Hybrid Rubbing Fault Identification Using a Deep Learning-Based Observation Technique

M.SRIRAM

Asso.Prof. Mr. J. JAYAPANDIAN

Krishnasamy College of Engineering and Technology,

Cuddalore.

Abstract

A rub-impact fault is a complex, nonstationary, and Nonlinear fault that occurs in turbines. Extraction features for Diagnosing rubbing faults at their early stages requires complex And computation expensive signal processing approaches that Are not always suitable for industrial applications. In this article, A hybrid approach that uses a combination of deep learning And control theory algorithms is introduced for diagnosing Rubbing faults of various intensities. Specifically, the system Is first models based on the autoregressive with eXonenous Input Laguerre (ARX-laguerre) technique. In addition, the ARX-Laguerre proportional-integral observer (PIO) is used to Increase the estimation accuracy for the vibration signals containing rubbing faults. Finally, a scalable deep neural network Is applied to the output signal of the PIO to perform fault Diagnosis and overcome potential problems that may appear When applying a linear observation technique to nonlinear Signals. The experimental results demonstrate that the proposed Hybrid approach improves the fault differentiation capabilities of A relatively simple linear observation technique when it is applied To a complex nonlinear rubbing fault signal and attains high Fault classification accuracy. This result means that the proposed Framework is highly suitable for applications in actual industrial Environments.

I.Introduction:

TURBINES are among the most important rotating Machines utilized in power plants. Their operating conditions are closely associated with high temperatures and high Rotating speeds. The crucial point in the design of turbines Is a small clearance between the stator and rotatory parts (i.e., the turbine blades), which is made to increase the torque And reduce air reluctance. The rubbing phenomenon appears in Turbines when the rotor blades start interacting with the stator. The main causes of the rubbing phenomenon are the presence Of various types of mechanical faults in the rotating machine, such as misalignment, blade extension due to the high operating temperatures, and self-excited vibrations . Rubbing faults can cause excessive damage to industrial equipment, as well as increase maintenance costs. Thus, the detection and diagnosis of rubbing faults in the early stages are essential to maintain the health of rotating machines.

Rubbing faults are recognized as complex, non stationary,and nonlinear mechanical faults. Due to these properties, most conventional signal analysis approaches that have been created for stationary and linear signals, such as time domain-based or fast Fourier transform (FFT)-based techniques, are not useful in extracting the discriminative features of this type of fault. Time– frequency signal analysis (TFSA)techniques are preferable over conventional ones due to their ability to simultaneously analyze characteristics of the collected signals in both domains (i.e., time and frequency).Some examples of widely utilized TFSA approaches for rubbing fault signal processing and feature extraction are the wavelet transform and its variation. The main advantage of these techniques is a good time–frequency localization, which allows the detection of transients appearing in signals. However, the crucial drawback of wavelet-based methods is that their performance is sensitive to the selection of a mother wavelet function. The selection of a mother wavelet function itself requires a series of experiments and subsequent analysis of the obtained results

