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# Data-Driven Approaches for Operation and Maintenance Decision on Power Plants

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The paper proposes a decision-making system based on Proactive Operation & Maintenance (POM) data-driven approaches, supported by Condition-Based Maintenance (CBM) and Statistical Data Analysis (SDA). The CBM approach is comprised of both online and offline data acquisition methods. To develop the system, the online CBM data acquisition involves the analysis of real-time sensor data at the asset of power plants that are categorized based on their numerical variables and then mapped on the asset register. On the other hand, offline CBM data acquisition is conducted by performing in-situ measurements at the power plants site. Statistical data analyses of failure data derived from the Computerized Maintenance Management System (CMMS) are also utilised to support the decision system. The POM approach supported by data-driven method and set point values of the controllable parameter is developed. In this decision-making system, the POM approach through the combination of CBM and SDA is enhanced to be structured by proactive online recommendations and comprehensive analysis space followed by expert judgments. This study presents a novel strategy for the creation and implementation of a proactive decision-making system in the context of operation and maintenance of power plants. It presents a decision-making paradigm that encompasses CBM and SDA, which can raise the amount of confidence in expert judgment, as well as the types of recommendations that can be made. The impacts show that the performance of the power plants increased..

*Keywords*: condition-based maintenance, data-driven, decision-making system, operation & maintenance, power plant, reliability.

## 1. Introduction

PT PLN (Persero), known as PLN, is an Indonesian government-owned corporation that is solely responsible in providing electricity supply in Indonesia. According to PLN's portfolio report, it has generated 279.511 Terra Watt hours (TWh) in 2021 and delivered to 82,543,980 customers dominated by households. In December 2021, 57,679.27 MW of total Indonesian generating capacity was installed. Compared to the situation on other islands (such as Sumatra, Sulawesi, and Kalimantan), where most places are supplied by localized networks frequently fueled by small diesel power plants, the energy supply in Java is more reliable. PT Indonesia Power, sometimes known as PT IP, is a subsidiary of PLN that generates electricity. In 2021, PT IP operates 17,718.0 MW of power generating independently at 42 locations to serve PLN. As a result, in its business process, PT IP carries out O&M management and constantly requires critical decisions to maintain the performance of its power plant units. Thus, the authors discuss a case study implementation of integrating a data-driven POM approach, including online and offline CBM and SDA implemented in PT IP.

Future Decision-Making System (DMS) should also include predictions and proactive actions. Engel provided a methodology for proactive event-driven computing with potential application to CBM. However, it is conceptually described and sets the guidelines for future development (Engel et al., 2012). Bousdekis et al. (2015) propose a framework for CBM that depicts the procedures that must be taken for proactive recommendations as well as the types of recommendations that can be offered. Depending on the sort of decision required, a company's maintenance management can use the framework to conduct CBM by employing real-time sensor data (Le & Pang, 2013).

Defining the best maintenance policy represents a critical issue for all kinds of production plants. This aspect particularly affects the process industry, as all the activities are sequentially connected. Many variables like temperature, flow rates, level and chemical characteristics of raw materials have to be measured and monitored (Yew Seng & Srinivasan, 2009). Data mining (DM) tools, like association rules (AR), can provide valuable support to maintenance processes (Antomarioni et al., 2018). The review of the principal condition monitoring techniques applied to fault detection of offshore wind turbines presented by Kabir et al. (2015) is a further example of DM applications to maintenance policy. The design of CBM systems highly impacts society in terms of maintenance cost (i.e. reduces the maintenance cost of automobiles, and safety by providing real time reporting of the fault using prognosis) (Prajapati et al., 2012).

Future failures could be predicted through statistical data referring to the equipment, a more accurate prevision is provided through the analysis of data related to the current condition captured from condition monitoring, life assessment, visual inspection, etc. Interestingly, monitoring a power plant operation is connected to several variables which generate a large amount of data. The data could come from various data acquisition, offline monitoring techniques, failure and maintenance data stored in a Computerized Maintenance Management System (CMMS), and real-time data-driven. Otherwise, analyzing a large amount of data need a great effort and is costly, so categorizing and selecting data based on Asset Criticality Ranking (ACR) becomes an important step.

