Nithin Aadharsh S, 2026, 14:5
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

Design and Development of an Intelligent DC Motor Health and Fault Diagnosis System Using NI LabVIEW

Nithin Aadharsh S[1], Shreeniva BA[2], Dr. Saravanakumar R[3]
School of Electrical Engineering Vellore Institute of Technology
Vellore, Tamil Nadu, India

Abstract – Condition monitoring of electrical machines is es-sential for improving operational reliability, reducing unexpected downtime, and enabling predictive maintenance. Direct current (DC) motors are widely used in industrial drives, robotics, electric traction, and automated systems, where degradation of electrical and mechanical components can adversely affect performance. This paper presents the design and development of an intelligent DC motor health and fault diagnosis system using the National Instruments LabVIEW graphical development environment. The proposed system acquires multiple motor parameters, including armature current, mechanical vibration, rotational speed, and temperature, through a multi-channel data acquisition interface. A queue-based Producer–Consumer architecture is employed to separate continuous data acquisition from computationally intensive signal-processing operations. The acquired current and vibration signals are subjected to digital filtering and frequency-domain analysis using the Fast Fourier Transform (FFT). Time-domain statistical features such as root mean square (RMS), peak value, kurtosis, and crest factor are extracted to characterize motor operating conditions. The extracted features are subse-quently supplied to an intelligent classification layer based on fuzzy logic and/or a machine-learning classifier. The diagnosed motor condition is displayed through a LabVIEW graphical user interface using numerical indicators, waveform charts, fault indicators, and threshold-based alarms. The proposed architecture provides a modular framework for real-time motor condition monitoring and automated fault diagnosis and can be extended for experimental validation under different electrical and mechanical fault conditions.

Keywords— DC motor, condition monitoring, fault diagnosis, LabVIEW, data acquisition, FFT analysis, vibration

I. INTRODUCTION

Direct current (DC) motors continue to be used in a wide range of industrial and electromechanical applications because of their controllable speed characteristics, high starting torque, and relatively simple control structure. Applications include industrial automation, robotics, electric traction, positioning systems, and process-control equipment. Reliable operation of these machines is important because degradation of electrical,

mechanical, and thermal components can eventually lead to performance deterioration or unexpected machine failure.

Traditional maintenance approaches generally involve cor-rective maintenance after a failure or periodic preventive maintenance based on predefined schedules. Although these methods can reduce the probability of catastrophic failure, they may result in unnecessary maintenance activities or fail to de-tect developing faults between inspection intervals. Condition-based maintenance provides an alternative by continuously monitoring measurable machine parameters and identifying deviations from normal operating conditions.

Electrical and mechanical faults in DC motors can produce characteristic changes in current, vibration, rotational speed, and temperature. Armature winding abnormalities can affect current characteristics, while mechanical unbalance and mis-alignment can produce periodic vibration components. Brush and commutator abnormalities can introduce transient electri-cal disturbances and high-frequency components. Temperature variations can additionally indicate excessive losses, overload conditions, or inadequate cooling.

© 2026 Nithin Aadharsh S his is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly credited.

Motor Current Signature Analysis (MCSA) and vibration analysis are commonly used for electrical-machine condition monitoring. However, simultaneous analysis of multiple pa-rameters can provide a more comprehensive representation of machine health.

A suitable monitoring system should be capable of acquiring these signals synchronously, processing them in real time, extracting meaningful diagnostic features, and presenting the resulting machine condition to the operator. National Instruments LabVIEW provides a graphical pro-gramming environment suitable for developing virtual in-strumentation systems.

Its DAQmx interface supports multi-channel data acquisition, while signal-processing and mathe-matical functions can be integrated into a single monitoring ap-plication. LabVIEW also supports parallel execution through structures such as Producer–Consumer architectures, making it suitable for separating high-speed data acquisition from signal-processing and classification operations [5].

This work proposes a LabVIEW-based intelligent DC motor health and fault diagnosis system. The system integrates multi-channel data acquisition, digital filtering, statistical feature ex-traction, FFT-based spectral analysis, intelligent classification, graphical monitoring, alarm generation, and event-based data logging within a single virtual instrument.