II.Existing system

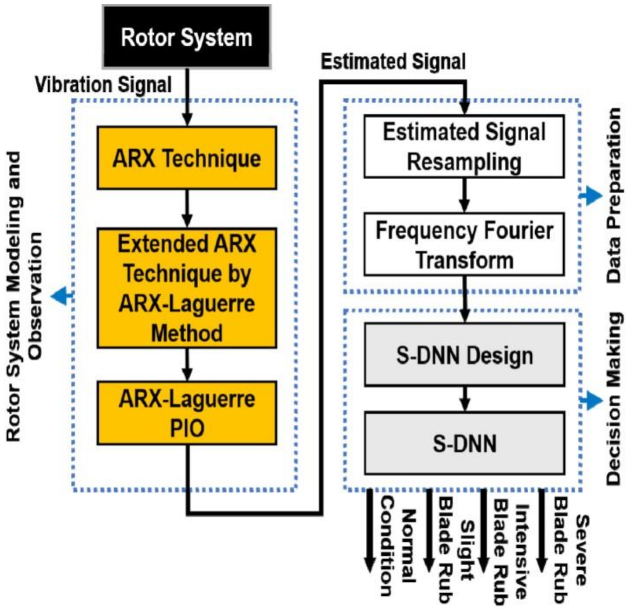
In the existing system, in any industries that utilise turbines for the power generation that perform several rotations to provide the power required. When the turbine moves continuously this heads to the rubbing of the turbines and it will lead to insufficient and faulty output. Thus they are attaining the detection of the fault so that they can determine the rubbing deepness and solve it to make the turbine works properly without any disturbance to the output. But the existing system disappoints to perform better as it handles only one type of fault. In this case, they missed identifying the more faults and the severity of the faults as it is not sufficient in finding out the exact solution to the arising problem. Thus the existing needs more transparency to find all faults were identifying the problem in one area is not sufficient.

III.Proposed system

In the proposed system, the quality of the steel material that is utilised for obtaining the big jet turbines is investigated. Thus for a healthy quality of the product, we must examine the quality before beginning the mass production in order to bypass the enormous mistake in producing the mass production of the product. A sole product that before delivered into the market has to pass through several quality checks. Like advancing through the different kinds and different levels of the quality checks. By practising a voting classifier in ensemble learning can optimize the product’s quality and can make further adjustments in the product. This voting classifier helps in determining the fault of the product after going through many quality checks. So when the design team when finding the fault they can decide whether to make minor changes and start the process or else the product is sent to the material management in order to mould the material and apply it for future production. Thus an efficient way of production is accomplished by the manufacturing team.

IV.Methodology

The proposed rub-impact fault identification framework It consists of three important steps: Data collection, system modeling and signal estimation, and decision making. First, the rub impact fault signals of different intensity levels are collected from the experimental testbed. Next, these vibration signals are used to build a linear ARXLPIO to estimate the rubbing signals in normal and abnormal conditions. To perform decision making about the condition of the system and improve the performance of the ARXLPIO, the S-
DNN is utilized for decision making during the final step of the algorithm. To use the SDNN effectively, the signals estimated by observation techniques are first resampled concerning the revolutions of the rotor, and their frequency power spectra are obtained using an FFT. Finally, the patterns that appeared in the power spectra of there sampled estimated signals are used as inputs for the S-DNNto identify rub-impact faults of various intensity levels.



V.Module Description

Module:

1) Production

2) Design

3) Quality

4) Material Management

5) Admin

1.Production

This module gives out the registration process for the production manager to log in to their respective work page. After this admin has to give access for the production manager to log in. Then manager login with the email id and password. Here there are furthermore submodules under the production module where the first is to request sufficient material for the production also this gives the form to upload the material requirement in kgs. The next submodule gives the required material with supplied and pending information. And this material management will be supplying the required material. In the initiate submodule, the production manager fixes the composition of the material for production. Then in production submodule displays the composition details where the production process is carried out and also manager can start the different types of the production process. The technicality submodule gives the physical properties for the producing material. After this production manager can log out from their page by using logout. In that login, the information of the production manager will be deleted from the session.

2.Design

In this design module, the registration process is initiated for the login purpose of the design member. Once the registration process is done then the admin has to give access for the design member to log in. After the login process of the designer, the page will be redirected to the home page of the design module. It also has the submodules where the first submodule has the form, in that produced material is partitioned to produce different types of design such as foil, sheet, coil, and bar. Also can give the dimension for the material to be produced. In dimension, the submodule table shows the dimension given for the different types of design such as kilogram, thickness, width, and diameter. The defect list submodule gives the table of information of the tested result with fault. In that designer can find and move the fault material either for redesign or for reuse from the production. In the redesign, the submodule designer can view the material allocated for redesigning. Finally, the designer can log out from their page by making use of logout, which removes the login details from the Production

