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SURVEY

A Review of Robotic Arm Joint Motors and Online Health Monitoring Techniques

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ABSTRACT The employment of robots in numerous emerging applications, e.g., disaster rescue, nuclear waste remediation, and space exploration, is of paramount importance due to their improved safety, flexibility, and productivity. Due to the harsh environmental conditions, the robotic arm joint motors and power electronic drives are vulnerable to electrical faults and mainly contribute to joint failures. To substantially improve the reliability and robustness of the robot arms utilized in remote, hazardous, and safety-critical environments, autonomous fault-tolerant and fail-active operation for these robotic arms experiencing joint failures should be developed. In the literature, many strategies have been proposed for fault prognosis, diagnosis, and health monitoring of electric motors and drives using online data analytics of the fault signature information. Thus, this paper presents an extensive up-to-date review of joint motor types, common fault types, and robot joint fault prognostics, diagnostics, and health management. First, various joint motors are introduced and compared, considering their performance advantages, disadvantages, and wide applications. Furthermore, joint motors for collaborative robotic applications are summarized and compared as illustrative examples. After that, fault types are reviewed with a further classification by fault locations, namely, stator windings, rotors, and bearings. In addition, health monitoring techniques are classified into methods for stator winding, rotor, and bearing faults. These methods are intensively compared with respect to motor and fault types, proposed health monitoring techniques, and control strategies. Finally, conclusions and future research trends are summarized.

INDEX TERMS Collaborative robots, joint motors, fault prognosis, fault diagnosis, health monitoring.

I. INTRODUCTION

Robots have demonstrated promising prospects in numerous emerging applications, such as space exploration [1], surgical applications [2], nuclear waste remediation [3], [4], rescue missions [5], and human-robot interaction [6], [7]. Robotic arms utilized in these applications should be reliable, robust, and fault-tolerant, since they are vulnerable to hardware failures due to harsh environmental conditions, e.g., high temperature, humidity, and radiation [8]. Particularly, electric motors and power electronic drives contribute to persistent robot joint failures [9], [10]. Thus, robot protection in remote, safety-critical, and hazardous environments has emerged as a crucial necessity to ensure the ability of the robotic arm to perform fail-active operation, which is defined as the ability of robots to continuously operate when unpredictable failures and degradation occur [11].

The existing electric motors and drive technologies in robotic modeling have been recently reviewed in [12]. The electric motors can be classified according to the magnetic flux directions, namely, radial, axial, and transverse magnetic flux motors. Radial-flux motors are the most commonly used motor type in robotic applications and can be further categorized into AC motors, brushed DC motors, brushless DC (BLDC) motors, servo motors, and stepper motors [13]. High-speed brushed DC and BLDC motors offer compact sizes; however, they are costly because they entail reduction gearboxes to improve torque production capability [14].

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For example, in [15], a BLDC motor has been utilized in fast-legged locomotion. On the contrary, stepper motors inherently exhibit high torque, but with a high weight [16]. Servo motors have several advantages, including improved efficiency and high power to motor size, albeit at a high cost and complicated controller [17].

The above-mentioned electric machines are prone to several faults, e.g., stator winding faults, rotor faults, and bearing faults [18]. The main causes of these faults, besides insulation degradation, are overloading and overheating. Faults in electric machines affect the overall system performance and may yield system failures. Therefore, fault prediction and early detection are crucial to avoid severe damage and enhance system reliability. Several fault prognosis and diagnosis strategies have been introduced in the literature [19], [20], [21], [22]. Moreover, health monitoring for electric machines can be defined as the process of checking the machines' parameters to recognize any undesirable faults at an early stage to increase the reliability and lifetime of the electrical machines, while decreasing the likelihood of breakdowns and maintenance expenses. Fault prognosis and diagnosis in electric machines have gained significant attention to ensure the reliability and robustness of the robotic arm.

This paper introduces several joint motors that can be employed in robotic applications. Since robotic arms are mainly proposed for safety-critical applications, their reliability and robustness are among the key design objectives. In this paper, a comprehensive overview of the state-of-the-art robotic arm joint motors is provided for engineers and researchers in the robotics area. First, joint motors are introduced and the utilized motors in commercial collaborative robots are summarized for illustration. After that, the electrical fault types in joint motors are thoroughly reviewed and classified into stator winding, rotor, and bearing faults. Finally, online health monitoring, which has been intensively studied in the recent literature, is presented in detail. Various techniques for fault prognosis, diagnosis, and health monitoring in electric machines have been summarized based on the fault types to enhance the system reliability and avoid economic loss.

The rest of the article is organized as follows. The research motivation and contribution are introduced in Section II to provide an overview of the recent research activities in the field of online health monitoring. Sections III and IV will cover the joint motor and fault types, respectively. In Section V, fault prognosis, diagnosis, and health monitoring methods are reviewed and compared with respect to several screening factors. Furthermore, future research trends are summarized in Section VI. Finally, conclusions are drawn in Section VII.

II. RESEARCH MOTIVATION AND CONTRIBUTION

In recent decades, various references reviewed and summarized the research content on robots from different perspectives, e.g., control techniques [23], [24], robot protection [8], [25], and artificial intelligence in robots [26], [27]. However, this paper gives an extensive review of robotic arm joint motors, which has not been conceived thus far.

Moreover, online health monitoring in electric machines has been recently surveyed in several applications, e.g., aircraft electromechanical actuators and electric vehicles (EVs). For instance, fault modes and health monitoring are the focus of the aircraft electromechanical actuators (EMA) comprehensive survey proposed by Yin et al. [28]. Besides, Xu et al. proposed an overview of intelligent fault diagnosis in EV applications [29]. In [30], fault diagnostic and health monitoring strategies for permanent magnet (PM) machines have been extensively reviewed, shedding light on unbalanced magnetic pull, PM demagnetization, rotor eccentricity, as well as short- and open-circuit windings faults. Moreover, smart health monitoring of electrical machines has been discussed using machine learning (ML) based artificial intelligence (AI) algorithms [31]. Furthermore, in [32], common mechanical and electrical faults in electric motors and suggested condition monitoring strategies to diagnose these faults are introduced.

Given the aforementioned discussion, it is clear that fault prognostics, diagnostics, and health monitoring are crucial to increase the system's reliability and reduce the risk of potential economic loss. Thus, motivated by these facts, this paper introduces state-of-the-art robotic arms, shedding light on joint motor types, common fault types, and robot joint fault prognosis, diagnosis, and health monitoring. Eventually, health monitoring strategies have been categorized by the fault types into strategies for stator winding, rotor, and bearing faults, a notable contribution of this survey. On the other hand, the main limitation of this study is that other fault modes of robots, e.g., electric drive, mechanical, and sensor faults, are not included and will be introduced in future work. A comparison of the proposed study with recent ones on health monitoring of electric motors is revealed in Table 1. Recent studies have been compared with the proposed one, considering main contributions, limitations, classification of fault detection methods, and targeted applications.

III. ROBOTIC ARM JOINT MOTOR TYPES

This section presents joint motors for robotic arms and summarizes the motor types in commercial collaborative robots as an illustrative example. The electric motors utilized in robotic arms include AC motors, brushed DC motors, BLDC motors, direct drive electric motors, servo motors, and stepper motors [13]. Compliant robot arms have been gaining attention in collaborative and personal robotics since they can interact with their surroundings. A servo motor based on brushless gimbal motors has been designed for a low-cost robot arm with seven degrees of freedom (DOF) [14]. The proposed servo motor consists of a brushless gimbal motor, controller board, and mounting plate. Eight servos have been used to drive the robot arm, which substantially decreases the cost of the overall system. Another example of a low-cost 7-DOF robotic manipulator has been presented in [16].

TABLE 1. Comparison of recent studies on health monitoring of electric motors.

Ref.	Contributions	Limitations	Fault Detection Methods	Applications
[28]	- Aircraft electromechanical actuator faults. - Fault diagnosis, prognosis, and health management.	- Fault prediction and health management are only slightly presented.	- Model-based. - Data-driven.	aircraft electromechanical actuators
[29]	- Intelligent fault diagnosis for PM machines. - Health monitoring in multi-physics environment. - Health monitoring in multi-variable working environment.	- Further investigation of coupling faults and their suggested fault detection methods.	- Support vector machine. - Expert system. - Neural network. - Fuzzy logic. - Deep learning.	Electric vehicles
[30]	- Fault diagnostic and health monitoring strategies for PM machines. - Faults in PM machine and drives.	- Fault diagnosis techniques for sensor and mechanical faults are not presented.	- Unbalanced magnetic pull. - PM demagnetization. - Rotor eccentricity. - Stator winding. - Power semiconductor switches.	PM motors and drives in general applications
[32]	- Mechanical and electrical faults in electric motors. - Condition monitoring strategies for motors.	- Other fault modes, such as electric drive and sensor faults are not investigated.	- Signature analysis. - Vibration monitoring. - Acoustic noise monitoring. - Temperature monitoring.	Various industrial applications
This work	- Robot joint motor and common fault types. - Robot joint fault prognosis, diagnosis, and health monitoring.	- Other fault modes of robots, e.g., electric drive, mechanical, and sensor faults, are not included.	- Stator winding faults. - Rotor faults. - Bearing faults.	Robotic arm joint motors

In [33], the design of a three-phase BLDC motor-based electromagnetic actuator for robotic applications is introduced. A genetic algorithm (GA) was used to optimize the original design with the torque-to-weight and torque-to-inertia ratios as the primary optimization goals. These goals are essential for machines to respond promptly. Besides, A new optimization technique for three-phase hybrid stepper motors (HSMs) has been presented in [34]. This optimization method reduces the computational time by combining the 3D finite element (FE) analysis and the Taguchi optimization method. Moreover, it aims at reducing the audible noise in the machine by optimizing the tooth shape of the employed HSM. As a result, the torque ripple is improved, and the total harmonic distortion (THD) is reduced by 21%, which yields a significant reduction in the optimized motor noise.

