Roller bearing faults classification using Artificial Neural Network based on Servo system with Observer design

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Abstract: - The roller bearing is the main component of rotating machines, which is used to reduce friction while the machine operation. The bearing faults are the key problem of the rotating machine because they affect the unusual operation and caused machine downtime. This paper presented the fault detection approach based on an Artificial Neural Network (ANN) to recognize the bearing conditions. Servo systems with observers were designed for motor control and estimating current signal. The bearing conditions demonstrated in three cases consisted of normal, no lubricant, and outer race defect. For ANN model training, four statistical parameters including mean, crest factor, kurtosis, and root-mean-square (RMS) were selected to identify the causal characteristics of the motor current from observer and observation error data. the result indicated that the fault detection model has been displayed a classification accuracy of 94.4% which appropriate using in real operations.

Key-Words: - roller bearing, fault classification, observer design, artificial neural network, DC motor control.

Received: August 19, 2021. Revised: October 18, 2022. Accepted: November 14, 2022. Published: December 8, 2022.

1 Introduction

Nowadays, many industries utilized the rotating machine as a power drive for several mechanisms and shafts. The rotating machine is required a control algorithm, for instance, a PID controller to regulate a speed at the desired operating point and other components to support their motion. The roller bearing is the main part used for supporting shaft rotation. In the real process, the machine was operated continuously under load situations. This condition caused the bearing element tends to failure effect control system performance and reducing the machine life cycle.

The roller bearing faults have various pursuits to detect and classify. Cui Lingli, [1], presented the fault diagnosis based on adaptive machining. The vibration signal was used as analytical data and the result affected to stability and controllability of the model. The statistical parameters consisting of RMS, crest factor, and peak value were studied to analyze the bearing defects scenario, [2]. P.D. McFadden, [3], has researched vibration monitoring in a high-frequency range to explain the envelope of signal utilized for the rolling element of bearing. To accurately control motor position and speed, the adaptive load torque compensation algorithm was applied. The state variables were estimated using the observer-based Kaman filter technique which suggests a reasonable result for the dynamics response, [4]. Debabrata Pal proposed a full-state observer with state feedback control that is simulated on motor speed control. To obtain the appropriate parameter, MATLAB software was implemented for designing the state feedback and observer gain. The experimental validation discussed in performance response and the noise signal influent the control system, [5]. In many works in fault detection and diagnosis, modern control design shame is a powerful method that combines an intelligence approach to produce fault-tolerant control which is used in high-speed machines, [6]. The spindle bearing fault diagnosis was investigated in multiple conditions using energy-fluctuate with machine learning technique that is provided by Xiaoxi Ding, [7]. Several signal processing has been developed for failure analysis due to handling data characteristics. Toumi Yassine, [8] worked on predictive maintenance for bearing fault analysis. Hilbert transform and the FFT technique were used for feature extraction that will be transferred to create an artificial neural network model. Pratik Phalle, [9], presented fault identification using condition monitoring which contributed to the bearing diagnosis. The inter race defect was fabricated as a faulty situation by using an electrical discharge machine (EDM). The classical control as PID controller cannot carry out the external disturbance and feedback measuring with uncertainty suggested by Jing Sun, [10].

This research purposed the development of bearing fault detection and classification approaches by using an artificial neural network. The PI servo system with state observer design is selected to control the motor angular velocity and it's used for estimating the motor current during operation. Three conditions of roller bearing which consist of normal, no lubricate, and outer race defect were investigated to demonstrate the different fault situations. The state observer variables were used as raw data for extracting into feature data which include mean, kurtosis, crest factor, and RMS. These parameters will be used to train an ANN model for the specific type of bearing fault.

2 Dc motor with rigid shaft modeling

There is a wide application of DC motors for driving a rotating machine, one of which coupling with the rotation shaft. The mathematical modeling of a DC motor with a shaft is important because of its use for system response analysis and controller design. This work discusses on modeling of a motor with a rigid shaft. Two roller bearings are supported on both sides of the shaft and it's also coupled with a loaded disc. The physical diagram illustrates the position of the DC motor and mechanical part in figure 1.

