1. Ajay Vasanth. X[1], 2. P. Sam Paul[2], 3. D. S. Shylu[3], 4. P. Mano Paul[4]

Department of Mechanical Engineering, Karunya Institute of Technology and Sciences, Coimbatore, India (1), (2)
Department of Electronics and Communication Engineering, Karunya Institute of Technology and Sciences, Coimbatore, India (3)
Department of Computer Science and Engineering, Alliance University, Bengaluru, India (4)
ORCID. 1. 0000-0003-1111-9835, 2. 0000-0003-3450-3127, 3. 0000-0001-5559-0202, 4. 0000-0003-0293-8687

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IoT based prognostics using MEMS sensor with single board computers for rotary machines

***Abstract**. In the recent past years prognostics has gained importance in the industry sector as they have reduced maintenance cost and time to a great deal. The term IoT has opened a wide variety of applications with it and there have been very few feeble attempts to integrate it with prognostics. Combining low-cost energy efficient MEMS sensor and IoT in prognostics has been a dream far-fetched by industries. This paper will be attempt where the MEMS sensor will be fused along with IoT in prognostics and the same was used in a rotary machine.*

Streszczenie. W ostatnich latach prognozy zyskały na znaczeniu w sektorze przemysłowym, ponieważ znacznie zmniejszyły koszty i czas konserwacji. IoT otworzył wiele różnych zastosowań i było bardzo niewiele prób zintegrowania go z prognozami. Połączenie niskokosztowego, energooszczędnego czujnika MEMS i Internetu Rzeczy w prognozach było marzeniem naciąganym przez przemysł. Ten artykuł będzie próbą, w której czujnik MEMS zostanie połączony z Internetem Rzeczy w prognostyce i to samo zostanie użyte w maszynie rotacyjnej. . (***Prognozy oparte na IoT z wykorzystaniem czujnika MEMS z komputerami jednopłytowymi do maszyn rotacyjnych***)

Keywords:. prognostics, IoT, MEMS sensor, rotary machine
Słowa kluczowe: Internet zeczy IoI, prognozowanie, maszynas rotacyjna

Introduction

When a product is coming out of an industry it is expected to have a good quality and also good reliability. But, the products will start to deteriorate due to prolonged usage whatever may the quality of it. The main reason is that they will be operating under certain stress or load in the real time scenario and to add to it sometimes randomness also creeps-in [1]. This is where the diagnostics and prognostics comes into picture though they originated in medical ground. They collectively bring in organization safety and effectiveness in terms of cost. In certain aspects almost one-third to one-half is being wasted though ineffectual maintenance [2]. In general, diagnostics is referred to a process when a fault has already occurred which is more likely like a reactive process. They do not have the capacity to prevent downfall and thereby the increase the maintenance cost. Maintenance on the other hand can be further classified into breakdown maintenance and preventive maintenance. As the name suggests in breakdown maintenance until the machines wears off completely from where it should either replaced or repaired. Preventive maintenance was introduced in 1950s where periodic intervals for monitoring machine health will be performed. A limitation in this scheme is that an optimal maintenance interval, if they are not fixed properly the whole system of preventive maintenance will collapse. In certain places mathematical modelling was employed [3] and in certain places decision models were developed by investigating reliability data and cost data [4]. Nevertheless, fixed time preventive maintenance was not capable to solve a global solution as each they can vary from case to case [5]. Though they have proved to reduce equipment failures, they also have drawback like catastrophic failures and undisputed maintenance. Thus it evolved to a proactive system where in the measurements is taken without causing and interruption to normal machine operations as 99% of mechanical letdowns have been heralded with noticeable indicators [6]. From diagnostics, a conventional fail and fix practice it eventually evolved to a predict-and-prevent methodology which is referred as prognostics. Prognostics is the least industrialized technique compared with diagnostic methods and fault detection though they have the capacity to provide economic benefits from condition monitoring.

