



A Comprehensive Review of IoT-Based Induction Motor Protection Systems Using Smart Sensors and Cloud Monitoring

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Abstract: Three-phase induction motors carry the bulk of the mechanical load in modern industry, and their unplanned failure translates directly into lost production, damaged driven equipment and, in the worst cases, safety hazards for plant personnel. Conventional electromechanical protection devices such as thermal overload relays and fuses respond only after a fault has fully developed, offer no record of the events preceding the trip, and cannot be interrogated remotely. The convergence of low-cost smart sensors, embedded wireless microcontrollers and cloud computing under the umbrella of the Internet of Things (IoT) has therefore reshaped the way induction motors are protected and monitored. This paper presents a comprehensive review of IoT-based induction motor protection systems reported in the literature, with particular emphasis on work published between 2020 and 2026. More than thirty representative studies are examined and compared with respect to their sensing arrangements, processing platforms, communication technologies and protective actions. The principal categories of motor faults are summarised, and the sensor technologies, wireless communication standards and cloud platforms that underpin contemporary protection architectures are evaluated against one another in a series of structured comparison tables. A taxonomy of IoT-based protection approaches and a generic layered system architecture are proposed to organise the surveyed material. The review reveals a clear migration from simple threshold-based telemetry systems toward edge-intelligent architectures employing machine learning, and identifies persistent research gaps concerning standardisation, cybersecurity, sensor reliability, benchmark datasets and true predictive protection. Future research directions, including TinyML-based edge diagnosis, digital twins, federated learning and self-healing protection schemes, are discussed to guide researchers and practitioners working toward the next generation of intelligent motor protection.

Index Terms - Induction motor protection, Internet of Things, condition monitoring, smart sensors, cloud computing, ESP32, machine learning, predictive maintenance, wireless sensor networks, fault diagnosis.

I. INTRODUCTION

Induction motors are frequently described as the workhorses of industry, and the description is well earned. Their rugged construction, low purchase cost, minimal maintenance demand and ability to operate directly from the alternating current supply have made them the default choice for pumps, fans, compressors, conveyors, crushers, machine tools and countless other drives. Estimates place induction machines at the centre of roughly two thirds of industrial electrical energy consumption, which means that both their efficiency and their availability have a measurable economic footprint [1]. When a motor that drives a critical process fails without warning, the cost of the event is rarely limited to the price of a rewind or a replacement machine; it extends to lost production hours, spoiled work in progress, collateral damage to couplings and driven loads, and in sectors such as mining, water treatment and petrochemicals, potential threats to personnel safety and the environment [2].

Classical motor protection has relied for decades on electromechanical and static devices: fuses and circuit breakers for short circuits, bimetallic or electronic overload relays for sustained overcurrent, and embedded thermistors or thermostats for winding temperature. These devices are reactive by design. They disconnect the machine once an abnormal condition has already reached a damaging magnitude, they provide little or no diagnostic information about the root cause, and they cannot communicate their status to a remote operator [3]. In plants where motors are installed in inaccessible, hazardous or geographically dispersed locations, such as irrigation pump sets, borewell installations and remote compressor stations, even the simple task of confirming whether a machine is running can require a site visit. The limitations of this paradigm have long been recognised, and condition monitoring techniques such as motor current signature analysis (MCSA), vibration spectrum analysis and thermography were developed to detect incipient faults before catastrophic failure [4], [5]. Historically, however, these techniques demanded expensive instrumentation and specialist interpretation, confining them to large, high-value machines.

The emergence of the Internet of Things (IoT) has fundamentally altered this cost-capability balance. Integrated wireless microcontrollers such as the ESP32 and ESP8266 can be purchased for a few dollars, MEMS accelerometers and Hall-effect current sensors cost less than a fraction of a traditional transducer, and cloud platforms such as ThingSpeak, Blynk, AWS IoT and Azure IoT Hub offer data ingestion, storage, visualisation and alerting either free of charge or at modest subscription rates [6], [7]. As a consequence, protection functions that once justified themselves only on megawatt-class machines can now be economically applied to fractional-kilowatt motors in small workshops and agricultural installations. A large body of literature has accordingly appeared in which sensors measuring current, voltage, temperature, vibration, speed and humidity are interfaced to embedded controllers, faults are detected either by simple thresholds or by machine learning models, protective relays disconnect the machine when required, and all measurements are streamed to cloud dashboards for remote observation [8], [9], [10].

Although several reviews address induction motor fault diagnosis in general [11], [12], [13] or machine learning based diagnosis in particular [14], [15], comparatively few consolidate the rapidly growing literature that treats the complete IoT protection chain, from smart sensor through communication network to cloud platform and protective actuation, as a single system. The present paper aims to fill that gap. Its contributions are fourfold. First, it reviews more than thirty published systems and methods spanning 2020 to 2026 and compares them in a structured table covering sensing, communication, controllers, advantages and limitations. Second, it develops a taxonomy and a generic layered architecture that organise the design space of IoT-based motor protection. Third, it provides comparative evaluations of the sensor technologies, wireless communication standards and IoT cloud platforms most frequently employed in this application. Fourth, it distils the open research gaps and sketches a roadmap of future directions. The remainder of the paper follows the structure outlined above: Section II surveys the literature, Section III describes the anatomy of IoT-based protection systems, Section IV categorises motor faults, Sections V to VII evaluate sensors, communication technologies and cloud platforms respectively, Section VIII offers a comparative analysis, Section IX identifies research gaps, Section X discusses future directions, and Section XI concludes the paper.

II. LITERATURE REVIEW

Research relevant to IoT-based induction motor protection can be grouped into three broad strands: foundational condition monitoring and diagnosis techniques, intelligent (machine learning and deep learning) diagnosis methods, and complete IoT monitoring and protection systems. This section traces each strand in turn; Table 1 then consolidates the surveyed works into a single comparative overview.

A. Foundations of Motor Condition Monitoring

The intellectual foundations of the field predate the IoT era. Thomson and Fenger demonstrated the industrial viability of motor current signature analysis for detecting broken rotor bars, air-gap eccentricity and certain mechanical problems from the stator current spectrum alone [4]. Benbouzid systematised the signature analysis approach and catalogued the characteristic fault frequencies exploited by later researchers [5], while Nandi et al. provided what remains one of the most cited surveys of electrical machine condition monitoring, covering stator, rotor, bearing and eccentricity faults together with their diagnostic media [3]. The statistical backdrop against which all protection systems are designed was established by the large IEEE motor reliability surveys, which found bearing failures to account for roughly forty percent of induction motor breakdowns, stator winding faults for over thirty percent, and rotor faults for around ten percent [16]. Stone et al. examined the insulation systems of rotating machines in depth and clarified the thermal, electrical, ambient and mechanical ageing mechanisms that protection systems ultimately seek to arrest [17]. More recent surveys by Choudhary et al. [12], Soother and Daudpoto [18] and Gangsar and Tiwari [11] updated this picture, the latter offering a state-of-the-art treatment of signal-based techniques spanning current,

vibration, acoustic and thermal media. Lee et al. summarised the industrial state of the art and argued that the future of machine monitoring lies in continuous, networked, automatically interpreted measurement rather than periodic expert surveys [2], a position that anticipates precisely the IoT architectures reviewed here. Antonino-Daviu extended the classical steady-state analysis paradigm to transient regimes, showing that startup current transients carry diagnostic information that steady-state spectra can miss [19].

B. Machine Learning and Deep Learning Based Diagnosis

The second strand concerns the replacement of hand-crafted diagnostic rules with learned models. Kumar and Hati reviewed machine learning algorithms for induction motor fault detection and highlighted the progressive shift from classical classifiers such as support vector machines toward deep architectures [14]. Zhang et al. contributed a comprehensive review of deep learning for bearing diagnostics, comparing autoencoders, convolutional neural networks (CNNs) and recurrent networks on public datasets [20]. Drakaki et al. surveyed machine learning and deep learning methods specifically in the context of Industry 4.0 predictive maintenance of induction motors [15], and Qiu et al. broadened the perspective to diagnosis and prognosis across industrial systems [21]. Among method-level contributions, Zaman and Liang proposed a graph-based semi-supervised learning approach that achieves strong accuracy when labelled fault data are scarce [22]; Yaman combined binary pattern features with neighbourhood component analysis for automated fault classification from motor acoustic and vibration signals [23]; Misra et al. applied spectral-imaging-based transfer learning to vibration data [24]; and Boushaba et al. compared physics-informed CNNs against principal component analysis for broken rotor bar detection through MCSA [25]. Barrera-Llanga et al. benchmarked several CNN architectures for the same fault family [26], Halder et al. reviewed the broken rotor bar literature systematically [27], and Sanchez et al. addressed the frequently ignored problem of faults in the sensors themselves, designing real-time neural classifiers that distinguish sensor faults from machine faults [28]. Li et al. surveyed deep transfer learning for industrial diagnosis, an approach of particular value to IoT deployments where each installed motor differs slightly from the machines on which models were trained [29]. Publicly available datasets, such as the broken rotor bar database released by Trembl et al. [30], have accelerated this strand by enabling reproducible comparison.

