

Predictive Maintenance for Automatic Weather Station (AWS) Based on Anomaly Detection Using Autoencoder: A Literature Review

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ABSTRACT

Automatic Weather Station or AWS is an instrument for measuring weather parameters automatically. The results of measuring weather parameters are very useful in the fields of meteorology and climatology, such as weather prediction, aviation and climate change. Especially in Indonesia, the Meteorology, Climatology and Geophysics Agency or BMKG has main tasks and functions in this field. Currently, data with accurate results is needed to produce accurate weather and climate predictions. However, sometimes there are anomalies in the data caused by AWS damage, resulting in inaccurate data. This will have an impact on modeling results in the fields of meteorology and climatology, where the modeling results are less precise. To overcome this problem, predictive maintenance is needed to avoid data errors in AWS operations. This research aims to build predictive maintenance at an Automatic Weather Station Based on Anomaly Detection using a Machine Learning Autoencoder. The anomaly data can be detected by machine learning autoencoders for monitoring AWS performance and conditions, that methodology applied in this study for build predictive maintenance in AWS. Finally, the expectation of this research is to make accurate predictive maintenance on AWS so perhaps that can reduce maintenance costs and increase the lifespan of the instrument before it breaks.

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1. INTRODUCTION

Automatic Weather Station or AWS is an automatic instrument system for measuring weather parameters in real time. The World Meteorology Organization (WMO) has defined an AWS as a meteorological station where weather parameters observations are automatically taken and sent. The amount of surface atmospheric observations are increased by using AWS and accuracy higher than using by manually [1]. One of the organizations that manages the field of meteorology and climatology in Indonesia is the Meteorology, Climatology and Geophysics Agency or BMKG.

Currently we have entered the industrial era 5.0. In industrial era 5.0, people and robots make a collaboration and disregard a competition in the future [2]. The appearance of rapidly expanding digital technology and artificial intelligence (AI)-based solutions is causing a rapid transition in the manufacturing sector today. The main issue for manufacturers worldwide is to increase production while still holding human involvement in manufacturing sectors [3]. The application of machine learning autoencoders for predictive maintenance is one example of implementation of artificial intelligence (AI) in contemporary society.

The goal and aim of predictive maintenance (PdM), that is the improvement of maintenance by a variation of preventive maintenance, is to extend the life and quality of equipment in AWS and guarantee

sustainable operational management while enhancing the manufacturing process's performance and efficiency. By providing or enabling the opportunity for interventions through failure prediction, this recommended for decreasing probability in downtime, failures, and the frequency of stops without control, together with a reduction in service, maintaining, and fixing them expenses [4]. predictive maintenance as repairing methods are designed to assist meteorological instrumentation sectors according to their needs and help in maintenance requirements, as was discussed in earlier sections. AWS is one of them. Depending on the extent and improvement of technological and digital technology, various PdM model types may be available and can be used [5]. A machine learning autoencoder is one of the models utilized in predictive maintenance based on anomaly detection.

An example of a type unsupervised learning algorithm is the autoencoder, a kind of neural network that does not need data labelling. Learning a data entry to rearrange the data to a fewer-dimensional output is the goal [6]. In this research, the autoencoder uses anomaly detection data to make predictive maintenance.

Finding anomalies is a significant and serious problem that has been researched for a long time currently. For various applications and implementations, a wide variety of unique techniques have been created and applied to identify abnormalities. The challenge of identifying data patterns that deviate from expected behaviour will be applied [7]. An anomaly in the output data indicates an error in measurement caused by equipment damage.

In order to extend and increase the lifespan of AWS and save spending high costs in repairing when damage occurs, the goal of this project is to develop an accurate predictive maintenance system based on anomaly detection data on AWS.

2. METHODOLOGY

2.1 Data dan Data Sources

The dataset used is data from observations of weather parameters using AWS at the BMKG Class 1 Banjarbaru Climatology Station. The data-based technique or method known as Predictive Maintenance (PdM) has become a key area of research or study among the many other maintenance systems currently in use and applied. it increases a system's reliability by modeling system behavior, identifying trends, and anticipating breakdowns and failure through the use of statistical analysis, Machine Learning (ML) models, and Deep Learning (DL) solutions [8]: Model-based prognosis, knowledge-based prognosis, and data-driven prognosis are the three primary categories into which PdM techniques or method belong. In both industry and academia, data-driven PdM tactics have attracted major attention and significance [9]. The dataset is divided into 3, namely normal data, gradual failure data and immediate failure data. Each data contains the results of measurements of weather parameters including temperature, pressure, rainfall, sunlight and wind.