A. JOINT MOTOR TYPES

1) AC MOTORS

AC motors are widely utilized for driving high dynamic load in industrial robots [35]. The common types of AC motors are induction motors (IMs) and synchronous motors. Stator cores, stator windings, rotors, and bearings constitute the essential parts of the AC motors [36]. Based on electromagnetics, a magnetic field is produced when an AC current is supplied to the stator windings. This magnetic field induces current within the enclosed rotor bars, which further produces the rotor magnetic fields. Thus, the motor start rotating as a result of the developed torque deriving from the interaction of the two magnetic fields. AC motors exhibit several advantages, such as high power to weight ratio, simple design, and less maintenance. On the contrary, rotor positioning control and eddy current loss might be among the main drawbacks of AC motors.

2) BRUSHED DC MOTORS

A brushed DC motor typically consists of the stator, rotor/armature, brushes, and commutator [37]. There are various types of brushed DC motors, including permanent magnet (PM), shunt-wound, series-wound, and compound-wound brushed DC motors. The PM brushed DC motors have been widely utilized in robotics [38]. The brushed DC motor generates torque when the rotor windings are energized by the DC supply. As a result, a magnetic field is produced, which will be attracted to the opposite poles generated by the stator and further drive the rotor to rotate. As the motor rotates, mechanical commutation is a basic necessity to ensure that the two fields from the stator and rotor do not overrun [39]. The low initial cost and simple control are among the advantages of brushed DC motors; however, high maintenance costs, low lifespan, and noise constitute their main shortcomings.

3) BLDC MOTORS

Unlike brushed DC motors, BLDC motors do not have brush assembly for commutation and are lighter for the same output power. BLDC motors mainly consist of a stator, stator windings, a rotor, and PMs [40]. Basically, the stator windings are supplied through a control circuit. After that, the rotor magnets tend to align with the energized stator windings, and the next stator winding is energized. Thus, torque is produced owing to the interaction between the magnetic fields developed by the stator windings and the PMs, and the rotor keeps rotating [41]. The main merits of BLDC motors are high efficiency, high reliability, and long lifespan. On the contrary, BLDC motors entail high initial costs and an electronic controller. Based on the above-mentioned advantages, the BLDC motors are of particular interest for robotic applications [15], [33].

4) DIRECT DRIVE MOTORS

In direct drive motors, either linear or rotary, the motor is tied directly to the load, and the transmission element and pulley systems are omitted. The proposed study in [42] focuses mainly on rotary direct drive motors because they are preferably utilized in selective compliance articulated robot arm (SCARA) and 6-axis robot arms. These motors can be brushless or synchronous motors, like a servo motor, albeit with a large number of poles. Moreover, they include typical motor parts with frameless designs [42]. Basically, rotary direct drive motors operate based on the interaction between magnetic fields from the stator windings and the rotor magnets. Direct drive motors have several advantages, such as dynamic performance, i.e., higher acceleration and deceleration with heavy loads, and less noise. Besides, these motors are capable of producing high torque at low speeds [43]. However, the main disadvantage of direct drive motors is the large size of the machines due to the scaling law of torque and size.

5) SERVO MOTORS

Servo motors consist of several key elements: motor (DC or AC) with a gear system, closed-loop position/speed controllers, potentiometer, and servo arm [44]. In order to control the rotational speed and position, servo motors consolidate closed-loop positional feedback, the most vital part of the servo motor. Thereafter, the servo motor receives either an analog or digital signal, which defines the amount of movement. Typically, speed and position feedback are provided by an encoder. Eventually, the motor stops when there is no difference between the reference signal and the signal generated by the position sensor [17].

Servo motors can drive an object with high precision, so they are used in many applications, such as airplanes and robotics. For example, positional rotational servo motors, which can be controlled from 0 to 180 degrees, are used in small-scale robots. Moreover, continuous rotation servo motors, which can be controlled from 0 to 360 degrees, are utilized in mobile robots and robotic arms. Lastly, linear servo motors are preferred in heavy-duty systems [44]. The main advantages of servo motors constitute high power to motor size and weight, high efficiency, and quiet at high speeds. On the other hand, high overall cost, complex controls, and limited peak torque to a 1% duty cycle constitute the main drawbacks of these motors.

6) STEPPER MOTORS

Unlike servo motors, stepper motors usually run in open-loop and can respond promptly and position accurately without costly sensors. Stepper motors consist of a stator, stator windings, a rotor, and PMs [45]. Stepper motors act as brushless motors with a much smaller step size due to the different structures of the magnets. When the driver, i.e., the controller, transmits pulses to the motor, it starts rotating with one step for each pulse. The number of motor steps is equal to the number of the controller pulses, and the motor will run at the frequency of those pulses [57]. The stepper motors are more advantageous than their servo counterparts since they offer smaller sizes, quicker responses, and lower costs. However, servo motors outperform stepper ones since they exhibit high torque at high speed and closed-loop operation [34].

TABLE 2. Comparison of electric drivelines for robotic arms.

Motor types	Advantages	Disadvantages	Applications
AC motors	- Simple design. - High power to weight ratio. - Less maintenance.	- Eddy current loss. - Poor positioning control.	Ref. [35, 46, 47]
DC motors	- High efficiency. - Simple control.	- High maintenance costs. - Short lifespan. - Noisy.	Ref. [48-50]
BLDC motors	- High efficiency. - High reliability. - Long lifespan.	- High initial cost. - Complex control.	Ref. [15, 33, 51]
Direct drive motors	- Dynamic performance. - High torque at low speeds. - Quiet.	- Torque limitations. - Complex control.	Ref. [52-54]
Servo motors	- High power to motor size. - High efficiency. - Quiet at high speeds.	- High overall cost. - Complex control. - Limited peak torque.	Ref. [14, 55, 56]
Stepper motors	- High torque at low speeds . - high precision. - Compact size.	- Lower torque at high speed. - No peak torque. - Open-loop operation.	Ref. [16, 34]

Several addressed motor types are compared according to their advantages, disadvantages, and applications. A broad comparison of these types is revealed in Table 2. According to the analysis of robotics introduced in [13], the servo motor is the most commonly used type in current robot arms. AC motors are not commonly used in small to medium-sized robotic arms [45]; however, they are mainly utilized in industrial robots where high torque is needed [35]. BLDC motors have been used in robotic applications due to their high reliability, improved torque-producing ability, and affordable maintenance costs [33].

B. JOINT MOTORS FOR COLLABORATIVE ROBOTIC APPLICATIONS

Collaborative robots, i.e., cobots, have shown promise in production and manufacturing industries since they can automate various tasks, such as pick-and-place and quality inspection [26], [58]. The main goal of collaborative robot designers and researchers is to increase human safety during human-robot interaction while boosting the robot's payload capacity [59]. In addition, they seek to maintain and improve mobility and flexibility in collaborative robots [60], [61]. The reliability of robotic arms is a key factor that affects their performance, i.e., reliable robotic arms ensure continuous operation, reduce maintenance and operational costs, and enhance worker and product safety. Joint motors are essential to guarantee the reliability robotic arms. It is worth mentioning that the payload capacity, a key characteristic of cobots, is the maximum amount of mass that a robotic wrist can support [62]. Besides, the robotic arm's utmost reach is

TABLE 3. Commercial collaborative robots' joint motor specifications.

Brand	Model	Year	Joint motor	Power (Watts)	Joint velocity (°/s)	Peak torque (Nm)	Continuous payload (kg)	Max. reach (mm)	Weight (kg)
KINOVA [65]	Gen3 ultra lightweight	2022	BLDC	36	180-250	54	4	902	8.2
UNIVERSAL ROBOTS [67]	THE UR5e	2021	Stepper	570	180	10	5	850	18.4
KUKA [69]	LBR iiwa 7 R800	2022	Servo	-	98-180	104	7	800	23.9
ABB [72]	IRB 14000	2022	AC motor	80	180-400	101	0.5	559	38
FRANKA EMIKA [74]	FRANKA Production 3	2022	BLDC	80	150-301	-	3	855	17.8
ZeroErr [75]	-	2022	Servo	75	180	19	3	600	13

measured from its center to its furthest extension. Robots typically consist of various key components, such as the base, actuators, and interface and vision modules [63], [64]. Kinova, ABB, Universal Robots, and KUKA are amongst the leading manufacturers in the robotics field.

