Smart EV Motor Predictive Maintenance System Using IoT - A Review of Sensor-Based Monitoring, Fault Detection and Health Assessment

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Abstract

Electric motors sit at the heart of an electric vehicle (EV); in fact, what's more, breakdowns, safety risks and costly repairs are being caused by a sudden motor failure, on the whole. Well the same, after a fault has already start; motor condition is still mostly verified at fixed service intervals. Low-cost sensors, microcontrollers with built-in Wi-Fi and cloud dashboards now make continuous condition monitoring practical; this review is evaluating motor fault mechanisms, condition-monitoring methods, sensor-based measurement of temperature, vibration, current and speed, Internet of Things (IoT) architectures, predictive maintenance and health-index methods, and examines recurring obstacles, like noisy signals, false alarms, scarce fault data, changing load conditions and the restricted computing power of embedded nodes, broadly speaking. The survey is, for all practical purposes, suggesting that most published work tackles one fault indicator at a time or rests on costly instrumentation. When you want to finish this gap, a Smart EV Motor Predictive Maintenance System is put forward that combines temperature, vibration, current and speed sensing on an ESP32 microcontroller, finds a motor health score, raises early maintenance warnings and offers all data on a real-time IoT dashboard; this model is at the design stage, such as no measured results are reported. Try this instead, we state the targets, the planned methodology, an evaluation protocol and the outcomes we expect, clearly marked as predictions to be tested, and argue that such a low-cost platform can shift motor maintenance from reactive repair to proactive, transparent and doable decisions.

Keywords, such as electric vehicle (EV); motor condition monitoring; predictive maintenance; Internet of Things (IoT); ESP32; vibration monitoring; motor current monitoring; motor health score; fault detection, in real-world scenarios.

1. Introduction

1.1 Background

An electric vehicle relies on its traction motor and the associated drive electronics to turn battery energy into motion [1]. Checked with an internal-combustion powertrain the electric drive has, put simply, fewer moving parts, but still, the motor still ages through the winding-insulation stress, bearing wear, overheating and overload [2, 3], in many respects. Clearly, the amounts that best uncover the condition of a motor are its temperature, vibration, supply current and rotational speed, to a significant degree.

In real life, though, motor maintenance still rests on fixed service intervals, fixed alarm limits and the judgement of whoever inspects the vehicle, in actual application; in fact, a increasing body of work is suggesting that low-cost sensors measuring these magnitudes can expose devising faults [2, 4].

1.2 Why Intelligent Motor Monitoring Is generally Needed

As EV drives are pushed harder and used in more varied conditions, standard maintenance runs into several complications:

- The vehicle can (to some degree) be stopped without warning by a sudden motor failure.
- Distinct faults can, as a matter of fact, yield akin symptoms, such as rising temperature, to a significant degree.
- One fault can, more accurately, disturb several parameters at once.
- Readings are changing with load, speed and ambient temperature.
- Some faults are, in effect, constructing slowly and never cross a single fixed limit.
- The real condition of the motor is being ignored by service schedules based only on fixed intervals, to a significant degree.

1.3 Role of IoT and Predictive Maintenance

IoT-based monitoring can turn raw sensor readings into the maintenance knowledge, through a staged pipeline [5], showed in Fig. 1; what's more, the outcome is delivered as a health assessment with a maintenance recommendation, to a significant degree. Each stage adds value, namely signals are got, and cleaned, abnormal behaviour is found and categorised, a likely cause is inferred, the risk of future failure is estimated, in real-world scenarios.

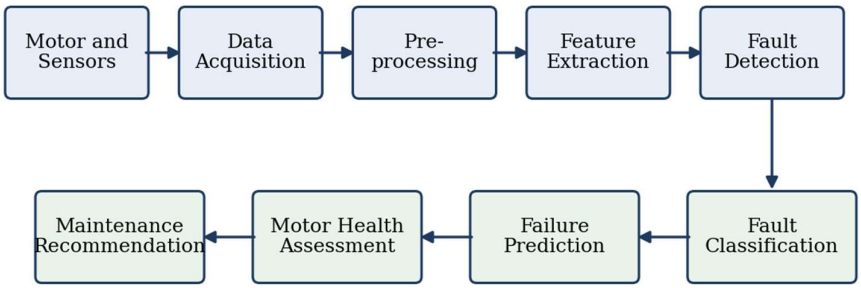


Fig. 1. Never ever mind, Standard IoT-based motor condition-monitoring and predictive maintenance workflow.

