A predictive maintenance model for an industrial fan in a cement plant

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Abstract: In cement plants, any unplanned stop or slowdown in industrial production leads to non-negligible sunk and maintenance costs. Cement production requires the use of expensive equipment to ensure continuous production. This study suggests a machine learning approach to predict and advise when a cement plant component will be at risk of failure. A predictive model was built based on data available for an industrial fan of a cement plant. This component has been chosen due to the maintenance criticality of rotating items. Component's health was monitored using parameters such as vibration, temperature, and speed values of the fan support bearings. Classification and regression algorithms have been tested. For the classification, logistic regression and boosted decision trees were applied to label whether the plant was in critical status or not. The threshold value used to tag the data refers to fan vibrations. For the regression, linear regression and decision forest regression were used to determine the residual useful life (RUL) of the fan. This model has provided significant benefits such as reducing unplanned stops, losses of production, and production in critical conditions.

Keywords: condition-based maintenance; cement plants; predictive maintenance; industrial fan; industrial plant; bearings.

1. Introduction

In the last decades, industrial plants became increasingly complex in terms of plant maintenance. Especially process plants are characterized by a complex combination of equipment, chemical substances, high temperatures, process parameters and high safety requirements which need to be periodically checked (Gao, Shen, Shen, Liu, & Chen, 2016), (Schneider, Romer, Tschudin, & Bolio, 2011). Unexpected equipment downtimes could cause dramatic consequences for manufacturing plants. These fails result in economic losses, loss of production, and dangers to workers. These failures can be prevented using predictive maintenance techniques. A proactive maintenance approach help business to avoid unnecessary maintenance activities and anticipate equipment failures. Predictive maintenance techniques have received much attention, as clearly presented by the literature review in (Jardine, Lin, & Banjevic, 2006) and in (R. Ahmad & Kamaruddin, 2012). This paper gives a contribution to this last stream of research, presenting an original case study that focuses on a condition-based maintenance (CBM) program. Specifically, this paper proposes an application case study that aims to study a critical component in the context of a cement manufacturing plant. The attention of the research is, therefore, the cement industry: a sector characterized by continuous and high-volumes production. Since its origins, cement has become a global commodity, manufactured at thousands of plants around the globe. With increased competition and demand, companies are forced to improve performance. Moreover, high costs of cement plant components and maintenance make necessary to ensure measures to avoid loss of production and unexpected costs (Shafeek, 2014).

The critical system studied is an industrial fan of the oven cooling system. The fan is mainly composed of bearing, motor, and blade and its performance depends on the life of these components. Therefore, monitoring the status of critical system components is very important to ensure safe and continuous operation (Yudong, Zhenhuan, Lixin, & Guoan, 2016).

Data used to train the model are collected from several sensors installed in the fan system. Prediction parameters concern vibration related to accelerometers on shaft-sited bearings; current; voltage; speed; temperature.

In the case study, a predictive maintenance solution is sought using two approaches: a regression approach where the remaining useful life (RUL) of the fan is predicted and a classification approach that predicts if the system is in a warning state.

The remainder of the paper is organized as follows. Section 2 presents the related literature. Section 3 introduces the case study. First, in this section the cement plant is briefly described. Later, both data acquisition and data processing models and methods are presented. The discussion of the paper results, the conclusions, and future research are summarized in Section 4.

2. Literature review

Plant maintenance means the set of actions that are necessary to keep machinery and equipment in good operating conditions. From the moment the first manufacturing plant was built, maintenance has always been considered one of the main industrial (Mobley, 2017). Back then the main idea was unplanned maintenance, also known as breakdown maintenance, based on the logic of run-to-failure management (Jardine et al., 2006). In this technique repairs and interventions are made after the machine is out of order. The cost related to this approach is substantial and the loss of production not sustainable with today's increase in products demand.

In the 1950's there was a rise of awareness in maintenance and the spread of preventive maintenance (Ahuja & Khamba, 2008). This concept reduces machine failures and extends machine life by performing planned check-ups. Maintenance scheduling is planned based on the probability that the equipment will breakdown in a periodic interval. It is a time-based procedure typically used for equipment that degrades with time (Duarte, Garbatov, Zio, & Sorensen, 2010).