Kinova Gen3 ultra-lightweight robotic arm offers various advantages, including enhanced closed-loop control, smart actuators with torque sensors, and infinite rotation of its joints [65]. Moreover, it is ideal for mobile robotics applications owing to its low power consumption, small footprint, and embedded controller. In [66], an algorithm for maximizing the probability of task completion has been illustrated for the Kinova Gen3 robot. The UR5e, by Universal Robots, is another interesting, adaptable, and lightweight collaborative industrial robot that is optimal for medium-duty applications [67]. Easy programming, fast set-up, flexible deployment, and safety constitute the main merits of this robot. An open-source training system has been introduced in [68] based on Virtual reality and the UR5e robot.

Furthermore, the KUKA LBR iiwa is the world's first robot that is compatible with human-robot collaboration (HRC [69]. It is advantageous due to its ability to learn, sensitivity, independency, and quick reactions. Moreover, its parameters have been identified in [70], taking into account the physical feasibility constraints. Moreover, the ABB and Franka Emika robots have been extensively introduced in the literature [71], [72], [73], [74]. The ZeroErr offers a variety of rotary actuators and suggests several configurations for robotic arms [75].

The above-mentioned collaborative robots have been compared, considering the brand, model, model year, joint motor, power, joint velocity, peak torque, continuous payload, maximum reach, and weight. Table 3 reveals the data and joint motors of the commercial collaborative robots. Among the presented robots, Kinova Gen3 exhibits the maximum reach at the lightest weight, with 902 mm and 8.2 kg, respectively. The maximum continuous payload is offered by the KUKA robot, while the minimum payload is achieved by the ABB one, with 7 kg and 0.5 kg, respectively.

IV. FAULT TYPES

This section introduces several fault types presented in the literature for electric machines, as shown in Fig. 1. The visualization of some common faults in the electric machines is therefore depicted in Fig. 2. It is worth noting that the fault modes are not limited to motor faults; however, electric drive, mechanical, and sensor faults can also occur to the robotic systems [28]. Since joint motors are the main focus of this study, other fault modes of robots are outside the scope of the present study and will be addressed in future work.

Motor fault modes are broadly categorized into stator winding, rotor, and bearing faults [28], [80]. Stator winding faults, e.g., short-circuit and open-circuit faults, usually occur in electric motors. The most common faults are the short-circuit ones, such as turn-to-turn, phase-to-phase, and coil-to-ground faults [81]. The main causes of these faults are insulation failure owing to overloading and overheating operations and high transient voltage. As a result, unbalanced winding impedance, excessive heat generation, and whole system failure are the main consequences of short-circuit faults. Unlike short-circuit faults, open-circuit ones due to large starting current are scarce and yield reduced output torque and substantial rise in current in healthy phases [81], [82].

Rotors are prone to two main faults: demagnetization when the rotor is equipped with rare-earth PMs and eccentricity [83], [84]. The PM demagnetization is caused by cooling system issues, aging of magnets, and overheating. Thus, the motor's lifetime time is highly impacted, and its efficiency deteriorates [85]. Moreover, improper mounting of the stator, rotor, or bearing and bent motor shaft constitute main causes of the eccentricity [86]. This fault type results in an unbalanced magnetic pull, excessive vibration, and high cogging torque.

Bearing faults are typical and represent the highest percentage of motor failures [87]. Bearing faults are affected by materials and environmental conditions, e.g., material fatigue and pollution. Besides, bearing and shaft currents and bad lubrication may yield bearing failures. Noise and vibration, low efficiency, and poor performance are the main impacts of bearing faults [88].

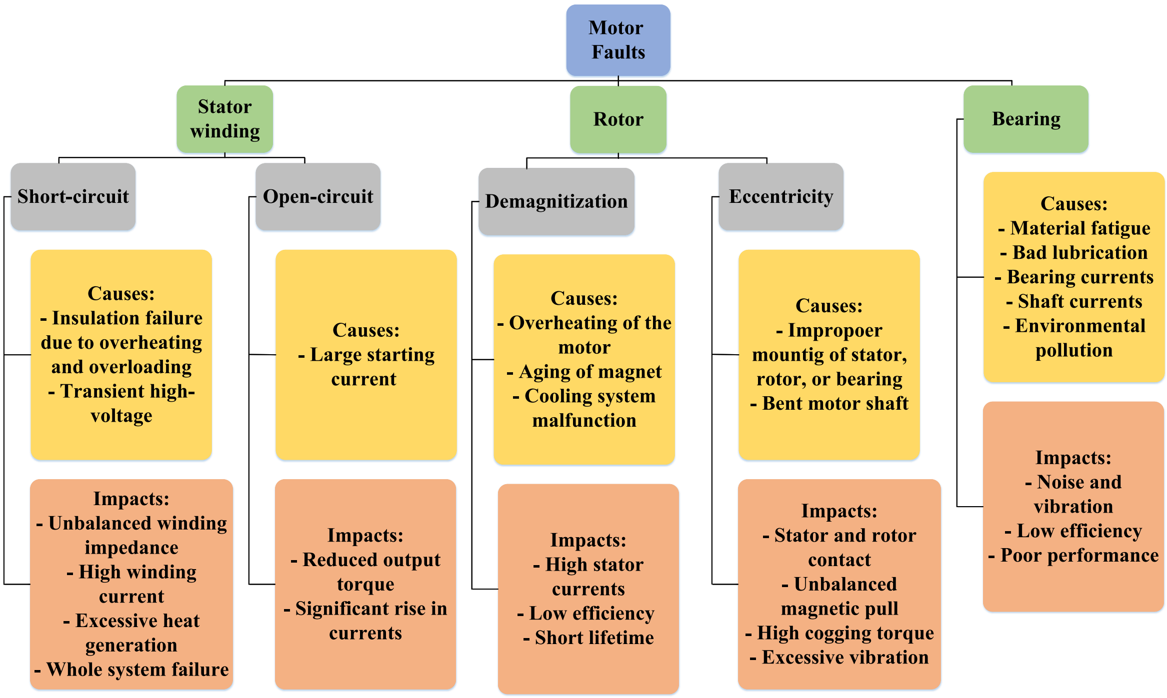

FIGURE 1. Fault types in robotic joint motors.

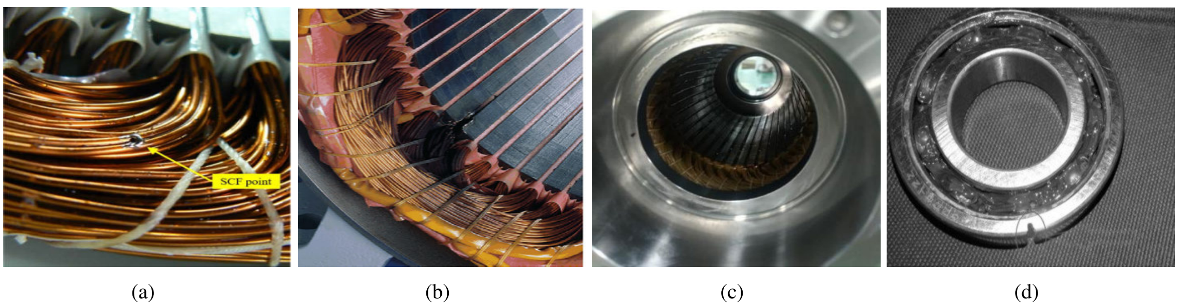

FIGURE 2. Common faults in electric motors. (a) Stator short-circuit fault (SCF) [76]. (b) Winding and stator core short-circuit fault [77]. (c) Stator rub caused by eccentricity [78]. (d) Bearing with outer race fault [79].

V. FAULT PROGNOSIS, DIAGNOSIS, AND HEALTH MONITORING

Based on the analysis of fault types presented in the previous section, fault prognostics and diagnostics in electric machines are of particular interest, not only for improving the system reliability but also for avoiding potential economic loss [29], [89], [90], [91]. This is mainly due to the fact that electric machines are susceptible to several failures, such as stator winding and bearing faults. Thus, fault prognosis, diagnosis, and health management have been extensively addressed in the recent literature [85], [92]. In addition to insulation deterioration, overloading and overheating are the main causes of these defects, as explained in the previous section. Electric machine faults can result in system breakdowns and have an impact on system performance as a whole. Therefore, it is essential to foresee faults and detect them early to reduce the previously mentioned demerits. In the literature, several fault prognosis and diagnosis methodologies have been developed using signal-based, model-based, and data-driven methods [93], [94] with a further classification by the employed technique: load angle [95], winding impedance [96], [97], torque ripple [98], and motor current and voltage signatures [51], [99].