1.4 Motivation and Contribution

Published studies usually concentrate on one indicator, for example vibration alone, current alone or the thermal behaviour of a single component, on the whole. As, well, (iv) is setting out a method, evaluation plan and projected outcomes for the project before it's checked. A fuller picture of motor condition would be given by a framework that's joining temperature, vibration, current and speed sensing with health scoring, early warning, automatic protection and a live dashboard; this paper (i) reviews the literature that supports such a combination, (ii) spots six research gaps, (iii) suggests the Smart EV Motor Predictive Maintenance System and its targets.

2. EV Motors and Condition-Monitoring Parameters

2.1 EV Motor Faults and Sensor Parameters

Several motor types, including permanent-magnet brushless, induction and switched-reluctance machines [1] are being employed by EV propulsion. Reliability surveys of induction motors report bearing and stator-winding faults among the most frequent causes of failure [3, 6]. No matter what the type, the principal failure sites are comparable: bearings, windings and insulation, the rotor and the air gap [2]. Excess heat shortens the life of winding insulation [7], and vibration reflects mechanical conditions such as imbalance, looseness and bearing wear [8], to a significant degree. In this effort a DC motor is used to show the behaviour of an EV motor, so brush and commutator wear can also appear

as irregular current. Seeing that many faults leave a measurable trace in one or more factors, sensor data are a rich diagnostic resource; Table I lists the coefficients monitored in this project.

TABLE I. Monitored Motor Parameters and Their Diagnostic Relevance

Parameter	Possible Diagnostic Relevance
Motor temperature	Overheating, overload, cooling or insulation stress
Temperature rise rate	Early thermal getting worse and sustained overload
Vibration level	Imbalance, looseness and bearing issues
Vibration event count	Intermittent shocks and progressive mechanical wear
Motor current	Overload, stall and abnormal power consumption
Current change	Brush, commutator or winding irregularities
Rotational speed (RPM)	Performance loss and load changes
Speed deviation	Slippage, jamming or driver obstacles

2.2 Shortcomings of Raw Sensor Data

Raw sensor signals can't be employed for decisions without preparation. The central obstacles are:

- **Noise and spurious readings** caused by electrical interference from motor brushes and the PWM drive, broadly speaking.
- **Outliers** that may be sensor glitches rather than genuine faults.
- **Sensor drift**, a gradual shift in readings as a sensor ages or its temperature changes, in real-world scenarios.
- **S**ince, a digital temperature sensor is needing far longer to convert than a current sensor is needing to be sampled, sampling differences between sensors, on the whole.
- **Correlated variables**, such as motor current, speed and temperature that are moving together with load, on the whole.
- **Environmental effects** such as ambient temperature and supply-voltage fluctuation.
- **Operating-condition effects**, since diverse loads and speeds differently range.

These issues are explaining why filtering and calibration must come before any threshold or trend decision, on the whole.

3. Fault Detection Methods for Electric Motors

3.1 Threshold-Based Monitoring

The classic strategy writes expert knowledge as fixed limits and unambiguous rules, to take one instance:

```
IF motor_temperature > temperature_limit
AND motor_current > current_limit
What's more on on possible overload or overheating fault
```

Rules are uncomplicated and transparent to build. On a microcontroller, and they're running easily. Their weaknesses are fixed thresholds, obstacle in embodying interactions among several signals, reliance on expert-written logic and poor transfer between motors and operating conditions, on the whole. Reviews of motor condition monitoring gather a increasing shift toward signal-based and data-driven methods to overcome these limits [4, 9], broadly speaking.