Later, the rapid development of modern technology and today's competitive business environment have made industrial plants more complex and in greatest need of safety and efficiency. As a matter of fact, the progress of maintenance technology has moved from breakdown or preventive maintenance to a condition-based maintenance approach. CBM involves a set of actions based on real-time assessment of equipment conditions. The monitoring of the state of components involves observing degradation measures such as vibration, temperature, sound, wear, etc. from an operating system to determine its state. The healthy state of the component is assessed by correlating its physical or chemical measures and identifying a threshold value which indicates if the component has a high probability of failure. Since every industrial system is composed of various equipment, which has different degradation and different maintenance strategies, continuously monitoring their status is not easy. However, this goal has recently become more achievable thanks to the advent of sensor technology (Kaiser & Gebraeel, 2009). Sensors have made easy collecting data and helped the spread of condition-based maintenance strategies.

CBM recommends actions based on data collected during condition monitoring (CM) and it is organized in three steps:

- data acquisition
- data processing
- maintenance decision-making.

Both diagnostic - the capacity to detect and identify a fault - and prognostic - the capacity to predict a fault - are used in CBM programs (Jardine et al., 2006).

CBM is a very valuable method for an industry operating high-valued asset (Shin & Jun, 2015), such as the cement industry considered in this case study.

The cement industry involves a complex continuous production and a high level of demand. Two studies have underlined the importance of implementing a continuous maintenance program in heavy industries (Shafeek, 2012) and (Shafeek, 2014). Moreover, their researches are among the first which stressed the importance of implementing a predictive maintenance model for this industry. Later (Allen, 2015) describes the need for implementing preventive and predictive maintenance strategies while at the same time underlines the high investment needed to change the maintenance approach. The same critical cost and complexity issues related to the use of CBM in cement plants are highlighted in (Yunusa-Kaltungo & Labib, 2020). On the one hand, the importance of maintenance strategies is emphasized in this research, while on the other hand the pros and cons of different strategies such as CBM, often preferred by maintenance managers, and planned preventive maintenance preferred by production managers are also discussed. Authors stressed the fact on the suitability of CBM for all those assets that experience catastrophic failures and high downtime for which constantly monitoring their condition would be a successful plan. The same authors discussed the high cost of downtime associated with a cement plant in (Yunusa-Kaltungo, Kermani, & Labib, 2017) investigating critical failures connected with a rotary kiln. Also (Saxena, 2009) affirmed how a single failure in a cement manufacturing process would be catastrophic for the operations and profitability of the plant. Among all the critical components, the author lists the industrial fans involved in the process such as raw mill fans, coal mill fans, cooler exhaust fans and cooling fans.

The case study proposed here will focus on an industrial cooling fan of the plant. The objective of the CBM implementation was to implement a condition monitoring on the fans and to trigger a warning upon any relevant change. Rotating machinery maintenance is a topic widely studied and different methods for predicting rotating machinery failures have been studied as described in (Heng, Zhang, Tan, & Mathew, 2009). CM concerning rotating machines is based on multiple factors such as vibration, speed, current and temperature analysis, among this the most popular technique used in CBM, especially for rotating equipment is vibration monitoring (Asoke K. Nandi, 2020), (Boudiaf, Djebala, Bendjma, Balaska, & Dahane, 2017). As also underlined by (Yunusa-Kaltungo & Labib, 2020), it is clear that a CM program which involves also the capacity to predict a fault, can only be implemented if a large amount of data is available and therefore if the critical components are equipped with sensors. Data for vibration analysis needs to be measured in in axial, horizontal and vertical directions (Orhan, Aktürk, & Çelik, 2006) and later interpreted, processed and used to train the predictive model. In this case study, sensors installed to monitor the health of the fan allow the factory to collect information about vibration, temperature, and amperes making it possible to develop a model to identify the RUL of the fan and label whether the plant is in a critical status or not. The case study will give an investigation of the phenomenon underlying a real-life scenario in a cement plant. The study also offers a comparison of different algorithms which will help to determine which one is preferable in a similar context.