Since BLDC motors are widely used in robotic applications, their health monitoring is necessary to ensure high reliability and avoid severe damage. BLDC motors are prone to various faults, such as stator winding and magnet faults [100]. In [87], possible faults and their proposed diagnosis techniques are reviewed for BLDC machines. Moreover, the fault diagnosis of inter-turn short circuit faults (ISCFs), i.e., widespread electrical faults, is of particular interest in BLDC motors [101]. An initial model-based fault diagnosis technique has been introduced for BLDC motors by comparing nominal and computed parameters [102]. Moreover, in [103], the effects of both stator ISCF and rotor demagnetization have been highlighted in SPM-type BLDC motors. Also, several fault modeling strategies have been reviewed. In fault cases, it is proved that the improved winding function theory (IWFT) enhances the winding inductance analysis. Finally, the steady-state performances, e.g., rotor back electromotive force (EMF) and radial magnetic flux density, have been realized with better accuracy and less computational time.

For PM motors, a fault prognostic and diagnostic method has been developed in [104] to forecast the remaining useful lifetime (RUL). Additionally, it modifies the system and reduces the fault using the output of the prognosis algorithm. In [105], a prognostic model of a servo motor has been presented using the hidden semi-Markov model. Accordingly, the RUL of a linear actuator driven by an AC servo motor is predicted using only current measurements. Another control methodology has been presented based on the hidden Markov model [106]. Moreover, optimal iterative learning control (ILC) has been recent presented for linear systems [107]. The efficacy of the proposed ILC has been validated by simulations of a mobile robot. In addition, a fault identification system has been introduced for servo actuators based on the logic-dynamic approach, which used linear techniques to study nonlinear systems [34]. A latter survey on motor fault diagnosis has been introduced based on motor phase current signatures [108]. Furthermore, an experimental data set has been designed to compare synchronous motor fault classifiers [109]. The data set includes five common electrical faults, namely, open-phase, phase-to-phase short-circuit, phase-to-neutral, rotor excitation voltage, and rotor excitation current faults. Eventually, the designed data set is available online and can be utilized by the community as a benchmark.

Health management of electric machines is crucial for safety-critical applications, where electric machines are vulnerable to several fault types [32]. Advanced signal processing and AI technologies have been used in health monitoring applications to facilitate online diagnosis and automatic interpretation since they offer fast calculations, smart analysis, and low cost [110], [111], [112]. The general procedures of fault prognosis, diagnosis, and health monitoring for electromechanical actuators have been intensively introduced in [28]. The health monitoring strategy mainly comprises three steps, namely, fault prognosis and RUL estimation, fault diagnosis, and fault-tolerant operation, and follows reasonable and adequate standards, as shown in Fig. 3.

In terms of the evaluation criteria of a health monitoring method, accuracy, robustness, no intrusion, computational time, and implementation cost represent the major criteria in electric machines' health monitoring. These standards can be briefly explained as:

1) Accuracy: accuracy of the fault identification and post-fault operation is of particular interest in electric machine condition monitoring.

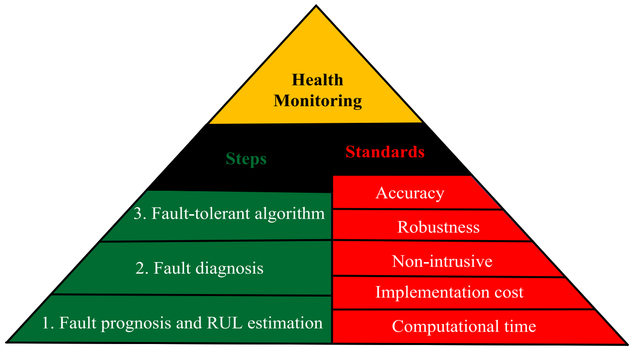

FIGURE 3. Health monitoring of robot joint motors.

2) Robustness: the proposed condition monitoring strategy should be robust to dynamic operating conditions [113].
3) Non-intrusive: due to the fact that the installation of speed and torque transducers is intrusive, it is hard to install these transducers in some situations where the motors are not accessible. Therefore, nonintrusive techniques have been preferred over their intrusive counterparts since they depend on terminal voltages and currents during the motor's normal operation [114].
4) Computational time: computational burden is an important factor in evaluating the health monitoring methodology. The improvement in computational time of fault prognosis and diagnosis is prominent without affecting the accuracy of the used method [115].
5) Implementation cost: lower implementation cost plays important role in machines' health monitoring from a practical realization point of view.

Multiple health monitoring methodologies for electric machines have been introduced in the literature [116], [117], [118]. An interesting solution using dual redundancy BLDC motor has been proposed for winding fault detection and thus increasing the drive system reliability [119]. In that case, the motor is equipped with two winding groups, and each group is individually controlled. This approach is more advantageous than using multiple motors since it offers low cost and is lightweight. In [120], another model-based technique for fault prognosis and diagnosis in BLDC motors has been developed. In the following subsections, several health monitoring strategies are summarized and broadly classified into techniques for stator winding faults, rotor faults, and bearing faults.

A. HEALTH MONITORING STRATEGIES FOR STATOR WINDING FAULTS

A new inter-turn short circuit fault (ISCF) diagnosis approach for PM synchronous motors has been developed, considering electromechanical torque, as shown in Fig. 4 [22]. An ISCF is prevalent in PMSMs and should be diagnosed since it may deteriorate the machine's performance. In that case, Fast Fourier Transform (FFT) is used to extract the torque frequency distribution, which is utilized in the stator winding fault detection. Particularly, the ISCF in the stator winding is determined by the 2^{nd} and 4^{th} torque harmonic components. Compared to the healthy case, the 2^{nd} and 4^{th} harmonic components are considerably increased in faulty cases. A similar approach has been prior introduced, considering the spatial harmonic owing to rotor PMs distribution [121].

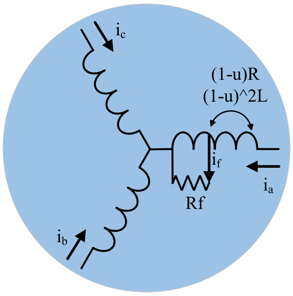

FIGURE 4. ISCF fault representation.

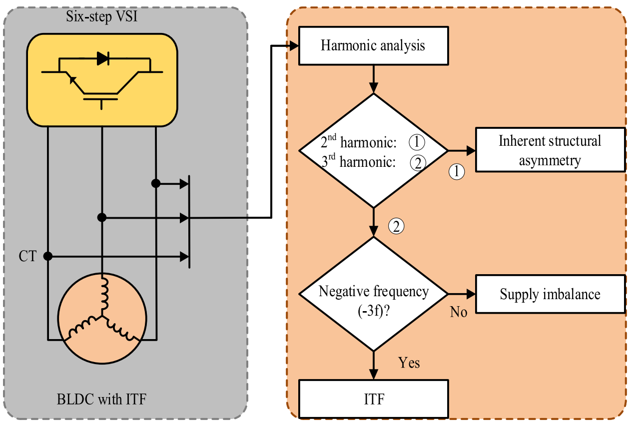

FIGURE 5. Flow chart of a fault diagnosis approach.

Moreover, a stator inter-turn fault (ITF) diagnosis technique has been proposed for PM-type BLDC motors with concentrated windings [51]. This methodology has been validated for both SPM and interior permanent magnet (IPM) BLDC motors. This methodology detects the ITFs based on the line currents' third harmonic components, which are significant for fault detection under supply imbalance and structural asymmetry. Therefore, a system-matrix-based FE model of the reemployed BLDC motor with an ITF has been proposed, taking into consideration the asymmetric magnetic fields. The proposed fault detection approach using the Kalman filter is shown in Fig. 5. Although the suggested approach can be utilized in traditional inverters with no extra sensors, it is not suitable in either light load or low-speed conditions.

Furthermore, fault diagnosis of the stator windings of a surface-mounted PM (SPM) machine has been presented using high-frequency (HF) voltage signal injection [19]. The main focus of the proposed technique is to detect the stator winding short-circuit faults and insulation degradation. Fig. 6 depicts the online detection scheme. It measures the online saliency profile of the SPM machine under normal operation and compares it with the magnetic signature of the machine under healthy conditions to detect abnormal incidents in the stator windings. The ability of the proposed monitoring approach to identify both elementary and full short-circuit faults has been experimentally verified.

Another technique that incorporates open-circuit fault detection for the three-phase PMSM is shown in Fig. 7 [21]. It utilizes the grey prediction theory which estimates the rule of the system by collecting some current data. The employed PMSM is controlled based on the vector control technique, and the inverter is driven by the speed and current controllers. In normal conditions, the proposed fault diagnosis approach identifies the running state of the motor in real time based on the acquired stator currents. After that, the currents are predicted at the next interval and compared with the actual current values. Finally, an open-circuit fault detection variable is determined according to the absolute value of the difference between the predicted and actual current values of a single phase. Compared to conventional current detection methods, the proposed one is fast and accurate.