C. IoT-Based Monitoring and Protection Systems

The third strand, and the core subject of this review, integrates sensing, communication, computation and actuation into deployed systems. Early demonstrations such as the wireless monitoring node of Sen and Kul established the feasibility of streaming motor parameters over IP networks using low-cost hardware [31]. Magadan et al. designed a deliberately low-cost real-time monitoring architecture for Industry 4.0 environments built around embedded gateways and standard messaging protocols [32]. Tran et al. constructed a complete experimental testbed in which induction machine signals are acquired, transmitted through IoT infrastructure and classified online by machine learning, explicitly targeting Industry 4.0 empowerment [8]. Cakir et al. designed and built an IIoT condition monitoring system and evaluated the most popular machine learning algorithms on the predictive maintenance data it produced [9]. Elkateb et al. reported an industrial deployment combining machine learning with IoT data flows for motor-driven production machinery, documenting practical gains in downtime reduction [10]. Achouch et al. offered a complementary experimental analysis on a multistage centrifugal compressor train, illustrating the transfer of the same methodology to larger rotating equipment [33].

A parallel body of work relocates intelligence from the cloud toward the network edge. Hafeez et al. examined edge intelligence for data handling and predictive maintenance in the industrial IoT and quantified the bandwidth savings available when raw waveforms are reduced to features locally [34]. Yu et al. embedded an autoencoder within an edge-assisted IoT framework for manufacturing fault detection [35], while Ong et al. applied deep reinforcement learning to schedule maintenance resources across an industrial IoT estate [36]. The TinyML movement compresses neural networks until they execute on the monitoring microcontroller itself: Dutta and Bharali surveyed the intersection of TinyML and IoT [37], Antonini et al. demonstrated an adaptable unsupervised TinyML anomaly detector operating in extreme industrial environments [38], Giordano et al. reported an ultralow-power smart sensing device with embedded TinyML for asset activity monitoring [39], and Ooko and Karume reviewed TinyML specifically for industrial predictive maintenance [40]. Piechocki et al. combined thermal imaging with edge processing to move toward explainable motor fault diagnosis [41]. At the system-of-systems level, Zonta et al. [42] and Peres et al. [43] surveyed predictive maintenance and industrial artificial intelligence within Industry 4.0, Hoffmann et al. described sensor and machine learning integration for switchgear [44], and Jamshed et al. reviewed the wireless sensor technologies that underpin every such deployment [45]. Table 1 summarises the surveyed works.

Table 1. Comparison of existing systems and methods for induction motor monitoring and protection

Author(s)	Year	Method / Focus	Sensors	Communication	Controller / Platform	Advantages	Limitations
Thomson and Fenger [4]	2001	MCSA spectral analysis	Current (CT)	None (offline)	Dedicated analyzer	Industrially proven; non-invasive	Offline; expert interpretation needed
Nandi et al. [3]	2005	Survey of CM and diagnosis media	Multi-signal (review)	Not applicable	Not applicable	Foundational fault-signature catalogue	Predates IoT integration
Sen and Kul [31]	2017	Wireless motor parameter telemetry	Current, voltage, temperature	Wi-Fi (IP network)	Embedded MCU node	Early low-cost remote monitoring	Threshold logic only; no analytics
Choudhary et al. [12]	2019	Review of CM and fault diagnosis	Multi-signal (review)	Not applicable	Not applicable	Broad technique coverage	Limited IoT system perspective
Soother and Daudpoto [18]	2019	Brief review of CM techniques	Multi-signal (review)	Not applicable	Not applicable	Concise comparison of media	No architectural treatment
Sarker et al. [46]	2019	LoRa with edge computing survey	Generic IoT sensing	LoRa / LoRaWAN	Edge gateways	Clarifies LPWAN-edge coupling	Not motor-specific
Gangsar and Tiwari [11]	2020	Signal-based diagnosis review	Current, vibration, acoustic, thermal	Not applicable	Not applicable	State-of-the-art signal techniques	Excludes system deployment issues
Lee et al. [2]	2020	Industrial CM state of the art	Electrical and mechanical (review)	Not applicable	Not applicable	Authoritative industrial outlook	No prototype evaluation
Zhang et al. [20]	2020	DL for bearing diagnostics review	Vibration (datasets)	Not applicable	GPU (offline)	Systematic DL comparison	Bearing faults only; offline
Antonino-Daviu [19]	2020	Transient current analysis	Current (startup transients)	Not applicable	Lab instrumentation	Detects faults missed at steady state	Requires transient capture capability
Magadan et al. [32]	2020	Low-cost real-time monitoring	Vibration, temperature	Wi-Fi / MQTT via gateway	Embedded SBC gateway	Deliberately low-cost Industry 4.0 design	Screening-grade sensing accuracy
Zonta et al. [42]	2020	PdM in Industry 4.0 (SLR)	Generic (review)	Not applicable	Not applicable	Maps PdM research landscape	No motor-level detail
Peres et al. [43]	2020	Industrial AI systematic review	Generic (review)	Not applicable	Not applicable	Positions AI within Industry 4.0	High-level treatment
Hoffmann et al. [44]	2020	Sensors and ML for	Novel electrical sensors	IIoT infrastructure	Industrial edge devices	Real medium-	Switchgear focus, not motors

Author(s)	Year	Method / Focus	Sensors	Communication	Controller / Platform	Advantages	Limitations
		switchgear PdM				voltage deployment	
Treml et al. [30]	2020	Public broken rotor bar dataset	Current, vibration (rig)	Not applicable	Lab DAQ	Enables reproducible benchmarking	Single machine and fault family
Tran et al. [8]	2021	Online IoT plus ML fault diagnosis testbed	Current, vibration, speed	Wi-Fi to cloud	DAQ with cloud ML	End-to-end validated architecture	Laboratory-scale validation
Cakir et al. [9]	2021	IIoT CM system with ML comparison	Vibration, temperature, current, humidity	MQTT over Wi-Fi	Low-cost SBC and cloud	Benchmarks popular ML algorithms	Single testbed generalisation
Kumar and Hati [14]	2021	ML-based fault detection review	Multi-signal (review)	Not applicable	Not applicable	Tracks ML technique evolution	No deployment guidance
Zaman and Liang [22]	2021	Graph-based semi-supervised diagnosis	Current, vibration (lab data)	Not applicable	Offline computation	Strong accuracy with few labels	Not integrated with IoT chain
Yaman [23]	2021	Binary pattern and NCA classification	Acoustic / vibration	Not applicable	Offline computation	Automated lightweight feature pipeline	Offline; single machine data
Bhole and Ghodke [47]	2021	MCSA review	Current	Not applicable	Not applicable	Concise MCSA synthesis	Narrow scope
Hafeez et al. [34]	2021	Edge intelligence for IIoT PdM	Generic IIoT sensing	Edge-cloud continuum	Edge nodes	Quantifies edge processing benefits	Not motor-specific
Dutta and Bharali [37]	2021	TinyML meets IoT survey	Generic embedded sensing	Constrained networks	MCU-class devices	Comprehensive TinyML landscape	Application-agnostic
Zhang et al. [48]	2021	Federated learning fault diagnosis	Vibration (multi-client data)	Distributed (federated)	Distributed trainers	Privacy-preserving fleet learning	Simulation-based evaluation
Boushaba et al. [25]	2022	Physics-informed CNN for BRB via MCSA	Current	Not applicable	Offline computation	Embeds physics in learning	Broken bar fault only
Misra et al. [24]	2022	Spectral-imaging transfer learning	Vibration	Not applicable	GPU (offline)	Transfers across operating conditions	Computational cost at edge
Halder et al. [27]	2022	BRB MCSA techniques review	Current	Not applicable	Not applicable	Systematic BRB	Single fault family

Author(s)	Year	Method / Focus	Sensors	Communication	Controller / Platform	Advantages	Limitations
						literature map	
Kumar et al. [13]	2022	Comprehensive CM approaches review	Multi-signal (review)	Not applicable	Not applicable	Bridges classical and intelligent methods	No hardware evaluation
Drakaki et al. [15]	2022	ML/DL PdM survey for IMs	Multi-signal (review)	Not applicable	Not applicable	Industry 4.0 framing	Survey only
Ong et al. [36]	2022	Deep RL maintenance scheduling	Telemetry streams	IIoT infrastructure	Cloud RL agent	Optimises fleet maintenance resources	Needs rich state information
Jamshed et al. [45]	2022	Wireless sensors for IoT review	Sensor technologies (review)	Multiple wireless standards	Not applicable	Sensor-network design guidance	Not protection-oriented
Giordano et al. [39]	2022	Ultralow-power TinyML sensing node	MEMS inertial (IMU)	BLE	Ultra-low-power MCU	Years-scale battery life with on-node ML	Activity monitoring, not full diagnosis
Sanchez et al. [28]	2023	Real-time neural sensor-fault classifiers	Current, voltage, speed	Not applicable	Real-time processor	Detects faults in the sensors themselves	Adds modelling complexity
Barrera-Llana et al. [26]	2023	CNN architecture comparison for BRB	Current	Not applicable	GPU (offline)	Objective architecture benchmarking	Offline; single fault family
Antonini et al. [38]	2023	Unsupervised TinyML anomaly detection	Vibration	Constrained IoT links	MCU (on-device ML)	Adapts to each machine unsupervised	Anomaly flagging, not fault naming
Yu et al. [35]	2023	Edge autoencoder fault detection	Manufacturing sensor streams	Edge-assisted IoT	Edge nodes plus cloud	Reduces cloud dependence and latency	Generic manufacturing focus
Achouch et al. [33]	2023	ML PdM on compressor train	Vibration, process signals	Plant IIoT network	Industrial historian and ML	Genuine industrial validation	Large-machine context
Piechocki et al. [41]	2023	Thermal imaging with edge XAI	IR thermal camera	Edge processing	Embedded vision device	Explainable, non-contact diagnosis	Thermal signatures only
Qiu et al. [21]	2023	DL diagnosis and prognosis review	Multi-signal (review)	Not applicable	Not applicable	Joint diagnosis-prognosis view	Survey only
Elkateb et al. [10]	2024	ML and IoT PdM industrial deployment	Current, vibration, temperature	Industrial IoT network	Edge gateway and cloud ML	Documented downtime reduction in production	Site-specific tuning required

Author(s)	Year	Method / Focus	Sensors	Communication	Controller / Platform	Advantages	Limitations
Ooko and Karume [40]	2024	TinyML for industrial PdM review	Embedded sensing (review)	Constrained networks	MCU-class devices	Maps TinyML PdM applications	Early-stage field

III. IOT-BASED INDUCTION MOTOR PROTECTION

An IoT-based protection system differs from a conventional relay panel in one decisive respect: it treats protection as an information problem rather than a purely electrical one. Instead of a single device that compares one quantity against one threshold, the IoT approach deploys a network of sensors whose measurements are digitised, fused, analysed and archived, with the protective trip being only one of several possible outputs alongside alerts, dashboards, trend logs and maintenance recommendations [49]. The design space that has emerged from the surveyed literature can be organised along four axes: the sensing modality employed, the processing paradigm that converts measurements into decisions, the communication layer that transports the data, and the protective response ultimately taken. Fig. 1 presents this taxonomy.

