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# Study on Predictive Maintenance of V-Belt in Milling Machines Using Machine Learning

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ABSTRACT

Towards industry 4.0, monitoring the degradation of machine tools' components becomes a key feature so that smooth productivity is achieved. To preserve the functionality and performance of the machine tools, proper maintenance activities must be planned and carried out. V-belt is important component in machine tools that transmits power from the electric motor spindle in order to machine to work and cut desired material properly. The purpose of this research is to develop a predictive maintenance system for v-belt milling machine Krisbow 31N2F using machine learning. The machine learning algorithm models using multiple and simple linear regression algorithm was developed in an open-source program. The test results show that the machine learning model has a high accuracy value in both the training data and the testing data. The multiple linear regression model has MSE value of $5.8830 \times 10^{-6}$ and MAE value of 0.002. The Simple linear regression model has an MSE value of $0.0004 \times 10^{-6}$ and MAE value of 0.162. The results shows that the use of the linear regression algorithm as a support for determining the prediction of RUL v-belt milling machine model 31N2F (BS) is successfully carried out.



***Keywords:*** *Linear regression, machine learning, milling machine, predictive maintenance, V-belt*

## I. Introduction

The manufacturing sector is witnessing a rapid digital transition to smart manufacturing with more emphasis on efficiency and effectiveness [1], [2]. The development of smart manufacturing intended to result in intelligent and autonomous products and production processes such as cyber-physical systems (CPSs), cloud computing, the Internet of Things (IoT), the Internet of Services (IoS), big data, robotics, and augmented reality under a single system [2–4]. Towards the so-called industry 4.0, monitoring the degradation of machine tools' components becomes a key feature so that smooth productivity is achieved [4]. However, many manufacturing companies are still reluctant to adapt to this new situation [5].

Machine tools are designed and constructed according to the standards and specifications in order to make a good quality product. Machine tools comprise hundreds of components that interact and function together during the machining process. Therefore, the cause and effect of machine tool degradation at the component and its subsystem becomes complex [6]. This complexity can lead to a lack of understanding of machine tool degradation. Thus, the effects of the failure of a single mechanical component and its propagation cannot be properly identified and assessed [7]. To preserve the functionality

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and performance of the machine tools, proper maintenance activities must be planned and carried out.

Predictive maintenance is a strategy for maintenance that takes the current state of the equipment into consideration when performing maintenance. Predictive maintenance allows corrective maintenance to be scheduled in time prior to a failure situation. In predictive maintenance, repetitive analysis and evaluation of gathered data drive failure mode forecasting models. These models are trained to forecast a component's health, failure probability, or remaining useful lifetime (RUL) [6], [7]. By predicting RUL, machine tools' condition could be monitored and might prevent failure prior to the event.

Current technological advancements provide a tremendous opportunity for predictive maintenance to use intelligent data condition monitoring. Machine learning (ML) has the potential to be applied [8]. ML can improve system availability, lowered maintenance costs, and boost workload. In addition, ML is capable of making recommendations about the optimal timing and actions to perform maintenance interventions [9]. Luo et al. and Kim et al. resume their review that almost all machining processes ranging from conventional to non-conventional, have been made through using ML [10], [11].

Milling machines are one of the machine tools that have been studied using ML. Tool wear monitoring and prediction using ML in milling machines have been studied by Cho et al. [12], Wu et al. [13], and D'Addona et al. [14]. Besides, chatter and vibration during the machining process in milling machines using ML have been studied by Peng et al. [15], Yuan et al. [16], and Zapciu et al. [17]. However, the v-belt in milling machine has not yet studied, although v-belt is important to transmit power from motor to spindle machine in order for machine to work and cut desired material properly.

In this research, the milling machine Krisbow type 31N2F in mechanical engineering laboratory at the University of Muhammadiyah Malang with the photo showed in Figure 1a is the subject of the research. In this milling machine, the electric motor generates power and transmits it to pulley 1 that attached in the output shaft of the motor to pulley 2 by v-belt 1. Then, the power is transmitted to pulley 3 that attached to the spindle system by v-belt 2 as it is shown using the flowchart in Figure 1b. This research only focuses on v-belt 1, since the development of the predictive maintenance program for v-belt 2 is coherence and identical to v-belt 1.