3. Case study

3.1. Plant description

The cement plant considered in this study is a cement plant in Italy. The part of the installation considered for the case study has a capacity production of 1500000 tons per year and produces the actual amount of 2500 tons of cement per day. This case study focuses on the industrial fan of the plant oven cooling system. Cement industries use a large number of cooling fans, they are heavy duty and perform basic but essential functions such as the supply of cooling air (Yudong et al., 2016). Figure 1 is the airflow scheme of the air who drops out from the miller and is dispersed into the ambient. This scheme shows how the fan is installed between a cooling tower and an oven tower. The air moves from the oven tower, pass through the fan and then is spread in two components: the cooling tower and the mill. In the first one, the air reaches room temperature and then goes out through the filters. The latter uses hot air to control humidity and later spread it into the room through a filter.

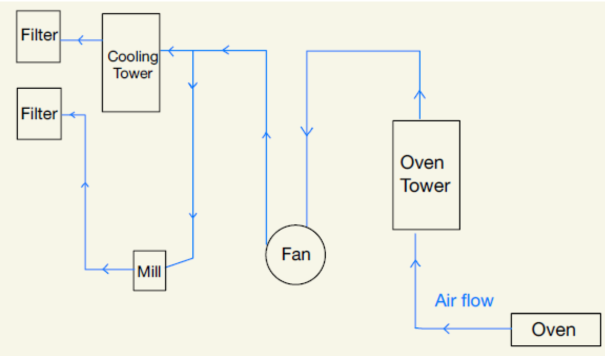

Figure 1 – Airflow scheme

The fan system is composed of two motors, two bearings, and the fan impeller (Figure 2). This system is equipped with multiple sensors to monitor the health of the fan. Sensors installed in the systems are:

- Two accelerometers on the bearing: for axial and radial vibrations
- Two hall effect sensors on the power cord of the motor to measure the amount of current.
- One thermocouple to measure the temperature on the inlet air.

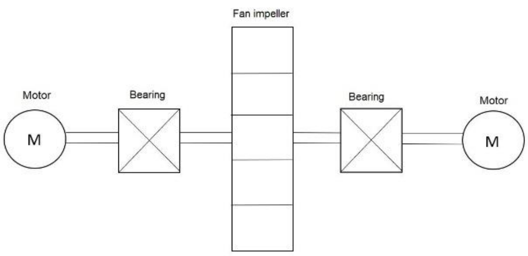

Figure 2 – Fan

3.2. Experimental setup

3.2.1. Algorithms selection

As stated before, the goal was to predict the machine failures of the fan. The prediction is performed through four supervised machine learning models. Algorithms tested can be divided into two: those related to regression and those to classification.

Regression models are used to predict a continuous value. Regression models are used in this study to predict the remaining useful life of the industrial fan. Algorithms tested here are linear regression and decision forest.

- Linear regression is a common statistical method. The idea behind linear regression is to examine if a set of significant predictors can predict an outcome value within a continuous range. As also described in (Mathew, Toby, Singh, Rao, & Kumar, 2018a) and (W. Ahmad, Ali Khan, & Kim, 2017) linear regression is a useful algorithm to predict the RUL of a critical component within an industrial environment. Linear regression is still a good choice used to describe a simple model for a basic predictive task, in this case, study linear regression was chosen to collect a result in output which could have been used as a benchmark for the other outcomes and a confirmation of the importance of using a more advanced approach for the analysis of critical components.
- Decision forest consists of an ensemble of decision trees. Decision trees are non-parametric models that perform a sequence of simple tests for each instance, traversing a binary tree data structure until a decision is reached. Every decision tree has a high variance, but when trees are combined then the resultant variance is low as each decision tree gets perfectly trained on that particular sample data and hence the output doesn't depend on one decision tree but multiple decision trees. It is generally used to predict a target by learning decision rules from features and can be applied both to classification and regression problems. In this case study, following also the study conducted by (Mathew, Toby, Singh, Rao, & Kumar, 2018b), decision forest has been applied for a regression problem.

Classification models are instead used to identify the class to which a new observation belongs. The algorithms tested are logistic regression and a two-class boosted decision tree.

