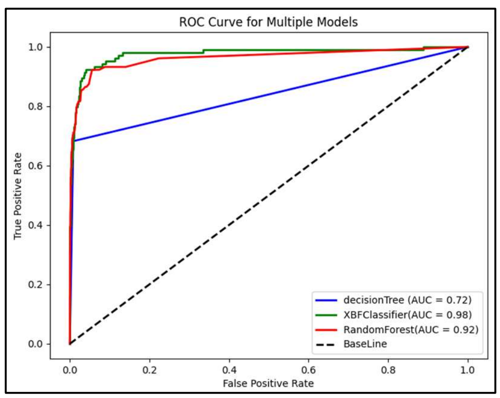

Figure 9: ROC graph for multiple models

Increasing order of the success of Machine Learning models are given below.
Decision Tree < Random Forest < XGBoost Classifier

V. CONCLUSION

Three out of four strategies show increased efficiency in both costs and resource management compared to the current strategy. Two of these also show increased efficiency with higher availability of the machines. Only one strategy, condition-based maintenance, places higher demands on the resources for analytical competence.

The recommended strategy depends on what the future need looks like regarding availability. If the need is still high, it is recommended:

- The mixture of predictive maintenance and preventive maintenance at operating time.

If, however, the future need shows that accessibility is not as relevant as today, then it is recommended:

- The mixture of preventive maintenance at operating time and condition-based maintenance.

In both recommendations, remedial maintenance is still included for handling the emergency break downs that may occur. The recommended strategy demonstrates a positive effect in both costs and resource management. Depending on future needs, it is possible to choose a strategy that also demonstrates increased accessibility. This work has been done with consideration to verify all the facts through sources and acquisition of data. The matrix of results is rough. There are partly difficult boundaries between what is accessibility and what is finance, as well as difficulty in assessing how large investments are needed for certain strategies.

REFERENCES

[1] S. V. Amari, L. McLaughlin, and H. Pham, "Cost-Effective Condition-Based Maintenance Using Markov Decision Processes," in Proc. Annual Reliability and Maintainability Symposium., vol. 3, pp. 464-469, Feb. 2006.

[2] M. Barlow, Predictive Maintenance, Sebastopol, CA: O'Reilly Media, Inc., 2015.

[3] M. Bellgran and K. Säfsten, Production development. First Ed., Lund, Sweden: Studentlitteratur, 2005.

[4] A. Cachada et al., "Maintenance 4.0: Intelligent and Predictive Maintenance System Architecture," in 2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA), vol. 4, pp. 139-146, Sept. 2018.

[5] J. Jakubowski et al., "Artificial Intelligence Approaches for Predictive Maintenance in the Steel Industry: A Survey," arXiv.org, https://arxiv.org/abs/2405.12785 (accessed May 24, 2024) May 21, 2024.

[6] B. Marcello, D. Castrogiovanni, and M. Fumagalli, "An integer linear programming approach to maintenance strategies selection," Int. J. Qual. & Reliab. Manage., vol. 30, no. 9, pp. 991-1016, May 2013.

[7] R. K. Mobley, Maintenance Engineering Handbook, 7th ed. New York, NY, USA: McGraw-Hill, 2008.

[8] D. Galar and M. Kans, "The Impact of Maintenance 4.0 and Big Data Analytics within Strategic Asset Management," in Proc. 6th Int. Conf. Maintenance Performance Measurement and Management (MPMM), vol. 2, pp. 96-104, Nov. 2016.

[9] Q. Hao et al., "A decision support system for integrating corrective maintenance, preventive maintenance, and condition-based maintenance," in Construction Research Congress 2010, pp. 1-10, May 2010.

[10] A. Jain, R. S. Bhatti, and H. Singh, "Total productive maintenance (TPM) implementation practice: a literature review and directions," Int. J. Lean Six Sigma, vol. 5, no. 3, pp. 293-323, 2010.

[11] K.-E. Johansson, Operational safety and maintenance, 2nd ed. Lund, Sweden: Studentlitteratur, 1997.

[12] S. El-Ferik and M. Ben-Daya, "Integrated maintenance production model underage-based maintenance policy & non-negligible maintenance times," Asia Pac. J. Oper. Res., vol. 27, no. 4, pp. 539-558, 2010.

[13] M. Ilangkumaran and S. Kumaran, "Application of hybrid VIKOR model in selection of maintenance strategy," Int. J. Inf. Syst. Supply Chain Manage., vol. 5, no. 2, pp. 59-81, 2012.

[14] P. Möller and J. Steffens, Maintenance technology, 2nd ed. Stockholm, Sweden: Liber AB, 2006.

[15] M. A. Crepo and J. N. D. Gupta, "Contemporary maintenance management: process, framework and supporting pillars," Int. J. Manage. Sci., vol. 34, no. 1, pp. 313-326, 2005.

[16] O. David and S. T. Irani, "Preventive maintenance in a multiple shift and high-volume manufacturing operation," Int. J. Oper. & Prod. Manage., vol. 13, no. 10, pp. 7

[17] DTDC. Annual and Sustainability Report 2019 [Online]. Available: https://www.instafinancials.com/company/dtdc-express-limited/U85110KA1990PLC011089 (accessed May 10, 2020).

[18] L. Wang, J. Chu, and J. Wu, "Selection of optimum maintenance strategies based on fuzzy analytic hierarchy process," Int. J. Prod. Econ., vol. 107, no. 1, pp. 151-163, May 2007.