## II. Material and Methods

ML has enabled machines to learn, improve, and perform a certain activity using data without being explicitly programmed. The problem-solving process using ML is shown in Figure 2. At first, the problem must be defined, and a suitable ML analysis method must be chosen. There are several ML algorithms provided, such as supervised learning, unsupervised learning, and reinforced learning [11]. Therefore, the data must be collected and preprocessed into a form that can be directly used for the analysis. A model for the data is then developed and evaluated. Finally, the results are analyzed to obtain the solution to the problem. Several iterations are typically required in order to obtain the desired results. Traini et al. have made an initial machine-learning framework for the wear level of the tools at milling machines with a variety of cutting parameters [18].

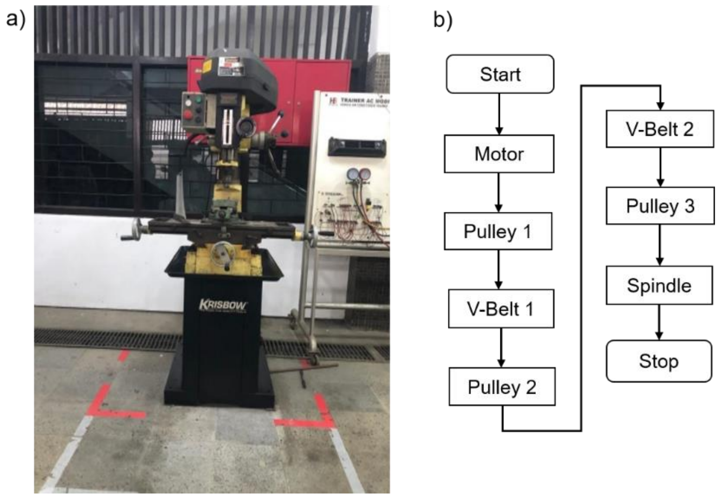


Fig. 1. (a) Krisbow milling machine type 31N2F and (b) its power transmission flowchart.

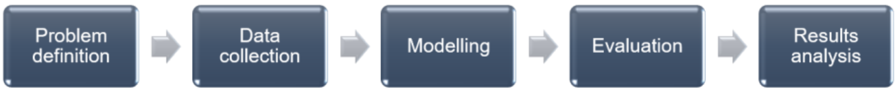


Fig. 2. Problem-solving process using machine learning [11].

In this research, the rotational motor speed and the usage duration of the milling machine are the most critical parameters. Rotational motor speed is the main input value from an electric motor that could be further calculated for the force analysis in the v-belt during the machining process. This force is further analyzed in the v-belt life calculation. Usage duration determines how long v-belt life remained until the program that we used gives a warning to the operator.

### A. *V-Belt life calculation*

The calculation was carried out using several parameters shown in Table 1. Belt circumferential speed (*V*) was calculated using Equation 1, where *D* is motor pulley diameter and *N* is rotational motor speed. Thus, by measurements and using known data obtained from the machine catalogue and measurement, we got 43 mm for *D* and 1420 rpm for *N*. We then obtained *V* was 3.195 m/s. The value of *N* is not changed, although the variation of cutting speed used to cut workpiece material varied, since the variation of cutting speed is subject to change with v-belt configuration. Then, motor torque (*T*) was calculated using Equation 2, where *P* is the motor power. Using data from the machine catalogue and checking it by observation, we got *P* is 1.5 kW, and we then got *T* equal to 1,028.873 kgf.mm.

$$V = \frac{\pi D\, N}{60{,}000} \quad (1)$$

$$T = 9.74 \times 10^5 \times \frac{P}{n} \quad (2)$$

**Table 1.** Parameters and calculation results to calculate the RUL of the v-belt.

| Parameter | Symbol | Calculation Result |
|---|---|---|
| Belt circumferential speed | $V$ | 3.195 m/s |
| Motor torque | $T$ | 1,028.873 kgf.mm |
| Belt effective force | $\boldsymbol{F_e}$ | 47,854 kgf |
| Number of belt revolutions per second | $U$ | 3.496 rev/s |
| Maximum belt tension | $\boldsymbol{\sigma_{max}}$ | 102.293 kg/cm$^2$ |
| *Fatigue limit* or endurance limit | $\boldsymbol{\sigma_{fat}}$ | 90 kg/cm$^2$ |
| The basis of fatigue test | $\boldsymbol{N_{base}}$ | $10^7$ |
| Number of pulleys | $X$ | 2 |
| For materials made of rubber and cotton | $m$ | 8 |