3.Quality

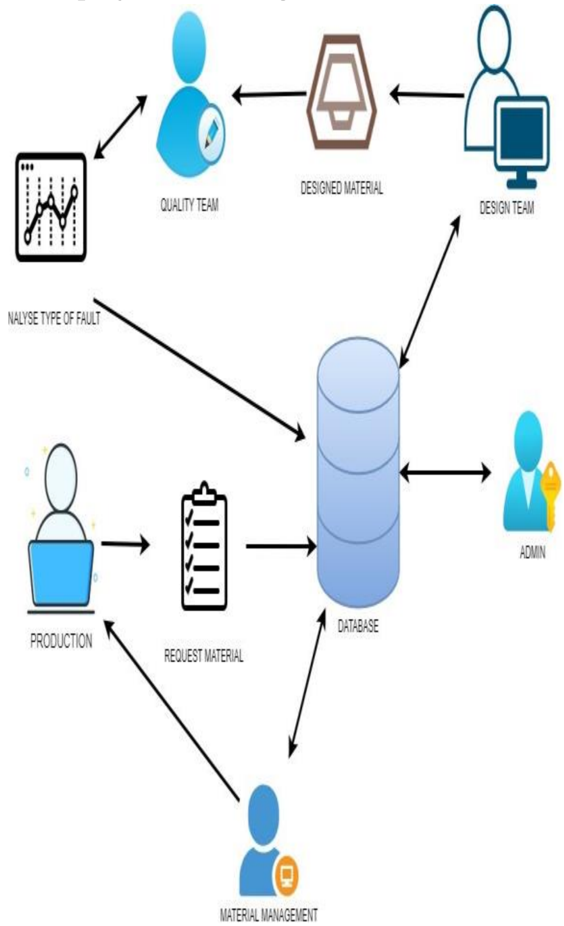
This module gives the registration page where the quality tester can register for the testing of material quality. After the registration process, the admin has to give access to the quality tester for the login process. Once the login process is done the page will be redirected to the home page quality testing. It has a submodule test queue that shows the dimension details of the material along with the testing option. Once the tester has chosen the type and used the test option, the page will be redirected to where the tested output from different types of testing with the type of testing and value as output is displayed as a table. Also in that analyze option is given for analyzing the tested output for the material has whether fault or not, and also if there is any fault, the specific fault is categorized. After analyzing the output will be displayed on the new page and the tester must report the output to the designer by using the report link. Here also the quality tester logs out by using the logout module which removes the login details from the session.

4.Material Management:

In this module initially, the management team is login, then it will be redirected to the home page of material management. In the requested material submodule it shows the form where the management team can choose to view the requested material from the name and the request-id. Then the page will display the requirement of the material in kgs. Then management team can supply the material. Defects submodule shows the table contains the details of the tested value along with the test name and with the type of fault. In reusing submodule shows the table also gives the tested value with test name along with the type of fault but it is for the reusing process. The reusing process will start from the initial production process. After this, the management team can log out using the logout module which removes the login information from the session.

5.Admin

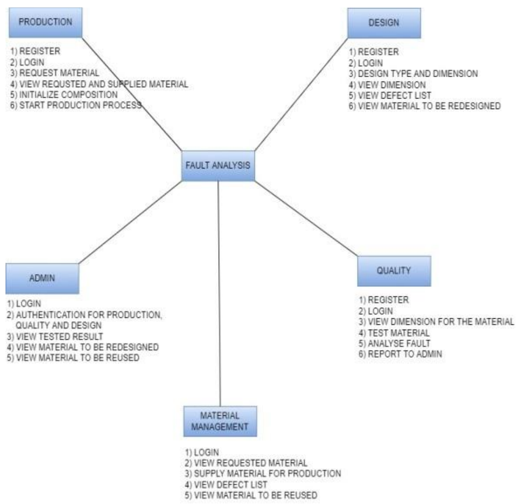
In this admin module initially, the admin will log in to redirect to their home pane. This has six sub-modules where three submodules are for accessing the production manner, designer, and quality tester, If the registration request from these modules is displayed, then the admin can access the respective person for authority to login. In tested sub module all the data from the quality testing will be displayed including material that has