The major objectives of the proposed system are:

- To acquire multiple DC motor parameters using a multi- channel DAQ system
- 2) To implement a real-time Producer–Consumer architeture in LabVIEW3) To process current and vibration signals using digitalc-filtering and FFT analysis.
- 4) To extract time-domain and frequency-domain diagnos-tic features.
- 5) To classify motor operating conditions using an intelli-gent decision-making layer.
- 6) To provide real-time visualization and fault indication through a LabVIEW front panel.
- 7) To record abnormal operating events for subsequent analysis.

II. DC MOTOR FAULTS AND DIAGNOSTIC PARAMETERS

1. DC Motor Electrical Model

The electrical behavior of the armature circuit of a sepa-rately excited DC motor can be represented by

$$V_a(t) = R_a i_a(t) + L_a \frac{di_a(t)}{dt} + e_b(t) \qquad (1)$$

where Va is the armature voltage, ia is the armature current, Ra is the armature resistance, La is the armature inductance, and eb represents the back electromotive force.

The back EMF is related to motor speed by

$$eb(t) = K_e \Phi \omega_m(t) \qquad (2)$$

where Ke is the back-EMF constant, Φ is the magnetic flux, and ωm is the angular speed.
The mechanical dynamics of the motor can be represented as

$$T_e(t) - T_L(t) = J \frac{d\omega_m(t)}{dt} + B\omega_m(t) \qquad (3)$$

where Te is the electromagnetic torque, TL is the load torque, J is the rotor inertia, and B is the viscous friction coefficient.
The electromagnetic torque is given by

$$Te(t) = K_t \Phi ia(t) \quad (4)$$

where Kt is the torque constant.
These relationships establish the coupling between electrical current, electromagnetic torque, and mechanical speed. Con-sequently, abnormalities in the electrical or mechanical system can result in measurable changes in the acquired signals.

2. Motor Fault Characteristics

The proposed diagnostic system considers several motor operating conditions.

Rotor Unbalance: Mechanical unbalance occurs when the mass distribution of the rotating assembly is not uniform. The resulting centrifugal force increases with the square of rotational speed and can produce strong vibration components at the rotational frequency.
The rotational frequency is

$$f_r = \frac{N}{60} \quad (5)$$

where N is the motor speed in revolutions per minute. The corresponding fundamental vibration component is commonly referred to as the 1X component.

Shaft Misalignment: Misalignment between the motor shaft and the coupled load can produce increased vibration and harmonic components around the rotational frequency. Changes in the relative amplitudes of the 1X and 2X com-ponents can provide useful information for identifying me-chanical abnormalities.

Brush and Commutator Faults: Brush wear, poor brush contact, commutator surface degradation, and electrical arcing can introduce transient disturbances into the armature cur-rent. These disturbances may also appear as increased high-frequency components in vibration measurements.

Armature Winding Faults: Inter-turn winding faults can alter the effective armature resistance and cause abnormal current circulation. Such conditions can produce characteristic variations in the current waveform and its frequency spectrum.

Thermal Abnormalities: An increase in motor temperature may indicate excessive current, increased mechanical loading, electrical losses, or inadequate heat dissipation. Temperature is therefore used as an additional health indicator.

III. PROPOSED SYSTEM ARCHITECTURE

The proposed system consists of four major functional stages:

- Sensor and data acquisition layer
- Real-time signal processing layer
- Intelligent fault classification layer

Monitoring and data logging layer

The monitored motor parameters are armature current, vibration, rotational speed, and temperature. These signals are acquired through a multi-channel NI DAQ interface and transferred to the LabVIEW application.The software architecture follows a Producer–Consumer design pattern. The Producer Loop is responsible for continuous data acquisition, while the Consumer Loop performs signal processing, feature extraction, classification, and visualization. This separation prevents computational processing from unnecessarily interrupting the data acquisition process.
The overall signal flow can be represented as
Motor → Sensors → NI DAQ → Producer Loop → Queue → Consumer