Prognostics has been in the maintenance field for almost a decade, where-in the predict the failure of machines by forecasting from the data collected by sensors. These data include that of vibration [7], acoustic emission (AE) [8], temperature [9] and wear debris [10]. Statistical reliability, data-driven evolutionary trend, dynamic systems, physical-based modelling are a few of the approaches upon which prognostics has been developed. Though prognostics seems to be the advanced area in the field of diagnostics and maintenance, still the ever-demanding maintenance sector expects a leap from it. Certain places in prognostics where improvement is needed includes that related to cost and data maintenance. Cost related to sensors being employed, involved in collection of data and manipulating from the data are a few of the points where in a detailed analysis is do required. In general prognostics is being used as a stand-alone process. And similarly, the collection of data also plays a vital role as certain data will be directly affected by the surrounding. It has been proposed that vibration data has a direct implication on operational status of equipments and is not affected by external factors which includes temperature and humidity and the most vital point is that vibration will change drastically with aging equipments [11]. The above facts clearly indicate that vibration will be a clear and an early indicator of failures and problems.

When the data is narrowed down to vibration, it comes with its own limitations such as the noise and other related problems. The raw data collected has to be will be in time series which can’t be used for any sort of prediction as they will not give a clear-cut picture of the machine working condition. If the data is converted to a frequency domain into a Fast Fourier Transform (FFT) then the signal can be used to predict the machine working condition and it has been proved that it works very effectively [12], [13].

Summing all the above-mentioned facts, in this paper a vibration data will be obtained using a MEMS sensor and conversion from time frequency to frequency domain will be done and after which the data will be used for prognostic purpose and all these processes will be done through Internet of Things (IoT). Thus, the machine can be monitored from any location and the data collected can be saved and retrieved either for further study of the machine. And to top it all these tried to be accomplished at a lower cost method since that is where the technology developed can be used by all personal and even in small scale industries. This will also aid in the better understanding of the machine which can be used to train either a supervised or unsupervised machine learning or deep learning.

Methodology

Selection of Components for IoT

In the recent past for developing low cost automated monitoring and control system microcontroller-based platforms or single-board microprocessor were preferred. Each had its own unique hardware architecture and it includes Arduino, STM32, Raspberry Pi [14]. They are preferred as they cost effective and also perform the intended functions without any sort of problem. In this work Raspberry Pi 3 single board computer will be used and the methodology will be attempted as shown in Figure 1.

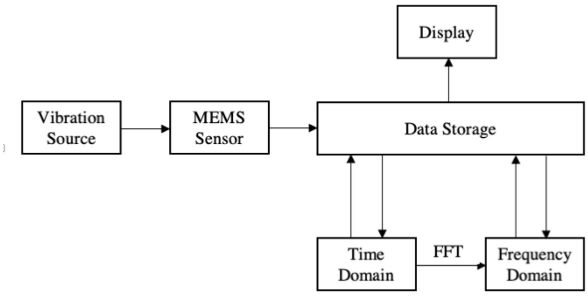


Fig.1. An example of the figure inserted into the text

The process will be carried out in cyclic order for every 120 seconds. For this work MPU 6050 GY-521 sensor was used, as it has been proved that they are capable of vibration measurement in various places [15], [16]. One of the major advantages of using a MEMS sensor is that they smaller in size and also the power required for operation is comparatively less than the conventional piezo-electric sensors. Jung et al. [11] pointed out the advantages that is present in MEMS sensor (Table 1). The connection between the MEMS sensor and Raspberry Pi 3 is as shown in Figure 2.

Table 1: Comparison between Piezo-electric sensor and MEMS

	Piezo-electric Sensor	MEMS Sensor
Power	27mW	3mW
Size	50*25*25.4 mm	5*5*1.27 mm
Noise Density	700μg	4000μg
Resonance Frequency	20kHz	22kHz
Accelerate Range	10g	100g

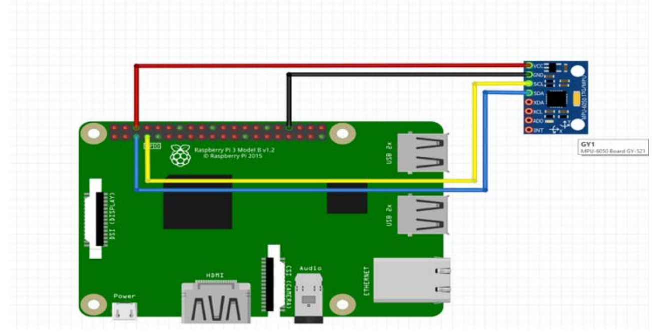


Fig 1: Connection between MEMS and SBC

Method for obtaining Fast Fourier Transform (FFT)