A smart maintenance decision support system integrates optimization algorithms and analytic decision models to provide useful suggestions on maintenance execution (Bumblauskas et al., 2017). Manco et al. (2017) performed an outlier-based fault prediction by studying non-normal signals provided by sensors and validated their approach through an experimental case study. Proactive enterprise systems will be able to suggest early on to the decision-makers the most appropriate process adjustments to avoid singular system behavior and optimize its performance (Magoutas et al., 2014). Furthermore, this paper proposes a data-driven decision-making system that is essential in supporting experts to provide accurate recommendations for O&M activities.

## 2. Literature Review

In the energy business, the dependability of power plants and transmission lines is of utmost importance to ensure that sufficient electricity is supplied to customers. If the power plants are not properly maintained and cannot be operated reliably, a considerable amount of damage could be incurred by society as a result of a power shortage (Velayutham & Alnaimi, 2018). Newly developed decision support tools for effective maintenance operations should include: (1) data-driven identification of short-term throughput bottlenecks, (2) estimation of maintenance windows of opportunity, (3) prioritization of maintenance tasks, (4) joint production and maintenance scheduling systems, and (5) maintenance staff management. The concepts of these decision assistance systems are exemplified using mathematical algorithms and simulation techniques (Ni & Jin, 2012).

The Decision Support System needs to be capable of the extraction and mash-up of heterogeneous data using the concepts of artificial intelligence and data mining. This will allow the data and human expertise to be combined in the process of developing new services, experiences, decisions, and maintenance rule-bases, among other things. In addition to this, it must integrate data in a seamless way from a variety of sources and formats by utilizing a data-aware correlation engine. This will make the data currently available more useful for technical and professional users by providing them with a more effective decision-making and predictive capabilities.

Proactive maintenance (POM) seeks to eliminate, decrease, automate, or simplify maintenance without jeopardizing safety or dependability. In its simplest form, proactive maintenance covers three key concepts: maintenance elimination, maintenance prevention, and maintenance enhancement. In addition to regular work lists and reactive repairs, proactive maintenance necessitates an investigation into why a component failed in the first place. It may involve the discovery of a procedure, product, or practice that extends the life of a component and reduces the frequency of inspections. It may be as simple as standardizing screws, improving access to tough inspection areas, or teaching to internal customers how to fill out a work request correctly (Muganyi, 2018). A method known as proactive maintenance looks to either lengthen the useful life of machines or equipment by removing the factors that lead to the need for maintenance in the first place (Chumai, 2009) .

In general, CBM can be viewed as a way for reducing the uncertainty of maintenance activities and is carried out in accordance with the equipment condition's requirements (Shin & Jun, 2015). There are three types of approaches within CBM: (1) the data-driven approach, (2) the model-based approach, and (3) the hybrid method (Lee, 1998). By utilizing remote monitoring technology, Internet of Things (IoT) technology can make it possible to perform highly distributed elevator equipment servicing. This shift from traditional corrective maintenance (CM) and time-based maintenance (TBM) to more predictive, condition-based maintenance (CBM) is necessary in order to realize a variety of benefits (Lai et al., 2019). According to Caesarendra (2010), a data-driven method can translate high-dimensional data into information with lower dimensions. It is often referred to as the data mining or machine learning technique since it leverages past data to automatically create a model of system behavior. Nonetheless, this method is dependent on the quality of operational data and physical knowledge of the target product.

Commonly, maintenance tasks are managed by a CMMS, but comparatively, few businesses review their maintenance records. Behind these data is frequently a treasure trove of potential for improvement that may be used to enhance basic maintenance. Every component has a finite lifespan. For some types of components, the variance in lifetime is quite limited, but other types may have a very variable lifetime, typically due to inherent inconsistent quality. Numerous components, particularly mobile ones, exhibit apparent degradation patterns that can be tracked using a variety of methods. Weibull distribution is used to examine the lifespan distribution of components in reliability engineering. By documenting failure reports, disturbances, planned preventive maintenance, etc. in CMMS, the maintenance efficiency and efficacy of the components have been enhanced (Salonen et al., 2020).

When analyzing the performance of a system, there are two possible techniques to examine. While the intrinsic Reliability, Availability, Maintainability and Safety (RAMS) depends solely on the design of the asset and the time necessary to undertake a remedial action, with no external variables involved, the operational RAMS takes into consideration the maintenance performance and the external elements specific to the site (the environment, human factors, random failures, logistics, etc.). For the intrinsic approach, a model could be based on the theory of failure by studying the different components and the theory of failure for each of them. However, for the operational approach, a data-driven decision model would be preferable, since corrective maintenance records reflect the performance of the system in relation to all external factors involved in its operation and maintenance (Morant et al., 2016).