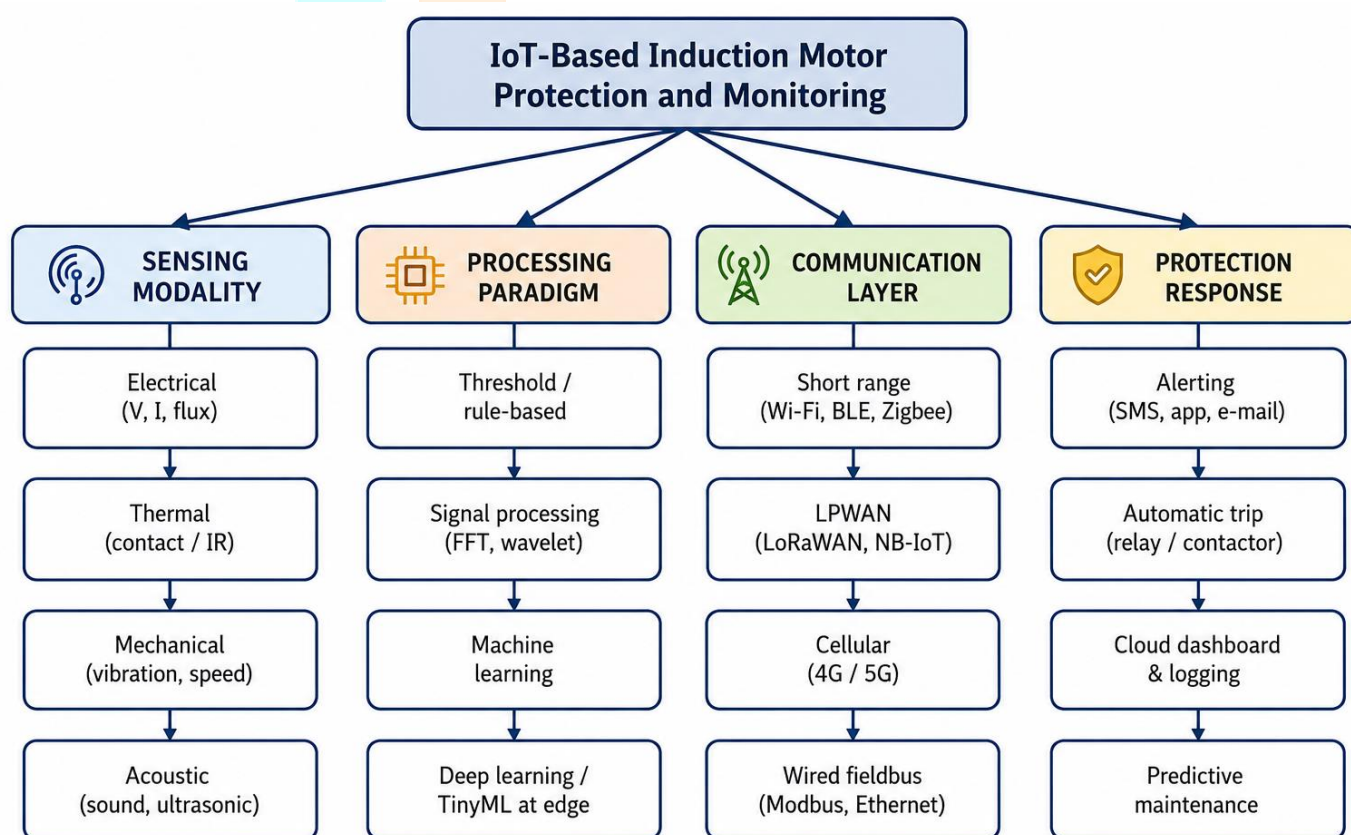


Figure 1. Taxonomy of IoT-based induction motor protection approaches

Most reported systems can be located as a path through this taxonomy. A minimal agricultural pump protector, for example, combines electrical sensing, threshold-based processing, Wi-Fi communication and a relay trip with SMS alerting, whereas a factory-grade predictive system might fuse electrical, thermal and vibration sensing, run a TinyML classifier at the edge, backhaul summaries over LoRaWAN or NB-IoT, and schedule maintenance through a cloud analytics pipeline [46], [38]. The taxonomy also exposes design tensions: richer sensing and heavier analytics improve fault coverage but raise cost, energy consumption and latency, while cloud-centric processing eases development but makes the trip decision dependent on network availability, an issue examined further in Section IX.

Architecturally, the surveyed systems converge on the four-layer organisation shown in Fig. 2, which adapts the generic IoT reference stack to the motor protection application [6]. The perception layer hosts the smart sensors attached to the machine: current transformers or Hall-effect sensors on the supply conductors, voltage dividers or potential transformers across the phases, contact or infrared temperature sensors on the frame and

windings, MEMS accelerometers on the bearing housings, and optionally speed and flux transducers. The network layer moves the digitised measurements from the machine to the computing infrastructure using short-range wireless standards, low-power wide-area networks or wired fieldbuses, most commonly carrying MQTT or HTTP payloads [50]. The cloud layer provides ingestion, time-series storage, visualisation, rule engines and, increasingly, machine learning inference [51]. The application layer finally delivers value to the user through dashboards, mobile applications, alarm notifications and integration with computerised maintenance management systems. Crucially for protection, a feedback path descends the stack: when an abnormal condition is confirmed, a trip command drives a relay or contactor that isolates the machine, either issued locally by the edge controller for speed or remotely by the operator for supervised shutdowns [8].

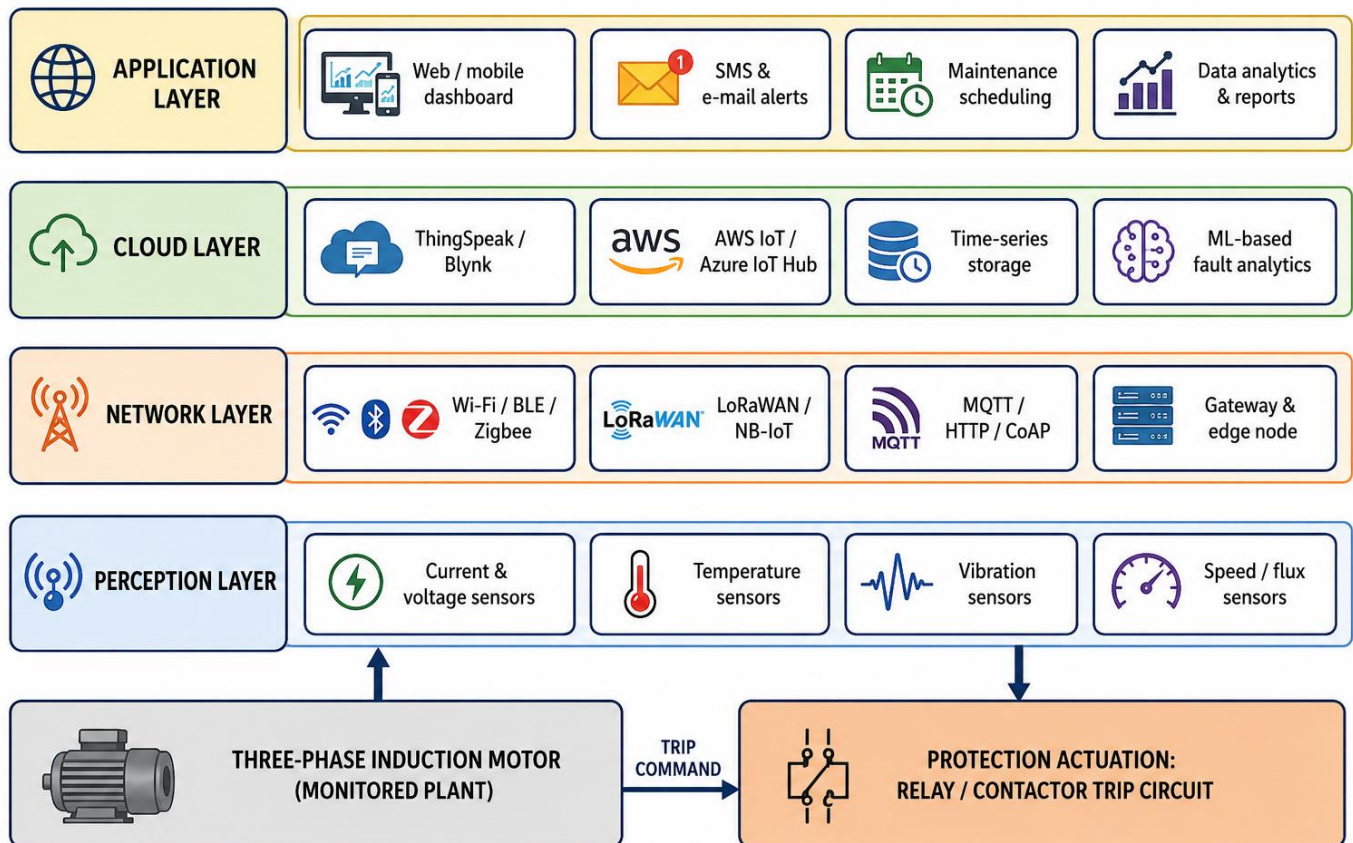


Figure 2. Overall layered architecture of an IoT-based induction motor protection system