Fast Fourier Transform (FFT) is an algorithm that is used for calculating the Discrete Fourier Transform (DFT). For converting the signal from time domain to a frequency domain FFT can be used with lesser computational time. In general, DFT will decompose a sequence of values into different frequency components. Though this may seem simple the computational time will increase with the size of the data sequence. This can be overcome by using a FFT, which will rapidly compute by factorizing into the DFT matrix into a product of sparse factors. Thus, is manages to save the complexity and time related to computation.

(1) $$x(k)=\sum_{n=0}^{N-1} x(n)e^{\frac{-j2\pi nk}{N}}$$

Where: $k=0$ to $N-1$; $n=0$ to $N-1$; N is the number of samples

Equation (1) is the backbone that will be used as a function in the program for FFT algorithm to be processed. Once it is revoked in the program it will time domain series to the frequency domain. In the recent year or so many researchers are trying to frequency domain for analysis various aspects related to vibration [17], [18]. And in these works, though there has been attempts to use FFT to find the related aspects of vibration, there were feeble attempts to implement with IoT.

Presently in industries the diagnostics as well as prognostics are carried in such a way that data collected from equipment and the data analysis are stand-alone process. An attempt will be made to integrated all the above-mentioned process with IoT. For effective functioning of IoT there was a need of a dynamic server with cloud space and storage, since the work was in the pilot stage a static server was created to check for its effective functioning.

Experimentation

For checking whether the system works in the intended direction a rotating machinery was used. The set-up used for experimentation is shown in Figure 3, it’s a simple set-up used for determining the whirling speed of shaft. Here, in this work since the experimentation is performed to find the effectiveness of the MEMS sensor and SBC to measure vibration and use it for prognostics though IoT rotational speed of motor and cross section of the rod were kept constant during experimentation. To induce some sort of change in the experiment the boundary condition of the shafts was altered. This change in the boundary condition will ensure that the vibration pattern is altered and the same can be viewed in the data. The different boundary conditions are brought about in the tail stock rigid support (Figure 4) and fixed support (Figure 5). For each boundary condition the MEMS sensor will be fixed to the tail stock. The vibration change with respect to time domain will be obtained and by using FFT algorithm they will be converted to frequency domain. The difference in the reading will be clearly indicated.

Fig 3: Whirling of shaft

Fig 4: Rigid support of tail stock

Fig 5: Flexible support of tail stock

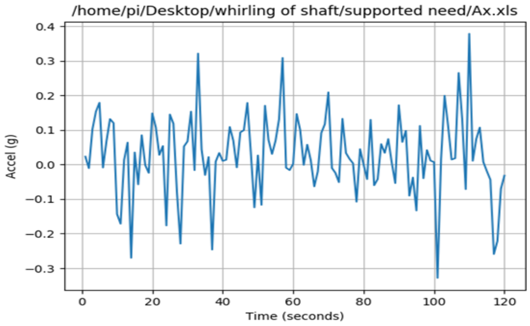
To ensure that whirling of shaft does not occur, the shaft is rotated at a lower rotational speed, as the whirling of shaft will produce higher and random vibrations. The connections will be made as per the Figure 2. MEMS sensor will be placed on the tail stock. SBC will act as a data acquisition unit which will be collect the data and as well as transmit the data and based on the data preventive and corrective measures can be adopted to ensure smooth running the equipment. The vibration readings will be taken for a constant shaft length of 1000mm and when it is rotating at a constant 720rpm.