## 3. Data Driven Decision-Making System

The purpose of this study is to present an O&M data-driven decision-making system that integrates resources from POM in order to enhance the level of confidence that decision makers have in their abilities to maintain the performance and reliability of the power plant. A case study from the deployment of a data-driven decision-making system in the PT IP is used by the authors for the assessment of the proposed system in this study. The system's architecture collects information from various sensors that have been put in power stations across Indonesia. The architecture of the data flow system is divided into two sections, one of which is installed within the IT system of the power plant and the other within the PT IP data center.

### 3.1.*System architecture*

The system architecture on the power plant side, as shown on Figure 1 is comprised of data inputs from sensors, in-situ monitoring and historical failure data from CMMS, data communication protocols, and human-machine interface units. The system is also supported by firewalls to protect the system against unauthorized access. Readings and detections made by sensors, transmitters, and analyzers that have been installed within the power plant unit are utilized to gather parameters relating to the process cycle and the condition of the power plant unit. These parameters would then be transmitted to the Distributed Control System (DCS) or the Programmable Logic Control (PLC) in Asset Performance Management (APM) system. The data is then transferred to the PT IP data center through a Wide Area Network (WAN).

In the PT IP data center, the data are transmitted from the WAN to PT IP internal server, which acts as a data archiving unit. The server also includes a customizable repository to develop hierarchical, asset-centric systems of objects and equipment arranged according to specified relationships. It combines data from numerous sources, including external relational databases, categorizes, adjusts, connects, and performs additional analysis on the data. In order to be processed further for advanced forecasting analyses, for instance, predicting material failure or outage detection, parameters from the sensor, in-situ monitoring and CMMS are stored in a server which is located in a saved place, whereas the visualization system can be accessed through web from anyplace, include the PT IP headquarter.

The purpose of the data lake here is to scale and maintain real-time and historical data in their unprocessed form for one or more systems for the purpose of data analysis, since the data is streamed in a massive and rapid manner. Figure 1 depicts the next stage of the DMS workflow. It is then visualized through a dashboard. In addition to being utilized for predictive analysis, POM sensor data that has been stored in the server is also used to trigger dispatch after analyzed by the O&M experts. The dispatch system would alert the power plant unit operators if an anomaly or malfunction is detected. The detailed steps of the DMS workflow is described on the section 3.2.

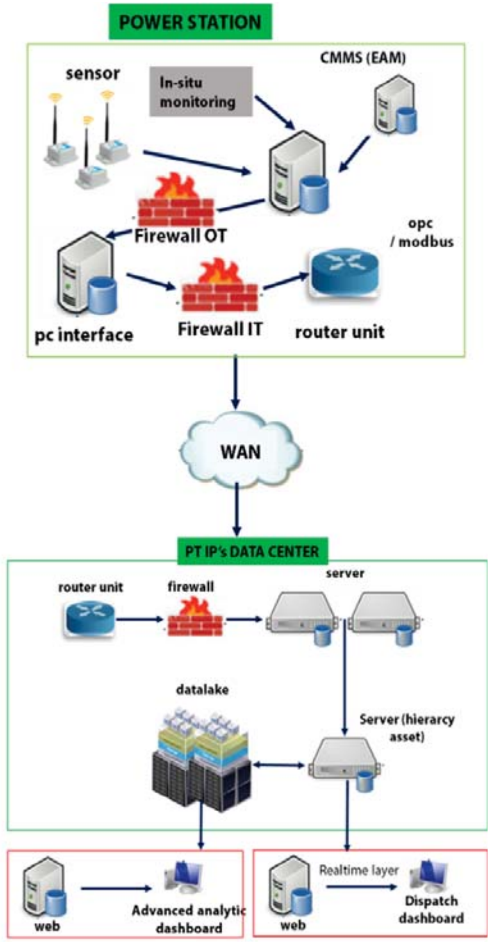


Fig. 1. IT system architecture

### 3.2.*Decision-making system (DMS) workflow*

The goal of the data-driven decision-making system proposed in this paper, is to reduce the amount of uncertainty that often presents during O&M activities. Expert judgment is not always adequate to determine whether or not corrective action is necessary when a failure has been discovered. The DMS not only integrates the analytical parameters stored in the APM, but the system is also supported by CMMS. APM plays a critical role in the DMS as it delivers continual insights to enhance asset performance and reliability. CMMS is also included in the system due to its function in controlling asset data and work process. The elimination of data silos would be accomplished by combining CMMS and APM; this, in turn, would make it possible for the organization to maintain a single asset registry, includes all of the associated procurement, warranties, and O&M information, all of which would the organization in reducing costs and preventing failures.

