

# Fault Prognosis System on Face-Mask Body Machine with Adabelief-Backpropagation Neural Network

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**Abstract**— Ultrasonic welding workload on vertical roller welding components on face-mask body machine in making masks has a high vibration of up to 20kHz. This high vibration causes the locking bolt to loosen the serrations, thus causing a greater failure of function, such as wear and tear on the teeth. If this function fails, it will cause downtime and high costs in the waiting process for the cleat component to be remanufactured. The damage prognosis system based on the condition of this machine implements a Classification of types of damage along with recommendations for maintenance activities that need to be carried out on the Face-Mask Body Machine. Classification of the type of damage to this system using There is a Belief-Backpropagation Neural Network (BPNN), a method for looking for weight settings on a neural network based on the error rate obtained in the previous iteration. This method is optimized using AdaBelief, which can adapt the step size based on the "confidence" of the previous gradient to get Convergence rates and generalization abilities better so that these types of problems can be known from the vibration signal of the machine which previously the signal was parsed using wavelet packet decomposition into frequency bands to obtain component data with low or high frequency. From the results of system performance testing, the modeling accuracy is 98.4%, so this system can be declared good and feasible to use in slack detection of vertical roller welding cleat fixing bolts.

**Keywords**— *AdaBelief-Backpropagation Neural Network, Condition-Based Maintenance, Face-Mask Body Machine, Prognosis*

## I. INTRODUCTION

Damage to one of the machine components can cause the machine not to operate because the machine runs serially. The method applied to this company in overcoming damage is corrective maintenance, i.e., maintenance is done by identifying and fixing the causes of failure (Wang et al., 2014). Damage can cause the production process to stop suddenly, and production time can be reduced so that production targets are not achieved, and production costs will be high. Damage to one of the machine components can cause the machine not to operate because the machine runs serially. The method applied to this company in overcoming damage is corrective maintenance, i.e., Maintenance is done by identifying and fixing the causes of failure [1]. Damage can cause the production process to stop suddenly, and production time can be reduced so that production targets are not achieved, and production costs will be high. One example of a problem is the Vertical Welding Roller which shifts so that the welding results do not shift according to the standards set by the company. This problem can be caused by several things, such as the cleat locking bolts loose and loose roller fixing bolts. Inspection of these components requires machine breakdown, which takes quite a long time resulting in a loss of time.

Treatment is one important factor in supporting a competitive production process in the market. According to [2] be able to achieve things. For this reason, production support equipment is needed to work every time, current and reliable.

Maintenance of production equipment is needed in the production process to prevent production results from defective production processes. [3] stated that Maintenance is a combination of actions taken to maintain equipment by repairing it to an acceptable condition. In maintaining the reliability of production machines, [4] mentions that maintenance has Some of these approaches are run-to-failure is a reactive management technique that waits for a machine or equipment failure before maintenance activities occur. This technique is the most expensive maintenance management method because it only performs a rebuild or major repair once the machine fails to operate. Expenditure The biggest problem with this technique is the high cost of spare parts inventory, overtime costs for employees, high machine downtime, and low product availability because there is no effort to anticipate [5]. Preventive Maintenance is a management program based on the length of time the machine is operating. Machine repair or rebuild scheduled based on MTTF (mean-time-to-failure) statistics. This program assumes the machine will experience degradation over time and follow the time-frame classification. The problems arising from this approach are the mode of operation and the system or factory-specific variables directly affecting the machine's normal operating life. The result of using MTTF statistics to schedule Maintenance is a no-no fix needed or even severe damage because it does not match the statistical calculations MTTF [6]. Predictive Maintenance uses the actual operating conditions of the machine (condition

based) and thoroughly manage the maintenance program to optimize operations whole factory. Comprehensive predictive maintenance management system uses the most cost-effective equipment to get the actual condition of the system Critical on the machine, and a schedule is compiled for required Maintenance from the actual data obtained. Using this management will optimize the availability of machines and will greatly reduce maintenance costs. It also improves product quality, productivity, and profit from the production plant. On application to the machined aircraft, this method can identify the degradation and estimation required at the time in the future based on various usage scenarios [7]. A dynamic predictive maintenance system uses a variety of sensors to determine care decision making which has the advantage of being able to know 2 aspects namely regarding prognostic estimation and decision-making after it is known prognostic [8]. Use of Modeling predictive maintenance can be combined in a hybrid way to get predictive results better [9]. [10] mentioned the advantages of applying predictive maintenance systems in the industry include:

- a. Increase machine productivity because it can avoid the resulting downtime unexpected failure.
- b. Increase intervals between overhauls because maintenance is performed only when the engine is need.
- c. Reducing routine overhauls in the form of 'open, inspect, and repair if' activities needed' because the predictive maintenance system can determine the damage specifically, so that maintenance activities can be more focused than investigate all available opportunities.
- d. Improve repair times because repair strategies have been better formulated before implementation.
- e. Increase engine life.
- f. The need for repairs can be planned properly as well as personnel work, the equipment used, and the spare parts needed are known before damage occurs.
- g. Improve product quality because the machine runs optimally.
- h. Reducing maintenance costs where studies show that system implementation predictive maintenance can reduce up to 20-25% of costs.

Vibration analysis is used to determine a tool's operational and mechanical conditions. The most superior advantage of vibration analysis is identifying problems before they become fatal and cause unscheduled downtime. This can be done by doing Routine measurement of engine vibration levels at any time or predetermined intervals scheduled. Observation through the machine's vibration level is the most effective technique in detecting mechanical damage to rotating machines. Regular vibration level measurements can detect worn, loose bearings on mechanical components and worn or damaged cleats. Vibration analysis can also detect imbalance and misalignment before it results in bearing or shaft damage [11]

Moreover, lost production will increase. Loosening the locking bolts can result in cleat wear caused by imperfect rotation. If the cleats need to be replaced, the costs will increase, and the time for procuring new cleats will also

increase, causing production to stop. Machine failure can also pose a safety hazard for operators [12]. The determination of corrective solutions to problems that are currently occurring is also not based on a comprehensive consideration of the level of impact of these problems. The use of resources in repairs has yet to be discovered at the priority level, so it does not work effectively. Based on these problems, this research aims to be able to detect potential damage using the Wavelet Packet Decomposition and AdaBelief Backpropagation Neural Network methods so that malfunctions can be controlled, stock spare parts can be prepared efficiently, and time and production quantities can be increased so that production targets are achieved.

One example of a problem is the Vertical Welding Roller which shifts so that the welding results do not shift according to the standards set by the company. This problem can be caused by several things, such as the cleat locking bolts loose and loose roller fixing bolts. Inspection of these components requires machine breakdown, which takes quite a long time resulting in a loss of time, and lost production will increase. Loosening the locking bolts can result in cleat wear caused by imperfect rotation. If the cleats need to be replaced, the costs will increase, and the time for procuring new cleats will also increase, causing production to stop. Machine failure can also pose a safety hazard for operators. The determination of corrective solutions to problems that are currently occurring is also not based on a comprehensive consideration of the level [13] of impact of these problems. The use of resources in carrying out repairs is not known at the priority level, so it doesn't work effectively. Based on these problems, this research aims to be able to detect potential damage using the Wavelet Packet Decomposition (WPD) and AdaBelief Backpropagation Neural Network methods so that malfunctions can be controlled, stock spare parts can be prepared efficiently, and time and production quantities can be increased so that production targets are achieved.

## II. METHOD

The device is using vibration analyzes, especially on machines' face-mask body production. In building the Vibration Analyzer that will be used for detecting damage to the face-mask body production machine, decomposition is carried out as a signal until used in neural network modeling.

In the Vibration Analyzer design, 2 main systems are built, in Among them are data acquisition and damage prognosis systems. In the data acquisition process, Data recording is carried out as a vibration signal from the ADXL345 accelerometer sensor. Sensors are placed on the bearings that support the shaft of the vertical welding roller. Rollers This vertical welding is rotated by an AC motor connected using a chain on a mechanical circuit.