The placement of the trip decision within this architecture is a defining design choice. Systems that evaluate thresholds on the microcontroller itself achieve reaction times in the tens of milliseconds and continue protecting the motor during network outages, at the cost of limited analytical sophistication [31]. Systems that centralise the decision in the cloud can bring arbitrarily complex models to bear and can correlate observations across an entire motor fleet, but inherit the latency and availability characteristics of the communication path [34]. The literature increasingly favours a hybrid arrangement in which fast, safety-critical protection remains at the edge while slower predictive analytics run in the cloud, mirroring the classical division between primary protection and condition monitoring [35], [10].

IV. TYPES OF MOTOR FAULTS

Effective protection presupposes a clear understanding of what can go wrong. Induction motor faults are conventionally divided into electrical and mechanical categories, overlaid by the supply-side and environmental abnormalities that provoke them. Reliability surveys consistently attribute the largest shares of failures to bearings and stator windings, with rotor defects, external supply problems and miscellaneous causes accounting for the remainder [16], [3].

A. Stator Winding Faults

Stator faults usually begin as inter-turn short circuits within a single coil, caused by insulation degradation under thermal, electrical, ambient and mechanical stresses [17]. Because a shorted turn carries a large circulating current, the local hot spot grows rapidly and the fault escalates, sometimes within minutes, into phase-to-phase or phase-to-ground failure. The diagnostic signatures include negative-sequence current

components, asymmetry among phase currents and a rising winding temperature. IoT systems address stator protection through per-phase current measurement, winding or frame temperature sensing and voltage unbalance monitoring; the short escalation time is a strong argument for retaining this protective function at the edge rather than in the cloud [2], [13].

B. Rotor Faults

Broken rotor bars and cracked end rings develop through thermal cycling, frequent direct-on-line starts and manufacturing defects. A broken bar modulates the air-gap field and imprints characteristic sidebands around the supply frequency in the stator current spectrum, the classical target of MCSA [4], [27]. Rotor faults evolve slowly and rarely trip conventional relays until severe, which makes them an ideal subject for the trend-oriented analytics of IoT platforms: a system that logs spectral features over months can flag the gradual sideband growth long before torque pulsation and vibration become destructive [25], [26].

C. Bearing Faults

Bearing defects, the single most common failure mode, progress from microscopic subsurface fatigue through spalls on the races, balls or cage to eventual seizure [20]. Their earliest observable symptoms are high-frequency vibration components at characteristic defect frequencies determined by the bearing geometry and speed, followed by rising acoustic emission, temperature and finally current-borne signatures. MEMS accelerometers costing a few dollars have brought vibration-based bearing monitoring within reach of low-cost IoT nodes, although their bandwidth and noise floor remain inferior to piezoelectric transducers, a limitation discussed in Section V [45], [24]. Vibration severity limits standardised in ISO 20816 provide widely used thresholds for alarm and trip levels [52].

D. Supply-Side and Thermal Abnormalities

Many motor failures are provoked from outside the machine. Undervoltage increases slip and stator current for a given load; overvoltage stresses insulation; single-phasing, the loss of one supply phase, forces the remaining phases to carry heavily unbalanced currents and is a notorious killer of rural pump motors; voltage unbalance of even a few percent produces a disproportionate negative-sequence heating effect; and harmonics from nearby converters add further losses [11]. Sustained overload and impaired cooling raise winding temperature, and every ten-degree rise above the insulation class rating roughly halves insulation life [17]. These conditions are exactly the ones that inexpensive voltage, current and temperature sensors detect reliably, which explains why supply-side and thermal protection dominates the low-cost IoT literature [31], [8].

E. Mechanical and Environmental Faults

Air-gap eccentricity, shaft misalignment, coupling wear, soft foot and load-induced torque oscillations complete the fault inventory. Eccentricity produces its own family of current and vibration signatures and, if uncorrected, culminates in rotor-stator rub [3]. Environmental factors such as moisture ingress, dust accumulation on cooling fins and corrosive atmospheres accelerate several failure mechanisms simultaneously; humidity sensing therefore appears in a number of surveyed systems as an inexpensive proxy for environmental stress [9]. A protection system aspiring to comprehensive coverage must consequently fuse several sensing modalities, since no single measurement reveals every fault class, a conclusion reached repeatedly across the surveyed literature [13], [21].

V. SENSOR TECHNOLOGIES

The perception layer determines the ceiling of any protection system: faults whose signatures are never measured can never be detected. The surveyed literature draws on a remarkably consistent palette of sensors, largely because the maker-grade ecosystem around Arduino-compatible and ESP32 controllers has standardised a set of inexpensive, well-documented devices [7], [45]. Table 2 compares the principal options; the subsections below discuss each parameter in turn.

A. Current Sensing

Current is the single most information-rich electrical quantity, carrying overload, single-phasing, unbalance, stall and, through its spectrum, rotor and eccentricity signatures [4]. Low-cost systems overwhelmingly employ the ACS712 family of Hall-effect sensors, which provide galvanic isolation and a simple analogue output but suffer from temperature drift and a modest signal-to-noise ratio, or split-core current transformers such as the SCT-013 series, which clamp around a conductor without interrupting the circuit and suit retrofit installations [31], [8]. Industrial-grade systems favour conventional protection-class current transformers or Rogowski coils feeding dedicated metering front ends. For MCSA-oriented systems the effective sampling

rate and resolution of the analogue-to-digital conversion matter as much as the sensor itself, since sideband components may lie forty decibels or more below the fundamental [27].

B. Voltage Sensing

Voltage measurement enables detection of undervoltage, overvoltage, phase loss and unbalance. The ZMPT101B miniature voltage transformer module dominates the low-cost literature because it delivers an isolated, scaled replica of the mains waveform directly to a microcontroller analogue input [9]. Resistive dividers are cheaper still but sacrifice isolation, an unattractive trade-off in systems that human operators will handle. Three-phase installations require one sensing channel per phase if unbalance and phase-sequence conditions are to be evaluated properly, a point on which several single-channel published prototypes fall short [11].

C. Temperature Sensing

Thermal protection remains the most direct guard against insulation loss of life [17]. Contact sensors span the LM35 and DS18B20 semiconductor devices, the DHT11 and DHT22 combined temperature-humidity modules, and industrial PT100 resistance thermometers; the DS18B20 is particularly popular because its one-wire bus allows several probes, for example one per bearing and one on the frame, to share a single microcontroller pin [9]. Non-contact alternatives, chiefly the MLX90614 infrared thermometer and low-resolution thermal cameras, avoid mechanical attachment and can observe rotating parts; thermal imaging additionally supports spatial diagnosis, as demonstrated in the edge-processed explainable system of Piechocki et al. [41] and the thermography study of Glowacz [53]. The chief limitation of all surface measurements is the thermal lag between the winding hot spot and the accessible measurement point, which protection settings must anticipate.

D. Vibration and Speed Sensing

Vibration sensing is indispensable for bearing and mechanical fault coverage. MEMS accelerometers such as the ADXL345, ADXL335 and the MPU6050 inertial unit are essentially free at the scale of an IoT node, but their usable bandwidth of a few kilohertz and comparatively high noise floor restrict them to detecting moderately advanced defects; piezoelectric IEPE accelerometers extend the bandwidth by an order of magnitude at an order-of-magnitude higher price [45], [39]. Several surveyed works therefore position MEMS sensing as a screening layer that escalates suspicious machines to precision measurement [32]. Speed is measured with infrared or Hall-effect tachometer pickups or incremental encoders and supports slip estimation, stall detection and normalisation of vibration signatures against operating point [8]. Acoustic sensing with electret microphones offers a non-contact alternative that has proven surprisingly effective when paired with learned classifiers [23].