- Logistic regression is a statistical method that is used to predict the probability of an outcome. It is a special case of linear regression where the target variable is categorical. The algorithm predicts the probability of occurrence of an event by fitting data to a logistic function. It is a widely used algorithm in multiple disciplines ranging from social science to medicine. It can be used for example for cancer detection problems, to compute the probability of an event or, as tested also in the study of (H. Li & Wang, 2013) to estimate the failure of a rolling bearing.

- Two-class boosted decision tree algorithm is an ensemble model based on the construction of more than one decision tree. The logic behind this method is that boosted trees incrementally build an ensemble by training each new instance to emphasize the training instances previously modeled. Predictions of the target output are then based on the entire ensemble of trees together. The selection of this method was driven by the will of applying an up-to-date strong classifier. This decision was also supported by previous studies such as (Vasilić, Vujnović, Popović, Marjanović, & Durović, 2018) and (L. Li, Lu, Wang, & Li, 2016).

3.2.2. Dataset analysis and pre-processing

Sensors installed in the industrial cooling fan made it possible to collect a large amount of data. Data collected relate to 4 years of work and were recorded with a frequency of 5 minutes. Moreover, data were checked and further explained by the maintenance managers and engineering of the plant. More than 400000 records have been collected. Since they were simply raw data, a pre-processing and mining process was necessary. The historical data analyzed also showed that the problem of production slowdowns due to malfunctions and sudden breaks are noticeable. In the four years considered, 8 times the system exceeded the threshold set for the vibrations causing a slowdown in production, and 4 times cement production was completely stopped for a major failure.

First, to perform classification, before training the model, it was necessary to attach to each record a label that describes the operational state of the equipment at the time of collecting the data. A label column was created: if a record is labeled as "1", the system is considered in an abnormal state whereas a label "0" means the system is in a healthy state. The fan system was labeled at risk of failure when vibrations exceed 18 $\frac{mm}{s^2}$. This threshold value is the result of several semi-structured interviews conducted with the production and maintenance manager and the plant engineers. This value was also confirmed by analysis, conducted by the authors, of the plant's historical data and report of fan breakdown comparing the vibrations recorded when the system experienced a deterioration in its operating conditions. Besides, the models were set with the intention of communicating the possible failure eight hours in advance to have a full shift available to solve it. The approach used to predict the RUL is the regression. The process of predicting a real RUL value associated with an input pattern based on the estimate of the relationship between a training set of patterns whose associated values are known. The dataset was pre-processed to have a training dataset that could be utilized with the regression algorithms. First, instances related to vibrations that exceed the threshold value were removed and instances re-indexed. Second, a cycle column was created to keep track of the duration of each cycle and then inverted to obtain the RUL value used to train the model.

Once the dataset was ready, it was split into a training dataset (70%), that contains the labeled output and the model learns on this data. The model test works on the remaining 30% of the dataset, to score the performance of the algorithms.

Moreover, to deal with highly imbalanced classes in the classification algorithm a sampling strategy was implemented. The strategy used was to downsample the majority class randomly removing its observations and keeping all the minority class observations.

3.3. Results

Table 1 shows the regression results. Linear regression reports weak results which are probably linked to the non-linearity of the data. The decision forest regression model instead fits the data well. These results are shown also in Figure 3 and Figure 4 which specifically shows the variation between predicted RULs and actual RULs. Figure 3 describes linear regression results and as also confirmed by the metrics in Table 1, results are visibly poor. More interesting are the results of the decision forest regression algorithm showed in Figure 4. The graph clearly shows how the predicted blue trend almost totally covers the actual red trend. This is also stressed by the high coefficient of determination value R^2 shown in Table 1.