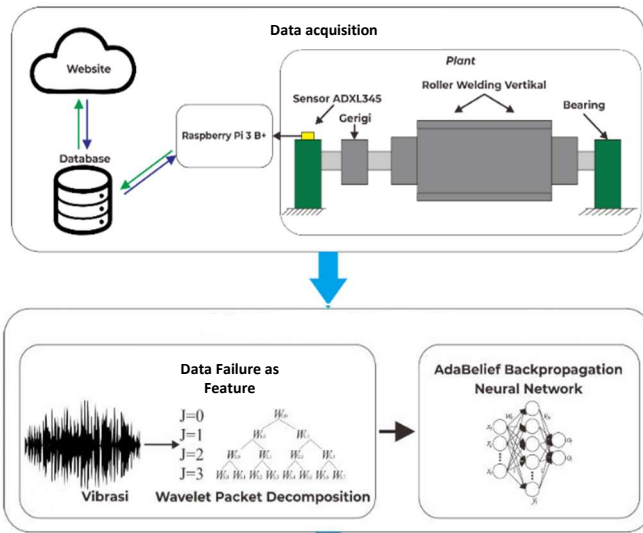


Figure 1. Data Collection Scheme

In the damage prognosis stage, the component vibration data is analyzed using the WPD method to produce new coefficients shaped like a full binary tree. The coefficients contain approximations and details of each level resulting from the level breakdown. Previously, the results of each approximation and detail will be extracted for each feature, the signal decomposition coefficient. Then the value of each approximation and the details are extracted for its features by looking for the average, maximum, minimum, and standard deviation.

WPD will be applied to vibration data with 2 conditions, namely bolt slack (bolt loosen) and normal conditions so that signals with different frequency bands are obtained, as many as 8 bands produced from 3 layers of WPD. Then do the reconstruction on the ribbon frequency to get a reconstructed signal with a lower energy level. The energy of each frequency band will be calculated and normalized to the shape of the damage feature vector of vertical welding rollers. Results data, the extraction will be the feature or input to the neural network to be used, i.e., There is WPD that generates a Belief-Optimized Backpropagation Neural Network with 8 frequency bands. Will be 8 neurons in the input layer, while 2 vertical roller welding conditions, i.e., slack bolt & normal, are labeled as 2 bits, so it becomes 2 neurons in the output layer. In this study used, the number of neurons in the input layer is 8, so the structure The neural network adopted in this study is 8-node input layer, 12-node hidden layer, and 1-node output layer. 70% of the sample data is used as a training data set to train the neural network, while 30% of the sample was used to test accuracy from system models.

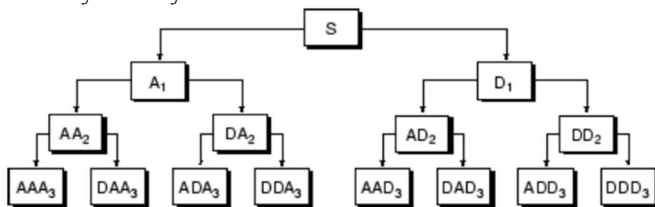


Figure 2. WPD Topology

After the classification results are obtained, the data is sent and stored in the database. The data is then called by the Flask web framework so that it appears on the page-related website with information on the latest engine conditions along with recommendations for repairs that need to be done by the technician so that the machine can return to running optimally.

Face-Mask Body Machine (FBM) is part of a mask-making machine function to create a body mask that consists of the specified mask layer company. Body masks can be made through several stages, including merging layers masks and nose wires, horizontal welding, folding terracing folds, vertical welding, and cutting. In each process, the mask passes through rollers connected to a motor asynchronous 3 phase as drive. In the process of horizontal and vertical welding, the machine uses ultrasonic welding so that the mask folds can be glued together layers.

The rollers on the FBM machine will rotate continuously without stopping during production. This mechanical component comprises various constituent components such as shafts, bearings, serrations, and bearings. The constituent components have a great impact on roller functionality. When a problem occurs, such as a bolt that slacks, it will impact the result of a defective mask. The loose bolt can Prognosis or prediction is carried out through roller rotation that starts abnormally with marked by a changing vibration level. The components studied can be seen in figure 3.



Figure 3. Bearings on Face-Mask Body Machine

Fault Tree Analysis (FTA) is a method used to analyze risk related to security and economically important assets, such as power plants, aircraft, and data centers. The FTA method consists of various modeling techniques and analysis supported by various software. An example shape from FTA can be seen in Figure 3. The structure of the FTA is a directed acyclic graph (DAG) which has 2 types of nodes Events and gates. An event in an ordinary system represents a failure of a subsystem down to the individual components. Meanwhile, the gate represents how failures extend into the system, such as how failures in the subsystems can combine to cause system failures. Every gate has one output and one or more inputs (Ruijuters & Stoelinga, 2015). Gate Commonly used in FTA can be seen in table 1.