Next, the value of motor torque ($T$) obtained was used to calculate belt circumference force ($F_e$) with $r$ is pulley radius 21.5 mm as shown in Equation 3. We then obtain $F_e$ 47,854 kgf. The value of belt circumferential speed ($V$) was used to calculate Number of belt revolutions per second ($U$) in Equation 4 where $L$ is the length of v-belt. The length of v-belt was 0.914 m obtained from measurement. We then obtained $U$ 3.496 turns/s.

$$F_e = \frac{T}{r} \quad (3)$$

$$U = \frac{V}{L} \quad (4)$$

Next, the value of $F_e$ was used to calculate the maximum tension on belt ($\sigma_{max}$) with the formula shown in Equation 5 where $\sigma_o$ is stress within v-belt 12 kg/cm$^2$ obtained from machine catalog, $A$ is the surface area of v-belt 1.38 cm$^2$ obtained by measurement, $E_b$ is modulus elasticity of the belt 300 kg/cm$^2$ obtained from machine catalog, $h$ is belt width 10.5 mm, $D_{min}$ is motor pulley diameter 43 mm, γ is the density of solid woven cotton belt which is $7.5 \times 10^{-4}$ kg/cm$^3$ obtained from machine catalogue, and g is gravitational value 9.81 m/s$^2$. Therefore, we obtained $\sigma_{max}$ is 102.293 kg/cm$^2$.

$$\sigma_{max} = \sigma_0 + \frac{F_e}{2A} + E_b\frac{h}{D_{min}} + \gamma\frac{v^2}{10.g} \quad (5)$$

At last, the life of the v-belt ($H$) was calculated using Equation 6 where the basis of fatigue test ($N_{base}$) is $10^7$, number of pulleys ($X$) is 2, $\sigma_{fat}$ is fatigue limit of the given v-belt material 90 kg/cm$^2$, and $m$ is a constant value of the given v-belt material made of rubber and cotton 8. Hence, according to the calculation, the age of the belt reaches 142,486 hours which means v-belt could be used properly without any wear and fatigue issues until 142,486 hours of use.

Based on our observation, rotational motor speed ($N$) does not change whether the milling machine is idle or in a cutting state. This number was used as the basis for determining the RUL, as shown in Equation 7. 40 hours is selected as a threshold time by our observation in a factory where the milling machine is fully operational for five days with eight hours for each workday. Threshold time is used to give the operator a warning that the v-belt is going to not work properly in the upcoming 40 hours. So, the RUL used in this study is 102,486 hours. As a result, if the RUL is reached at a certain time in the future, the maintenance operator could order a new v-belt and schedule the maintenance to change the v-belt. However, observation of the exact time of milling machine usage is quite tough. Therefore, we build and try the implementation of a machine learning algorithm to help the operator monitor the condition of the milling machine.

$$H = \frac{N_{base}}{3600\, U\, X}\left(\frac{\sigma_{fat}}{\sigma_{max}}\right)^{m} \quad (6)$$

$$\boldsymbol{H = \frac{10^7}{3600.3.5.2}\left(\frac{90\, kg/cm^2}{102.293\, kg/cm^2}\right)^{8} = 142{,}486\ hours}$$

*Remaining Useful Life (RUL)* = Belt life (*H*) – Threshold time ....................... (7)

*RUL* = 142,486 hours – 40 hours = 102,486 hours

## B. *Data collection*

Machine learning was implemented using a synthetic dataset of 50 data points starting from 5 minutes to 250 minutes with increments of 5 minutes for each data as shown in Table 2. We use a synthetic dataset to develop the predictive maintenance program since no prior sensor has been applied to the machine yet so that history data could not be obtained. Several studies have used synthetic datasets for driver telematics, telemedicine, and healthcare [19]–[21]. These studies depend on the synthetic dataset as an input because real data were lacking. Those studies show great promise to develop the machine learning prediction with up to 96% data compared to real data were included. Therefore, the use of synthetic data is appropriate for this research.