2.2 System Design Method

Fig. 1 below shows an example of a visualization of an autoencoder architecture. Applications such as dimensionality reduction, signal reconstruction, and anomaly detection have made complicated use of autoencoders [10].

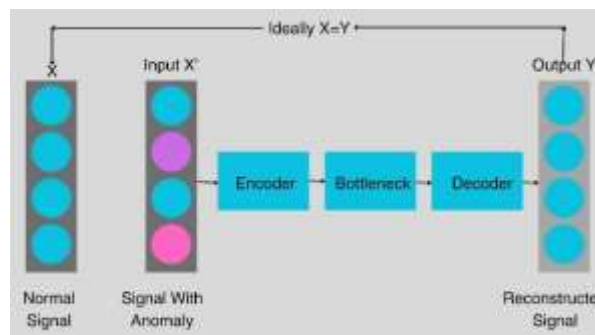


Fig. 1. Visualization of an autoencoder architecture [10]

The Explanation of illustration of autoencoder architecture. The network simplifies the input data into a smaller hidden modelling in the encoder section. it interventions or strategy to collect the most significant aspects of the data being collected. The original data is reconstructed from the encoder's hidden representation in the decoder's section. It attempts to generate and produce the supplied data as precisely as it can.

The network efficiently learns to filter out noise and irrelevant information during the learning phase by lowering variance between the input and reconstructed output or result.

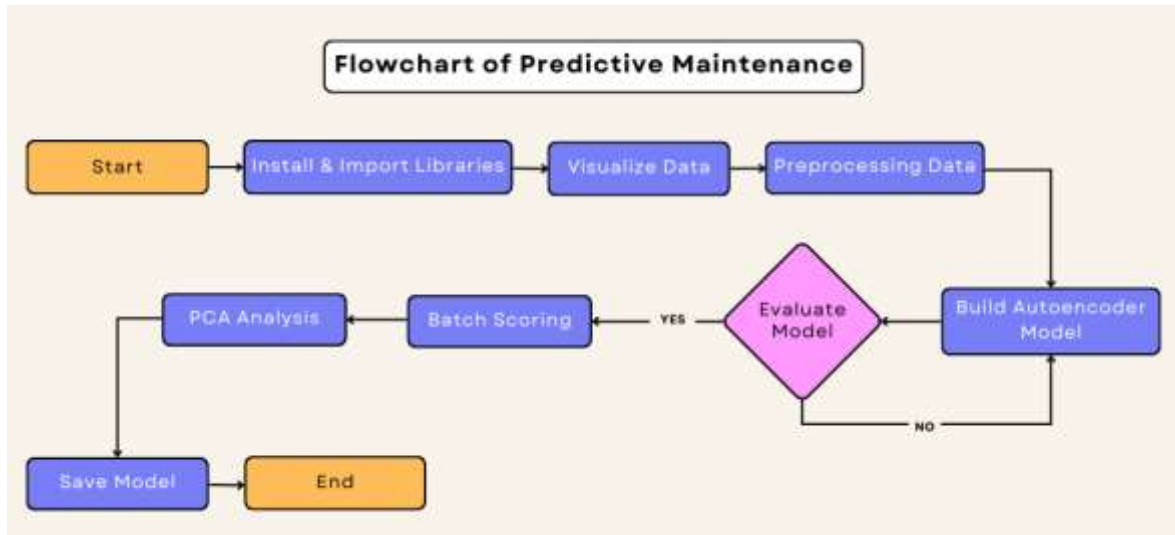


Fig. 2 Flowchart of predictive maintenance.

This the explanation about the step of flowchart that describes the predictive maintenance for AWS process using an autoencoder:

- **Start:** The initial stage of this process is predictive maintenance for AWS.
- **Install & Import Libraries:** Installed and imported necessary libraries for data analysis in predictive maintenance for AWS that are useful in predictive maintenance, such as pandas, tensorflow, and matplotlib.
- **Visualize Data:** Analyze data by creating visualizations to understand patterns, distribution, and outliers in the data.
- **Preprocessing Data:** Regulate the data to be normalized and divide it into testing and training data sets so that it is prepared and ready for use in model training.
- **Build Autoencoder Model:** Build autoencoder models using frameworks like Keras. This model will be used to detect anomalies.
- **Evaluate Model:** Test and evaluate model performance using appropriate metrics, such as Mean Squared Error (MSE).
- **Batch Scoring:** Perform batch scoring on test data to detect anomalies based on the trained model.
- **PCA Analysis:** Carrying out PCA (Principal Component Analysis) analysis to reduce data dimensions and visualize scoring results.
- **Save Model:** For later usage, archive the scalar and trained model.
- **End:** The final stage of the process, indicating that all steps have been completed predictive maintenance for AWS.