Table 2. Comparison of sensor technologies for IoT-based motor protection

Parameter	Representative devices	Typical interface	Indicative cost	Strengths	Limitations
Current	ACS712, SCT-013 split-core CT, protection-class CT, Rogowski coil	Analogue / metering IC	Very low to moderate	Richest single diagnostic signal; enables MCSA, overload, unbalance and stall detection	Hall devices drift with temperature; MCSA needs high-quality sampling
Voltage	ZMPT101B module, potential transformer, resistive divider	Analogue	Very low	Detects under/over-voltage, phase loss, unbalance; isolated modules available	Per-phase channels needed for unbalance; dividers lack isolation
Temperature (contact)	LM35, DS18B20, DHT11/DHT22, PT100, NTC, thermocouple	Analogue / 1-Wire / digital	Very low to low	Direct guard on insulation life; multi-point probing on one bus (DS18B20)	Surface lag behind winding hot spot; DHT-class accuracy is modest
Temperature (non-contact)	MLX90614 IR thermometer, low-resolution thermal camera	I2C / SPI / camera	Low to high	Observes rotating parts; imaging supports spatial and explainable diagnosis	Emissivity calibration; cameras raise cost and processing load

Parameter	Representative devices	Typical interface	Indicative cost	Strengths	Limitations
Vibration	ADXL335, ADXL345, MPU6050 (MEMS); IEPE piezoelectric accelerometer	Analogue / I2C / IEPE	Very low (MEMS) to high (IEPE)	Earliest indicator of bearing and mechanical faults; ISO severity limits available	MEMS bandwidth and noise floor limit incipient-defect detection
Speed	IR / Hall tachometer pickup, incremental encoder	Digital pulse	Very low to moderate	Supports slip estimation, stall detection and signature normalisation	Requires shaft access or target marking
Acoustic	Electret microphone, MEMS microphone, ultrasonic sensor	Analogue / I2S	Very low	Non-contact; effective with learned classifiers	Sensitive to plant background noise
Flux / other	Search coil, Hall flux probe; humidity (DHT22)	Analogue / digital	Low	Flux aids eccentricity and inter-turn detection; humidity proxies environment	Flux probes need installation expertise; indirect indicators only

Two cross-cutting observations emerge from Table 2. First, sensor cost is no longer the limiting factor in protection system design; the engineering effort has migrated to signal conditioning, sampling strategy and data quality. Second, the sensors themselves fail, drift and detach, and remarkably few surveyed systems monitor sensor health, an omission that undermines trust in unattended protection and that Sanchez et al. begin to address with dedicated sensor-fault classifiers [28].

VI. COMMUNICATION TECHNOLOGIES

The network layer must reconcile four competing demands: sufficient throughput for the chosen sensing strategy, latency compatible with the protection philosophy, power consumption compatible with the node's energy budget, and range compatible with the plant geography [49]. Table 3 compares the technologies encountered in the surveyed literature.

Wi-Fi is by a wide margin the most frequently used medium, primarily because it is integrated at zero marginal cost into the ESP32 and ESP8266 controllers that dominate prototype construction [7]. It offers megabit-class throughput that comfortably carries raw waveform snapshots, but its power draw effectively mandates mains supply, and enterprise plant networks frequently quarantine ad hoc Wi-Fi devices for security reasons [54]. Bluetooth Low Energy serves short-range commissioning and local readout roles, and Zigbee retains a niche in mesh-topology retrofits where many machines share one gateway [45].

Low-power wide-area networks alter the deployment economics for dispersed assets. LoRaWAN provides kilometre-scale range at milliwatt transmit power, at the price of duty-cycle limits and a payload of a few hundred bytes, which forces the node to transmit features rather than waveforms and thus couples naturally to edge processing [55], [46]. NB-IoT offers comparable energy characteristics with licensed-spectrum reliability and operator-managed infrastructure, attractive where private gateways are impractical [56]. Cellular 4G falls back as the default for isolated pump stations, and early 5G deployments promise the combination of high bandwidth and low latency that would allow even trip-critical traffic to traverse the network, although no surveyed motor protection system yet exploits ultra-reliable low-latency communication in production [49]. Wired fieldbuses, chiefly Modbus RTU over RS-485 and industrial Ethernet, remain the reference solution inside panels and continue to carry a substantial share of real deployments, IoT gateways then bridging the fieldbus to the cloud [32].

Above the physical layer, MQTT has become the de facto application protocol of the surveyed systems owing to its publish-subscribe decoupling, small header overhead and quality-of-service tiers; HTTP REST interfaces persist mainly because entry-level cloud platforms expose them, and CoAP appears occasionally in constrained-node research [50]. A recurring weakness is that a large fraction of published prototypes

transmit unencrypted payloads with static credentials, leaving both the telemetry and, more seriously, the trip path open to interference; transport layer security and device identity management are treated as optional extras rather than protection requirements [54].

Table 3. Comparison of communication technologies used in IoT motor protection systems

Technology	Typical range	Data rate	Power demand	Latency class	Suitability for motor protection
Wi-Fi (802.11)	Tens of metres indoor	Tens to hundreds of Mbps	High (mains supply assumed)	Low (tens of ms)	Default for prototypes; carries raw waveforms; enterprise security constraints apply
Bluetooth Low Energy	Up to ~50 m	Up to ~2 Mbps	Very low	Low	Commissioning, local readout and ultra-low-power nodes; limited backhaul role
Zigbee (802.15.4)	10-100 m, mesh extendable	Up to 250 kbps	Low	Moderate	Many-node retrofits sharing one gateway; modest throughput
LoRaWAN	2-15 km	0.3-50 kbps	Very low	High (seconds; duty-cycled)	Dispersed assets such as pump sets; forces feature-level (edge-processed) payloads
NB-IoT	Cellular coverage	Tens to ~250 kbps	Very low	Moderate to high	Operator-managed alternative to private LPWAN; licensed-band reliability
4G / 5G cellular	Cellular coverage	Mbps to Gbps	Moderate to high	Low (5G URLLC very low)	Isolated sites; 5G promises trip-grade latency but is not yet exploited in the literature
Modbus RTU / industrial Ethernet	Panel and plant wiring	kbps to Gbps	Wired supply	Very low, deterministic	Reference for in-panel links; gateways bridge fieldbus data to the cloud

VII. CLOUD PLATFORMS

The cloud layer converts streams of measurements into retained knowledge and user-facing services. The platforms adopted in the surveyed literature divide into education-and-prototype oriented services, open-source self-hosted stacks and hyperscale commercial platforms; Table 4 summarises their characteristics. ThingSpeak occupies a singular position in the academic literature: its free tier, native MATLAB analytics and channel-based data model make it the default destination for university prototypes, and a substantial fraction of all published ESP32-based motor monitors terminate in a ThingSpeak dashboard [57], [31]. Blynk complements it on the mobile side, providing drag-and-drop smartphone interfaces and push notifications with negligible programming effort. Both, however, impose update-rate and retention limits that preclude waveform-resolution logging, and neither offers protection-grade guarantees on message delivery [9]. At the industrial end, AWS IoT Core and Azure IoT Hub provide authenticated device fleets, rule engines, serverless processing and integration with managed machine learning services; Pierleoni et al. benchmarked the leading hyperscale platforms and found broadly comparable performance with differing pricing and

ecosystem trade-offs [51]. Google's first-party IoT device service has been retired, its workloads migrating to partner solutions, a reminder that platform longevity is itself a design risk. Between the extremes, open-source stacks, most prominently ThingsBoard and combinations of an MQTT broker with InfluxDB and Grafana, offer self-hosted deployments that keep data on premises, an increasingly common requirement where production data are commercially sensitive [32], [10]. Ubidots and Adafruit IO serve the small-commercial niche with modest subscription pricing.

Across all platforms, three functional gaps recur in the motor protection context. Retention policies on free tiers silently discard exactly the long-baseline data that prognostics require; alert latency is specified loosely, if at all, making cloud-issued trips unsuitable as primary protection; and analytics offerings stop at generic anomaly detection, leaving motor-specific interpretation, fault frequency extraction, severity grading, remaining-life estimation, to the system designer [42], [36]. These gaps reinforce the architectural conclusion of Section III: the cloud excels as the predictive and supervisory tier of a protection system, not as its reflexive core.

Table 4. Comparison of IoT cloud platforms adopted for motor monitoring

Platform	Category	Protocols	Analytics support	Alerting	Cost model	Suitability
ThingSpeak	Prototype / academic	HTTP REST, MQTT	Native MATLAB analysis and visualisation	ThingHTTP / React triggers	Free tier; paid licences	Dominant in academic prototypes; update-rate and retention limits
Blynk	Prototype / mobile-first	Proprietary over TCP, HTTP	Basic widgets and automations	Push notifications, e-mail	Freemium subscription	Rapid smartphone dashboards for small deployments
AWS IoT Core	Hyperscale industrial	MQTT(S), HTTPS	Rules engine; managed ML services	SNS, Lambda-driven actions	Pay-as-you-go	Authenticated fleets and serverless analytics at scale
Azure IoT Hub	Hyperscale industrial	MQTT(S), AMQP, HTTPS	Stream Analytics; Azure ML	Event Grid, Logic Apps	Tiered pay-as-you-go	Deep enterprise and digital-twin integration
ThingsBoard	Open-source / self-hosted	MQTT, CoAP, HTTP	Rule chains; dashboards	Configurable alarms	Free CE; paid PE	On-premises data ownership; sensitive production data
MQTT broker + InfluxDB + Grafana	Open-source stack	MQTT	Time-series queries; plugins	Grafana alerting	Free (self-managed)	Flexible research-grade stack; requires administration
Ubidots / Adafruit IO	Small commercial / education	MQTT, HTTP	Dashboards; simple rules	SMS, e-mail, webhooks	Freemium subscription	Small commercial pilots and teaching deployments

VIII. COMPARATIVE ANALYSIS OF EXISTING SYSTEMS

Viewed collectively, the systems of Table 1 trace a clear evolutionary arc, which Fig. 3 summarises as a thematic timeline. Work published around 2020 concentrates on demonstrating feasibility: single-board nodes, threshold logic, Wi-Fi backhaul and free dashboards [32], [31]. Between roughly 2021 and 2023 the centre of gravity moves to analytics, with cloud-hosted machine learning applied to accumulated telemetry [8], [9], and with MQTT displacing HTTP as the transport idiom [50]. From 2023 onward the dominant themes become edge intelligence and resource-constrained learning, TinyML classifiers executing on the

sensing node itself [38], [39], [40], alongside growing attention to interoperability, explainability and security [41], [54]. The most recent literature gestures toward federated learning across motor fleets and digital-twin-assisted protection [48], [58].