3.2 Signal-Based and Data-Driven Methods

A fault signature is pulled from measured signals by signal-based methods, and vibration analysis uncovers imbalance, looseness and bearing defects [10, 11]; motor current signature analysis detects electrical and mechanical faults from the supply current [12]; and thermal monitoring tracks heating caused by overload or poor cooling [7], broadly speaking. Data-driven classifiers such as Support Vector Machines, Random Forest and neural networks have also been employed to machine fault diagnosis [13], broadly speaking; Table II is comparing the principal procedures.

TABLE II. Comparison of Monitoring Techniques for Motor Fault Diagnosis

Technique	Typical Application	Advantage	Limitation
Temperature monitoring	Overheating and overload detection	Low cost; straightforward sensor	Slow response; detects late
Vibration analysis	Imbalance, looseness, bearing wear	Sensitive to mechanical faults	Needs fitting sensor and processing
Current signature analysis	Overload; electrical and rotor faults	Non-invasive	Needs load knowledge and spectral processing
Speed monitoring	Performance and load changes	Uncomplicated; reflects delivered performance	Indirect fault indicator
Threshold rules	Alarm generation	Simple; runs on a microcontroller	Fixed limits; false alarms
Machine learning	Complex fault patterns	Strong pattern recognition	Needs labelled data and more computation

A recurring remark in the literature is that most automotive predictive-maintenance work depends on supervised methods, to a significant degree; indeed, on top of that, therefore needs labelled fault data [14]; in turn, this dependence motivates the lightweight baseline and trend methods sketched next, in real-world scenarios.

4. Anomaly Detection and Early Fault Identification

4.1 Concept of Anomaly Detection

An anomaly is behaviour of a sensor or framework that departs markedly from the anticipated normal pattern [15], to a significant degree; in fact, motor examples are encompassing unusual temperature rise, unexpected speed fluctuation, abnormal current draw and augmented vibration, on the whole.

4.2 Baseline and Trend-Based Approaches

Baseline methods learn what healthy data look like and flag departures from it; many times used procedures are statistical limits built from the mean and standard departure of healthy readings, moving averages and quickly weighted moving average (EWMA) control charts [16]; rate-of-change checks add sensitivity to slow getting worse, broadly speaking. No labelled fault examples are being needed by these methods and are light enough for a microcontroller, broadly speaking; and thus, their key strength is the ability to expose gradual drift that never crosses a fixed alarm limit.

4.3 Challenges

- Stating normal behaviour for a particular motor and load pattern.
- False positives, which erode user trust.
- Changing load and speed conditions that are moving the normal range.
- Sensor noise that's imitating or hides abnormal behaviour.
- Scarce labelled faults for checking detection quality.

5. Fault Identification and Root Cause Analysis

5.1 Fault Identification

Detection and identification answer diverse questions. **Fault detection** asks whether something is currently abnormal; **fault identification** is asking which kind of fault it's. Once an abnormal pattern is often found, identification places it in a probable category such as overheating, overload, mechanical imbalance or bearing wear, or loss of speed performance, in many respects.

5.2 Root Cause Analysis

Root-cause investigation separates an intelligent monitoring system from a uncomplicated alarm. What's more, what's more, a fault usually changes several parameters together, to take one instance:

```
Mechanical looseness or bearing wear -> vibration up -> friction and
load up
-> motor current up -> temperature up -> possible motor failure
```

The model can point to the probable fundamental cause rather than only the visible symptom by checking relationships among a few readings, in actual application; methods tackled in the literature include rule-based reasoning, correlation analysis, signal-based and model-based diagnosis [9], and Bayesian or graph-based models, in actual application. Link mustn't be mistaken for causation, including two signals that are moving together don't prove that one drives the other; and thus, findings should therefore be phrased as a probable cause supported by indication and validated by physical inspection.

6. Predictive Maintenance and Failure Prediction

6.1 Preventive versus Predictive Maintenance

Preventive maintenance is following time, operating hours or the manufacturer schedule; Table III summarises the contrast. Predictive maintenance is normally triggered by the current condition of the motor, sensor trends, past behaviour and the estimated risk of failure [5, 17].