2.3 Program Tool

In this research, the tool used is Google Collab as a tool for executing predictive maintenance for AWS. To transport out the entire experiment using a dataset, Google collab is utilized [11].

2.4 Programming

In this research, the author uses Python as a programming language to create predictive maintenance for AWS. while the machine learning used is a machine learning autoencoder. The modeling and execution is done in Google Collab.

3. LITERATURE REVIEW

3.1 Predictive Maintenance

In the industrial and meteorological instrument sector, maintenance is crucial and vital because it can provide explanations for an important percentage of a company's or agency operating costs [12]. Today, where technological developments grow faster, maintenance efficiency is needed to avoid more serious equipment or instrument damage. One of the solutions is through predictive maintenance. Condition-Based Maintenance (CMB) delivered rise to more advanced and successful methods or techniques, like predictive maintenance

(PdM), which combines capabilities in automation, engineering information technology, and data analytics with the concepts of IoT and Cyber Physical System (CPS) [12].

Predictive maintenance has been applied in some industries to efficiency cost. For example, Ref. [16] Apply deep learning methods to avoid Metro do Porto Trains Air Production Unit (APU) technology from malfunctioning. They were also able to increase the accuracy of failure estimations, which results in higher-quality maintenance. To prevent or avoid inaccurate data in the necessary continuous anticipation and accuracy, however, they have to upgrade the sensor. Reference [17] used predictive maintenance to overcome traditional maintenance strategies either risk machine downtime or replace parts prematurely, leading to financial losses and inefficiencies. This also has similar results with [18] being successful in reducing unplanned downtime. Hopely in the future they can require extensive data for training to produce accurate results. To effectively manage the high number of vehicle data, Theissler et al. [19] applied machine learning (ML)-enabled predictive maintenance. From several researchers, they have demonstrated the effectiveness of predictive maintenance for efficiency and reducing instrumentation failure.

Reference [41] builds predictive maintenance by applying a set-based design method by using a physical model of the equipment to identify and mitigate potential failures or downtime. Reference [42] to reconstructed corrupted signals and reduce maintenance downtime, so they design a predictive maintenance system using computational fluid dynamics (CFD) to get operational efficiency of the HH-60G Helicopter. The improvement of predictive maintenance by integration of data analytic and AI has demonstrated by [43]. Similar to [44], they make expansion to emerging technologies in development of predictive maintenance. Reference [45] applied predictive maintenance in the Dry 8 Production machine line by implementing the Support Vector Machine (SVM) to reduce downtime or failure and also effectively increase productivity.

From the statement above, that can conclude if researchers have made some improvement in predictive maintenance. In this paper, the author wants to make an improvement to the Automatic weather Station (AWS).

3.2 Anomaly Detection

Determining data values that significantly disappear from the expected pattern is the focus of anomaly detection. A number of variables could be dependable for the anomaly, like malfunctioning sensors, low batteries, or data transmission errors; other factors could be industrial equipment or sensors if it results in AWS failures, or events, like production line changes or curative arrests. Anomalies produced by incidents in the machinery present the analyzer with accurate details, whereas anomalies caused by sensor weaknesses lack and could result in data to be misinterpreted. These anomalies could be classified as noise, however as previously stated, the process by which anomalies and noise are explained varies depending on the kind of data [13].