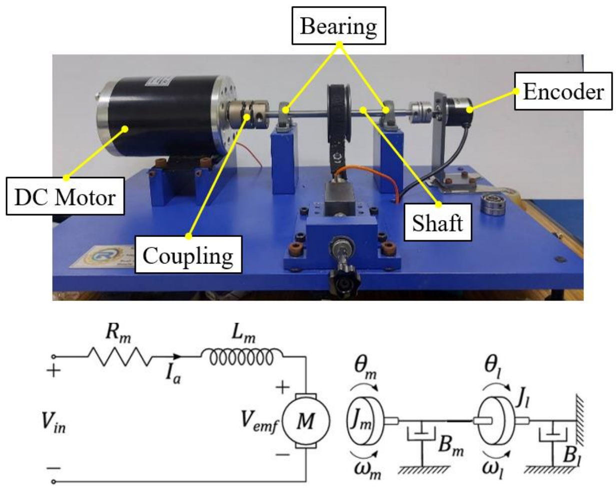

Fig.1: Physical Model of DC motor with Shaft

The model was considered through electrical and mechanical relations. The electrical part can be derived from basics series electrical circuit which follows as:

$$L_m \dot{i}(t) + R_m i(t) + k_b \omega_m(t) = V_{in}(t) \quad (1)$$

The model parameter R_m is armature resistance, L_m is armature inductance k_b is back emf constant, and ω_m is motor angular velocity in rad/s. the mechanical shaft is connected to the load disk which can explain by newton's second law which refers to (2).

$$J_m \dot{\omega}_m(t) + B_m \omega_m(t) = T_m - T_L \quad (2)$$

Where J_m is motor inertia, J_L is load inertia, B_m is motor viscous damping, and the motor torque T_m and load torque T_L are shown in (3) and (4) respectively.

$$T_m = k_t i(t) \quad (3)$$

$$T_L = J_l \dot{\omega}_l(t) + B_l \omega_l(t) \quad (4)$$

The shaft speed illustrates by ω_l, however, we assume that the motor and shaft speed are equal that can arrange into (5) as follow

$$J_e \dot{\omega}_l(t) + B_e \omega_l(t) = k_t i(t) \quad (5)$$

Where $J_e = J_m + J_l$ and $B_e = B_m + B_l$

From (1) and (5) the state space model is represented as

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} \dot{i} \\ \dot{\omega}_l \end{bmatrix} = \begin{bmatrix} -\frac{R_m}{L_m} & -\frac{k_b}{L_m} \\ \frac{k_t}{J_e} & -\frac{B_e}{J_e} \end{bmatrix} \begin{bmatrix} i \\ \omega_l \end{bmatrix} = \begin{bmatrix} \frac{1}{L_m} \\ 1 \end{bmatrix} V_{in} \quad (6)$$

system identification is a common technique based on measuring system input and output data to approximate the system parameters. It was used for estimating the motor with shaft parameters as shown in Table 1.

Table 1. Motor with Shaft parameter

parameter	value	Unit
L_m	0.057	H
R_m	0.86	Ω
k_t	0.134	Nm/A
k_b	0.06	$V \cdot s/rad$
J_m	0.0014	$kg \cdot m^2$
J_l	0.0003	$kg \cdot m^2$
B_m	0.0072	$Nm \cdot s/rad$
B_l	0.00052	$Nm \cdot s/rad$

3 State feedback with observer design architecture

The purpose of the servo system as shown in figure 2 is one of the modern control arts which is a design using the pole placement method. This control system needs to be done by feedback state variable to compute optimal input but normally some variables are difficulted to measure directly therefore, the observer is utilized for its estimation. The functional

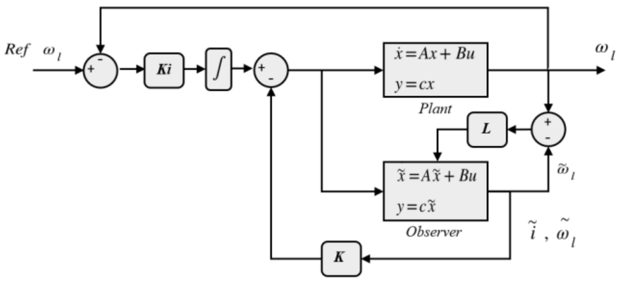

Fig.2: Servo system with observer architecture

block diagram exposed a vital parameter which relevant in each state. The actual speed is measured for the feedback loop and compared with their estimation from the observer. The design of response specification is defined based on the second order overdamped response with suppose 8 sec of settling time. Therefore, the closed-loop pole location is placed at -0.5, -20, and -50. In addition, the observer pole must be faster than 10 times of close-loop pole in practice. The result of designing is feedback gain K is [2.95, 0.46], observer gain L is [45.1, 150.56] and Ki = 0.36 respectively. The state observer estimated the current and shaft rotational speed through the matrix L which can reduce the error between actual and estimate output. To validate the control system performance, reference input tracking was implemented. The set point is set as a step test by changing the profile from 500 to 600 RPM as indicated in figure 3.