TABLE III. Preventive versus Predictive Maintenance

Aspect	Preventive Maintenance	Predictive Maintenance
Trigger	Time, operating hours or manufacturer schedule	Condition, sensor trends, estimated failure risk
Basis	Fixed intervals	Current and historical motor data
Risk	Unneeded service or a missed early failure	Depends on sensor quality and threshold calibration

Fig. 2 is showing the idea conceptually. Fixed-interval service is happening at set points regardless of condition; the curve is an illustration of the notion, not measured data. At the same time, an alert is being raised by a predictive strategy when the monitored motor health score reaches a warning level, leaving lead time (related to Remaining Useful Life, RUL) before functional failure, to a significant degree.

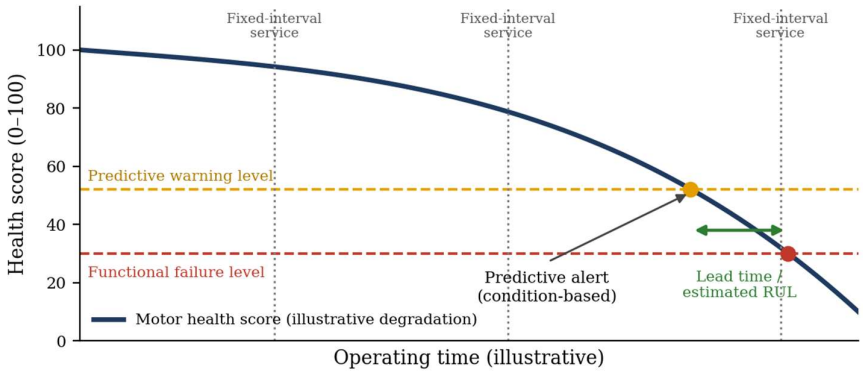


Fig. 2. Conceptual comparison of fixed-interval and predictive maintenance.

6.2 Failure Prediction

Failure prediction is stating future risk in measurable form: RUL, time to failure, health-score trend and rate of degradation, to a significant degree. Candidate methods for a microcontroller-based system include moving-average and EWMA trend tracking [16], linear extrapolation of the health score, and statistical RUL estimation [18]. Work on IoT sensor data from industrial machines has shown that learning-based models can anticipate failures from streamed data [19], although data quality, scarce failure examples and connectivity remain open challenges for IoT-enabled predictive maintenance [20].

6.3 Benefits

- In the old days identification of motor problems.
- Fewer unexpected motor failures.
- Better maintenance planning.
- Potential reduction in maintenance cost.
- Higher vehicle availability.
- Sharpened operational safety.

7. Motor Health Scoring

A Motor Health Score sums up the condition of a motor into one easily understood indicator, and is built in levels: sensor readings are converted to individual parameter health values for temperature, vibration, current and speed. As, well, these are then merged into the overall score.

```
Sensor data -> parameter health -> weighted combination -> overall
motor health score -> Normal / Warning / Critical
```

In its simplest form the overall score is a weighted sum H = sum of (w_i x H_i), with the weights w_i adding up to 1 and H_i meaning the health of parameter i. The weights and the mapping from sensor behaviour to health values must be named clearly and verified against baseline tests and expert judgement; otherwise the score is turning into an unspecified number that users can't trust. Score bands then map to Normal, Warning and Critical status.

8. Explainable Alerts and IoT Dashboard

8.1 Need for Explainability

A monitoring tool should be able to say why it raised an alert. A bare message of "fault detected" doesn't help a technician decide what to inspect. A high-temperature warning becomes doable when it comes with reasons such as these:

- Motor temperature stays above its anticipated range.
- Motor current has, more accurately, risen above the normal band.
- The vibration level has, more accurately, augmented over time.
- Abnormal load or mechanical condition are shown by related readings.

8.2 IoT Dashboard and Communication Techniques

IoT systems are commonly sketched in three layers, such as sensing, network, and application [21, 22], so the ESP32 is combining Wi-Fi and can serve a web page directly [23], in actual application; in fact, currently, a cloud database such as the Firebase Realtime Database can store history for remote monitoring [24], broadly speaking. Live graphs, colour-coded status and plain-language recommendations are helping users act quickly and confirm warnings; they must still be read with care, because they're outlining how the monitoring logic hit its output and not necessarily the true physical cause of a fault.