Anomaly detection has been used in some research. For example, Anomaly detection has been applied to predictive maintenance (PdM) models in industrial settings in Ref. [15]. They used data from rolling mills in the steel sector to show data that was abnormal. Similar to [16] created a predictive maintenance using framework for one of the machines in railways, the air production unit (APU) that operates Metro do Porto trains using anomaly detection. Reference [17] improves predictive maintenance by accurately detecting anomalies using data from industrial equipment. So they can improve asset health and performance. Ref. [18] used anomaly detection by time-series sensor data from an electrical rotary machine, including normal and fault data. This data needed to identify anomalies knowing the difference of normal and fault data. Similar to [20] employed SpectraQuest's Machinery that has an event Trouble Simulator to detect deviations in time series data from sensors, including healthy and abnormal states. Also, Fathi *et al.* [23] employed time-series using data from a three-dimensional Department of Fisheries delta robot conducting pick process-and-place tasks to find anomalies. Karapalidou *et al.* [25] used anomaly detection by multivariate time series data from industrial blower ball bearing units. Breux *et al.* [26] used anomaly detection by Sensor data from a data center's UPS system collected between January 2019 and May 2021. Roelofes *et al.* [27] used anomaly detection by wind turbine sensor data, including an open dataset with artificially added errors for controlled testing. Ref. [28] utilized SpectraQuest's gearbox fault-diagnostics simulator to detect anomalies in gearbox vibration data, including both broken-tooth and healthy states. Ref. [29] Using historical information from a KUKA, which is a KR6R 900 SIXX robot for manufacturing to find anomalies. Ref. [30] Utilized anomaly detection by acceleration data collected from sensors during container handling operations. Overall researchers have used anomaly detection to label data and use it in prediction. They also use health data to identify deviations.

3.3 Automatic Weather Station (AWS)

AWSs (automated weather stations) are widely used to collect climate and meteorological data. Guidelines for the deployment, setup, and operation of these stations are published by the World Meteorological Organization (WMO) [14]. There are four (4) types of AWS, according to WMO:

- a. Use light AWS to measure a few variables, such as air temperature and/or precipitation. The only limitations of this AWS are in air and rainfall measurements.
- b. Simple AWS for measuring the fundamental meteorological parameters (atmospheric pressure, precipitation, wind direction and speed, air temperature, and relative humidity). Meteorology typically makes use of this AWS.
- c. Extended AWS measures evaporation, soil temperature, sunshine duration, and solar radiation. This enhances AWS, which is typically utilized in climatology.
- d. AWS that automate visual observations (current weather and cloud base height). All of the categories offer the option to transfer data using a range of techniques and to log data utilizing a proprietary data logger [1].

AWS is usually implemented to measure weather parameters. Some research has been built on AWS with some improvement. For example, Ref. [31] To improve and develop learning, create and execute an instructional model of an Internet of Things weather station that makes use of cloud services. The weather station is incorporated into the Internet of Things (IoT) and effectively measures environmental characteristics such as temperature, humidity, and pressure. But, this research needs improvement so the weather station can be used for outdoor conditions. Similar to [32] design weather station device that measures both weather conditions and air quality using IoT technology. The researcher improved air quality measurement. Reference [33] the development of AWS and Precision Grid Meteorological Information System (PGMIS) enhances the accuracy and timeliness of meteorological data, contributing to better disaster management and energy use. The improvement of IoT and sensors help AWS to produce data with high accuracy and precision. However, manually still needed to complete the data, like [34] confirm that data from Automatic Weather Stations (AWSs) is of comparable quality to manually observed data and can bridge data gaps. For more information about research in AWS, Ioannoue *et al.* [1] Examine and investigate the methods and technology utilized to implement Automatic operation Weather Stations (AWS), especially in relation to the Internet of Things (IoT).

Reference [35] makes an improvement of AWS using Artificial Neural Network (ANN) to detect sensor errors so that it can increase a number of accuracy data. Reference [36] developed a website called Automatic Weather Station Data Tool (ADT) using integrated data from various AWS networks that can assist National Meteorological Services (NMS) access, process, perform quality control and visualize data from different AWS networks in one place. Some researchers also build and design AWS with low cost for meteorological upper observation, that implemented by [37]. Reference [38] design AWS using microcontroller and weather forecasting device as based. This has advantages in techno economics and meteorological data collection. But, continuous maintenance is needed. The integration of AWS with IoT has been implemented by [39], the researcher designed an AWS with intelligence based on Internet of Things (IoT) to improve data accuracy and real time monitoring. The last, Ref. [40] design Automatic Weather Station with low cost and also based DIY in IoT to result in accurate and real time weather data.

Conclusion, AWS has been built with some improvement technology and also to complete manually data observation. But, they have not improved in maintenance. So, in the next research, perhaps the author can develop predictive maintenance in AWS.

3.4 Autoencoder

Autoencoder is classified as unsupervised type, where anomaly detection techniques aim to find abnormalities based on the inherent structure of data and lack labeled data. This algorithm has the advantage that it can learn complex, non-linear relationships, Robust to noise with denoising and variational variants. But this also has disadvantages, where requiring large amounts of training data can be computationally expensive [22].