A recent ISCF detection and evaluation strategy has been developed for BLDC motors, as shown in Fig. 8 [101]. The proposed methodology to diagnose an ISCF comprises two steps: analyzing the zero-sequence voltage component (ZSVC) spectrum to deduce the fault feature and evaluating the faulty phase and the severity of the ISCF based on fault indicators. It is worth mentioning that the fault indicators are defined by monitoring the slope variation of phase current and ZSVC. The proposed technique is fast and accurate and offers real-time fault diagnosis. The efficacy of the proposed fault detection strategy has been validated through simulation and experimental tests.

In [122], A stator inter-turn-short fault (ITSF) has been extensively analyzed in an IPM machine equipped with fractional-slot concentrated winding (FSCW). This paper investigated the effect of the control drive on the characteristic of the ITSF since the fault signatures are affected by controller actions during online fault detection. In that case, the six-step square-wave control (SSC) in an open-loop control drive is compared to field-oriented control (FOC) in a closed-loop one. The latter outperforms the former since it exhibits improved ITSF mitigation capability, lower common-mode voltage, and lower peak-to-peak torque ripple. Thus, FOC assures that the drive is functional during faults. It can be noted that the proposed controllers can alleviate the ITSF based on flux weakening strategy, i.e., decreasing the magnitude of circulating current. Finally, a three-phase 400 W FSCW-based IPM motor has been developed to validate the theoretical findings.

A novel localization technique for PMSMs with ITSFs has been recently introduced based on the search coil (SC) array [123]. The proposed SC method is utilized to observe the stator tooth flux and is introduced for m-phase

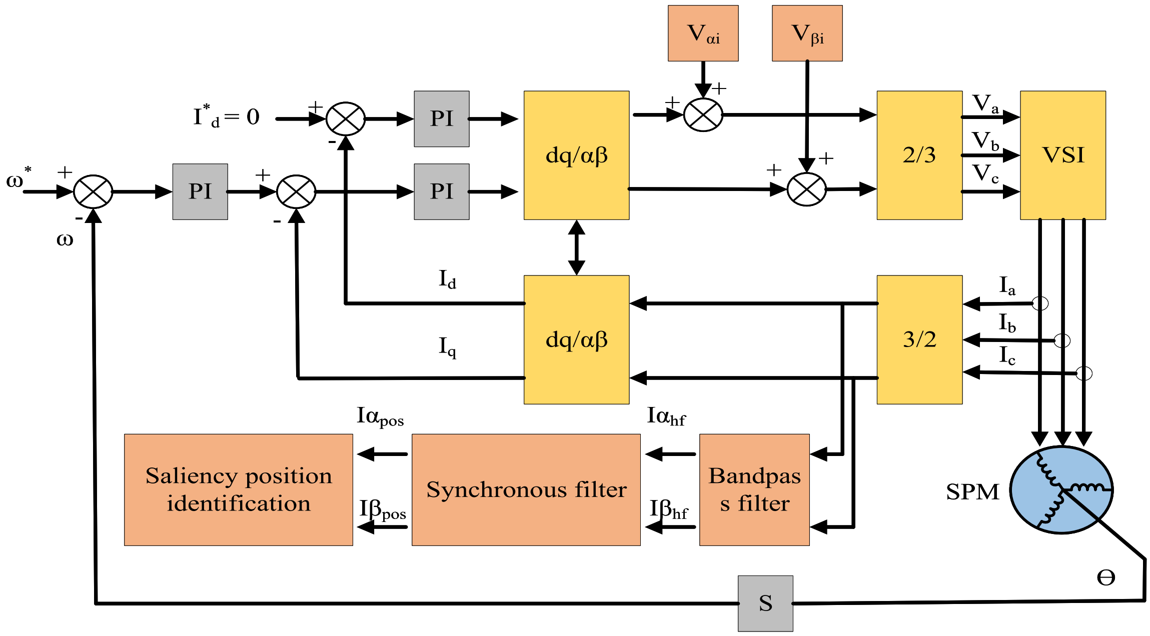

FIGURE 6. Short-circuit fault detection strategy using HF signal injection.

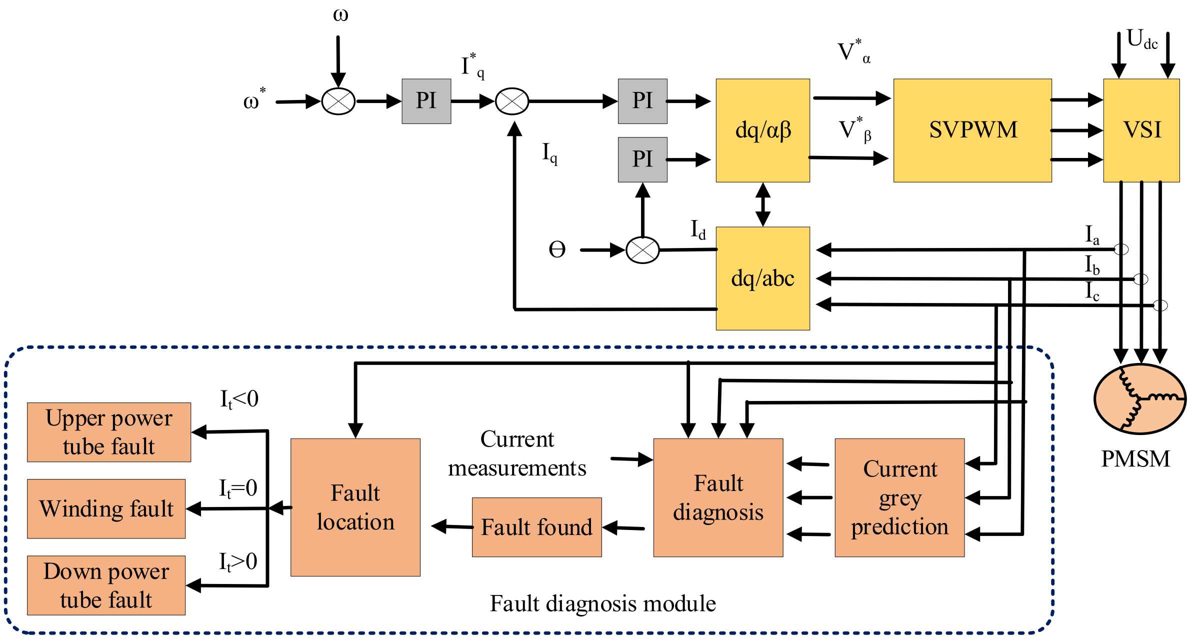

FIGURE 7. Open-circuit fault diagnosis technique using grey prediction theory.

direct-drive PMSM. It can be noted that the SC is presented for m-phase PMSM with n branches per phase and z coil groups per branch. In this case, the proposed SCs are wrapped around a stator tooth through the proposed arrangement to avoid any unnecessary complications of the fault coil localization technique. Moreover, the back EMF and the residual back EMF are identified and used as ITSF indicators. Thus, an analytical model has been developed to study the mapping relationship between the fault coil location and each SC's back EMF. Finally, the proposed approach has several advantages, including less complexity and lower computational burden, which have been verified using simulation and experimental results.

An interesting methodology for measuring stator insulation capacitance of inverter-fed machines has been investigated using accelerated ageing experiments [124]. The proposed method is capable of monitoring the ground-wall insulation based on a multi-frequency measurement

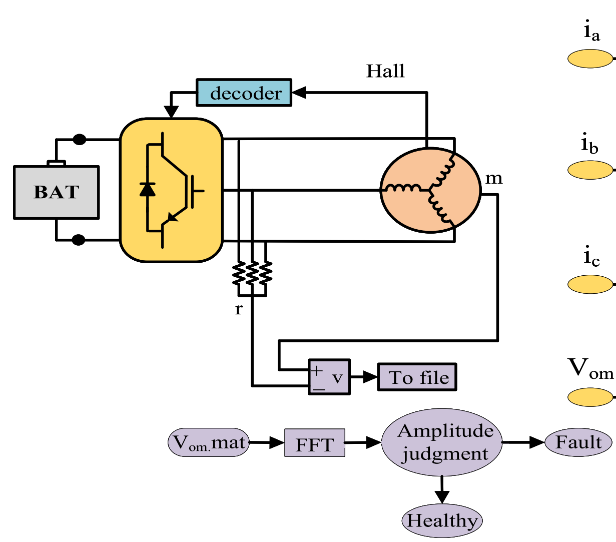

FIGURE 8. Block diagram of the ISCF diagnostic strategy.

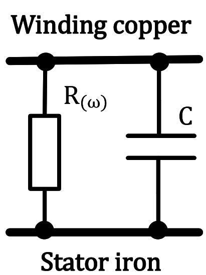

FIGURE 9. Model of ground-wall insulation.

of equivalent capacitance. The ground-wall insulation is considered as a parallel plate with the stator iron and winding copper forming the insulating dielectric, as shown in Fig. 9. Based on the long-term ageing experiments of four machines, it is clear that the remaining useful lifetime (RUL) can be estimated based on the equivalent capacitance, i.e., a significant indicator of ageing. The consistency of the capacitance pattern over time for all test samples and the normalized capacitance value at the end of life were the most key findings. In recent machine drives, the suggested method shows a practical and precise tool for real-time insulation health monitoring.