The accuracy of classification models, both the logistic regression and two-class boosted decision trees, is represented in the confusion matrix (Table 2, Table 3, Table 4) and in the classification results described in Table 5. The confusion matrix (Table 2, Table 3, Table 4) shows how many cases were classified correctly versus those classified incorrectly. Two-class boosted decision tree performed well registering a 98% accuracy and a 90,1% recall rate. Logistic regression did not obtain good results, this is probably linked to an unbalanced dataset. In fact, after a downsampling strategy the model performance improved (Table 3). However, this solution cannot represent the real mechanical behaviour of the industrial fan and to better describe the phenomenon a decision tree model is more appropriate. Deepening the results obtained with the two-class decision tree model and considering the number of true positive the model performed well. For what concern false negative and false positive a further explanation is required. A false negative describes a case in which the system is operating in healthy state while not. Its value is still high and further research must be addressed to improve the results. A further aspect is the number of false positive. If, on the one hand, it can be considered not a problem for the safety of the plant, on the other hand it might cause unnecessary maintenance work.

	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error	Relative Squared Error	Coefficient of determination R^2
Decision forest regression	0.0143	0.0312	0.1549	0.0514	0.9485
Linear Regression	0.0894	0.1331	0.9666	0.9346	0.0653

Table 1 – Regression results

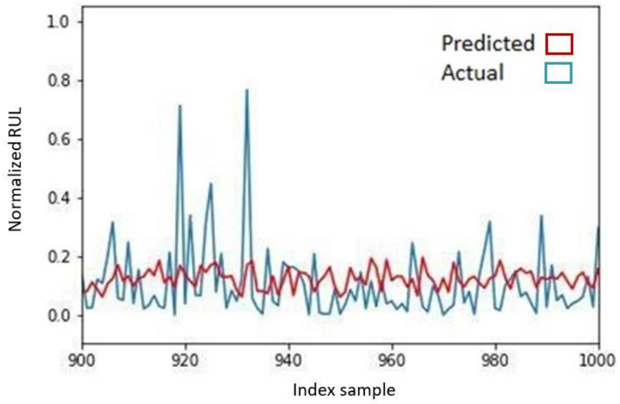

Figure 3 - Linear Regression

Logistic Regression down sample		**Prediction**	
		Positive	**Negative**
Actual	**Positive**	5322	0
	Negative	1297	39795

Table 3 - Logistic Regression down sample confusion matrix

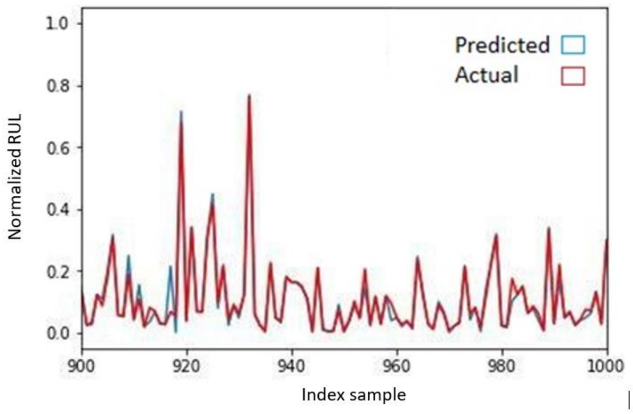

Figure 4 - Decision Forest Regression

Boosted Decision Tree		**Prediction**	
		Positive	**Negative**
Actual	**Positive**	5977	657
	Negative	484	48578

Table 4 – Boosted Decision Tree confusion matrix

Logistic Regression		**Prediction**	
		Positive	**Negative**
Actual	**Positive**	0	6634
	Negative	0	49062

Table 2 - Logistic Regression confusion matrix

	Accuracy	Precision	Recall
Two class boosted decision tree	0.98	0.93	0,90
Logistic Regression	0.97	0.80	1

Table 5 – Classification Results

4. Conclusion

In this paper, a machine learning approach to identify in advance failures of an industrial fan of a cement plant has been elaborated.

The case study has combined the results of previous works available focusing on the cement industry which has received less attention in terms of predictive maintenance. A condition monitoring of vibrations, speed, current, and temperature of the industrial fan of an oven cooling system was conducted. The plant considered is currently following ordinary maintenance which leads to stopping the production when a critical situation occurs. These stops not only are correlated with loss of production and increase of cost maintenance but also force the plant to work in critical and sometimes dangerous conditions.

This study has proved that a condition-based maintenance program could prevent unexpected equipment downtime, improve service quality, and reduce the additional cost caused by over-maintenance. Moreover, since the model can identify a potential issue within 8 hours before it occurs, a timely repair can be planned. This prevents costly collateral damage and catastrophic failures.