Some studies related to problems in the below information that can be solved using machine learning autoencoders. Autoencoders have been used in some research. For example, Ref. [15] used Variational Autoencoder (VAE) for unsupervised anomaly detection and SHapley Additive exPlanations (SHAP) for model explainability. This need requires further validation and optimization for improvement. Ref. [16] implemented a Sparse Autoencoder (SAE) network to detect anomalies. Beneficially this is reduced false alarms and enhanced maintenance planning. Ref. [17] suggests a brand-new deep learning method for anomaly identification in predictive maintenance that combines Automatic encoders and LSTM (Long Short Term Memory) models. By precisely identifying anomalies, this combined approach can result in predictive maintenance. Ref. [18] utilizes stacked autoencoders (SAEs) to model normal machine behavior and detect anomalies. This enables early fault detection and intervention in industrial motors.

Another research also can be our references. Like, Ref. [21] without the need for domain-specific physics knowledge, machine learning with Autoencoders (AE) is used to forecast the current-voltage (IV) and

capacitance-voltage (also known as CV) curves of FinFET transistors. This study improves the efficiency of semiconductor devices. Ref. [20] Comparison between a regular autoencoder and an LSTM-autoencoder model, focusing on MSE deviations, training duration, and decline function for anomaly detection in Electric Motors. The result is that the LSTM-autoencoder model is better than regular autoencoder. Although slower because of the intricacy of the LSTM layers, the LSTM-autoencoder displayed significantly lower loss values and MSE anomalies than the standard autoencoder. Ref. [23] using autoencoders (AEs) for anomaly detection and maintenance prediction in a 3 DoF delta robot, even without Run-to-Failure (R2F) data. This has advantages in simple data because no need for R2F data. But, this affects the accuracy and complexity of data. Ref. [24] using PredMax, a predictive maintenance tool that combines the use of principal component analysis (PCA) along with deep convolutional neural networks autoencoders (DCAE) for data grouping and dimensionality reduction. All things considered, this effectively located the most delicate machine components and times of unusual operation in an industrial gearbox case study. Ref. [25] using multivariate time-series information of industrial blower ball bearing units, an organized sparse LSTM Autoencoder is trained on typical operational data to identify anomalies. This is effective in anomaly detection but still requires extensive data preprocessing and computational resources for improvement. Ref. [26] uses multiple autoencoders, each for a different sensor, to reconstruct inputs and detect anomalies with a random forest classifier in a data center. F1-score of this method achieved 83.60% that showed the balancing of precision and recall that has relation in high accuracy. Ref. [27] use autoencoders for anomaly detection and ARCANA for root cause analysis by optimizing reconstruction errors to highlight significant features. The result, ARCANA successfully identified the wind speed sensor as the root cause of anomalies with higher accuracy than traditional methods. Ref. [28] a deep learning framework for industrial machine anomaly detection and fault investigation based on a six-layer autoencoder. The proposed model achieved an overall accuracy of 91%. That showed the high accuracy. But, that still has potential overfitting and the need for further validation with different industrial data sets. Ref. [29] identifying irregularities in robot activities using the SWCVAE model. The suggested model proved useful for condition-based maintenance since it was able to identify abnormalities in the robot. This has the advantages in effective real time detection. Ref. [30] to find irregularities in the acceleration data, an auto-encoder model was employed. The auto-encoder successfully detected critical impacts, showing improved speed and accuracy over IDM. Depending on the container sway axis, it detected anything from nine to eighteen impacts. In a lab setting, the system was evaluated and contrasted with the Impacts Detection Methodology (IDM). Perhaps in future, this research needs improvement on Requires proper programming and testing in various real-life scenarios for high accuracy and any conditions.

Several researchers have demonstrated that autoencoders are highly effective in anomaly detection. In this research, the author wants to use autoencoders to design predictive maintenance in AWS.

4. CONCLUSION

In order to improve the efficiency of AWS maintenance, the primary goal of this article is to build predictive maintenance for AWS based on identifying anomalies utilizing artificial intelligence autoencoders that can speed up the predictive maintenance flow. To be able to design the desired predictive maintenance, the machine learning autoencoder is used. Anomaly detection is used to predict AWS before failure. This research will be designed in Google collab, which is easy using applications and simple features. The main objective of this study is to create predictive maintenance for Automatic Weather Station (AWS) to avoid the failure of instrumentation.

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