Table 1. FTA Gate

Gate Name	Function
AND	The output event occurs if all the input events occur
OR	The output event occurs if any of the input events occur
k/N	Also known as VOTING, has N input. Output events occur if at least the input k events occur. This gate is the same as OR.
INHIBIT	The output event occurs if the input event occurs when the condition. Depicted on the right side of the gate also occurs. This gate is the same as AND

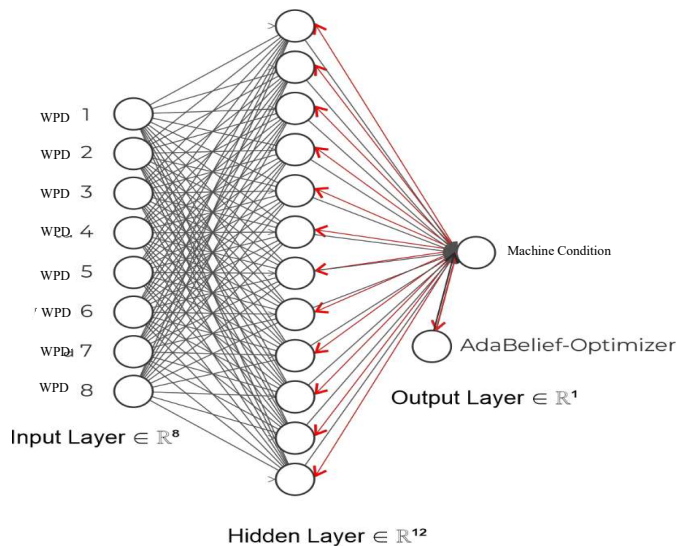


Figure 5. AdaBelief-Backpropagation Neural Network

Figure 5 shows the architecture of AdaBelief-Backpropagation Neural Network. The neural network model consists of an 8-node input layer, a 12-node hidden layer, and a 1-node output layer. The mean absolute error (MAE) is used as the loss function. the optimizer used is AdaBelief. For hyperparameter values use recommendations from the optimizer compiler, namely using the learning rate  $1 \times 10^{-3}$  and epsilon  $1 \times 10^{-4}$

### III. RESULTS AND DISCUSSION

#### A. WDP process

The ADXL345 sensor is a multi-axis accelerometer sensor so that the data obtained is data from all axes (X, Y, and Z) whose axis directions correspond to following picture.

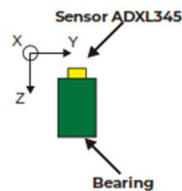


Figure 4. Sensor ADXL345 on Bearing

Data collection was carried out during April and May by recording vibrations directly with 2 engine conditions, namely optimal engine conditions and bolt conditions the vertical welding roller cleat lock is loose. Data is taken with a sampling rate of 1 data per second. The data taken is as much as 12,600 data consisting of 2 conditions different.

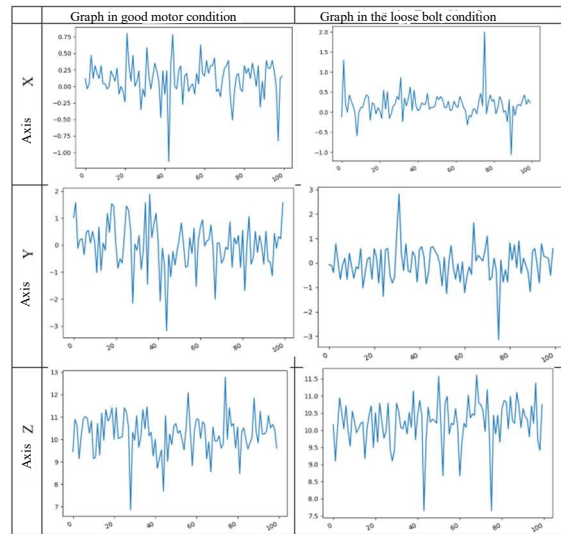


Figure 6. Graph Comparison of Vibration Signals Under Different Conditions

100 sample of vibration signal data are used in 2 conditions, namely optimal engine conditions and machine condition with loosened vertical welding roller cleat fixing bolt-on all vibration signal data (12,600 data) so that a dataset of 126 data is obtained. Signal parsing is done using the Wavelet Packet method Decomposition (WPD). The WPD configuration used is Daubechies-5 (db5) with 3 levels so that 8 pieces of output are obtained in the form of frequency bands that are reconstructed and normalized to get the damage feature vector which can be seen in table 2.

