



## Health Monitoring and Predictive Maintenance of DC Motor

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### Abstract

*The health monitoring of induction motor is a technology which involves the measurement of machine during operating condition like temperature rising, burning of winding, over current, over voltage etc. Predictive maintenance is the way to improve asset management in every manufacturing industry, while handling advance costlier machinery in the industry, the predictive maintenance knowledge will be essential to protect the machinery before gets degradation performance. Now days the maintenance of AC or DC motor is most common requirement in industries. Routine maintenance is essential to reduce plant downtime which is costly in any manufacturing facility. The goal of our device which is connected to motor is to calculate the run time values and continuously compare these values with standard values of motor. Using vibration, current and temperature sensor, we can predict the values. If the values are exceeds the limits then VI developed in Lab VIEW will pop-up a message. This can determine a fault for an overhaul or replacement of motor. We can easily connect this wireless device to AC or DC motor. This maintenance programs is to reduce maintenance cost by detecting problems early which allows for better planning and less expected failure. The use of DC motor is done in a maximum way, to avail advantages of high starting toque, preferably in crane applications.*

**Keywords:** Health Monitoring, Predictive maintenance, DC Motor Faults Arduino kit, Temperature sensor, Current sensor, Vibration sensor.

### Introduction

Machine monitoring is a process through which we can monitor the parameter of the machine condition, such that a considerable change is the indication of a failure in development. Condition monitoring of a machine can be realized by monitoring the following characteristics, such as voltage, current, noise, vibration, temperature etc. The predictive maintenance is monitoring all activities and development trend analysis of characteristic parameters, properties of performance and electrical equipment for detecting degradation trends and incipient fault detection to avoid them. The predictive maintenance is encountered in the specialist area and the conditions of state-based maintenance CBM (Condition Based Maintenance) The frequency of predictive maintenance interventions depends on the type of system and how to use him. So, depending on experience and knowledge gained over time and analyzing the history of defects, based on these data we can achieve a maintenance plan to include periods of intervention on the machinery here, critical components that must be replaced at a certain number of hours of operation or a certain time<sup>1</sup>.

As we move to industry 4.0 the demand for automation in the industries has increased. The reliability safety, efficiency and productivity all depend upon the technologies which do not fail and can be predicted. Unplanned stoppages, can lead to decreased market adaptability of a company. Time-based maintenance primarily focuses on a conservative method of

preventive maintenance which happens in a fixed period of time. This system has been flanked by various disadvantages due to which there has been exploration into other kinds of Maintenance techniques. One such maintenance techniques which has become popular is condition-based monitoring system is popularly known as predictive maintenance. The ability of this maintenance technique to predict the failure helps in reducing the mean time between the failures and its inclusive operational capability of social cyber physical systems has helped to increase the machine life and also helped in optimization of the operational cost considerably. In this paper an effort has been made to discuss, the methodology of how a condition-based monitoring system can be implemented effectively is taken up with the example of a vibration, current and temperature analysis of a motor in industry<sup>2</sup>.

### Different methods of curriculum based measurement

**Mechanical based vibration analysis:** As very nearly 70 percent of basic rotating machines issues are identified with misalignment and unbalance, vibration examination is a significant apparatus that can be utilized to take out repeating issues. By and large, the general vibration level of the machine is adequate to analyze mechanical problems. Survey stats that most of the bearing fault diagnoses are based on vibration analyses like Fast Fourier transforms or current-based analysis. It is illustrated how eccentricity faults can be identified from

vibration analysis using condition monitoring techniques Bearing and eccentricity fault diagnoses can be effectively carried out with analysis of vibrations with the help of algorithms like wavelength transform and Hilbert transforms<sup>2</sup>.

**Temperature Monitoring:** Temperature effects must be taken into account in order to appropriately apply DC motors in any kind of application. As the motor temperature varies, performance will also fluctuate. Do these curves show the motor's performance at room temperature or at the maximum rated temperature? is a concern that users should consider while examining DC motor curves. The performance difference between "cold" and "hot" conditions might be substantial, depending on the temperature and the needed operating point on the motor curve. Therefore, increased temperatures can lead to motor faults, and thermal analysis is a useful tool for diagnosing these faults<sup>2</sup>.