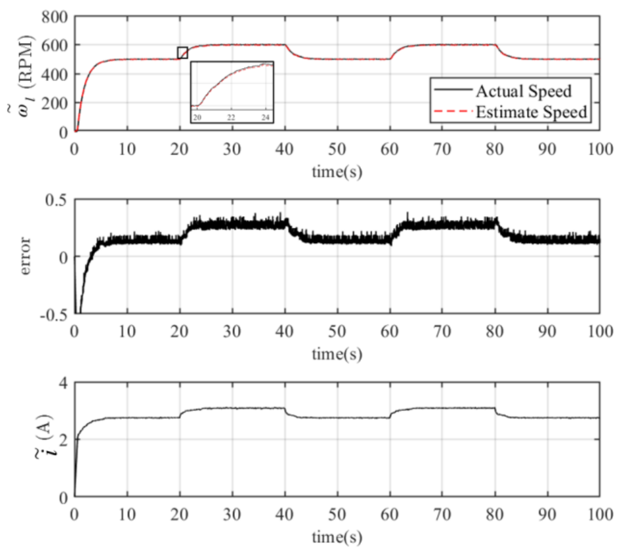

Fig.3: Reference input tracking test and state variables

From the response, the graph is clear that the control system can control the motor speed nearly by the desired operating point with properly transient and steady-state behavior. Moreover, the observer presented a good estimation of output speed and provided the motor current from its computation.

3 The purpose of feature extraction for time domain data.

Signal processing is the standard approach for handling measurement data. there is various method which is applied in the time and frequency domain that depends on signal characteristics. Signal noise is a usual term that comes with raw data, and it needs to be curtailed. This paper employed both low-pass and band-pass filters to reduce the influent of an unexpected signal. After the data pre-processing, the statistical features including mean, crest factor, kurtosis, and root mean square (RMS) was declared to extract the crucial manner of data. The significant feature that will be implemented to fabricate the artificial neural network model for classifying the bearing fault conditions. the mathematical formulas are following (7) to (10).

Mean $$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{7}$$

Crest factor $$C = \frac{x_{peak}}{x_{rms}} \tag{8}$$

Kurtosis $$K = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}}{\sigma}\right)^4 \tag{9}$$

Where σ is the standard deviation.

Root Mean Square $$rms = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{10}$$

4 Experimental setups

The functional diagram of testing and data collection is shown in figure 4. The procedure started with defining of reference speed input profile. The bearing conditions are prepared for three different situations. In each state will be recorded the estimation current and observation error which contribute to the MATLAB environment. Finally, feature extraction is a minor step for generating learning data set that is deployed to ANN model creation.

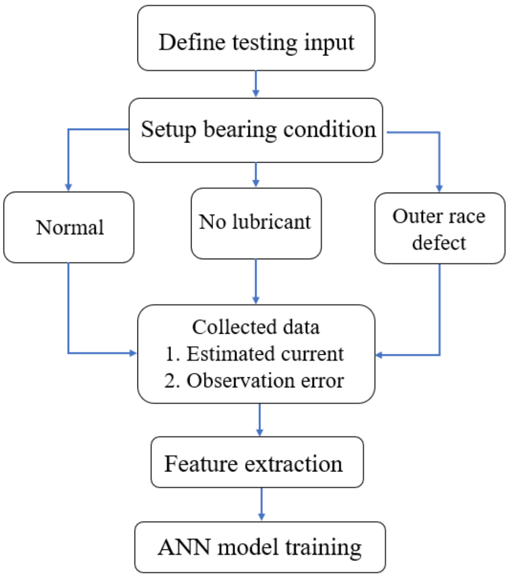

Fig.4: Experimental scheme.