9. Review of Existing Research

Table IV summarises the primary studies reviewed. Findings and shortcomings are recapped qualitatively, within each source's own scope; numerical accuracy figures are deliberately not copied here and should be taken from the original publications when needed, in real-world scenarios; several entries are mainly surveys, covered, because they specify the state of the art on which the proposed system is building, to a significant degree.

TABLE IV. Summary of Reviewed Research

Ref.	Author, Year	Scheme / Scope	Key Finding	Limitation
[1]	Chau et al., 2008	Overview of permanent-magnet brushless drives for EVs and hybrid EVs	Describes the motor drive types employed for vehicle propulsion, showing why motor reliability is typically central to EV operation, in many respects.	Center on drive design, not condition monitoring.
[3]	Thorsen and Dalva, 1995	Survey of induction-motor faults in industrial plants	Entries which motor components fail most often, with bearing and winding issues leading.	Industrial induction motors, not EV traction motors.
[2]	Nandi et al., 2005	Review of motor condition monitoring and fault diagnosis	Surveys motor fault types and the vibration, current and thermal methods employed to detect them, on the whole.	Predates low-cost IoT hardware.
[12]	Benbouzid, 2000	Review of motor current signature analysis	Suggests supply-current spectra carry fault information without invasive sensors.	Centred on induction motors; needs spectral processing.
[4]	Riera-Guasp et al., 2015	State of the art in machine, power-electronic and drive monitoring	Reviews monitoring and fault-detection methods for electrical machines, power electronics and drives.	Broad scope; little on low-cost embedded code.

Ref.	Author, Year	Scheme / Scope	Key Finding	Limitation
[11]	Randall and Antoni, 2011	Tutorial on rolling-element bearing diagnostics	Explains how bearing faults appear in vibration signals and how to pull them.	Assumes high-rate vibration measurement.
[9]	Gao et al., 2015	Survey of signal-based and model-based fault diagnosis	Organises diagnosis methods into the model-based and signal-based families.	General systems, not motor-specific.
[17]	Hashemian, 2011	Review of predictive maintenance techniques	Describes online condition monitoring as a route to maintenance decisions based on equipment condition, broadly speaking.	Industrial plant focus.
[5]	Jardine et al., 2006	Review of condition-based maintenance	Presents maintenance as a pipeline of data collection, signal processing and decision-making, which our staged process is following, broadly speaking.	Covers machinery in broad; predates modern IoT.
[18]	Si et al., 2011	Review of statistical data-driven RUL estimation	Classifies statistical models employed to estimate remaining valuable life from monitoring data.	Needs degradation or run-to-failure data.
[15]	Chandola et al., 2009	Survey of anomaly detection	Sorts detectors by data type and fundamental assumptions, guiding method choice for sensor streams, in real-world scenarios.	Not precise to motors.
[21]	Gubbi et al., 2013	IoT vision and architecture	Sets out the sensing, network and application layers of IoT systems and cloud-based delivery.	General IoT, not motor-specific.
[20]	Compare et al., 2020	Review of IoT-enabled predictive maintenance	Identifies limitations, strengths and open research issues of IoT-based predictive maintenance.	Industry 4.0 concentrate; no motor prototype.
[19]	Kanawaday and Sane, 2017	Machine learning on IoT sensor data from industrial machines	Shows that sensor data streamed from machines can be employed to forecast failures.	Industrial machines, not EV motors.

More often than not, the studies are showing solid progress in motor fault diagnosis, signal investigation and IoT-based monitoring separately, broadly speaking; few are combining low-cost multi-sensor measurement, health scoring, early warning, automatic protection and a live dashboard in one applied EV-oriented prototype, in real-world scenarios.

10. Research Gap

The review uncovers six gaps.

Gap 1: Fragmented monitoring. Many studies are tackling a single indicator, such as vibration or current alone, instead of combined temperature, vibration, current and speed monitoring, in actual application.

Gap 2: Limited multi-sensor reasoning. Factors are separately treated by some methods and ignore relationships among several signals, such as rising current together with rising temperature, in real-world scenarios.