Besides, a custom power converter has been developed for online stator winding insulation health monitoring based on high-frequency current oscillations, as shown in Fig. 10 [125]. The proposed converter is not only capable of performing the FOC, but also capable of measuring the high-frequency current ringing during the switching transitions and acquiring parameters, references, and commands through communication with an external PC. These functions are implemented using a single Xilinx Zynq System-on-Chip (SoC), which contains two processor cores and a field-programmable gate array (FPGA) and is mounted on a control board. In this study, the insulation status has been assessed based on selected metrics, e.g., RMS and peak values of the MHz-range current ringing. In order to emulate the various insulation conditions, external capacitors were inserted between turns and between turns and ground. Therefore, a quasi-linear behavior can be noticed with respect to the changes in capacitance. Moreover, the proposed measurements were assessed on hardware with lower requirements while keeping their monitoring capabilities. Finally, these measurements could also be performed with straightforward analog circuits to prevent the requirement for a greater sampling frequency.

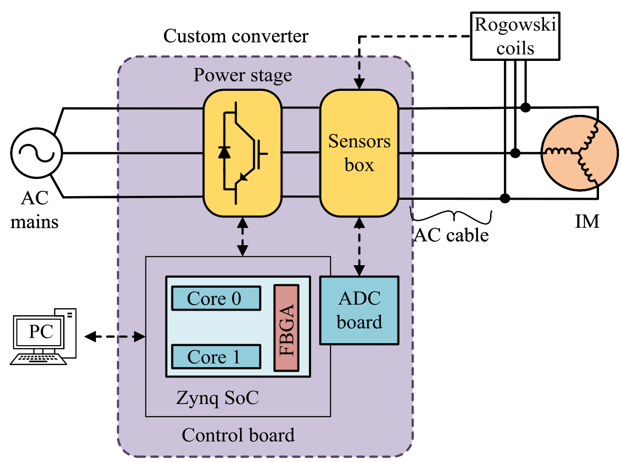

FIGURE 10. Custom power converter control scheme.

B. HEALTH MONITORING STRATEGIES FOR ROTOR FAULTS

An innovative motor fault diagnosis approach has been recently presented using convolutional neural network (CNN) feature fusion, as depicted in Fig. 11 [56]. Primarily, the preprocessing of the vibration and current signals is performed. Thereafter, the processed data is sampled

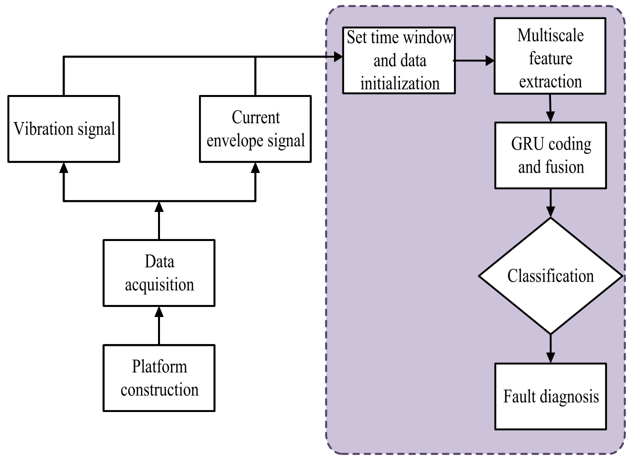

FIGURE 11. Architecture of the CNN-based fault diagnosis.

using a segmented multi-time window synchronous window. Finally, motor faults can be accurately distinguished through time series fusion and feature extraction procedures of the preprocessed signals. The proposed fault detection approach has been validated by simulating various motor faults, i.e., bearing outer and inner ring, rotor broken bar, and inter-turn short-circuit faults. As a result, the fault diagnosis is enhanced by combining the fault features of the motor vibration and current signals. Eventually, higher accuracy and greater stability of the motor fault detection are provided through the multi-signal input compared to its single signal counterpart.

In [126], experimental verification of a progressive fault diagnosis method (PFDM) for an electro-hydrostatic actuator (EHA) is carried out using double redundancy EHA servo mechanism, loading equipment, and servo controller. Moreover, monitoring DSPs are used to monitor the system status and detect system faults. The flowchart of the proposed PFDM consists of sensor fault diagnosis based on the Kalman filter, threshold-based fault detection, and discrimination based on EHA system logic and analysis, as shown in Fig. 12. Unlike conventional fault diagnosis techniques, the proposed PFDM uses double redundancy EHA system to enable system reconstruction after fault diagnosis. It is concluded that the proposed PFDM offers accurate and fast fault detection and thus improves system reliability. A recent IM fault detection methodology has been introduced to investigate rotor and bearing failures based on neural networks, vector machine, and boosting methods [127]. In this case, fault diagnosis was performed using the obtained real-time vibration data. It is concluded that the vector machine and neural networks have the highest accuracy; however, the boosting methods offer the shortest computational time.

Furthermore, a PM demagnetization fault diagnostic methodology has been latterly introduced for PMSM based on the ML approach [128]. First, feature extraction of the PM fault from the stator currents has been performed using a short-time Fourier transform (STFT). After that,

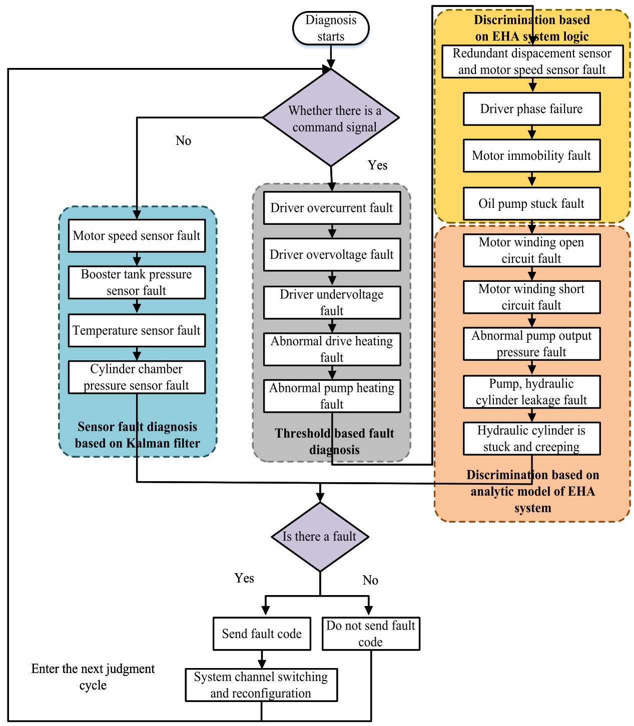

FIGURE 12. Progressive fault diagnostic technique.

two ML algorithms, namely, k-nearest neighbors (KNN) and multilayer perceptron (MLP) are used for automatic PM demagnetization fault diagnosis. Moreover, the effects of the key parameters, input vector elements, and ML algorithms' structures on the efficacy of the proposed detection technique have been verified. The KNN algorithm outperforms its MLP counterpart since it offers high diagnosis effectiveness at a shorter response time. For example, the response time of the KNN model is 0.002 seconds in comparison with the 0.0071 seconds needed by the MLP model. Another methodology to differentiate between short-circuit and local PM demagnetization faults has been recently elaborated in [129].

In [130], a recent approach for PM health management and diagnosis has been investigated using a magnetic sensor, as depicted in Fig. 13. The proposed FBG-based air-gap magnetic sensor is of particular interest, not only for monitoring the rotor PMs' health in SPM machines but also for straightforward installation without invasive behavior to core parts in comparison with conventional methods. The main idea is to identify the air-gap magnetic flux density of an inverter-fed synchronous machine under healthy and demagnetized PM cases. Experimental results show that the proposed magnetic sensing scheme can recognize the magnetization degree of the rotor PMs, allowing for the monitoring of their health. Ultimately, the application of in-situ magnetic sensor measurements for the relative quantification of PM demagnetization fault severity is made possible by a diagnostic index that is presented and experimentally verified.

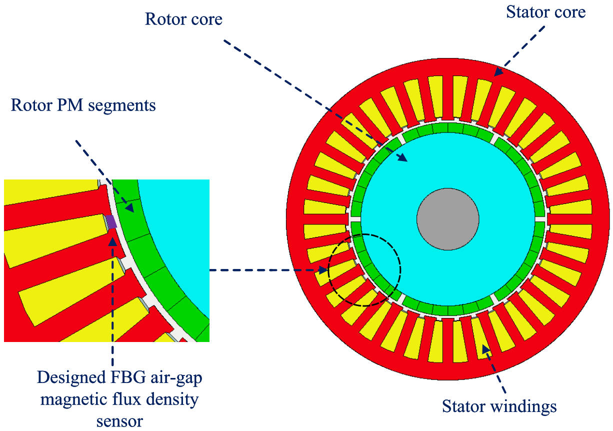

FIGURE 13. PM health monitoring of a SPM motor.