**Current analysis:** A voltage drop is brought on by current passing through a conductor. Ohm's law provides the relationship between current and voltage. An increase in current beyond what is needed for electrical devices might cause overload and harm to the DC motor. Current measurement is required for a motor to operate properly. Voltage measurement is a passive job that can be performed without impacting the system. On the other hand, measuring current requires intrusion and cannot be done directly like measuring voltage. Hence using current analysis to diagnose undercurrent or over current faults can be done successfully<sup>3</sup>.

## Methodology

This project uses an ESP32 interfaced with LabVIEW to perceive a variety of sensor data. A temperature sensor (LM35) is used to monitor the temperature of the DC motor or measure changes in temperature, and current sensors are used to measure any fluctuations in current or overcurrent. Fast Fourier transform is used to monitor sensor data, and if any kind of fault is diagnosed, a prepared VI in LabVIEW will generate a popup message. Vibration sensors are used to measure vibration changes or any misalignment. This data is sent to the Blynk cloud and then received by LabVIEW<sup>3</sup>.

**System hardware:** The following are the components that are used in the system and it is explained as follows:



Figure-1: ESP-32.

The SoC (System on Chip) microcontroller known as ESP32 has been extremely popular recently. It is arguable as to whether the debut of ESP32 spurred the growth of IoT or the other way around. It is likely that 7–8% of the 10 individuals you know who have contributed to the firmware development of any IoT device have worked on the ESP32 at some point. The integrated Wi-Fi and Bluetooth stacks on the ESP32 have changed the game when it comes to data transmission. It is not necessary to attach an additional module (such as an LTE or GSM module) in order to test cloud communication. All you need to get started is the ESP32 board and an active Wi-Fi network. With the ESP32, you can utilize Wi-Fi in both station and access point mode. It supports HTTPS in addition to HTTP, MQTT, TCP/IP, and other conventional communication protocols. Yes, you heard correctly. It is equipped with a crypto-accelerator, also known as a crypto-core, which is a specialized piece of hardware designed to speed up the encryption process. Thus, you can safely connect with your web server in addition to doing so otherwise. Support for BLE is also essential for a number of applications. Of course, the ESP32 can be interfaced with LTE, GSM, or LoRa modules. Consequently, ESP32 surpasses expectations in terms of "transmitting data" as well<sup>3</sup>.

**LM35 Temperature Sensor:** A temperature sensor called the LM35 produces an analog signal that is proportionate to the current temperature. It is simple to interpret the output voltage and get a temperature reading in Celsius. LM35 has a benefit over thermostat in that it doesn't need to be calibrated externally. It is additionally shielded from self-heating by the covering. Due to its lower cost (about \$0.95) and increased precision, amateurs, students, and do-it-yourself circuit makers find it to be appealing. Due to their lower cost, higher accuracy, and use of the LM35, many low-end goods. After being released more than 15 years ago, the sensor is still in use today and may be found in many devices<sup>3</sup>.

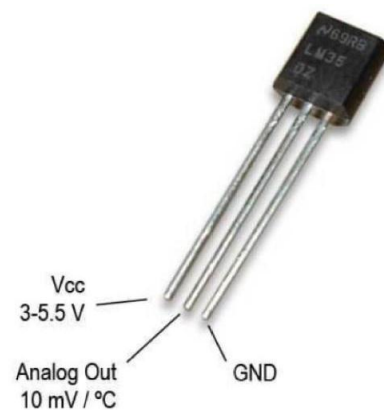


Figure-2: LM35 temperature sensor.

The temperature range that the LM35 can measure is -55 to 150 degrees Celsius. When the system is operating at ideal humidity and temperature, the accuracy level is quite high. It's also simple and straightforward to convert the output voltage to centigrade<sup>3</sup>.