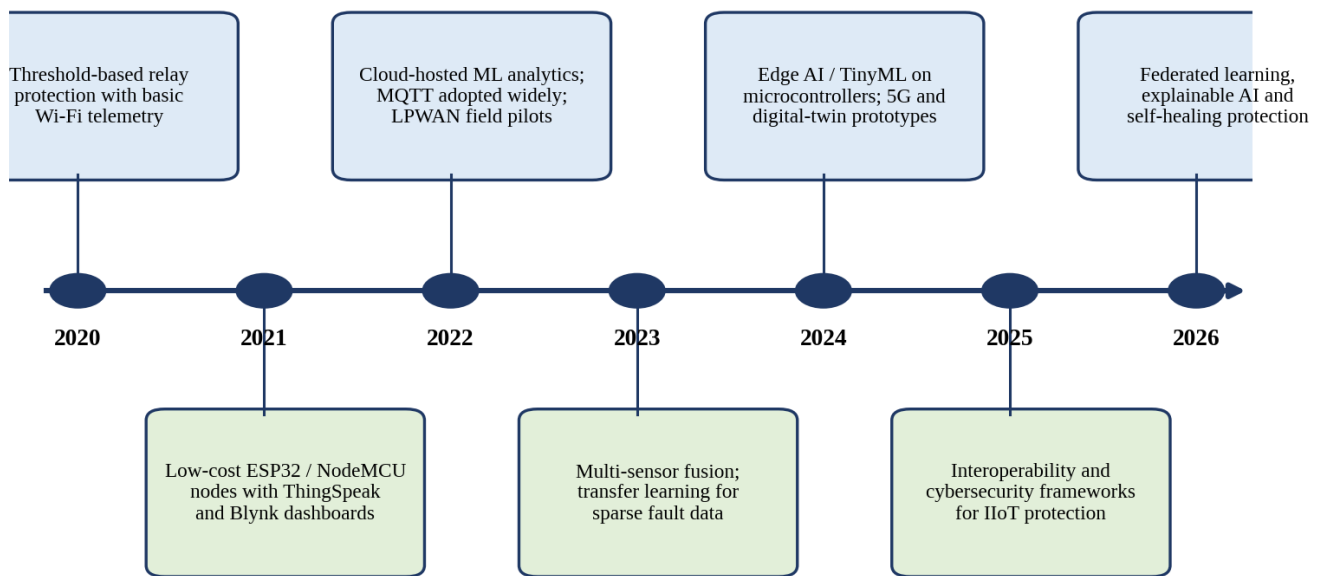


Figure 3. Research trend and thematic evolution of IoT motor protection (2020-2026)

Several quantitative contrasts sharpen this picture. In sensing, roughly three quarters of the surveyed prototype systems measure current and temperature, about half add vibration, and only a minority measure all electrical phases or any flux quantity, which bounds their fault coverage as analysed in Section IV. In processing, threshold logic remains the trip mechanism even in most systems that apply machine learning for diagnosis, the learned model advising the human rather than driving the contactor; only the edge-intelligent minority closes the loop automatically [35]. In communication, Wi-Fi plus MQTT accounts for the majority of implementations, with LPWAN confined to dispersed-asset studies [46]. In evaluation methodology, laboratory rigs with artificially seeded faults dominate; longitudinal industrial validation of the kind reported by Elkateb et al. [10] and Achouch et al. [33] remains exceptional, and no two studies share a common benchmark, motor size or fault protocol, which frustrates numerical comparison of claimed accuracies [30]. The comparative reading also clarifies complementary strengths. Threshold-based edge systems are unmatched in simplicity, determinism and independence from connectivity, and they remain the correct choice for the reflexive protection tier. Cloud-analytic systems contribute fleet-level learning, long-baseline trending and integration with maintenance workflows. Edge-AI systems promise the best of both, local intelligence with global learning, but presently carry the heaviest engineering burden in model development, deployment and lifecycle management [37], [29]. A mature protection architecture therefore layers these paradigms rather than choosing among them.

IX. RESEARCH GAPS

Notwithstanding the volume and vigour of the literature, substantive gaps separate the published state of the art from dependable, widely deployable IoT motor protection. Table 5 consolidates the principal gaps together with their present status and promising remedies; the discussion below elaborates the most consequential of them.

First, standardisation and interoperability are essentially absent. Each research group assembles its own combination of sensors, payload formats, dashboards and alert semantics, so that no two systems interoperate and no component is replaceable without redesign [49]. Second, cybersecurity is systematically neglected: prototypes routinely expose unencrypted MQTT topics and hard-coded credentials, despite the fact that a protection system is by definition capable of switching plant equipment and is therefore an attack surface of consequence [54]. Third, the sensor layer itself lacks supervision; drift, detachment and failure of low-cost transducers can silently blind a protection system or provoke spurious trips, and systematic sensor-health monitoring of the kind initiated by Sanchez et al. [28] is rare. Fourth, the community lacks shared

benchmarks: publicly available datasets cover isolated fault types on isolated machines [30], and there exists no reference testbed on which competing IoT protection systems could be evaluated under identical faults, loads and network conditions, leaving reported accuracy figures incomparable [21].

Fifth, genuine prediction remains scarce. Most deployed analytics detect present abnormality rather than estimating remaining useful life, and the transfer of prognostic models trained on laboratory rigs to heterogeneous field motors is largely unsolved, notwithstanding advances in transfer learning [29], [15]. Sixth, the energy autonomy of sensing nodes is under-explored; battery replacement at scale erodes the economic case, while energy harvesting from the motor's own vibration and thermal gradients has yet to move beyond demonstrations [39]. Seventh, trip-path latency and dependability are rarely quantified: publications report diagnostic accuracy but seldom the end-to-end time from fault inception to contactor opening, nor behaviour under network degradation, precisely the figures a protection engineer requires [34]. Finally, explainability and operator trust receive little attention; a maintenance technician asked to act on a neural network's verdict deserves an interpretable justification, a need that early explainable AI work is only beginning to address [41], [59].

Table 5. Research gap analysis for IoT-based induction motor protection

Gap area	Current status in literature	Consequence	Suggested direction
Standardisation and interoperability	Ad hoc payloads, dashboards and hardware per study	Systems and components are not portable or comparable	Open payload schemas and reference architectures
Cybersecurity of the protection path	Unencrypted transport and static credentials common	Telemetry and trip commands exposed to interference	TLS, per-device identity and signed firmware by default
Sensor health supervision	Low-cost sensors deployed without self-diagnosis	Silent blinding or spurious trips of the protection system	Sensor-fault classifiers and redundancy-based validation
Shared benchmarks and datasets	Isolated rigs; incomparable accuracy claims	Progress cannot be measured across studies	Community testbeds; multi-fault, multi-machine open datasets
True prognostics	Detection dominates; little remaining-life estimation	Maintenance remains reactive or scheduled	Physics-informed and transfer-learned prognostic models
Edge-cloud trip latency quantification	Diagnostic accuracy reported; trip timing rarely measured	Protection-grade dependability cannot be certified	End-to-end latency and degraded-mode benchmarking
Energy autonomy of nodes	Mains or battery supply assumed	Battery logistics erode economic case at scale	Vibration and thermal energy harvesting integration
Explainability and operator trust	Black-box classifiers with little justification	Technicians hesitate to act on model verdicts	Explainable AI and severity-graded reporting
Model lifecycle management	One-off training; no drift handling	Accuracy decays as machines and loads change	Continual, federated and self-supervised adaptation
Scalability evidence	Single-motor prototypes dominate	Fleet-level behaviour unknown	Longitudinal multi-site industrial deployments

X. FUTURE RESEARCH DIRECTIONS

The trajectory of the field, together with the gaps just enumerated, suggests a coherent research agenda, which Fig. 4 organises as a phased roadmap supported by cross-cutting enablers.

In the near term, the most valuable contributions are consolidating rather than novel: reference hardware designs with self-diagnosing sensor front ends, open payload schemas that make motor telemetry portable across platforms, and secure-by-default firmware in which transport layer security, per-device identity and signed updates are the baseline rather than the exception [54], [49]. Community benchmark testbeds and

expanded public datasets covering multiple fault families, machine sizes and network conditions would permit the reproducible comparison that the field presently lacks [30].

In the short-to-medium term, edge intelligence will deepen. Advances in TinyML compression, quantisation and neural-architecture search are steadily raising the sophistication of models that fit within microcontroller memory budgets, pointing toward nodes that perform full spectral diagnosis locally and transmit only conclusions [37], [40]. Unsupervised and self-supervised approaches that learn each motor's individual healthy baseline, as demonstrated by Antonini et al. [38], sidestep the scarcity of labelled fault data that hampers supervised deployment. Transfer learning and domain adaptation will be central to moving models trained on laboratory rigs onto the heterogeneous installed base [29]. Federated learning offers a complementary path: motor fleets distributed across sites can jointly improve a shared diagnostic model without centralising commercially sensitive raw data [48].