no fault with the type. And reuse submodule displays the table which has the quality tested details that are to be reused. Next, the redesign gives the tested result with the type where these materials going to be redesigned for further process. Finally, the logout process for the admin will be initiated by using the logout link where the session details of the admin will be removed

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 06 Issue: 07 | July - 2022 Impact Factor: 7.185 ISSN: 2582-3930

VI.Data flow diagram



VII.EXPERIMENTAL RESULTS

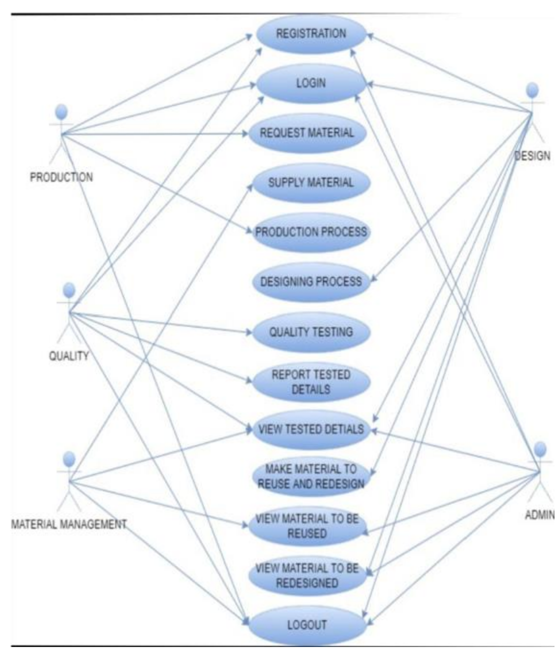
A. Training, Validation, and Testing

Subsets Configuration to evaluate the fault diagnosis capabilities of the proposed Hybrid approach, the resampled data set corresponding to the Estimated rubbing fault signals of different intensity levels
(which contained 7470 data samples) was randomly split into Training, validation, and testing subsets. The complete process Of subset creation is as follows. First, the whole data set was Separated into training and testing subsets at a ratio of 8:2.Then, the obtained training subset was again divided into Training and validation subsets using the same proportion as In the previous step. Thus, the overall training, validation, and Testing subset configurations can be summarized as follows. The training subset consisted of 4780 samples, the validation Subset comprised 1196 instances, and the remaining 1494Unseen data instances were used for testing the proposed Solution.

B. Case Study of Building the S-DNN

In this section, the details on building the S-DNN are Presented. Before starting the process of creating SDNN, let Us summarize the initial conditions that are utilized to select The architecture best suitable for solving the classification Problem in this work. The number of the nodes in the input Layer is equal to 787 to match the dimensionality of the Input data vectors that contain the frequency power spectra Of resampled signals without a mirrored part.

VIII.Use case diagram



IX.CONCLUSION

In this article, a novel, hybrid DL based observation technique is presented for diagnosing rub-impact faults of various Intensity levels. In the proposed model, system modeling and Observation is first accomplished by the linear ARXLPIO. Next, the blade rubbing signal estimated by the ARXLPIOIs resampled with a 15% overlap based on the rotating speed and the time needed to perform one shaft revolution. Finally, The frequency power spectra of