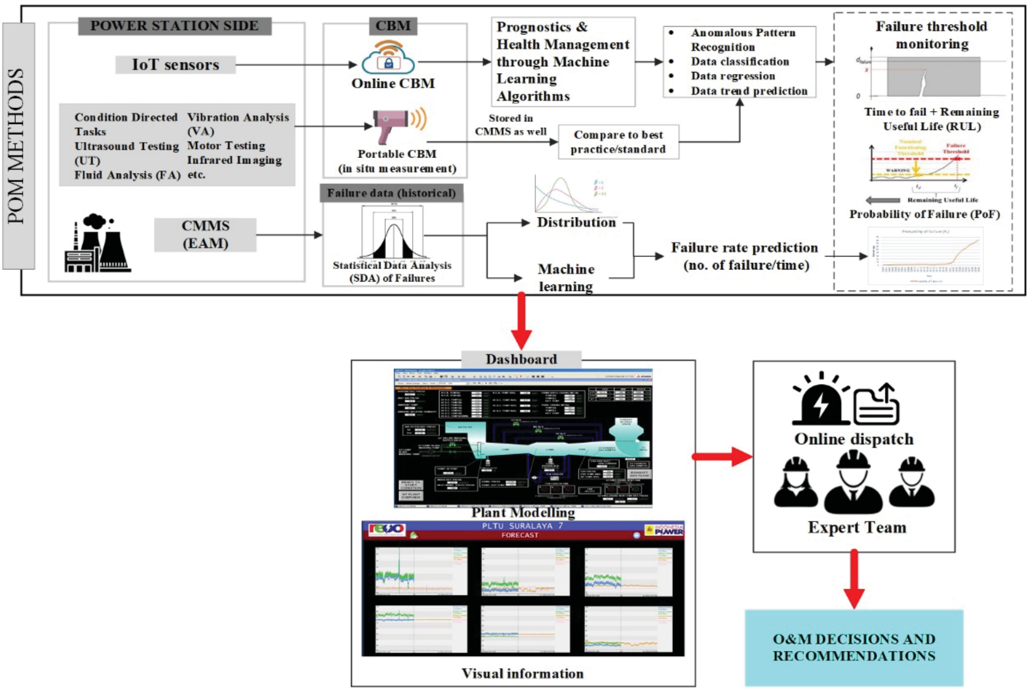


Fig. 2. DMS workflow includes APM and CMMS integration

Multiple IoT sensors that are installed in the power station are processed in the APM system to be analyzed using Machine Learning Algorithms (Prognostics and Health Management) such as Linear Regression, Long Short-term Memory (LSTM), Random Forest, Convolutional Neural Network and so forth. It is then continued to advanced diagnostic tools and techniques, such as anomalous pattern recognition, regression and trend prediction to obtain failure threshold from various real-time parameters available, e.g. temperature, speed, vibration and so on. In addition, parameters obtained from offline CBM technique are managed in CMMS to be compared with the failure threshold from good practice or standard. Both parameters will be used to identify when the equipment would fail, and later on to obtain Remaining Useful Life (RUL) of the equipment (Zio, 2019). Systematically, historical failure data that are stored in CMMS would be processed with the combination of statistical analysis and machine learning simulation to obtain the Probability of Failures (PoF), in which would support the failure rate prediction. There are two possible outputs of the analytic, one would be processed through an online dispatch system and a dashboard through a human-interfaced machine. This dashboard offers insights via chart, graphic, and time series presentation that will be used by the experts.

The online dispatch system has the role to notify the operators in the power plan units in the event of anomaly or malfunction through multiple IoT real time sensor that has been calculated through machine learning algorithm. On the other hand, the analytics from the dashboard will be received by the experts, stationed at the PT IP headquarter who will carry out further analysis by considering maintenance activity data. The O&M decision output from the experts would trigger maintenance activities, alarms or notifications in the form of an event or anomaly of equipment and generating units, and notifications in the form of the cause of an event, predictions of events that will occur next, and recommendations for steps to be taken. In addition, experts are required to verify the output of data-driven POM method in the DMS. If the process results are unsatisfactory, the Power Diagnostics Center experts will alter and/or redesign the algorithm. The results from the additional analysis will be transmitted to the CMMS in the generating unit and utilized as input for maintenance actions.