Results and discussion

Figure 6 shows the time domain graph that has been obtained through IoT from MEMS sensor. Tri-axis MEMS accelerometer has captured vibrations through acceleration in x, y and z axis for each tail stock condition respectively. It can be observed from Figure 6 that the vibration picked up is higher for the fixed tail stock condition for all the three axes. This can be validated by the fact that flexible tail stock condition will allow the shaft to move to certain degree thereby the vibrations produced will be comparatively less than the rigid tail stock. But when the time domain is only used for maintenance and prognostics there is possibility that noise can also be picked up by the sensor and it may be giving a false indication. One way of eliminating the problem is by measuring it at certain interval of time. But the best method that can be adopted for solving this problem is by converting the data from time to frequency domain there by any sort of noise abnormalities will be removed and the maximum frequency will be available for further analysis.

In Figure 7 it can be observed that certain amount randomness being present as the raw time data is being implemented for conversion. The main ideology of this work was to develop a low cost IoT based prognostics tool. Using filter like low pass filter and others into the raw time data will be the future scope of it. After which the data can be used to train supervised or unsupervised learning algorithm after which they will be able to predict the failure and alert the personal involved in it. This process will eliminate human intervention and also makes the life of the user very simple as only supervision is needed thereby eliminating the time used for analyzing the data and then arriving at a conclusion.

a)



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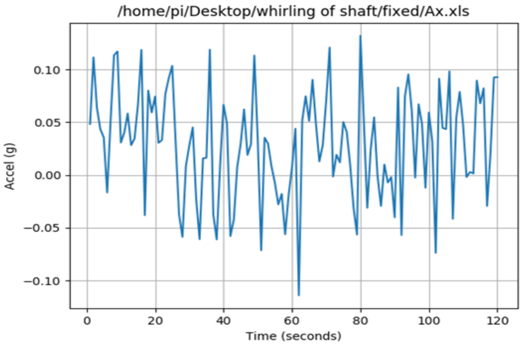

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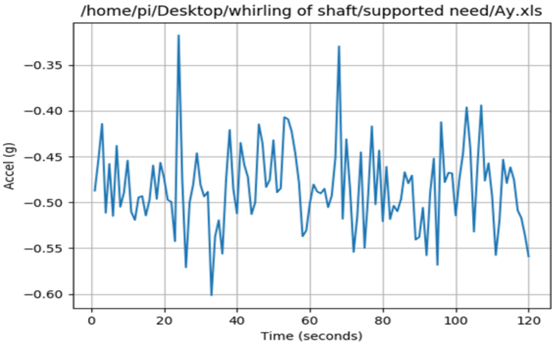

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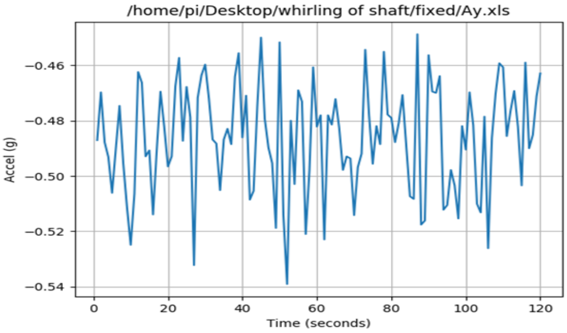
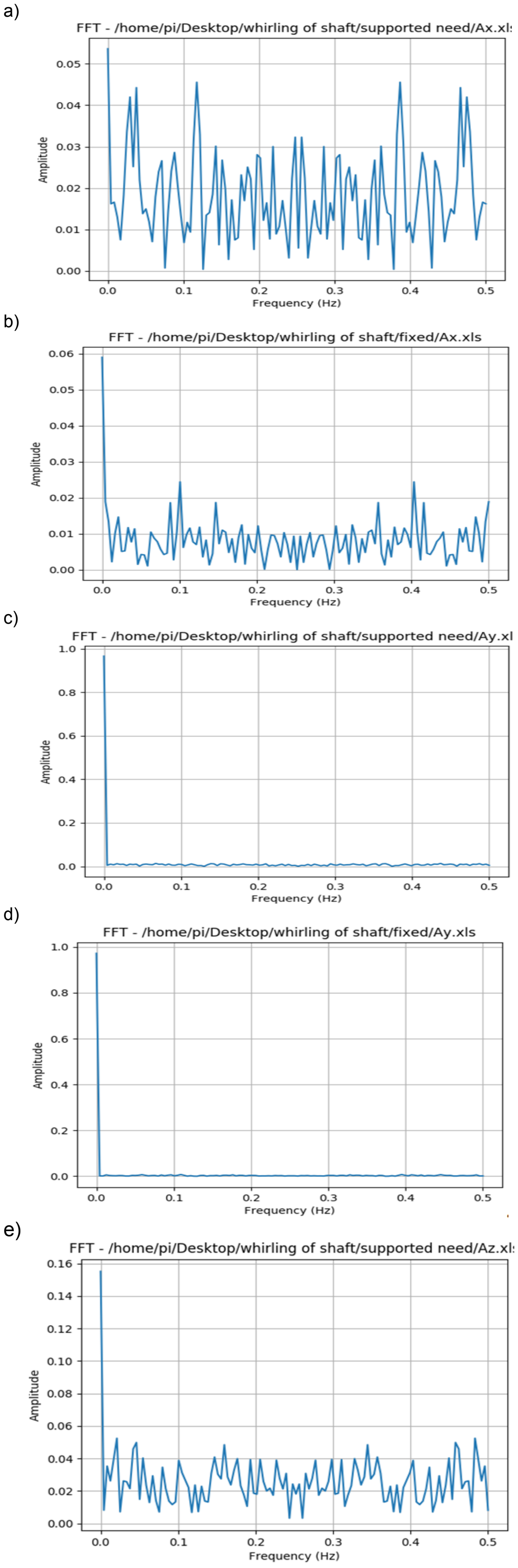