**Current Sensor (INA219):** This post will cover the INA219 Current Sensor module, which allows us to measure a circuit's power, voltage, and current. The INA219 Current Sensor is a bi-directional, zero drift, and I2C-supported interface-based current/power monitoring module. It is simple to measure current, power, and shunt voltage with the Arduino and the INA219 Current Sensor. In order to meet the requirement of current measurements, this sensor module comes with a 1% shunt resistor and 0.1 ohms of resistance. DC voltage up to +26V can be measured using the INA219 Current Sensor. We will talk about a ton of other topics in a moment<sup>3</sup>.

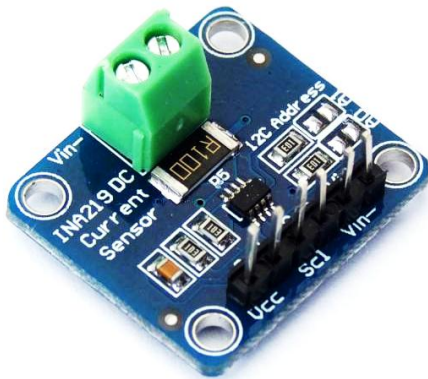


Figure-3: current sensor INA219.

**ADXL335 accelerometer:** An accelerometer is a tool that measures the vibration, motion, or acceleration of a structure. Cameras and smart phones these days use an accelerometer consisting of an axis-based motion sensor. It is an electromechanical device that measures either static or dynamic acceleration. Acceleration, as we know, is the measure of change in velocity upon a given time<sup>4</sup>.

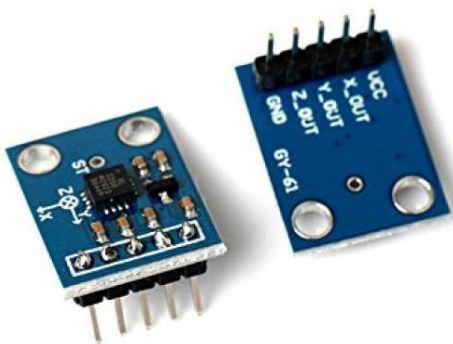


Figure-4: ADXL335 accelerometer.

Generally, there are two types of capacitive accelerometers right now. One is MEMS (Micro electro mechanical sensor). MEMS generally have a silicon-based material with a mass attached to it and it is fused into a circuit. As the acceleration is applied, the mass moves, and because of this, the silicon material also

moves. This creates a charge in the circuit. With the use of charge, we can calculate the acceleration<sup>4</sup>.

The other type is analog accelerometers. They work on two different principles which we discuss above: piezoelectric sensing and capacitive sensing. ADXL335 works with the principle of capacitive<sup>4</sup>.

ADXL335 is a capacitive accelerometer. It works on the principle that when the acceleration is applied to the sensor, the capacitance inside the sensor changes. This change in capacitance is then used to measure the acceleration of the object<sup>4</sup>. This is a 3-axis accelerometer. Therefore, we can use it to calculate all the accelerations in three dimensions<sup>4</sup>.

## System Software

**Practical experimentation with accelerometer:** The ADXL335 accelerometer was utilized in this experiment. The maximum capability of the 3-axis analog-output accelerometer, the ADXL335, is within  $\pm 3g$ , where 1G is equivalent to 9.08m/s<sup>2</sup>. Positioning the accelerometer on a mounting board. The schematic of the EVAL-ADXL335Z board is displayed by EVAL-ADXL335Z [14]. shows the pin configuration for EVAL-ADXL335Z, which consists of ST, V+, Z, Y, X, and ground pins. The low voltage of 3.3V powers the ADXL335 device. In this experiment, the ADXL335 was interfaced with an Arduino Mega. The AT Mega microcontroller powers the Arduino Mega.

The programming environment used to write C-language instructions that allowed the microcontroller to synthesize the accelerometer reading is called the Arduino Integrated Design Environment (IDE). The accelerometer's measurements, which were obtained via the serial monitor, show that the accelerometer was tilted in the X-axis direction, resulting in a g acceleration<sup>4</sup>.