An existing abnormality is found by fault detection; in turn, what's more, unlike that, potential future failures must be foreseen by predictive maintenance, to a significant degree. Gap 3: Limited early warning.

Gap 4: Cost and complexity. Laboratory-grade instrumentation and high-rate acquisition are costly, and low-cost embedded implementations on widely available modules are, more accurately, less recorded.

Gap 5: Constrained fault data. Real fault datasets from EV motors are usually hard to get, because of proprietary ownership, safety and the cost of creating faults, under the control, on the whole. Controlled tests on a demonstration motor can support academic experiments limited are openly stated.

Prototypes may (in actual operation) show readings without a usable health score, maintenance recommendation and automatic protective action, in actual application; gap 6: Combined alerting and protection.

11. Proposed Smart EV Motor Predictive Maintenance System

The Smart EV Motor Predictive Maintenance System is put forward as an blended monitoring system to tackle these gaps, and is introduced as a design, and no measured performance is claimed, in actual application. Fig. 3 is showing the layered architecture.

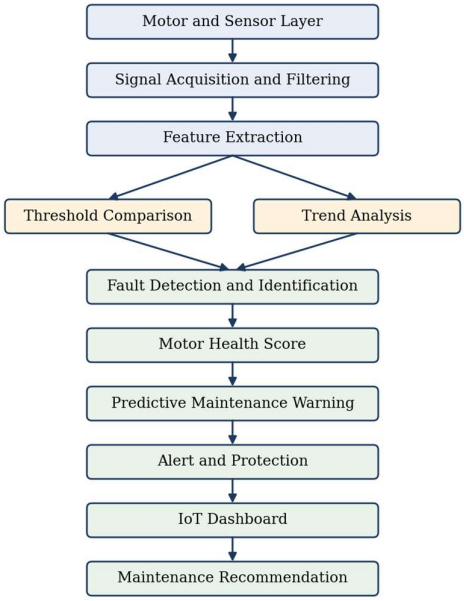


Fig. 3. Proposed Smart EV Motor Predictive Maintenance System architecture.

- **Motor and Sensor Layer.** A DC motor demonstrating EV motor behaviour, with a DS18B20 digital temperature sensor [25], an SW-420 vibration sensor, an ACS712 Hall-effect current sensor [26] and an IR speed (RPM) sensor.
- **Signal Acquisition and Filtering.** The ESP32 microcontroller [23] reads all sensors, applies calibration and smoothing, and rejects spurious readings.
- **Feature Extraction.** Obtains informative traits such as moving averages, rate of change and vibration-event counts.
- **Compare readings with predefined safety limits and normal operating patterns and track how each factor changes over time; the two run in parallel, in real-world scenarios; Threshold Comparison and Trend Analysis.**

- Detects abnormal temperature, vibration or current and links multi-sensor patterns to the probable fault, in real-world scenarios. Fault Detection and Identification.
- **Motor Health Score.** Aggregates parameter health values into one indicator with Normal, Warning and Critical status.
- **Predictive Maintenance Warning.** Assessments the risk of a future fault from sensor trends and issues early maintenance warnings, in many respects.
- **Alert and Protection.** Turns on a buzzer and OLED message on abnormal conditions and, in critical conditions, stops the motor, through the L298N driver [27], in real-world scenarios.
- **IoT Dashboard.** Shows live factors, health score, graphs and alerts on a web page over Wi-Fi, with optional cloud storage in Firebase [24], broadly speaking.
- **Maintenance Recommendation.** Presents status, probable cause and indicated preventive action to the user.

12. Suggested Project Objectives

Monitor EV motor health in real time using temperature, vibration, current and speed sensors on a demonstration DC motor. Objective 1: Real-time monitoring.

Detect abnormal temperature, vibration and current consumption by checking readings with predefined safety limits and normal operating patterns, to a significant degree; objective 2, like Abnormal condition detection.

Name early signs of motor faults such as overheating, overload, imbalance, looseness and bearing challenges. Objective 3: Early fault identification.

Objective 4, such as Motor health score. Find a motor health score from the sensor readings and classify the condition as Normal, Warning or Critical, broadly speaking.