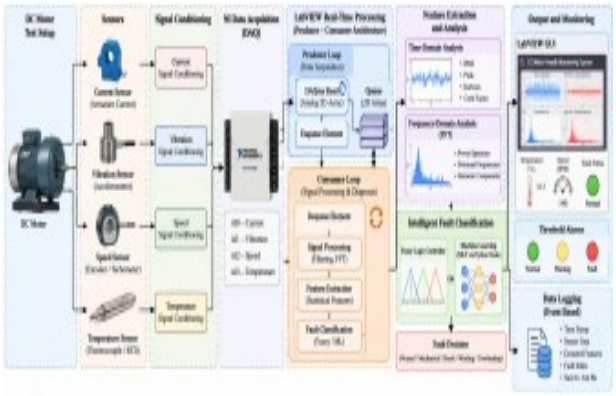


Fig. 1. Overall architecture of the proposed intelligent DC motor health and fault diagnosis system.

TABLE I
DAQ CHANNEL CONFIGURATION

Channel	Measured Parameter
AI0	Armature Current
AI1	Mechanical Vibration
AI2	Motor Speed
AI3	Motor Temperature

followed by Filtering → Feature Extraction → FFT Analysis → Fault Classification → Display and Logging. (7)

IV. HARDWARE AND DATA ACQUISITION

The proposed experimental setup consists of a DC motor, current sensor, vibration sensor, speed measurement sensor, temperature sensor, and NI data acquisition hardware. The four measurement channels are assigned as shown in Table I. The DAQ system is configured for continuous acquisition at a sampling frequency of fs = 10, 000 Hz (8) with a block size of N = 1000 (9) samples per channel. Thus, each acquisition block represents Tb = N fs (10) Tb = 1000 10000 = 0.1 s (11) of sampled data. The acquired data are represented as a two-dimensional array of double-precision values, where each row corresponds to one measurement channel.

Subsystem	Component / Specification
DC Motor	220 V shunt DC machine, 0.75 kW, 1500 RPM
Current Sensor	LEM LA 25-NP Hall-effect current transducer
Vibration Sensor	PCB Piezotronics 352C33 accelerometer
Speed Sensor	Optical encoder / tachometer, 1024 PPR
DAQ	NI USB-6009 / NI cDAQ-9174

1 Hardware Components The hardware configuration described in the original design is summarized in Table II. The component specifications are based on the hardware configuration described in the uploaded design document. :contentReference[oaicite:2]index=2

V. LABVIEW SOFTWARE IMPLEMENTATION

A. Daq Initialization The first stage of the LabVIEW program establishes the data acquisition task. The DAQmx Create Virtual Channel.vi is used to configure the analog input channels. The required channels are configured for voltage acquisition: Dev1/ai0:3 (12) The acquisition task is subsequently connected to DAQmx Timing.vi, which is configured for continuous sampling at 10 kHz with 1000 samples per channel. The resulting DAQ task provides a continuous stream of synchronized sensor data to the LabVIEW application. B. Producer–Consumer Architecture A queue-based Producer–Consumer architecture is used to separate acquisition and processing operations. The Obtain Queue.vi creates a FIFO queue whose element type corresponds to the acquired two-dimensional array. The Producer Loop continuously executes

DAQmx Read → Enqueue Element (13) while the Consumer Loop independently executes Dequeue Element → Signal Processing. (14) A timeout of 200 ms is used for the dequeue operation. This architecture allows the acquisition process to continue independently while the Consumer Loop performs computationally intensive operations.

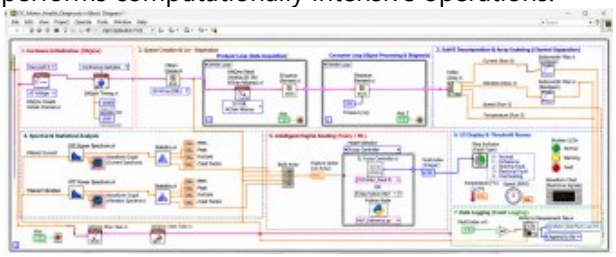


Fig. 2. Integrated LabVIEW block diagram for real-time DC motor health monitoring and fault diagnosis.