Another interesting study has been previously presented for fault diagnosis of PMSMs using the SC-based electromagnetic signature analysis [131]. In this case, several fault types are considered, e.g., eccentricity, inter-turn short circuit, and PM demagnetization faults. The proposed technique is not affected by the induced harmonics by power electronic dive circuits because fault diagnosis is performed using only the first-order harmonic. Moreover, the need for a pattern recognition algorithm is omitted since the faults' signatures are easily recognized which saves considerable computational time. Besides, it is capable of locating the direction of eccentricity and winding short-circuit turns. Due to the fact that the proposed method is of an invasive nature, it is designed for an electric machine during the manufacturing process to install the search coils. Finally, the proposed technique has been verified using 2D FE simulations and experimental results.

C. HEALTH MONITORING STRATEGIES FOR BEARING FAULTS

In [132], an intelligent and adaptive bearing fault diagnosis approach has been introduced using tacholess order tracking (TOT) for various electric machines, e.g., BLDC motor and PM synchronous generator (PMSG). In addition to decomposing the machine current signal, the proposed adaptive synchrosqueezing wavelet transform (ASWT) additionally reconstructs the component associated with rotation by adaptively choosing the instantaneous frequency (IF) curve. Fig. 14 depicts the flowchart of the proposed methodology. Digital signal processing techniques are used to test the efficacy of the suggested method on machine current signals. The proposed technique is also justified by creating and analyzing an electric machine model through mathematical derivation. Finally, the diagnosis of bearing defects in other electric machines operating at varying speeds can be accomplished using the ASWT approach.

Other solutions have been introduced in the available literature for bearing fault diagnostics of PMSMs. In this context, a new approach for bearing damage diagnosis is depicted in Fig. 15 [133]. The proposed methodology

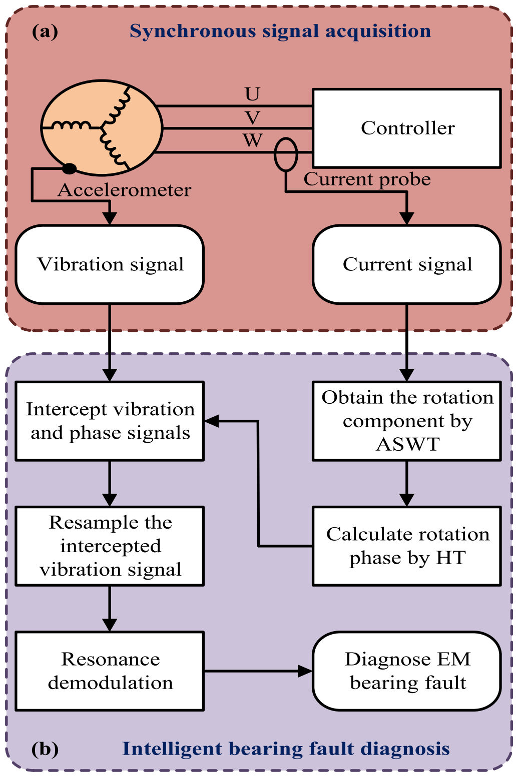

FIGURE 14. Framework of smart bearing fault diagnosis method.

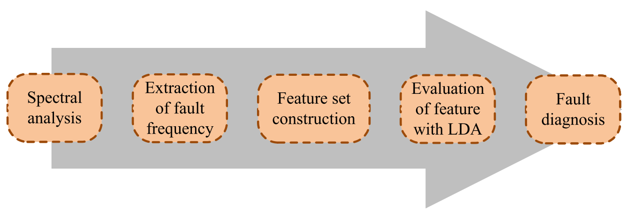

FIGURE 15. Block diagram of bearing damage diagnosis method.

identifies the bearing damages based on the stator current feature developed by a frequency selection in the current spectrum. After that, linear discriminant analysis (LDA) assesses these features, and the Bayes classifier performs the fault diagnosis. To verify the proposed methodology, two bearing damages at various load cases have been experimented. The faulty bearings are, therefore, identified from the healthy ones. On the other hand, bearing fault diagnostics cannot be performed using the proposed approach in specific load conditions, such as low speeds and radial forces.

A novel method for bearing health monitoring has been presented under both healthy and faulty conditions using fiber Bragg grating (FBG) sensors [134]. This paper utilizes concurrent thermo-mechanical sensing to identify the operational status of inverter-fed IMs. Fig. 16 depicts the architecture of the proposed technique for bearing healing monitoring. First, the sensing heads are embedded on the bearing outer ring surface. Thus, its parameters are measured

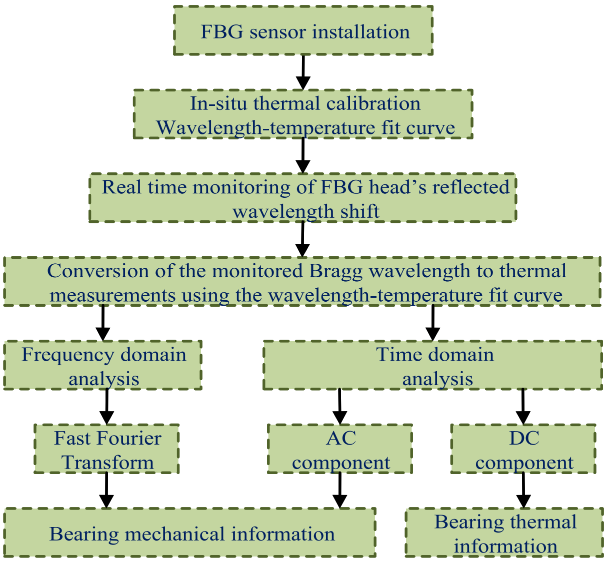

FIGURE 16. Flowchart of the bearing health monitoring.

with the healthy bearing operation and faulty cases with rolling element fault. After that, the thermal and mechanical effects are distinguished through the thermal calibration of the sensor before its in-service application. It is worth mentioning that the sensitivity can be improved by placing the FBG sensor in the bearing load area. Finally, the efficacy of the proposed technique has been proved in the monitoring of electric machine bearings, i.e., thermal and mechanical operating information.

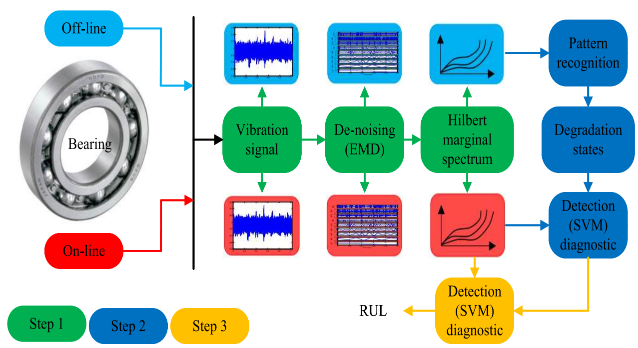

FIGURE 17. Bearing fault prognosis and diagnosis using Hilbert-Huang transform.

In order to monitor ball bearings, the study in [135] introduces a novel method that consolidates the Hilbert-Huang transform, the support vector machine (SVM), and the support vector regression (SVR), as shown in Fig. 17. The proposed method employs the Hilbert-Huang transform to separate health indicators from stationary/non-stationary sound signals that can track the deterioration of vital bearing components. A supervised classification method, SVM, is used to identify the degradation states, and the extracted health indices are examined to provide a fault diagnosis. Furthermore, the remaining useful lifetime (RUL) is estimated based on SVR, i.e., one-step time series prediction. According to experimental findings, the proposed approach has shown promise in improving the diagnostic and prognostic of bearing deterioration. The applicability of this approach is limited in cases where historical data about the bearings' degradation are hard to acquire, a notable demerit of this method. Another approach for bearing health monitoring has been recently introduced based on vibration signals analysis [136].

Unlike conventional diagnostic techniques with limited capability of dealing with real-time environments, a vibro-acoustic fusion technique has been latterly presented for precise fault detection under various conditions. The proposed technique utilizes multi-input CNN (MI-CNN) to fuse the features of acoustic and vibration signals. Therefore, the diagnosis efficiency is highly improved [137]. Another CNN-based bearing fault detection technique has been introduced in [138]. Unlike traditional strategies, the proposed method is not affected by the surroundings and can achieve accurate remote detection. Another FBG-based approach for monitoring motors' vibrations has been presented [139]. In this case, a wideband optical accelerometer is proposed to substantially enhance the sensitivity and the resonant frequency when compared to conventional FBG accelerometers. In addition, In [140], a novel bearing fault diagnosis technique has been presented on the basis of time-frequency information fusion. Unlike the current diagnosis methods which are based on supervised learning, this paper proposed an unsupervised cross-domain diagnosis technique, which leverage the processing capability of the wavelet packet decomposition approach, i.e., extract more fault signatures, eliminate redundant information, and preprocess the vibration signal.