Above all, this study has shown that a successful predictive maintenance program only works if a great amount of data is collected, analyzed and actions are taken. To implement a successful condition-based maintenance program, cement industries have to make consistent investment and install sensor technologies to gather data. If these strategies are implemented, companies' top priority such as continuous production and deadlines can be achieved. Moreover, an efficient predictive model will prevent minor failures from becoming catastrophic reaching the most important safety goal.

Future research will primarily focus on improving the performance of the machine learning models training them on a bigger dataset and possibly testing new classification algorithms. Moreover, the aim is to extend this research to other critical components of a cement plant making predictive maintenance possible throughout the plant.

5. References

Ahmad, R., & Kamaruddin, S. (2012). An overview of time-based and condition-based maintenance in industrial application. *Computers and Industrial Engineering*, *63*(1), 135–149. https://doi.org/10.1016/j.cie.2012.02.002

Ahmad, W., Ali Khan, S., & Kim, J. M. (2017). A hybrid prognostics technique for rolling element bearings using adaptive predictive models. *IEEE Transactions on Industrial Electronics*, *65*(2), 1577–1584. https://doi.org/10.1109/TIE.2017.2733487

Ahuja, I. P. S., & Khamba, J. S. (2008). Total productive maintenance: Literature review and directions. In *International Journal of Quality and Reliability Management* (Vol. 25). https://doi.org/10.1108/02656710810890890

Allen, W. (2015). Preventative maintenance and root cause analysis for critical process conveying equipment. *IEEE Cement Industry Technical Conference (Paper)*, *2015-June*. https://doi.org/10.1109/CITCON.2015.7122607

Asoke K. Nandi, H. A. (2020). *Condition Monitoring with Vibration Signals: Compressive Sampling and Learning Algorithms for Rotating Machines*. Retrieved from https://books.google.it/books?hl=en&lr=&id=oPm4DwAAQBAJ&oi=fnd&pg=PR17&dq=Condition+Monitoring+with+Vibration+Signals:+Compressive+Sampling+and+...+By+Asoke+K.+Nandi,+Hosameldin+Ahmed&ots=cV9pXpZvSu&sig=yu2skncImd5ai5eBODu7lpOHZlU#v=onepage&q=Condition Mo

Boudiaf, A., Djebala, A., Bendjma, H., Balaska, A., & Dahane, A. (2017). A summary of vibration analysis techniques for fault detection and diagnosis in bearing. *Proceedings of 2016 8th International Conference on Modelling, Identification and Control, ICMIC 2016*, 37–42. https://doi.org/10.1109/ICMIC.2016.7804187

Duarte, J., Garbatov, Y., Zio, E., & Sorensen, J. (2010). Framework for maintenance planning. *Safety and Reliability of Industrial Products, Systems and Structures*, (November), 33–52. https://doi.org/10.1201/b10572-6

Gao, T., Shen, L., Shen, M., Liu, L., & Chen, F. (2016). Analysis of material flow and consumption in cement production process. *Journal of Cleaner Production*, *112*(February 2018), 553–565. https://doi.org/10.1016/j.jclepro.2015.08.054

Heng, A., Zhang, S., Tan, A. C. C., & Mathew, J. (2009, April). Rotating machinery prognostics: State of the art, challenges and opportunities. *Mechanical Systems and Signal Processing*, Vol. 23, pp. 724–739. https://doi.org/10.1016/j.ymssp.2008.06.009

Jardine, A. K. S., Lin, D., & Banjevic, D. (2006, October). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, Vol. 20, pp. 1483–1510. https://doi.org/10.1016/j.ymssp.2005.09.012

Kaiser, K. A., & Gebraeel, N. Z. (2009). Predictive maintenance management using sensor-based degradation models. *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*, *39*(4), 840–849. https://doi.org/10.1109/TSMCA.2009.2016429

Li, H., & Wang, Y. (2013). Rolling bearing reliability estimation based on logistic regression model. *QR2MSE 2013 - Proceedings of 2013 International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering*, 1730–1733. https://doi.org/10.1109/QR2MSE.2013.6625910