VI. SIGNAL PROCESSING AND FEATURE EXTRACTION

1**. Channel Separation The dequeued two-dimensional array is supplied to Index Array.**vi. Individual rows are extracted according to the corresponding sensor channel:

- Row 0 – Armature current
- Row 1 – Vibration
- Row 2 – Motor speed
- Row 3 – Motor temperature Current and vibration signals are subsequently passed through digital filtering.

2 . Digital Filtering The Butterworth Filter.vi is used to suppress unwanted frequency components and noise. The current and vibration signals can be processed using an appropriate low-pass or band-pass configuration according to the sensor characteristics and diagnostic frequency range. Filtering can reduce:

- DC offsets,

- unwanted low-frequency components,
- electrical interference,
- high-frequency noise,
- measurement artifacts.

The filtered signals are then supplied to both time-domain and frequency-domain analysis blocks. The original implementation description specifies Butterworth filtering for the current and vibration signals. :contentReference[oaicite:3]index=3

VII. TIME-DOMAIN FEATURE EXTRACTION

Several statistical parameters can be extracted from the acquired signals to represent motor operating conditions. A. Root Mean Square The RMS value of a discrete signal x[n] is

XRMS = ⌜ ı ı√ 1 N ∑ N n=1 x 2[n]. (15)

RMS represents the effective energy level of the measured signal and can be useful for detecting changes in current or vibration amplitude. B. Peak Value The peak value is defined as Xpeak = max |x[n]|. (16)

It represents the maximum instantaneous magnitude of the signal. C. Crest Factor The crest factor is calculated as

CF = Xpeak XRMS . (17)

An increase in crest factor can indicate the presence of impulsive events or abnormal transient behavior.

D. Kurtosis Kurtosis is used to quantify the impulsiveness of a signal and can be represented as

K = 1 N ∑N n=1(x[n] − μ) 4 σ 4 , (18)

where μ is the mean and σ is the standard deviation. These statistical features are calculated for the current and vibration signals and subsequently supplied to the intelligent classification stage.

VIII. FREQUENCY-DOMAIN ANALYSIS

Time-domain features alone may not sufficiently distinguish different motor faults. Therefore, frequency-domain analysis is incorporated into the proposed system. The filtered current and vibration signals are processed using FFT-based spectral analysis. For a discrete signal x[n], the discrete Fourier transform is X[k] = N ∑−1 n=0 x[n]e −j2πkn/N . (19) The magnitude spectrum is obtained from |X[k]| (20) and the corresponding power spectrum can be used to identify dominant frequency components. The FFT stage is implemented using the LabVIEW FFT Power Spectrum.vi. The resulting spectrum is displayed using waveform graph indicators on the front panel. Important spectral components include: • rotational frequency, • 1X component, • 2X component, • higher harmonics, • commutator-related frequency components, and • broadband high-frequency components. These spectral characteristics can provide additional information for differentiating mechanical and electrical faults

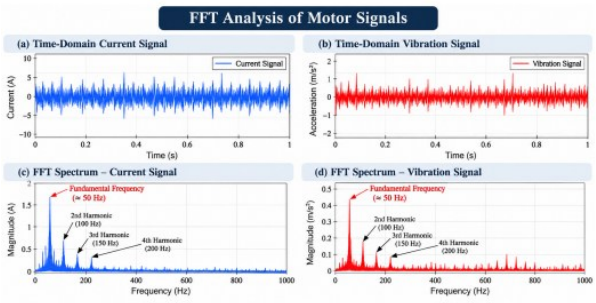


Fig. 3. Representative FFT-based analysis of current and vibration signals.