In the medium-to-long term, digital twins promise to close the loop between measurement and physics. A continuously updated electro-thermo-mechanical model of each machine would allow observed signatures to be interpreted against simulated fault scenarios, severity to be graded quantitatively and protection settings to be adapted to the machine's actual condition [58]. Coupling twin-based prognostics with maintenance optimisation of the kind explored through deep reinforcement learning [36] points toward self-scheduling maintenance ecosystems. The eventual horizon is self-healing protection: systems that not only disconnect a faulted machine but reconfigure the process around it, coordinate with smart-grid energy management, and, for converter-fed machines, actively mitigate certain faults through control action. Throughout, four enablers cut across every phase: cybersecurity engineered into the trip path, interoperability through open standards, energy-autonomous sensing that harvests its power from the monitored machine [39], and explainable, trustworthy analytics whose reasoning an operator can audit [59]. Progress on these fronts will determine whether IoT motor protection matures from a fertile research topic into critical infrastructure.

Evolution roadmap for IoT-based induction motor protection

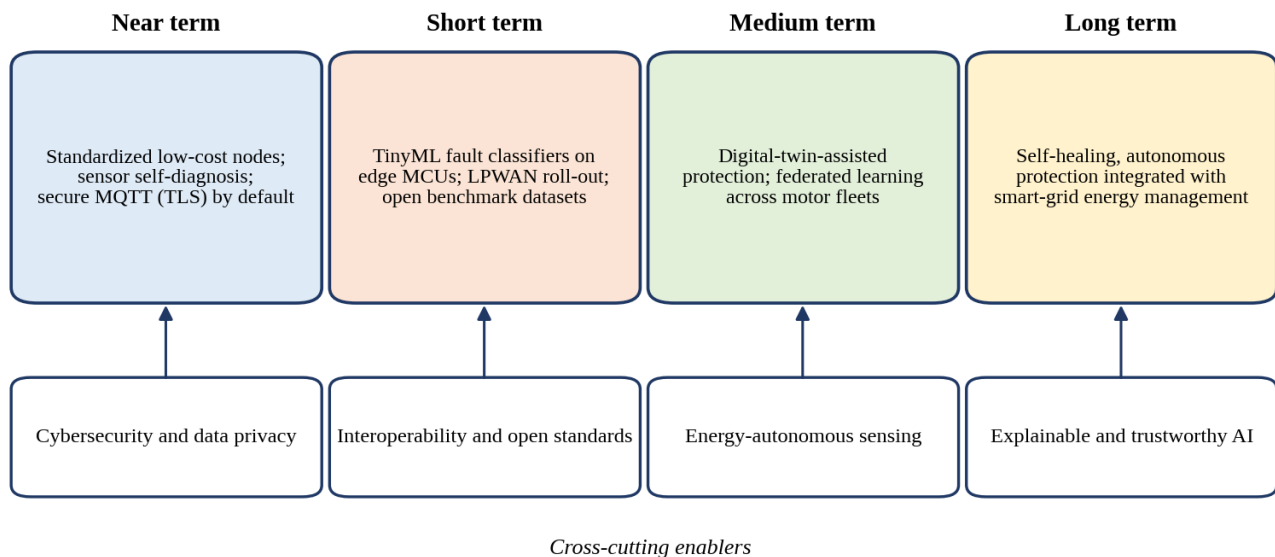


Figure 4. Future roadmap for IoT-based induction motor protection

XI. CONCLUSION

This review has surveyed the state of IoT-based induction motor protection across more than thirty published systems and methods, organising the field through a taxonomy of sensing, processing, communication and response choices and through a generic four-layer architecture that most reported systems instantiate. The comparative analysis shows a field that has progressed rapidly from threshold-based Wi-Fi telemetry demonstrations to edge-intelligent architectures in which machine learning models execute on the sensing node itself, while cloud platforms have settled into a supervisory and predictive role for which they are well suited. Low-cost smart sensors have removed the historical price barrier to comprehensive motor monitoring, and mature messaging protocols and cloud services have made system assembly accessible far beyond the specialist protection community.

At the same time, the review has identified persistent shortfalls, in standardisation, cybersecurity, sensor health supervision, shared benchmarks, genuine prognostics, energy autonomy, quantified trip-path dependability and explainability, that presently separate research prototypes from protection-grade infrastructure. The proposed roadmap argues that the next phase of the field will be defined less by novel dashboards than by consolidation: secure, interoperable, self-monitoring nodes; reproducible evaluation; and the fusion of edge intelligence with fleet-level learning and digital-twin physics. Researchers and practitioners who address these gaps will convert the demonstrated promise of IoT-based protection into dependable, economically compelling systems capable of guarding the machines on which industry runs.

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REFERENCES

- [1] A. H. Bonnett and C. Yung, "Increased efficiency versus increased reliability," *IEEE Industry Applications Magazine*, vol. 14, no. 1, pp. 29-36, Jan.-Feb. 2008.
- [2] S. B. Lee, G. C. Stone, J. Antonino-Daviu, K. N. Gyftakis, E. G. Strangas, P. Maussion, and C. A. Platero, "Condition monitoring of industrial electric machines: State of the art and future challenges," *IEEE Industrial Electronics Magazine*, vol. 14, no. 4, pp. 158-167, Dec. 2020.
- [3] 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, Dec. 2005.
- [4] W. T. Thomson and M. Fenger, "Current signature analysis to detect induction motor faults," *IEEE Industry Applications Magazine*, vol. 7, no. 4, pp. 26-34, Jul.-Aug. 2001.
- [5] 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, Oct. 2000.
- [6] 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 and Tutorials*, vol. 17, no. 4, pp. 2347-2376, 2015.
- [7] A. Maier, A. Sharp, and Y. Vagapov, "Comparative analysis and practical implementation of the ESP32 microcontroller module for the Internet of Things," in *Proc. Internet Technologies and Applications (ITA)*, Wrexham, UK, 2017, pp. 143-148.
- [8] M. Q. Tran, M. Elsis, K. Mahmoud, M. K. Liu, M. Lehtonen, and M. M. F. Darwish, "Experimental setup for online fault diagnosis of induction machines via promising IoT and machine learning: Towards Industry 4.0 empowerment," *IEEE Access*, vol. 9, pp. 115429-115441, 2021.
- [9] M. Cakir, M. A. Guvenc, and S. Mistikoglu, "The experimental application of popular machine learning algorithms on predictive maintenance and the design of IIoT based condition monitoring system," *Computers and Industrial Engineering*, vol. 151, p. 106948, Jan. 2021.
- [10] S. Elkateb, A. Metwalli, A. Shendy, and A. E. B. Abu-Elanien, "Machine learning and IoT based predictive maintenance approach for industrial applications," *Alexandria Engineering Journal*, vol. 88, pp. 298-309, Feb. 2024.
- [11] P. Gangsar and R. Tiwari, "Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review," *Mechanical Systems and Signal Processing*, vol. 144, p. 106908, Oct. 2020.
- [12] A. Choudhary, D. Goyal, S. L. Shimi, and A. Akula, "Condition monitoring and fault diagnosis of induction motors: A review," *Archives of Computational Methods in Engineering*, vol. 26, no. 5, pp. 1221-1238, 2019.
- [13] R. R. Kumar, M. Andriollo, G. Cirrincione, M. Cirrincione, and A. Tortella, "A comprehensive review of conventional and intelligence-based approaches for the fault diagnosis and condition monitoring of induction motors," *Energies*, vol. 15, no. 23, p. 8938, Nov. 2022.
- [14] P. Kumar and A. S. Hati, "Review on machine learning algorithm based fault detection in induction motors," *Archives of Computational Methods in Engineering*, vol. 28, no. 3, pp. 1929-1940, 2021.
- [15] M. Drakaki, Y. L. Karnavas, I. A. Tzifafettas, V. Linardos, and P. Tzionas, "Machine learning and deep learning based methods toward Industry 4.0 predictive maintenance in induction motors: State of the art survey," *Journal of Industrial Engineering and Management*, vol. 15, no. 1, pp. 31-57, 2022.