these resampled estimated signals are computed and used as inputs for the S-DNN designed according to the proposed algorithm. The advantage of the Introduced scalable network is the presence of scalable layersThat can be adjusted based on the input signal dimensionality and simplify the process of developing the DNN architecture for a specific task. In this work, the S-DNN is used to Increase the performance of the linear ARXLPIO (when it Is used for estimating nonlinear signals) and to perform a Rubbing fault identification procedure. The proposed hybrid Approach outperformed most of the counterpart techniques Used for the comparison in terms of the macro averaged recall, Precision, and f1 score performance metrics as well as of FCA. Specifically, the proposed hybrid solution reached an FCA of99.8% during the experiment. Moreover, the simplicity and Flexibility of designing ARXLPIO along with the autonomous Design of S-DNN allow the proposed framework to be applied In industrial environments. In our future work, we will focus On improving the proposed algorithm for designing S-DNN And adapt it to the designing non-triangular shapes of neural Networks.
Furthermore, the proposed hybrid fault diagnosis Approach should be verified by applying it to other prognostics and health management problems, such as bearing Fault diagnosis, gearbox fault identification, and pipeline fault Detection.

X.REFERENCES

[1] Y. Zhang, B. Wen, and A. Y. T.Leung, “Reliability analysis for rotor Rubbing,” J. Vibrat. Acoust., vol. 124, no. 1, p. 58, 2002, doi: S10.1115/1.1423635.

[2] E. Rubio and J. C. Jáuregui, TimeFrequency Analysis for RotorRubbingDiagnosis. London, U.K.: Citeseer, 2011.

[3] J. Zhihao, J. Shangwei, J. Wen,and W. Bangchun, “Rubbing faultDiagnosis of rotary machinery based on wavelet and support vector machine,” in Proc. 1st Int. Workshop Database Technol. Appl.,Apr. 2009, pp. 287–290, doi: 10.1109/DBTA.2009.163.

[4] Y. Lu, F. Meng, and Y. Li,“Research on rub impact fault diagnosisMethod of rotating machinery based on wavelet packet and supportVector machine,” in Proc. Int. Conf. Measuring Technol. MechatronicsAutom., Apr. 2009, pp. 707–710, doi: 10.1109/ICMTMA.2009.539.

[5] S. D. Roy, S. K. Shome, and S. K.Laha, “Impact of wavelets and filterOn vibration-based mechanical rub detection using neural networks,” inProc. Annu. IEEE India Conf. (INDICON), Dec. 2014, pp. 1–6.

[6] P. W. Tse, W.-X. Yang, and H. Y.Tam, “Machine fault diagnosis throughAn effective exact wavelet analysis,” J. Sound Vibrat., vol. 277, nos. 4–5,pp. 1005–1024, Nov. 2004, doi: 10.1016/j.jsv.2003.09.031.

[7] N. Bessous, S. E. Zouzou, W.Bentrah, S. Sbaa, and M. Sahraoui, “Diagnosis of bearing defects in induction motors using discrete wavelet transform,” Int. J. Syst. Assurance Eng. Manage., vol. 9, no. 2, pp. 335–343,Apr. 2018, doi: 10.1007/s13198-016-0459-6.

[8] B. Bessam, A. Menacer, M.Boumehraz, and H. Cherif, “WaveletTransform and neural network techniques for inter-turn short circuitDiagnosis and location in induction motor,” Int. J. Syst. Assurance Eng.Manage., vol. 8, no. S1, pp. 478–488, Jan. 2017, doi: 10.1007/s13198-015-0400-4.

[9] N. E. Huang et al., “The empiricalmode decomposition and the HilbertSpectrum for nonlinear and non-stationary time series analysis,” Proc.Roy. Soc. London. Ser. A, Math., Phys. Eng. Sci., vol. 454, no. 1971,pp. 903–995, Mar. 1998.s

[10] Y. Zhao, E. Liu, J. Zhu, B.Zhang, J. Wang, and H. Tian, "Rubimpact fault diagnosis of rotating machinery based on Hilbert-huang transform,"In Proc. IEEE Int. Conf. Mechatronics Autom. (ICMA), Aug. 2015,pp. 32–36, doi: 10.1109/ICMA.2015.7237452