## 4. DMS Impact

Following the implementation of the proposed DMS on the case study in the PT IP power plants, it has been identified some significant improvements in terms of power plant equipment performance and efficiency. The following are the result of performance and efficiency improvement.

### 4.1. *Power plant Performance*

To collect evidence on the impact of DMS implementation on the IP's power plant could improve the performance, this paper presents the positive trend of Equivalent Availability Factor (EAF) increase and the lower values of Equivalent Forced Outage Rate (EFOR).


Fig.4(a). EAF trends


Fig.4(b). EFOR trends

In the year of 2018, the DMS pilot projects started to be initiated for the implementation in PT IP's power plant units. Figure 4(a) indicates the increase in EAF values of numerous power plants that implements the DMS for managing its O&M activities and strategies. EAF is one of the indicators of the power plant's performance. It represents an energy ratio of the amount available in a period and the theoretical maximum, which also indicates the impact of scheduled and forced outages of components along with any deratings. Generally, the graphic depicts the increase of EAF values since the initiation in 2018 and the impact of the DMS in 2019. Figure 4(b) also shows the lower value of EFOR from the beginning of 2018-2019, which represent the number of hours a unit is forced off line, compared to the number of hours a unit is running. Some anomalies of the lower EAF value and increase of EFOR also appeared due to scheduling overhaul of the power plant units. It can be concluded that the implementation of the DMS supports the power plant units to be able to operate in its better performance.

### 4.2. *Efficiency*

In terms of the impact of the DMS in increasing the efficiency, the authors identified the case of Labuan Coal Fired Power Plant condensor. Before applying the DMS, the condensor unit efficiency is 41.48 %, and through POM methods, that includes data analysis, visualization and expert judgment, the management could create a decision of altering the regular vacuum pressure of the condensor from 89.9 Kpa to 91.8 Kpa. The result of this decision execution is the condensor efficiency had been increased to 53.47%.

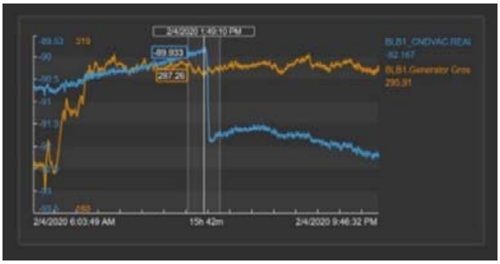


Fig.5. Visualization of the equipment dashboard

## 5. Conclusion and Recommendation

The DMS proposed in this paper highlights the methodology that involves proper data collection, advanced analytics using statistical calculation and machine learning algorithms. Additionally, the data, procedures, and strategies necessary to put the data-driven approach into action have been discussed. In addition to that, some case studies have been presented in a general overview. Based on these case studies, it has been determined that the deployment of data-driven DMS based on POM methodology has a great influence on sustaining power plant performance and efficiency. This is because it is able to support the experts in the formulation of O&M decisions and recommendations. It is also identified from the case study presented in this paper that since the implementation of the DMS, the power plant performance has been increased, demonstrated by some indicators such as the increase of EAF and lower EFOR. In terms of efficiency, the DMS also supported the achievement of the efficiency of power plant's equipment.

For future study, the definition of particular support and confidence levels for each component that belongs to a specified equipment may be a future area of development that is being considered. In addition, there is the possibility of including a financial analysis into the DMS in order to boost its level of applicability. It has to be ensured as well that the data input for the system and analyses are in good quality, adhered to standards.

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**Reference**

Antomarioni, S., Bevilacqua, M., Potena, D., & Diamantini, C. (2018). Defining a data-driven maintenance policy: An application to an oil refinery plant. International Journal of Quality & Reliability Management, 36. https://doi.org/10.1108/IJQRM-01-2018-0012

Bousdekis, A., Magoutas, B., Apostolou, D., & Mentzas, G. (2015). A proactive decision making framework for condition-based maintenance. *Industrial Management & Data Systems*, *115*(7), 1225–1250. https://doi.org/10.1108/IMDS-03-2015-0071

Caesarendra, W. (2010). *Model-based and Data-driven Approach for Machine Prognostics*. https://repository.pknu.ac.kr:8443/handle/2021.oak/9964