Li, L., Lu, W., Wang, X., & Li, Z. (2016). A frequency domain feature based cascade classifier and its application to fault diagnosis. *Proceedings of the 28th Chinese Control and Decision Conference, CCDC 2016*, 5957–5961. https://doi.org/10.1109/CCDC.2016.7532063

Mathew, V., Toby, T., Singh, V., Rao, B. M., & Kumar, M. G. (2018a). Prediction of Remaining Useful

Lifetime (RUL) of turbofan engine using machine learning. *IEEE International Conference on Circuits and Systems, ICCS 2017*, *2018-January*, 306–311. https://doi.org/10.1109/ICCS1.2017.8326010

Mathew, V., Toby, T., Singh, V., Rao, B. M., & Kumar, M. G. (2018b). Prediction of Remaining Useful Lifetime (RUL) of turbofan engine using machine learning. *IEEE International Conference on Circuits and Systems, ICCS 2017*, *2018-Janua*, 306–311. https://doi.org/10.1109/ICCS1.2017.8326010

Mobley, R. K. (2017). *An introduction to predictive maintenance* (Vol. 37). https://doi.org/10.1016/b978-0-7506-7531-4.x5000-3

Orhan, S., Aktürk, N., & Çelik, V. (2006). Vibration monitoring for defect diagnosis of rolling element bearings as a predictive maintenance tool: Comprehensive case studies. *NDT and E International*, *39*(4), 293–298. https://doi.org/10.1016/j.ndteint.2005.08.008

Saxena. (2009). Prod & Oper Mgmt,2E. In *Prod & Oper Mgmt,2E*. Retrieved from https://books.google.it/books?id=vzvHYmX4aYQC&pg=PA452&lpg=PA452&dq=cement+plant+and+condition+based+maintenance&source=bl&ots=FZeXMXhle6&sig=ACfU3U2MVLHqx74vGDZl8YDL9XYyzh01GA&hl=en&sa=X&ved=2ahUKEwj_rfqs9fnpAhUy5uAKHaYCDrkQ6AEwCHoECAoQAQ#v=onepage&q=cem

Schneider, M., Romer, M., Tschudin, M., & Bolio, H. (2011). Sustainable cement production-present and future. *Cement and Concrete Research*, *41*(7), 642–650. https://doi.org/10.1016/j.cemconres.2011.03.019

Shafeek, H. (2012). Maintenance Practices in Cement Industry. *Asian Transactions on Engineering (ATE)*, *01*(06), 10–20.

Shafeek, H. (2014). Continuous improvement of maintenance process for the cement industry - A case study. *Journal of Quality in Maintenance Engineering*, *20*(4), 333–376. https://doi.org/10.1108/JQME-07-2013-0047

Shin, J. H., & Jun, H. B. (2015). On condition based maintenance policy. *Journal of Computational Design and Engineering*, *2*(2), 119–127. https://doi.org/10.1016/j.jcde.2014.12.006

Vasilić, P., Vujnović, S., Popović, N., Marjanović, A., & Durović, Ž. (2018). Adaboost algorithm in the frame of predictive maintenance tasks. *2018 23rd International Scientific-Professional Conference on Information Technology, IT 2018*, *2018-January*, 1–4. https://doi.org/10.1109/SPIT.2018.8350846

Yudong, F., Zhenhuan, W., Lixin, W., & Guoan, Y. (2016). Research on the fan bearing reliability of the weibull distribution. *Proceedings of 2016 IEEE Information Technology, Networking, Electronic and Automation Control Conference, ITNEC 2016*, 632–636. https://doi.org/10.1109/ITNEC.2016.7560437

Yunusa-Kaltungo, A., Kermani, M. M., & Labib, A. (2017). Investigation of critical failures using root cause analysis methods: Case study of ASH cement PLC. *Engineering Failure Analysis*, *73*, 25–45. https://doi.org/10.1016/j.engfailanal.2016.11.016

Yunusa-Kaltungo, A., & Labib, A. (2020). A hybrid of industrial maintenance decision making grids. *Production Planning & Control*, 1–18. https://doi.org/10.1080/09537287.2020.1741046