4.1 Bearing fault conditions

In certain situations, the rotating machine has several problems that occur with roller bearings. Whereas there are some faults which marginal arise before the huge damage. Thus, two fault conditions of bearing were investigated. The starved lubricant condition was considered as one of all faults which are exploded to clean the grease to 0% level. Another fault is an inside surface outer race defect It was created by a computer numerical control (CNC) machine. This status explained the bearing that initiated a deep groove caused by fatigue that is run for a long time. Figure 5 illustrated the difference in bearing conditions which use for testing.

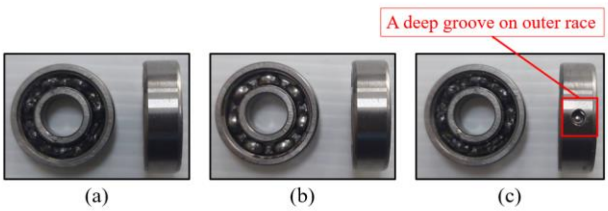

Fig.5: The bearing condition (a) Normal (b) No lubricant and (C) Outer race defect

4.2 Data collection

The estimated motor current and observation error from the control system was considered the fundamental data for the feature extraction process. The MATLAB/Simulink software is applied for data collection and interface with the ARM Cortex-a72 microcontroller to run as hardware-in-loop testing. The configuration consists of setting up the desire speed accounting for 500 to 600 RPM. Figure 6 is showed the comparison of current and error for each bearing condition. The data were recorded in 30 samples per condition.

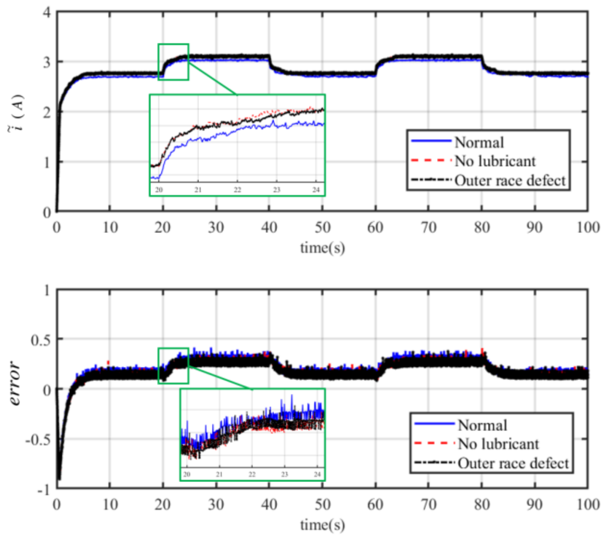

Fig.6: Fundamental data of each bearing condition.

It was found that the current between normal and other faults is distinguishable, on the other hand, two types of faults are quite tough to separate. As a result, the artificial neural network (ANN) will be an appropriate approach to classify these fault symptoms.

4.3 Feature data and ANN model training

The maps as shown in figure 7 and figure 8 are represented by essential feature current and error data. it contains 30 data points for each condition thus, there are 8 different inputs to supervise the model. From the graph, it can be classified as normal and other cases of fault. On the other hand, all features are difficult to distinguish between no lubricant and outer race defect condition.