e)

f)

Fig 6: Time domain vibration(a) x-axis fixed tail stock (b) x-axis flexible tail stock (c) y-axis fixed tail stock (d) y-axis flexible tail stock (e) z-axis fixed tail stock (f) z-axis flexible tail stock



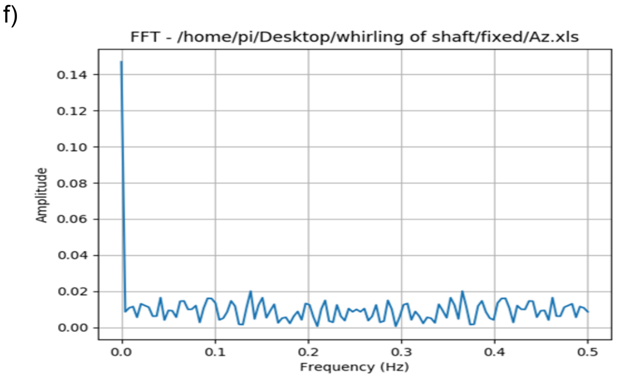


Fig 2: Frequency domain vibration data (a) x-axis fixed tail stock (b) x-axis flexible tail stock (c) y-axis fixed tail stock (d) y-axis flexible tail stock (e) z-axis fixed tail stock (f) z-axis flexible tail stock

Conclusion

ome of the observations from this work, where a low cost IoT based prognostics system was developed are

1. Rigid fixed condition in tail stock produces maximum vibration but specifically higher in the lateral directions, in this x-axis as it was aligned in that direction.
2. Flexible condition in tail stock will be producing a less amount of vibration comparatively.
3. The readings present do exhibit some randomness which will taken up as future work in-line where-in it can be removed by adding some filters in it.
4. The IoT interface created here was not a dynamic rather in static server as a dynamic server involved the usage of cloud storage. In case of static server, a local server was used. To make in to certain industry model the same can be adopted for a dynamic server with cloud storage model.

***Authors**: Dr Ajay Vasanth. X, Department of Mechanical Engineering, Karunya Institute of Technology and Sciences, Coimbatore, India, E-mail: vasantajay@gmail.com; Dr P. Sam Paul, Department of Mechanical Engineering, Karunya Institute of Technology and Sciences, Coimbatore, India, E-mail: psam_paul@rediffmail.com.*