Chumai, R. (2009). *System Dynamic Modeling of Plant Maintenance Strategy in Thailand*. https://www.semanticscholar.org/paper/System-Dynamic-Modeling-of-Plant-Maintenance-in-Chumai/560ef271fa9f8fb952614c8ab28189b97bad06f6

Engel, Y., Etzion, O., & Feldman, Z. (2012). A basic model for proactive event-driven computing. *Proceedings of the 6th ACM International Conference on Distributed Event-Based Systems*, 107–118. https://doi.org/10.1145/2335484.2335496

Kabir, M., Than Oo, A., & Rabbani, M. (2015, September 30). *A brief review on offshore wind turbine fault detection and recent development in condition monitoring based maintenance system*. https://doi.org/10.1109/AUPEC.2015.7324871

Lai, C., Jiang, W., & Jackson, P. (2019). Internet of Things enabling condition-based maintenance in elevators service. *Journal of Quality in Maintenance Engineering*, *25*. https://doi.org/10.1108/JQME-06-2018-0049

Lee, C.V., & Pang, C.K. (2013). An energy data-driven decision support system for high-performance manufacturing industries. *International Journal of Automation and Logistics*, *1*, 61–79. https://doi.org/10.1504/IJAL.2013.057453

Lee, J. (1998). Teleservice engineering in manufacturing: Challenges and opportunities. *International Journal of Machine Tools and Manufacture*, *38*(8), 901–910. https://doi.org/10.1016/S0890-6955(97)00135-1

Magoutas, B., Stojanovic, N., Bousdekis, A., Apostolou, D., Mentzas, G., & Stojanovic, L. (2014). Anticipation-driven architecture for proactive enterprise decision making. *CEUR Workshop Proceedings*, *1164*, 121–128.

Manco, G., Ritacco, E., Rullo, P., Gallucci, L., Astill, W., Kimber, D., & Antonelli, M. (2017). Fault detection and explanation through big data analysis on sensor streams. *Expert Systems with Applications*, *87*, 141–156. https://doi.org/10.1016/j.eswa.2017.05.079

Morant, A., Larsson-Kråik, P.-O., & Kumar, U. (2016). Data-driven model for maintenance decision support: A case study of railway signalling systems. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, *230*(1), 220–234. https://doi.org/10.1177/0954409714533680

Muganyi, P. (2018). *Proactive Maintenance Strategic Application to Advance Equipment Reliability*. https://www.semanticscholar.org/paper/Proactive-Maintenance-Strategic-Application-to-Muganyi/46d4bf0425dd10c188daa6262da86305e2f9955c

Ni, J., & Jin, X. (2012). Decision support systems for effective maintenance operations. *CIRP Annals - Manufacturing Technology*, *61*, 411–414. https://doi.org/10.1016/j.cirp.2012.03.065

Prajapati, A., Bechtel, J., & Ganesan, S. (2012). Condition based maintenance: A survey. *Journal of Quality in Maintenance Engineering*, *18*(4), 384–400. https://doi.org/10.1108/13552511211281552

Salonen, A., Bengtsson, M., & Fridholm, V. (2020). The Possibilities of Improving Maintenance Through CMMS Data Analysis. *SPS2020*, 249–260. https://doi.org/10.3233/ATDE200163

Shin, J.-H., & Jun, H.-B. (2015). On condition based maintenance policy. *Journal of Computational Design and Engineering*, *44*. https://doi.org/10.1016/j.jcde.2014.12.006

Velayutham, P., & Alnaimi, F. (2018). A Review on Power Plant Maintenance and Operational Performance. *MATEC Web of Conferences*, *225*, 05003. https://doi.org/10.1051/matecconf/201822505003

Woodhouse, J. (2015). Extending SALVO decision-making disciplines into procurement, spares & inventory strategies. *Asset Management Conference 2015*, 1–4. https://doi.org/10.1049/cp.2015.1750

Yew Seng, N., & Srinivasan, R. (2009). Data Mining for the Chemical Process Industry: In J. Wang (Ed.), *Encyclopedia of Data Warehousing and Mining, Second Edition* (pp. 458–464). IGI Global. https://doi.org/10.4018/978-1-60566-010-3.ch072

Zio, E. (2019). *Data Mining and Machine Learning Techniques for Fault Detection and Diagnosis and Failure Prognosis in Industrial Components and Systems*. 2019 Annual Reliability and Maintainability Symposium.