**Blynk Cloud:** Because it's constantly available and ready to go, the Blynk Cloud server is a great option for most projects. To make things easy for you to get started, we will use the Cloud server for the first few experiments in this course. You'll see, though, that there are restrictions placed by the Cloud Blynk server. Depending on where you live, the server may be on a different continent. In this case, communications between the app, the devices, and the server will be delayed because of the length of time it takes for packets to go over the Internet. Other limits are caused by the server's topology. You are limited to using a certain amount of widgets in the Cloud server, which is another enforced limitation. Blynk is implementing a price structure for its widgets by utilizing the idea of "energy." You can launch a new project in the cloud server with 1000 energy units. You might need 200 units for an LED widget, leaving you with 800 units for other widgets. You have control over your own energy thresholds on a private server. Your server can be set up to give new users 100,000 energy units. That is all up to you.

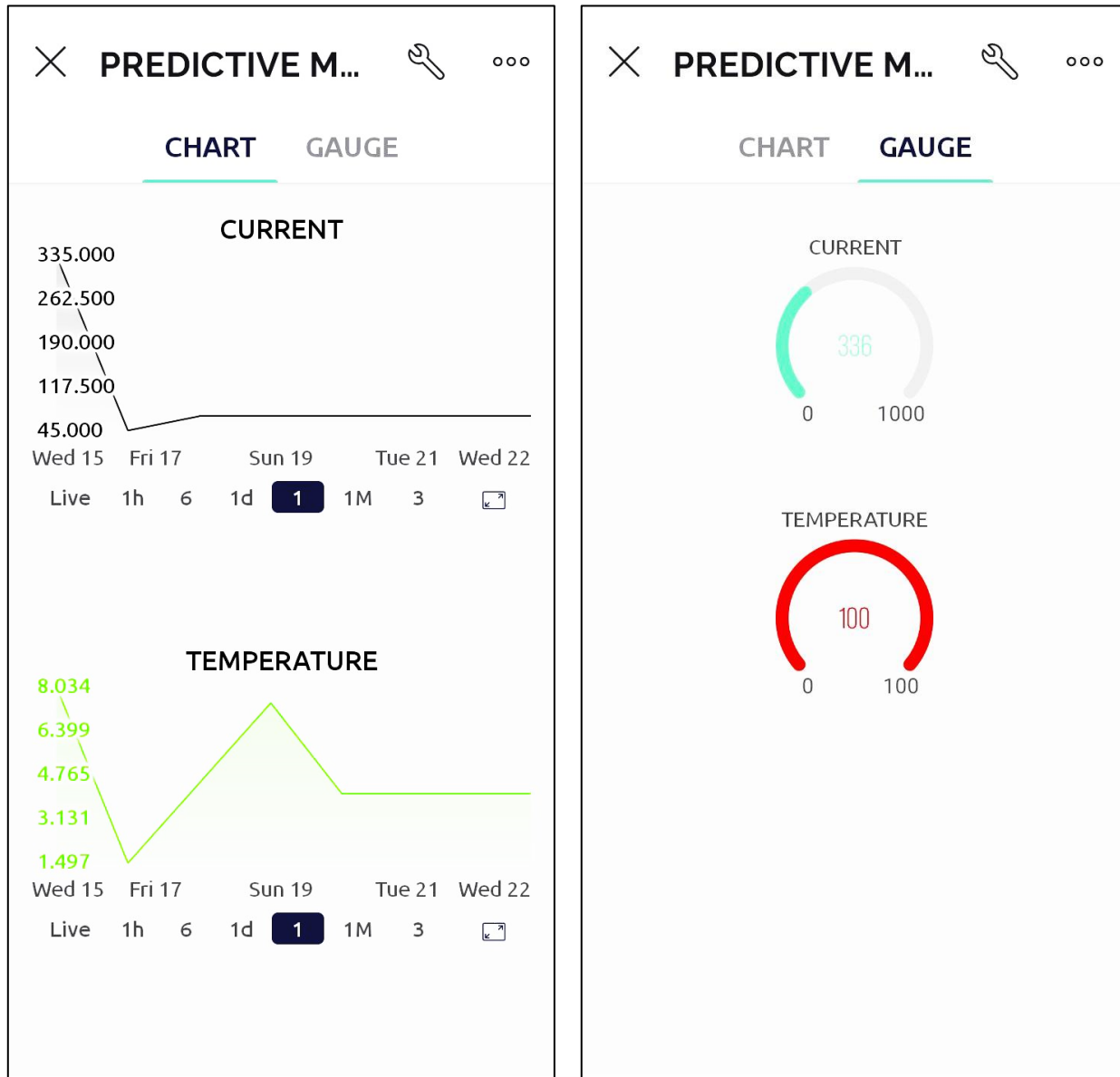


Figure-5: Predictive Maintenance.