REFERENCES

[1] A. K. S. Jardine, D. Lin, and D. Banjevic, ‘A review on machinery diagnostics and prognostics implementing condition-based maintenance’, Mech. Syst. Signal Process., vol. 20, no. 7, pp. 1483–1510, Oct. 2006.
[2] A. Heng, S. Zhang, A. C. C. Tan, and J. Mathew, ‘Rotating machinery prognostics: State of the art, challenges and opportunities’, Mech. Syst. Signal Process., vol. 23, no. 3, pp. 724–739, Apr. 2009.
[3] I. Bazovsky, Reliability Theory and Practice. Englewood Cliffs, NJ: Prentice - Hall, 1961.
[4] A. K. S. Jardine and A. H. C. Tsang, Maintenance, Replacement, and Reliability: Theory and Applications. CRC Press, Taylor & Francis Group, 2017.
[5] M. Sc. Kelly, Maintenance and its management. Farnham, Surrey : Conference Communication, 1989.
[6] H. P. Bloch and F. K. Geitner, Machinery Failure Analysis and Troubleshooting - 4th Edition. Butterworth - Heinemann, 2012.
[7] J. Mathew and R. J. Alfredson, ‘The Condition Monitoring of Rolling Element Bearings Using Vibration Analysis’, J. Vib. Acoust. Stress Reliab. Des., vol. 106, no. 3, pp. 447–453, Jul. 1984.
[8] D. Mba and R. B. K. N. Rao, ‘Development of Acoustic Emission Technology for Condition Monitoring and Diagnosis of Rotating Machines; Bearings, Pumps, Gearboxes, Engines and Rotating Structures.’, Jan. 2006.
[9] P. Guo, D. Infield, and X. Yang, ‘Wind Turbine Generator Condition-Monitoring Using Temperature Trend Analysis’, IEEE Trans. Sustain. Energy, vol. 3, no. 1, pp. 124–133, Jan. 2012.

[10] M. Kumar, N. Mohan Misra, and P. Shankar Mukherjee, ‘Advancement and current status of wear debris analysis for machine condition monitoring: a review’, Ind. Lubr. Tribol., vol. 65, no. 1, pp. 3–11, Feb. 2013.

[11] D. Jung, Z. Zhang, and M. Winslett, ‘Vibration Analysis for IoT Enabled Predictive Maintenance’, in 2017 IEEE 33rd International Conference on Data Engineering (ICDE), 2017, pp. 1271–1282.

[12] F. Al-Badour, M. Sunar, and L. Cheded, ‘Vibration analysis of rotating machinery using time–frequency analysis and wavelet techniques’, Mech. Syst. Signal Process., vol. 25, no. 6, pp. 2083–2101, Aug. 2011.

[13] J. d J. Rangel-Magdaleno, R. d J. Romero-Troncoso, R. A. Osornio-Rios, E. Cabal-Yepez, and A. Dominguez-Gonzalez, ‘FPGA-Based Vibration Analyzer for Continuous CNC Machinery Monitoring With Fused FFT-DWT Signal Processing’, IEEE Trans. Instrum. Meas., vol. 59, no. 12, pp. 3184–3194, Dec. 2010.

[14] T. Teslyuk, P. Denysyuk, A. Kernytskyy, and V. Teslyuk, ‘Automated control system for arduino and android based intelligent greenhouse’, in 2015 XI International Conference on Perspective Technologies and Methods in MEMS Design (MEMSTECH), 2015, pp. 7–10.

[15] Y. J. Chan and J.-W. Huang, ‘Multiple-point vibration testing with micro-electromechanical accelerometers and micro-controller unit’, Mechatronics, vol. 44, pp. 84–93, Jun. 2017.

[16] Morgenthal Guido, Rau Sebastian, Taraben Jakob, and Abbas Tajammal, ‘Determination of Stay-Cable Forces Using Highly Mobile Vibration Measurement Devices’, J. Bridge Eng., vol. 23, no. 2, p. 04017136, Feb. 2018.

[17] S. Korkua, H. Jain, W. Lee1, and C. Kwan, ‘Wireless health monitoring system for vibration detection of induction motors’, in 2010 IEEE Industrial and Commercial Power Systems Technical Conference - Conference Record, 2010, pp. 1–6.

[18] J. K. Sinha and K. Elbhbah, ‘A future possibility of vibration based condition monitoring of rotating machines’, Mech. Syst. Signal Process., vol. 34, no. 1, pp. 231–240, Jan. 2013.