- [16] Motor Reliability Working Group, "Report of large motor reliability survey of industrial and commercial installations, Part I," IEEE Transactions on Industry Applications, vol. IA-21, no. 4, pp. 853-864, Jul. 1985.
- [17] G. C. Stone, I. Culbert, E. A. Boulter, and H. Dhirani, *Electrical Insulation for Rotating Machines: Design, Evaluation, Aging, Testing, and Repair*, 2nd ed. Hoboken, NJ, USA: Wiley-IEEE Press, 2014.
- [18] D. K. Soother and J. Daudpoto, "A brief review of condition monitoring techniques for the induction motor," Transactions of the Canadian Society for Mechanical Engineering, vol. 43, no. 4, pp. 499-508, 2019.
- [19] J. Antonino-Daviu, "Electrical monitoring under transient conditions: A new paradigm in electric motors predictive maintenance," Applied Sciences, vol. 10, no. 17, p. 6137, Sep. 2020.
- [20] S. Zhang, S. Zhang, B. Wang, and T. G. Habetler, "Deep learning algorithms for bearing fault diagnostics - A comprehensive review," IEEE Access, vol. 8, pp. 29857-29881, 2020.
- [21] S. Qiu, X. Cui, Z. Ping, N. Shan, Z. Li, X. Bao, and X. Xu, "Deep learning techniques in intelligent fault diagnosis and prognosis for industrial systems: A review," Sensors, vol. 23, no. 3, p. 1305, Jan. 2023.
- [22] S. M. K. Zaman and X. Liang, "An effective induction motor fault diagnosis approach using graph-based semi-supervised learning," IEEE Access, vol. 9, pp. 7471-7482, 2021.
- [23] O. Yaman, "An automated faults classification method based on binary pattern and neighborhood component analysis using induction motor," Measurement, vol. 168, p. 108323, Jan. 2021.
- [24] S. Misra, S. Kumar, S. Sayyad, A. Bongale, P. Jadhav, K. Kotecha, A. Abraham, and L. A. Gabralla, "Fault detection in induction motor using time domain and spectral imaging-based transfer learning approach on vibration data," Sensors, vol. 22, no. 21, p. 8210, Oct. 2022.
- [25] A. Boushaba, S. Cauet, A. Chamroo, E. Etien, and L. Rambault, "Comparative study between physics-informed CNN and PCA in induction motor broken bars MCSA detection," Sensors, vol. 22, no. 23, p. 9494, Dec. 2022.
- [26] K. Barrera-Llana, J. Burriel-Valencia, A. Sapena-Bano, and J. Martinez-Roman, "A comparative analysis of deep learning convolutional neural network architectures for fault diagnosis of broken rotor bars in induction motors," Sensors, vol. 23, no. 19, p. 8196, Sep. 2023.
- [27] S. Halder, S. Bhat, D. Zychma, and P. Sowa, "Broken rotor bar fault diagnosis techniques based on motor current signature analysis for induction motor - A review," Energies, vol. 15, no. 22, p. 8569, Nov. 2022.
- [28] O. D. Sanchez, G. Martinez-Soltero, J. G. Alvarez, and A. Y. Alanis, "Real-time neural classifiers for sensor faults in three phase induction motors," IEEE Access, vol. 11, pp. 19657-19668, 2023.
- [29] W. Li, R. Huang, J. Li, Y. Liao, Z. Chen, G. He, R. Yan, and K. Gryllias, "A perspective survey on deep transfer learning for fault diagnosis in industrial scenarios: Theories, applications and challenges," Mechanical Systems and Signal Processing, vol. 167, p. 108487, Mar. 2022.
- [30] A. E. Treml, R. A. Flauzino, M. Suetake, and N. A. R. Maciejewski, "Experimental database for detecting and diagnosing rotor broken bar in a three-phase induction motor," IEEE DataPort, 2020, doi: 10.21227/fmm-bn95.
- [31] M. Sen and B. Kul, "IoT-based wireless induction motor monitoring," in Proc. XXVI International Scientific Conference Electronics (ET), Sozopol, Bulgaria, 2017, pp. 1-5.
- [32] L. Magadan, F. J. Suarez, J. C. Granda, and D. F. Garcia, "Low-cost real-time monitoring of electric motors for the Industry 4.0," Procedia Manufacturing, vol. 42, pp. 393-398, 2020.
- [33] M. Achouch, M. Dimitrova, R. Dhouib, H. Ibrahim, M. Adda, S. Sattarpanah Karganroudi, K. Ziane, and A. Aminzadeh, "Predictive maintenance and fault monitoring enabled by machine learning: Experimental analysis of a TA-48 multistage centrifugal plant compressor," Applied Sciences, vol. 13, no. 3, p. 1790, Jan. 2023.
- [34] T. Hafeez, L. Xu, and G. McArdle, "Edge intelligence for data handling and predictive maintenance in IIOT," IEEE Access, vol. 9, pp. 49355-49371, 2021.
- [35] W. Yu, Y. Liu, T. Dillon, and W. Rahayu, "Edge computing-assisted IoT framework with an autoencoder for fault detection in manufacturing predictive maintenance," IEEE Transactions on Industrial Informatics, vol. 19, no. 4, pp. 5701-5710, Apr. 2023.
- [36] K. S. H. Ong, W. Wang, D. Niyato, and T. Friedrichs, "Deep-reinforcement-learning-based predictive maintenance model for effective resource management in industrial IoT," IEEE Internet of Things Journal, vol. 9, no. 7, pp. 5173-5188, Apr. 2022.

- [37] L. Dutta and S. Bharali, "TinyML meets IoT: A comprehensive survey," *Internet of Things*, vol. 16, p. 100461, Dec. 2021.
- [38] M. Antonini, M. Pincheira, M. Vecchio, and F. Antonelli, "An adaptable and unsupervised TinyML anomaly detection system for extreme industrial environments," *Sensors*, vol. 23, no. 4, p. 2344, Feb. 2023.
- [39] M. Giordano, N. Baumann, M. Crabolu, R. Fischer, G. Bellusci, and M. Magno, "Design and performance evaluation of an ultralow-power smart IoT device with embedded TinyML for asset activity monitoring," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1-11, 2022.
- [40] S. O. Ooko and S. M. Karume, "Application of tiny machine learning in predicative maintenance in industries," *Journal of Computing Theories and Applications*, vol. 2, no. 1, pp. 131-150, 2024.
- [41] M. Piechocki, T. Pajchrowski, and M. Kraft, "Unraveling induction motor state through thermal imaging and edge processing: A step towards explainable fault diagnosis," *Eksploracja i Niezawodnosc - Maintenance and Reliability*, vol. 25, no. 3, 2023.
- [42] T. Zonta, C. A. da Costa, R. da Rosa Righi, M. J. de Lima, E. S. da Trindade, and G. P. Li, "Predictive maintenance in the Industry 4.0: A systematic literature review," *Computers and Industrial Engineering*, vol. 150, p. 106889, Dec. 2020.
- [43] R. S. Peres, X. Jia, J. Lee, K. Sun, A. W. Colombo, and J. Barata, "Industrial artificial intelligence in Industry 4.0 - Systematic review, challenges and outlook," *IEEE Access*, vol. 8, pp. 220121-220139, 2020.
- [44] M. W. Hoffmann, S. Wildermuth, R. Gitzel, A. Boyaci, J. Gebhardt, H. Kaul, I. Amihai, B. Forg, M. Suriyah, T. Leibfried, V. Stich, J. Hicking, M. Bremer, L. Kaminski, D. Beverungen, P. zur Heiden, and T. Tornede, "Integration of novel sensors and machine learning for predictive maintenance in medium voltage switchgear to enable the energy and mobility revolutions," *Sensors*, vol. 20, no. 7, p. 2099, Apr. 2020.
- [45] M. A. Jamshed, K. Ali, Q. H. Abbasi, M. A. Imran, and M. Ur-Rehman, "Challenges, applications, and future of wireless sensors in Internet of Things: A review," *IEEE Sensors Journal*, vol. 22, no. 6, pp. 5482-5494, Mar. 2022.
- [46] V. K. Sarker, J. P. Queralta, T. N. Gia, H. Tenhunen, and T. Westerlund, "A survey on LoRa for IoT: Integrating edge computing," in *Proc. 4th International Conference on Fog and Mobile Edge Computing (FMEC)*, Rome, Italy, 2019, pp. 295-300.
- [47] N. Bhole and S. Ghodke, "Motor current signature analysis for fault detection of induction machine - A review," in *Proc. 4th Biennial International Conference on Nascent Technologies in Engineering (ICNTE)*, Navi Mumbai, India, 2021, pp. 1-6.
- [48] W. Zhang, X. Li, H. Ma, Z. Luo, and X. Li, "Federated learning for machinery fault diagnosis with dynamic validation and self-supervision," *Knowledge-Based Systems*, vol. 213, p. 106679, Feb. 2021.
- [49] E. Sisinni, A. Saifullah, S. Han, U. Jennehag, and M. Gidlund, "Industrial Internet of Things: Challenges, opportunities, and directions," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 11, pp. 4724-4734, Nov. 2018.
- [50] N. Naik, "Choice of effective messaging protocols for IoT systems: MQTT, CoAP, AMQP and HTTP," in *Proc. IEEE International Systems Engineering Symposium (ISSE)*, Vienna, Austria, 2017, pp. 1-7.
- [51] P. Pierleoni, R. Concetti, A. Belli, and L. Palma, "Amazon, Google and Microsoft solutions for IoT: Architectures and a performance comparison," *IEEE Access*, vol. 8, pp. 5455-5470, 2020.
- [52] *Mechanical Vibration - Measurement and Evaluation of Machine Vibration - Part 1: General Guidelines*, ISO Standard 20816-1:2016, International Organization for Standardization, Geneva, Switzerland, 2016.
- [53] A. Glowacz, "Fault diagnosis of electric impact drills using thermal imaging," *Measurement*, vol. 171, p. 108815, Feb. 2021.
- [54] M. Serror, S. Hack, M. Henze, M. Schuba, and K. Wehrle, "Challenges and opportunities in securing the industrial Internet of Things," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 5, pp. 2985-2996, May 2021.
- [55] U. Raza, P. Kulkarni, and M. Sooriyabandara, "Low power wide area networks: An overview," *IEEE Communications Surveys and Tutorials*, vol. 19, no. 2, pp. 855-873, 2017.
- [56] Y. P. E. Wang, X. Lin, A. Adhikary, A. Grovlen, Y. Sui, Y. Blankenship, J. Bergman, and H. S. Razaghi, "A primer on 3GPP narrowband Internet of Things," *IEEE Communications Magazine*, vol. 55, no. 3, pp. 117-123, Mar. 2017.
- [57] S. Pasha, "ThingSpeak based sensing and monitoring system for IoT with MATLAB analysis," *International Journal of New Technology and Research*, vol. 2, no. 6, pp. 19-23, Jun. 2016.

[58] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital twin in industry: State-of-the-art," IEEE Transactions on Industrial Informatics, vol. 15, no. 4, pp. 2405-2415, Apr. 2019.

[59] R. Machlev, L. Heistrene, M. Perl, K. Y. Levy, J. Belikov, S. Mannor, and Y. Levron, "Explainable Artificial Intelligence (XAI) techniques for energy and power systems: Review, challenges and opportunities," Energy and AI, vol. 9, p. 100169, Aug. 2022.