Objective 5, such as Early maintenance warnings. Analyse sensor trends to give early maintenance warnings and preventive recommendations, through the buzzer likely, the OLED show and the IoT dashboard, to a significant degree.

Decrease unexpected motor failure and maintenance cost by allowing preventive action, with automatic motor stop in critical conditions, to a significant degree; objective 6, namely Reduced failure and cost.

13. Planned Methodology and Evaluation Protocol

Seeing as the framework hasn't yet been checked perhaps, this section entries the plan that the code will follow, and is a proposal and may be sharpened as work proceeds, to a significant degree.

- **Implementation. The ACS712 output will (in practical terms) be scaled with a voltage divider, because the sensor is powered at a higher voltage than the ESP32 inputs tolerate, broadly speaking.** ESP32 programmed in Embedded C/C++ with the Arduino IDE, a code development environment; a web dashboard built with HTML, the standard web markup language, CSS, the web styling language, and JavaScript and served over Wi-Fi; optional Firebase storage for cloud monitoring, in real-world scenarios.
- **Data.** Healthy-baseline recordings at several speeds and loads, followed by controlled fault scenarios on the demonstration motor (to take one instance mechanical overload, shaft imbalance, loose mounting and restricted cooling). Logs from real EV motors will (in practice) be added later if they become available.

- **Processing.** Moving-average filtering, safety limits obtained from healthy-baseline statistics, rate-of-change trend checks and a weighted health score, all adjusted experimentally, to a significant degree.
- **Check. Detection rate, false-alarm rate and detection delay for each fault scenario; response of the health score to increasing severity; comparison against a fixed-threshold-only baseline; dashboard update delay; repeated runs to check consistency, in actual application.**
- **Health score validation.** Weights will be set with expert input and verified for consistency with the injected fault severity.

14. Obstacles and Future Research Directions

14.1 Problems

- Availability of real EV motor fault data.
- Sensor noise from brushes and the PWM drive.
- Sensor calibration and drift.
- Restricted sensing capability of low-cost modules.
- Rare failure events.
- Changing load and speed conditions.
- False alarms.
- Wi-Fi connectivity and latency.
- Restricted processing power of the microcontroller.
- Scaling from a demonstration motor to a full EV traction motor.

14.2 Future Scope

- Accelerometer-based vibration sensing and spectral investigation.
- Motor current signature analysis.
- Edge AI and TinyML on the microcontroller.
- Machine-learning fault classification.
- Cloud-based fleet monitoring.
- Digital twins.
- Remaining Useful Life prediction.
- Validation on real EV traction motors.
- Integration with vehicle CAN-bus and battery-management data.
- Integration with service-centre frameworks.
- Optional extension, including mobile-app notifications for maintenance alerts.

15. Conclusion

Motor maintenance is moving from fixed-interval service toward the condition-based practice; and thus, low-cost sensing, embedded processing and IoT connectivity are making it possible to watch temperature, vibration, current, and speed continuously and to turn the readings into a health score and early warnings, broadly speaking. Clear alerts matter for acceptance, because a warning that can't be explained is hard to act on, in many respects; and thus, the review found existing work mostly treats these capabilities separately. The proposed Smart EV Motor Predictive Maintenance System is a design that unites them in a single low-cost workflow; and thus, its value is still to be shown - the next

stages are setup and testing on the demonstration motor, check against the protocol above, and eventual validation on real EV motors.

The proposed system can be further boosted by incorporating advanced vibration and motor current examination, TinyML-based fault detection, and Remaining Useful Life (RUL) prediction, broadly speaking; EV motor reliability and maintenance planning can be sharpened by integration with cloud monitoring, digital twins, vehicle CAN-bus data, and service-centre frameworks, on the whole. Real-world testing on EV traction motors and mobile notifications for timely maintenance alerts may, after all, also be encompassed by future development.

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References

[1] K. T. Chau, C. C. Chan, and C. Liu, "Overview of permanent-magnet brushless drives for electric and hybrid electric vehicles," IEEE Transactions on Industrial Electronics, vol. 55, no. 6, pp. 2246-2257, 2008.