**LabView based monitoring system:** Virtual instruments (VI) can be created using a graphical programming language with the help of National Instruments (NI) LabVIEW software. For this reason, an application programmable interface (API) for the experiment has been created using LabView Interface for ESP32. This was accomplished utilizing the VI protocol, which translates all of the esp32 data with LabVIEW. The HTTPs protocol is used to communicate with the esp32 board in LabVIEW; the esp32 transmits data to the Blynk cloud, and LabVIEW receives it via the HTTPs protocol. It is also necessary to install the JKI VI Package Manager (VIPM), which enables the installation and updating of LabVIEW libraries. The data will be fetched from the cloud into LabVIEW using the specific URL that Blynk Cloud produced based on its API<sup>5</sup>.

**FFT Analyzer:** FFT analyzer is currently used as a reliable instrument for measurement of vibration. It gives an analysis in both time domains as well as in frequency domain. In this setup, it is used as to compare and validate the data obtained from the accelerometer. For this purpose of comparison measurements on both FFT Analyzer and Arduino carried-out simultaneously for known frequency on exciter The data simultaneously recorded from Arduino as well as FFT Analyzer is to be processed. The data generated by FFT is in time domain as well as in frequency domain. For proposed work, the data processed in time domain. Similarly, Arduino also generate data in time domain. The time domain data from both instruments is converted to frequency domain by using MATLAB software<sup>6</sup>.

**Predictive Maintenance (PDM):** In order to schedule maintenance as soon as there is a divergence from the equipment's typical operating parameters and before an actual breakdown occurs, predictive maintenance considers the health of the equipment. By avoiding needless component replacement, the equipment may receive maintenance as needed, extending component life and reducing machine downtime.

The enormous volume of data collected by sensors enables predictive maintenance, which is essentially an advancement and expansion of condition monitoring (CM). Because of its advantages, the industry is paying attention to predictive maintenance, which is the most efficient kind of maintenance. On the other hand, if historical data is lacking, predictive maintenance may prove challenging to execute and costly to establish in the absence of appropriate hardware and analytical expertise<sup>7</sup>.

**Fault Diagnosis:** For better production performance, fault diagnosis systems that examine the operating state of the equipment to identify issues early on are essential. Depending on the methodologies and presumptive data employed, fault detection approaches are typically categorized into three primary groups: knowledge-based, model-based, and signal-based<sup>7</sup>.

Signal-based approaches make use of signal processing techniques to analyze the measured operational status of the equipment, extract and highlight elements that are normally difficult to see, and provide a diagnosis based on past experience with functioning systems. These techniques still need specialized knowledge to recognize the signs of erroneous signals. Depending on the signal processing technique used, signal-based methods are typically classified into three categories: time-domain (standard deviation, trends, slope and magnitudes), frequency domain (motor current signature analysis), and time frequency (Fourier transform, wavelet transforms, Hilbert–Huang transform, instantaneous power FFT, high resolution spectral analysis, bi-spectrum, Park's vector approach, adaptive statistical time-frequency method)<sup>7</sup>.

Large volumes of historical data are used in knowledge-based approaches, sometimes referred to as data-driven methods, which have the ability to automatically extract features without the need for prior signal processing procedures. Data-driven approaches, in contrast to model- and signal-based approaches, do not call for a priori information, making analysis possible even in the absence of expert knowledge. Artificial intelligence

(deep learning, machine learning), statistical, and probabilistic analysis are frequently used in data-driven strategies. With encouraging findings, academia is increasingly paying more attention to data-driven methodologies<sup>7</sup>.

## Conclusion

So, by analyzing vibration, current and temperature we can monitor and also able to predict the health of the motor. We can reduce downtime where these motors are installed, also we can save the maintenance cost.

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