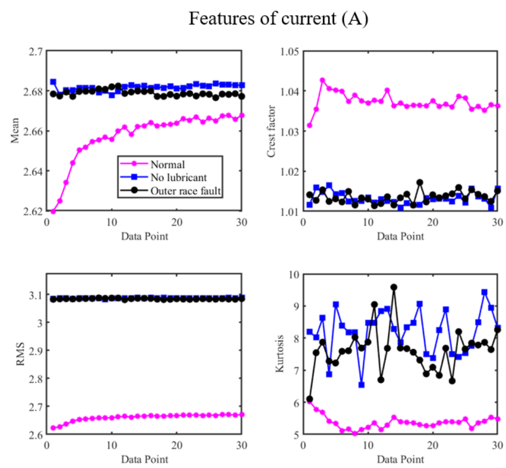

Fig.7: Feature map of current

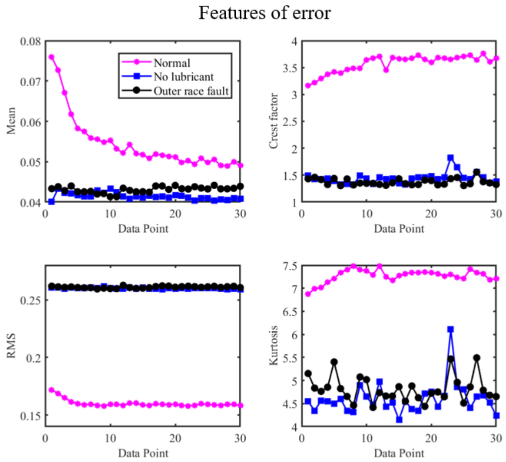

Fig.8: Feature map of error

Consequently, the ANN will be used to learn the featured trait that is ambiguous in each fault. The structure of the ANN model has multiple parameters that affect the prediction accuracy such as the amount hidden layer, activating function, learning algorithm, and the quality of the input data set. The observation of some neural in hidden layer change is presented to examine the highest model accuracy. In this studying, we have compared five different neural representing 5, 10, 15, 20, and 25 layers. The training data set was split to training 70% for supervising and the network is adjusted according to its error. the validation process is used 15% of data for measuring network generalization, and to halt training when generalization stops improving. The final step is model testing, it utilized the data by 15% that is for measure the model classification after training. In pattern recognition, the neural network is used for classifying inputs into a set of target categories it's which means three bearing conditions. The network will be trained with scaled conjugate gradient backpropagation and set the SoftMax function as activating function. The configuration of the model structure for 10 neural in the hidden layer is illustrated in figure 9.

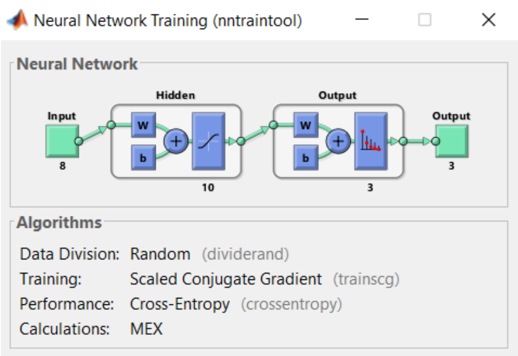

Fig.9: The example configuration of the ANN model

The result is revealed in table 2. It is clear from Table 2 that increasing the hidden layer number implied the optimal value representing 15 numbers which generates the model accuracy of 94.4%.

Table 2: Model accuracy with various neural number

Number of Neural	%Accuracy
5	66.7
10	90.0
15	94.4
20	91.1
25	88.9

Many loss functions are used for the optimization of model weight in the training process. This work has used the Cross-Entropy loss which is one of the powerful functions for model validation. The result can discuss the performance curve as shown in figure 10. All curves are demonstrated the optimal point to stop learning the highest accuracy model at epoch 30. Minimizing cross-entropy is given better results as can be seen from the result of the graph.

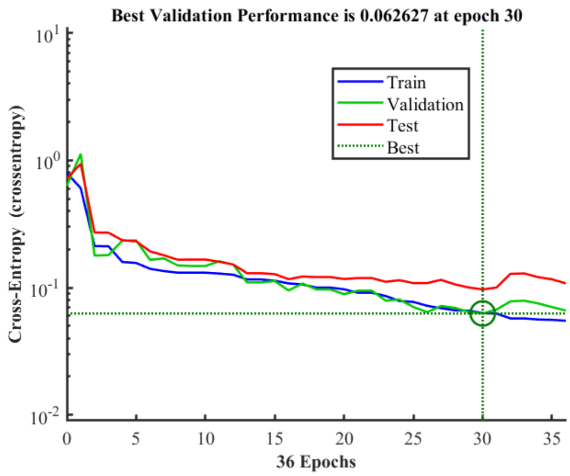

Fig.10: Cross-Entropy validation curve

4.4 Fault classification result

The confusion matrix is commonly used to interpret classification accuracy. As shown in figure 11 combined the detail of the neural network model for classifying the bearing conditions. the numbers 1, 2, and 3 are represented the normal, no lubricant, and outer race defect classes respectively. Training, validation, and test matrix appeared a correction of more than 90%, and all matrices denoted with 100% for detecting between normal and no lubricant class and overall indicated 94.4% of accuracy.