**Table 2.** Synthetic dataset for Krisbow 31N2F usage history data.

| Time | $t_1$ | $t_2$ | $t_3$ | … | $t_{49}$ | $t_{50}$ |
|---|---|---|---|---|---|---|
| Usage duration [min.] | 5 | 10 | 15 | … | 245 | 250 |

## C. *Modelling*

The step to implement machine learning for predictive maintenance is shown in Figure 3. Preparing the dataset is the first step in implementing machine learning. The data for this research were derived from a historical synthetic dataset about milling machine usage. The data was manually entered into Microsoft Excel. This data collection eventually result in training data, test data, and data containing predicted RUL targets. The datasets were inputted and managed in Python language using Pandas Dataframe library in Anaconda Navigator with a Jupyter notebook and Laragon integration software, which are all open-source programs. Laragon software is used as a data processor for the latest research results. The Laragon software can input the value of the result of Python programming so that the value obtained was used in the decision-making program.

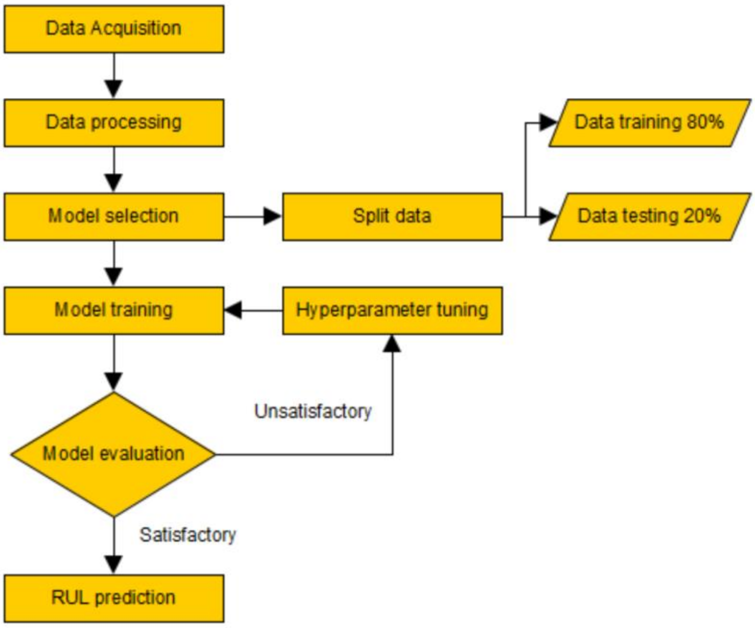


Fig. 3. Flowchart of implementing machine learning [22].

Next, the data is processed to determine the independent and dependent variables from the uploaded data, which are usage time and RUL, subsequently. Then, we separated the datasets for model selection. The data were divided into training data, which accounts for 80% of the total sample synthetic data, and testing data for the rest. The algorithm is determined at this stage. A linear regression algorithm will be used in this study as supervised learning is one of the most high-applicable method in ML [23]. Training data and testing data will be used to measure the accuracy value of the machine learning model created to be evaluated.

Further, the linear regression model is trained using training data. Python is the programming language used to train this model. Then, the model was evaluated. If the result is satisfactory, the step is continued to predict the RUL. On other hand, if the result is still considered unsatisfactory, hyperparameter tuning needs to be done to improve the result from the model. The term "tuning hyperparameters" refers to selecting parameter groups for machine learning. Hyperparameter tuning is used to obtain performance results that are significantly better than those obtained previously. In short, when creating a complex model, the variables affecting the output must be remapped. Typically, hyperparameter tuning is performed to optimize the performance of the created model. After training, evaluating, and testing the model with additional hyperparameters, the goal is to obtain the best performance, or the model with the lowest error value, and then predict the RUL using the test data. The predicted values are then compared to the test data's RUL target values. This is done to ascertain the model's performance on actual data.

Following the result, the obtained predicted value will serve as supporting data for the decision-making program. The decision-making program is updated in real-time using the most recent data from the database. The most recent data retrieval from the database is used to determine the age of the V-belt. Thus, the program will display the decisions that must be made based on the most recent data received by the program during this process. The results of the operation calculations will be entered into the database, serving as the most up-to-date information on the v-belt's RUL.