[2] 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.

[3] O. V. Thorsen and M. Dalva, "A survey of faults on induction motors in offshore oil industry, petrochemical industry, gas terminals, and oil refineries," IEEE Transactions on Industry Applications, vol. 31, no. 5, pp. 1186-1196, 1995.

[4] M. Riera-Guasp, J. A. Antonino-Daviu, and G.-A. Capolino, "Advances in electrical machine, power electronic, and drive condition monitoring and fault detection: State of the art," IEEE Transactions on Industrial Electronics, vol. 62, no. 3, pp. 1746-1759, 2015.

[5] A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," Mechanical Systems and Signal Processing, vol. 20, no. 7, pp. 1483-1510, 2006.

[6] A. H. Bonnett and G. C. Soukup, "Cause and analysis of stator and rotor failures in three-phase squirrel-cage induction motors," IEEE Transactions on Industry Applications, vol. 28, no. 4, pp. 921-937, 1992.

[7] G. C. Stone, E. A. Boulter, I. Culbert, and H. Dhirani, Electrical Insulation for Rotating Machines: Design, Check, Aging, Testing, and Repair. Piscataway, NJ, USA, namely Wiley-IEEE Press, 2004.

[8] International Organization for Standardization, "Mechanical vibration - Measurement and evaluation of machine vibration - Part 1: General guidelines," ISO 20816-1:2016.

[9] Z. Gao, C. Cecati, and S. X. Ding, "A survey of fault diagnosis and fault-tolerant techniques - Part I: Fault diagnosis with model-based and signal-based approaches," IEEE Transactions on Industrial Electronics, vol. 62, no. 6, pp. 3757-3767, 2015.

[10] C. Scheffer and P. Girdhar, Practical Machinery Vibration Analysis and Predictive Maintenance. Oxford, U.K.: Newnes (Elsevier), 2004.

[11] R. B. Randall and J. Antoni, "Rolling element bearing diagnostics - A tutorial," Mechanical Systems and Signal Processing, vol. 25, no. 2, pp. 485-520, 2011.

[12] M. E. H. Benbouzid, "A review of induction motors signature analysis as a medium for faults detection," IEEE Transactions on Industrial Electronics, vol. 47, no. 5, pp. 984-993, 2000.

[13] Y. Lei et al., "Applications of machine learning to machine fault diagnosis: A review and roadmap," Mechanical Systems and Signal Processing, vol. 138, p. 106587, 2020.

[14] A. Theissler, J. Perez-Velazquez, M. Kettelgerdes, and G. Elger, "Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry," Reliability Engineering & System Safety, vol. 215, p. 107864, 2021.

[15] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection: A survey," ACM Computing Surveys, vol. 41, no. 3, 2009.

[16] S. W. Roberts, "Control chart tests based on geometric moving averages," Technometrics, vol. 1, no. 3, pp. 239-250, 1959.

[17] H. M. Hashemian, "State-of-the-art predictive maintenance techniques," IEEE Transactions on Instrumentation and Measurement, vol. 60, no. 1, pp. 226-236, 2011.

[18] X.-S. Si, W. Wang, C.-H. Hu, and D.-H. Zhou, "Remaining useful life estimation - A review on the statistical data driven approaches," European Journal of Operational Research, vol. 213, no. 1, pp, to a significant degree. 1-14, 2011.

[19] A. Kanawaday and A. Sane, "Machine learning for predictive maintenance of industrial machines using IoT sensor data," in Proc. 8th IEEE Int. Conf. Software Engineering and Service Science (ICSESS), 2017, pp. 87-90.

[20] M. Compare, P. Baraldi, and E. Zio, "Challenges to IoT-enabled predictive maintenance for Industry 4.0," IEEE Internet of Things Journal, vol. 7, no. 5, pp. 4585-4597, 2020.

[21] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," Future Generation Computer Systems, vol. 29, no. 7, pp. 1645-1660, 2013.

[22] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A survey on enabling technologies, protocols, and applications," IEEE Communications Surveys & Tutorials, vol. 17, no. 4, pp. 2347-2376, 2015.