IX. INTELLIGENT FAULT CLASSIFICATION

The extracted features are combined into a feature vector before being supplied to the intelligent decision-making stage. A representative feature vector can be expressed as F = [IRMS, IPeak, IKurt, ICF, VRMS, VPeak, VKurt, VCF, S, T]. (21) Here, I represents current-related features, V represents vibration-related features, S represents speed, and T represents temperature. A. Fuzzy Logic Classification A fuzzy logic classifier can be implemented using the LabVIEW Fuzzy Logic Toolkit. The principal input variables can include: • Current RMS, • Vibration Crest Factor, and • Commutator spectral energy. Membership functions can be assigned to each input variable, and a rule base can be used to determine the corresponding motor condition. The output

classification can be represented by four states: 1) Normal 2) Mechanical Fault 3) Brush/Commutator Fault 4) Winding Fault The fuzzy inference output is converted into a discrete fault index using an appropriate defuzzification method. The original paper specifies the use of the LabVIEW FL Fuzzy Controller.vi for the fuzzy inference stage. :contentReference[oaicite:4]index=4

B. Machine Learning Classification As an alternative classification approach, a trained MultiLayer Perceptron (MLP) can be integrated through the LabVIEW Python Node. The proposed architecture consists of: • Input layer – extracted diagnostic features, • Hidden layer – nonlinear feature transformation, and • Output layer – motor condition classification. The output layer provides the probability or class index corresponding to the detected operating condition. For the present design, the fuzzy classifier and machinelearning classifier are considered alternative classification paths unless both are experimentally implemented and compared.

X. LABVIEW FRONT-PANEL MONITORING SYSTEM

A graphical monitoring interface is developed to provide real-time visualization of the motor condition. A. Waveform Displays Real-time current and vibration waveforms are displayed using waveform charts. B. Frequency Spectrum FFT magnitude or power spectra are displayed through waveform graphs. C. Temperature Indicator A numerical or thermometer-type indicator displays the measured motor temperature. D. Speed Indicator A dial or numerical gauge displays the measured motor speed in revolutions per minute. E. Fault Indicator A ring indicator displays the detected fault category. A representative fault-index mapping is 0 = Normal (22) 1 = Mechanical Fault (23) 2 = Brush/Commutator Fault (24) 3 = Winding Fault. (25) F. Alarm Indicators Boolean indicators provide an intuitive representation of the motor condition. • Green – Normal • Yellow – Warning • Red – Fault The alarm state is generated according to the output of the classification system and predefined threshold conditions.

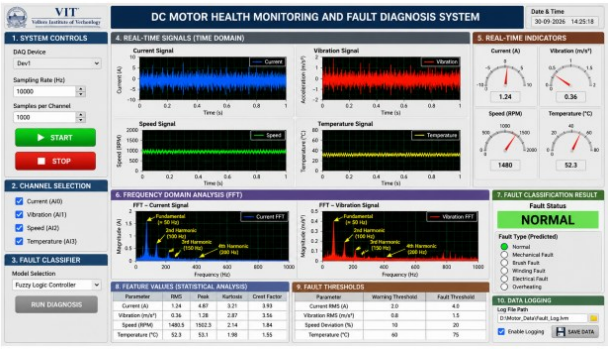


Fig. 4. LabVIEW front-panel interface for real-time motor monitoring and fault indication.

XI. EVENT-BASED DATA LOGGING

For condition-monitoring applications, storing abnormal events is important for subsequent investigation. The LabVIEW Write to Measurement File.vi can be incorporated into the Consumer Loop. The logging operation is triggered when the detected motor state differs from the normal condition: Fault Index≠ 0. (26) The recorded information can include: • Timestamp, • armature current, • vibration, • motor speed, • temperature, • extracted features, and • detected fault class. This creates a historical record of abnormal operating events that can subsequently be used for fault analysis and classifier development.

XII. EXPERIMENTAL METHODOLOGY

The proposed system is intended to be evaluated under different motor operating conditions. The experimental procedure consists of the following stages: 1) Operate the motor under normal conditions. 2) Acquire the four sensor signals through the NI DAQ system. 3) Process the signals using the LabVIEW acquisition and Consumer Loops. 4) Extract time-domain and frequency-domain features. 5) Introduce controlled abnormal operating conditions. 6) Repeat the acquisition and feature-extraction process. 7) Compare the extracted features between normal and abnormal states. 8) Evaluate the classification output. 9) Record the diagnostic response and classification performance. Potential test conditions include:

TAL FEATURE COMPARISON Condition Current RMS Vibration RMS Crest Factor Temperature Normal – – – – Unbalance – – – – Brush Fault – – – – Winding Fault – – – – • Healthy motor operation, • Rotor unbalance, • Shaft misalignment, • Brush/commutator abnormality, • Armature winding abnormality, and • Over-temperature condition. The exact fault conditions should correspond to the faults that are actually created and experimentally tested in the final prototype.