## III. Results and Discussions

It can be said that "Machine Learning algorithms use computational methods to learn information directly from data without using predefined equations as a model" [24]. Using our training and testing data, we evaluated using a scikit-learn library that our ML model has a 99.00% accuracy rate on all pieces of data, both training and testing, as shown in Figure 4a and Figure 4b, respectively. This accuracy value indicates that the machine learning model's primary performance has only a few errors. This demonstrates that the machine learning model performs optimally when the desired output is specified. The accuracy of the developed model is high due to only milling machine usage time is needed for predicting v-belt's RUL calculation as in a real condition. Therefore, we use synthetic dataset with milling machine usage time only. The value of belt life (*H*) and threshold are the one to look for in further research because of variety of belt used in another machine tools and ordering time of the machine tools' components according to its companies' policy.

Apart from determining the accuracy value, it can also determine the magnitude of an error in a machine-learning model using a scikit-learn library. The mean square error (MSE) and the mean absolute error (MAE) can determine the magnitude of the model error. The smaller MSE and MAE values, the better the regression model performs. As shown in Table 3, the MSE and MAE values are both less than one. This test demonstrates that the MSE and MAE values for each model are acceptable. This shows the effectiveness of the linear regression method in determining the prediction of the RUL v-belt milling machine model 31N2F compared to the Support Vector Regression (SVR) model by 98.95% for tool wear and RUL prediction by Benkedjouh et al. [25] and decision tree model by 94.30% for tool condition monitoring by Krishnakumar et al. [26].

**Table 3.** Model accuracy test results.

| Model | Value Accuracy | | Evaluation Size | |
|---|---|---|---|---|
| | *Training* | *Testing* | MSE | MAE |
| 1 | 99% | 99% | $5.8830 \times 10^{-6}$ | 0.002 |
| 2 | 99% | 99% | $0.0004 \times 10^{-6}$ | 0.162 |

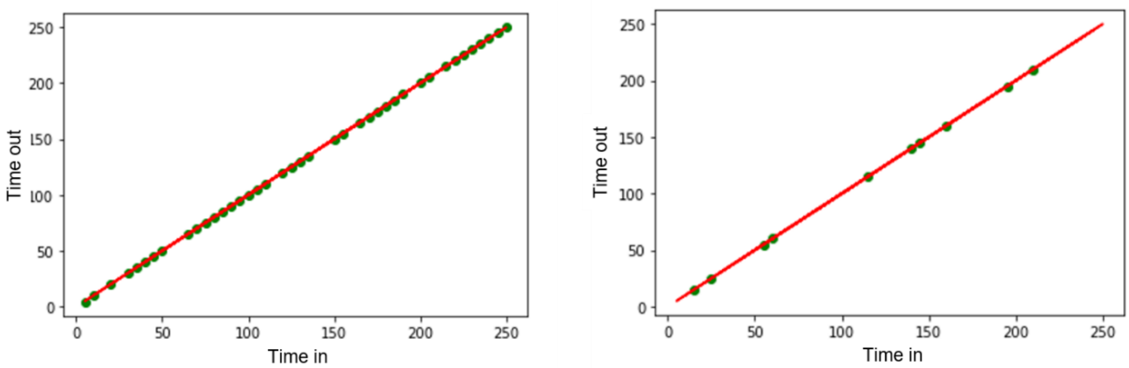


Fig. 4. Data visualization and their linear regression on (a) data training and (b) data testing.

## IV. Conclusions

This study obtained that the RUL of the v-belt in a milling machine could be predicted using the linear regression method using machine learning to use an open-source program such as Phyton programming, Anaconda, Laragon, and Jupyter Notebook. The use of simple and multiple linear regression algorithms has an accuracy of about 99% on all data, both training data and testing data. In addition, these two algorithm models have low error rates. The multiple linear regression model has an MSE value of $5.3880x10^{-6}$ and an MAE value of 0.002. The simple linear regression model has an MSE value of $0.0004x10^{-6}$ and an MAE value of 0.162. Further research needs to be carried out using real historical data to test the developed model, and further measurement system needs to be implemented in the machine to monitor the usage duration of the machine. All in all, the prediction of the RUL of v-belt Krisbow milling machine model 31N2F has been successfully carried out.

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