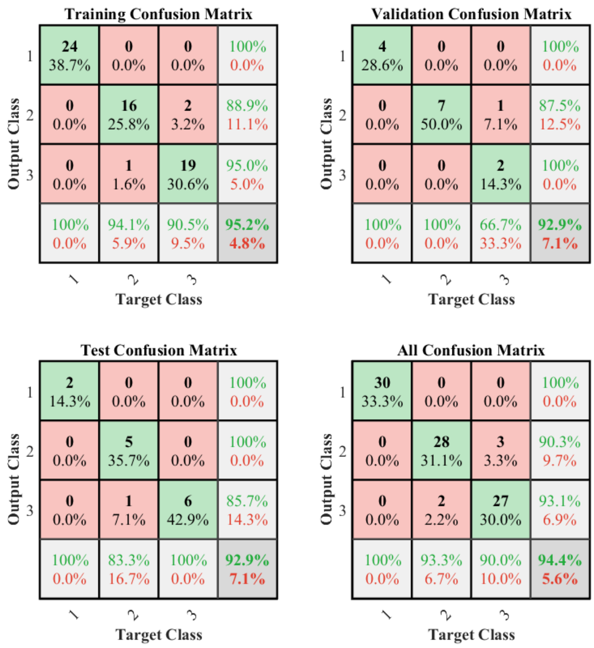

Fig.11: Confusion matrix of fault classify model

5 Conclusion

This article proposes a classification of roller bearing fault based on an artificial neural network (ANN) and servo system with stat observer design. the estimated motor current and observation error are utilized as preprocessing data. The parameters consisting of mean, kurtosis, crest factor, and root mean square are used to extract the crucial feature from current and error which is used to supervise the neural network model. Three conditions of bearing include normal, no lubricant, and outer race defect are investigated as the target of the model. The number of neural in the hidden layer was changed to examine a suitable model in the training process. using state variable data, signal processing, and ANN algorithm can be applied to fabricate the bearing fault detection model. The result revealed that the model has an accuracy of 94.4% for classifying demonstration roller bearing faults.

Acknowledgment:

The authors would like to thank Suranaree University of Technology for laboratory testing and financial support for this research project.

References:

[1] Cui, Lingli, Jing Wang, and Seungchul Lee. Matching pursuit of an adaptive impulse dictionary for bearing fault diagnosis. Journal of Sound and Vibration 333.10, 2014, 2840-2862.
[2] Tandon, N. A comparison of some vibration parameters for the condition monitoring of rolling element bearings. Measurement 12.3, 1994, 285-289.
[3] McFadden, P. D., and J. D. Smith. Vibration monitoring of rolling element bearings by the high-frequency resonance technique a review. Tribology international 17.1, 1984, 3-10.
[4] Khajorntraidet, C., J. Srisertpol, and C. Prattanarak. Alternative technique for DC servo motor control using adaptive load torque compensator. Advanced science letters 19.8, 2013, 2139-2143.
[5] Talole, Sanjay E., Jayawant P. Kolhe, and Srivijay B. Phadke. Extended-state-observer-based control of flexible-joint system with experimental validation. IEEE Transactions on Industrial Electronics 57.4, 2009, 1411-1419.
[6] Chommuangpuck, Prathan, et al. *Fault* Tolerant Control Based on an Observer on PI Servo Design for a High-Speed Automation Machine. Machines 8.2, 2020, 22.
[7] Ding, Xiaoxi, and Qingbo He. Energy-fluctuated multiscale feature learning with deep convnet for intelligent spindle bearing fault diagnosis. IEEE Transactions on Instrumentation and Measurement 66.8, 2017, 1926-1935.
[8] Yassine, Toumi, Lachenani Sidahmed, and Ould Zmirli Mohamed. Bearing fault classification based on envelope analysis and artificial neural network. 2019 International Conference on Advanced Electrical Engineering (ICAEE). IEEE, 2019.
[9] Phalle, Pratik, and Sangram Patil. Fault Diagnosis of Rolling Element Bearing Using Artificial Neural Networks. 2021 4th Biennial International Conference on Nascent Technologies in Engineering (ICNTE). IEEE, 2021.
[10] Sun, Jing, Chunyang Wang, and Ruihao Xin. On disturbance rejection control of servo system based on the improved disturbance observer. 2018 37th Chinese Control Conference (CCC). IEEE, 2018.