XIII. RESULTS AND DISCUSSION

The performance of the proposed system should be evaluated using experimentally acquired data rather than assumed values.

A. Signal-Level Analysis The current and vibration waveforms obtained under healthy and faulty conditions can be compared in the time domain. Changes in amplitude, transient behavior, and waveform characteristics can provide an initial indication of abnormal motor operation.

B. Spectral Analysis FFT spectra can be compared to identify characteristic frequency components associated with different operating conditions. Rotational-frequency components and higher-order harmonics may provide useful information for identifying mechanical abnormalities, while current-spectrum variations may provide information regarding electrical abnormalities.

C. Statistical Feature Analysis RMS, peak value, crest factor, and kurtosis can be compared across different motor operating conditions. A results table can be inserted after experimental measurements are completed. D. Classification Performance The intelligent classifier can be evaluated using Accuracy

$$= \text{Ncorrect Ntotal} \times 100. \quad (27)$$

Additional performance metrics may include precision, recall, F1-score, confusion matrix, and classification latency. E. Real-Time Performance The processing time between data acquisition and fault classification can also be measured to determine whether the proposed architecture is suitable for real-time monitoring. Note: The numerical performance values reported in the preliminary draft should be replaced with experimentally obtained values before submission. The current document contains claimed classification accuracies and latency values, but these require experimental evidence from the completed system.

XIV. CONCLUSION

This paper presented the design and development of an intelligent DC motor health and fault diagnosis system using NI LabVIEW. The proposed system integrates multi-channel data acquisition, queue-based Producer–Consumer processing, digital signal filtering, time-domain statistical analysis, FFTbased spectral analysis, intelligent fault classification, graphical monitoring, and event-based data logging. Armature current, mechanical vibration, rotational speed, and temperature are considered as complementary indicators of motor operating condition. Current and vibration signals are processed to obtain statistical and spectral features, which are subsequently supplied to an intelligent classification stage. The LabVIEW front panel provides real-time visualization of the measured signals, motor operating parameters, and diagnostic status. The modular architecture enables the acquisition, processing, classification, visualization, and logging functions to operate within a single virtual instrumentation platform. The proposed system can subsequently be experimentally validated using controlled motor fault conditions. Future work will focus on experimental data collection, classifier training, quantitative performance evaluation, and comparison of different intelligent diagnostic algorithms.

REFERENCES

1) P. Vas, Parameter Estimation, Condition Monitoring, and Diagnosis of Electrical Machines. Oxford, U.K.: Clarendon Press, 1993.
2) W. T. Thomson and M. Fenger, “Current signature analysis to detect induction motor faults,” IEEE Industry Applications Magazine, vol. 7, no. 4, pp. 26–34, 2001.

3) A. Bellini, F. Filippetti, C. Tassoni, and G. A. Capolino, "Advances in diagnostic techniques for induction machines," IEEE Transactions on Industrial Electronics, vol. 55, no. 12, pp. 4109–4126, 2008.
4) S. Nandi, H. A. Toliyat, and X. Li, "Condition monitoring and fault diagnosis of electrical motors—A review," IEEE Transactions on Energy Conversion, vol. 20, no. 4, pp. 719–729, 2005.
5) J. Travis and J. Kring, LabVIEW for Everyone: Graphical Programming Made Easy and Fun, 3rd ed. Upper Saddle River, NJ, USA: Prentice Hall, 2006.
6) National Instruments, NI-DAQmx User Manual. Austin, TX, USA: National Instruments.
7) National Instruments, LabVIEW User Manual. Austin, TX, USA: Na-tional Instruments.