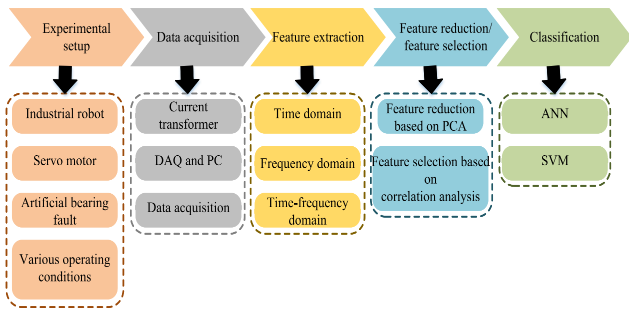

FIGURE 18. Flowchart of the health management method.

In [55], a robust fault diagnostic model for servo motors in robotic applications has been developed. The flowchart of the proposed method is given in Fig. 18. First, data acquisition and preprocessing have been performed, which are followed by feature extraction based on wavelet packet decomposition (WPD). Second, feature reduction/selection methods are utilized to reduce the computation burden. Finally, the classification performance is performed using both the artificial neural network (ANN) and SVM to find out defect features in various operating scenarios. Current data for both normal and fault scenarios are gathered to identify

TABLE 4. Comparison of motor fault prognosis and diagnosis approaches.

Ref.	Figure	Motors	Fault type	Technique	Control strategy	Evaluation Summary
[22]	Fig. 4	SPM	ISCF	Electromechanical torque	Vector control	- High accuracy fault detection. - Improves the accuracy of fault classification methods.
[51]	Fig. 5	BLDC	ITF	Third harmonic components of line currents	Six-step commutation	- Diagnosis of BLDC motor with concentrated windings. - Inadequate in low speed.
[19]	Fig. 6	SPM	Short-circuit	HF signal injection	Sensorless control	- Simple implementation. - No additional transducers. - Successful detection of full short-circuit faults.
[21]	Fig. 7	PMSM	Open-circuit	Grey prediction theory	Vector control	- Fast and accurate. - Diagnosis of the open-circuit faults and power switch.
[101]	Fig. 8	BLDC	ISCF	Signal analysis-based	Six-step commutation	- Considerable accuracy and rapid response. - Real-time fault diagnosis.
[122]	—	IPM	ITSF	Flux weakening strategy	SSC and FOC	- Consider the effect of the control drive. - Compare fault characteristics in open-loop and closed-loop control drives. - FOC is better than SSC from fault mitigation perspective.
[123]	—	PMSM	ITSF	Search coil array	—	- A fault coil localization methodology to decrease the complexity of fault diagnosis. - A generalized approach since it depends on the winding layout and does not entail any motor parameters. - Low computational cost.
[124]	Fig. 9	Servo	Stator insulation	Accelerated ageing methodology	Space vector PWM	- Effective in the gradual ageing detection. - Estimate the RUL based on the equivalent capacitance.
[125]	Fig. 10	IM	Stator insulation	High-frequency current ringings	FOC	- Develop a custom converter for high-frequency stator current oscillations. - Use analog circuits to implement the proposed metrics and thus obviate the need for higher sampling frequency.
[56]	Fig. 11	Servo	Various	CNN-based feature fusion	—	- Fault identification with high accuracy. - Improved motor fault diagnosis. - Greater stability with multi-signal input.
[126]	Fig. 12	Servo	Various	Progressive fault diagnosis	Three-loops control of position, speed, and current	- Identify 22 faults of the EHA with high accuracy. - Enhance the response time to 4 msec. - Increase the safety and reliability.
[128]	—	PMSM	PM	Current signal processing and ML algorithms	FOC	- An effective model in off- and on-line tests. - Employ simple ML algorithms for an effective symptom extraction process. - Offer shorter response and training time.
[130]	Fig. 13	SPM	PM	Air-gap magnetic flux density sensing	Vector control	- Effective determination of the magnetization level through in-situ measurements. - Extraction of the demagnetization severity data based on a fault index.
[131]	—	SPM	Various	Electromagnetic signature analysis with search coils	Vector control	- Distinguish between the various fault signatures easily. - Evaluate the severity of each fault. - Need to be consider during the manufacturing process.
[132]	Fig. 14	Various	Bearing	Tacholess order tracking	Six-step commutation for BLDC motor	- Intelligent and adaptive bearing fault detection. - Able to be extended to other AC motors.
[133]	Fig. 15	PMSM	Bearing	Linear discriminant analysis	Vector control	- Fault diagnostics based on the Bayes classifier. - Damaged bearings are identified with various loads. - Cannot be used in small load cases.
[134]	Fig. 16	IM	Bearing	Thermo-mechanical fibre optic sensing	V/f control	- Both thermal and mechanical operating conditions can be clarified based on the FBG sensors' measurements. - Improved sensitivity is obtained by the placements of sensors in the bearing load zone.
[135]	Fig. 17	AC motor	Bearing	Hilbert-Huang transform, SVM, and SVR	Speed control	- Focusing on ball bearings' fault prognosis and diagnosis. - Ability to track the degradation of bearings based on Hilbert-Huang transform. - The implementation of the proposed technique entails historical data about bearings' degradation.
[55]	Fig. 18	Servo	Bearing	Feature selection and reduction methods	—	- Proposed method mimics real environmental scenarios. - The employed algorithms are general and verified for two distinct ML classifiers. - Feature selection decreases computational burden.

servo-motor faults. The proposed model is viable in real environmental conditions under variable speed and loading.

Eventually, all the health monitoring strategies are compared according to the motor types, fault types, detection technique, and control strategy, as listed in Table 4.

VI. FUTURE RESEARCH TRENDS

This section aims to present the future research directions introducing the main opportunities and challenges in the field of robotic arm joint motors and their online health monitoring techniques, which are elaborated as follows:

A. SMART HEALTH MONITORING

1) Health monitoring based on deep learning applications, e.g., using neural networks (NNs) with another algorithm to avoid mistakes from approximating the function [31]. This approach can be extended to IMs with bearing faults.
2) Proper performance of artificial neural networks (ANNs) since overfitted sub-optimization systems may yield uncertain forecast outcomes [141], [142].
3) Intelligent health management with fast calculations, low cost, and smart analysis [143]. This method can be used to extend the lifetime of PM machines based on digital twin.

B. HIGH RELIABILITY SOLUTIONS

1) Accurate measurements and their impacts on the fault detection efficacy [128]. This technique can be utilized for demagnetization fault diagnosis of PMSMs.
2) Advanced data processing of the state signals to alleviate the effect of noise and transient behaviors.
3) Industry 4.0 standards and maintenance of electrical equipment [144]. This approach can be extended to IMs with various faults.
4) Fault prognosis and condition monitoring in industrial systems to ensure reliable, robust, and precise results [145], [146]. This method can be extended for IMs bearing faults to implement remote health monitoring.

C. JOINT MOTOR LIFETIME EXTENSION

1) Modern data-driven RUL prediction techniques, such as AI and statistical model-based ones [147], which can be utilized for bearing faults.
2) Considering the varying operating condition of the electric machine to predict the RUL in a better way [28]. This method can be extended to either IMs or PM machines with various fault types.
3) Development of deep learning-based RUL prognostic methods to precisely simulate the degradation aspects of features [148]. This technique can be used to extend the lifetime of several joint motors by adding new perspectives to the well-known data-driven methods.

D. HEALTH MONITORING BY FAULT TYPES

1) Monitoring sensitivity optimization and exploring fault signatures for rotor bearing health management [134].
2) KNN-based embedded microcontroller realization for PM fault detection [128].
3) Novel interturn short-circuit fault diagnosis in PMSMs with different winding layouts to estimate the fault severity [149].

VII. CONCLUSION

Robots have been increasingly utilized in harsh environmental conditions, such as operation fields with extreme temperatures or high radiations. These harsh environmental conditions may induce electrical and mechanical failures of the joint motors and their related power electronic drives. It is concluded that the robot arm with faulty joint motors cannot complete the assigned tasks, which manifests the prominence of online health monitoring for robot joint motors. Thus, online health monitoring for robotic joint motors is crucial to ensure the system's reliability and avoid downtime cost. This paper investigated the state-of-the-art robot joint motors, highlighting motor and possible fault types, online health monitoring of the presented joint motors, and examples of collaborative robotic applications. Various types of joint motors are presented while elaborating on their merits, limitations, and applications. Besides, different types of faults are summarized and visualized to highlight the impacts of these faults on the employed motors. Furthermore, the application of health management for joint motors is illustrated. These health monitoring strategies have been thoroughly investigated and their diagnostic characteristics are presented. In this study, commercial collaborative robots are introduced and compared based on screening factors, e.g., continuous payload and maximum reach.

This paper sheds light on the joint motors for robotic arms and provides researchers and engineers in the area of robots with an extensive survey that will help understand the joint motors, their common faults, and how to manage these faults with advanced online health monitoring strategies.

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