Table 2. WPD Result for Each Axis

1	2	3	4	5	6	7	8	State
<b>X</b>								
0.45	0.04	0.13	0.03	0.14	0.09	0.04	0.04	Loose bolt
0.24	0.07	0.09	0.13	0.15	0.14	0.08	0.05	Good
<b>Y</b>								
0.12	0.12	0.21	0.10	0.08	0.12	0.12	0.13	Loose bolt
0.25	0.15	0.09	0.09	0.17	0.07	0.04	0.10	Good
<b>Z</b>								
0.41	0.06	0.12	0.10	0.05	0.04	0.07	0.11	Loose bolt
0.45	0.09	0.05	0.09	0.05	0.10	0.08	0.07	Good

From the decomposition results on the vibration data of the X, Y, and Z axis, only the X axis which shows the difference in data between before and after being corrected. So, the result allows it to be used as a feature in the neural network modeling. Therefore, the data used is data from the X-axis. Distribution of energy level data in each frequency band between conditions before repair and after being corrected by taking 1 data sample each from 2 conditions.

#### B. AdaBelief-Backpropagation Neural Network

The input data for the neural network used are the energy levels in the 8 bands frequency. The data used for training is 126 frequency band data consisting of 2 conditions namely normal conditions and slack bolt conditions. Then the data divided into

70% for training, 30% for validation testing. Test data is data that includes training to assess the level of accuracy and loss of the modeling made.

Table 3. Neural Network Result

Number of Testing	Iteration	Accuracy	Loss
<b>ReLU-ReLU-Tanh</b>			
1	233	93%	0.1229
2	322	91%	0.1112
3	903	96%	0.0272
<b>ReLU-ReLU-ReLU</b>			
1	1000	73%	0.3367
2	1000	74%	0.2333
3	1000	73%	0.3367
<b>Sigmoid-Sigmoid-Sigmoid</b>			
1	1000	66%	0.3337
2	1000	73%	0.2671
3	1000	79%	0.2555

Table 3 shows the most neural network modeling obtained well is with the activation function ReLU-ReLU-Tanh. After training with iterations 903 times because the Callback function called due to accuracy exceeding 95%, then the iteration stops. Obtained accuracy of training and validation of 96% with validation loss of 0.0272.

Next, a comparison of the AdaBelief optimizer test was carried out with commonly used optimizers Adam and SGD. Testing was done with a combination of activation functions ReLU-ReLU-Tanh. The result of testing shows in the table 4.

Table 4. Testing Result

Number of Testing	Activation	Iteration	Accuracy	Loss
1	AdaBelief	903	96%	0.027
2	Adam	45	94%	0.123
3	SGD	48	91%	0.145

$$\text{Accuracy Formula} = \frac{TP+TN \text{ (the classification result)}}{TP+FN+FP+T \text{ (prediction total)}} \quad (1)$$

It was found that the accuracy of the system was 98.4%, where there was an error in the prediction detection of engine conditions when bolts are loose but neural network modeling detects them back to normal 2 times. The error is caused by the 2 data being normal engine conditions but approaching the condition of slack bolts, so modeling tends to give a decision that the condition is included in the condition of slack bolts.

#### IV. CONCLUSION

From the results of tests that have been carried out on the face-mask damage prognosis system body machine using Wavelet Packet Decomposition and Ada-Belief-Backpropagation methods Neural Network can be concluded several things, Signal parsing using the Wavelet Packet Decomposition method is capable produces 8 frequency bands that represent machine conditions with an error of 7.1%. AdaBelief-Backpropagation Neural Network modeling has 98.4% test accuracy in classifying machine conditions, with 96% training accuracy and 0.027 loss.

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