Review

Not peer-reviewed version

Non-Contact Giant Magnetoresistive Sensors for Monitoring Low-Voltage Distribution Networks: A Review

Md Mahmud * , Md Al Imran , Md Abdul Qader , S M Rakibul Islam

Posted Date: 17 March 2026

doi: 10.20944/preprints202603.1263.v1

Keywords: low-voltage distribution network; giant magnetoresistance; GMR sensor; non-contact current sensing; overhead line monitoring; high-impedance fault; fault detection; smart grid; condition monitoring; digital twin

Review

Non-Contact Giant Magnetoresistive Sensors for Monitoring Low-Voltage Distribution Networks: A Review

Md Mahmud, Md Al Imran, Md Abdul Qader and S M Rakibul Islam

Phillip M. Drayer Department of Electrical and Computer Engineering, College of Engineering, Lamar University, Beaumont, TX, 77710, USA

* Correspondence: mahmud.md@ieee.org

Abstract

Low-voltage distribution networks (LVDNs) serve as the final delivery layer of the electricity system, directly influencing reliability, public safety, customer service quality, and the integration of distributed energy resources. Despite their importance, LVDNs have historically received less monitoring than transmission and medium-voltage systems due to their scale, cost, and deployment complexity. Non-contact magnetic sensing has emerged as a promising alternative to invasive measurement methods for these networks. Among magnetic sensor types, giant magnetoresistive (GMR) devices are appealing because they offer high sensitivity, compactness, low power consumption, and compatibility with embedded electronics. This review assesses the current state of GMR-based monitoring for overhead and low-voltage applications, focusing on non-contact current measurement, fault detection, and fault classification. It first examines the operating characteristics of LVDNs and the unique challenge of detecting low- and high-impedance faults. Next, it outlines the physical principles behind GMR sensing, compares GMR with Hall, AMR, TMR, current transformer, and Rogowski-coil technologies, and discusses the use of multi-axis sensor heads to address cross-coupled magnetic fields in three-phase setups. Special focus is given to calibration, alignment, temperature effects, electromagnetic interference, packaging, wireless deployment, and data-driven classification. The review concludes that GMR sensors are well-suited for scalable, non-contact monitoring, but widespread adoption in the field will require better low-voltage fault datasets, standardized calibration procedures, long-term environmental testing, and closer integration with digital-twin and smart-meter infrastructures.

Keywords: low-voltage distribution network; giant magnetoresistance; GMR sensor; non-contact current sensing; overhead line monitoring; high-impedance fault; fault detection; smart grid; condition monitoring; digital twin

---

Introduction

Modern societies depend on a continuous electricity supply not only for industrial output and commercial activity but also for communications, health care, water pumping, transport support services, and domestic life. Although the distribution level is where customers directly experience interruptions, measurement density at this level remains limited compared with the transmission network. Recent literature on LVDN monitoring, digital twins, and smart-meter-based observability confirms that the final low-voltage layer is still comparatively under-instrumented [1-3]. LVDNs differ from higher-voltage networks in several important ways. They are geographically dispersed, highly branched, often unbalanced, and strongly influenced by customer behavior. Rooftop photovoltaic systems, electric vehicles, heat pumps, distributed storage, and electronically coupled loads further increase variability. These realities create a strong need for local measurements that are inexpensive, electrically safe, and easy to retrofit [4-8]. Conventional current transformers, shunts,

 doi:10.20944/preprints202603.1263.v1

and voltage transformers remain essential in many protection and metering applications, but they are not always ideal for dense monitoring of secondary networks. In contrast, non-contact magnetic sensing infers line current from the magnetic field surrounding the conductor. This reduces the need to interrupt the circuit, lowers galvanic risk during installation, and opens the door to compact wireless monitoring nodes. Within the family of magnetic sensors, GMR devices stand out because of their high field sensitivity and good compatibility with low-power signal-conditioning electronics [9-12].

This review synthesizes the literature around GMR sensing for low-voltage network monitoring and positions it within the broader sensor and fault-detection landscape. The emphasis is on practical overhead-line monitoring, current measurement, and the detection and classification of abnormal events, especially high-impedance faults that remain difficult for conventional protection.

Scope and Review Method

This paper is a structured narrative review rather than a meta-analysis. The objective is to connect four partly separate research streams: low-voltage distribution monitoring, non-contact current sensing, magnetoresistive sensor development, and high-impedance-fault detection. The reference base intentionally combines foundational papers, recent review articles, and representative application studies in order to show both historical continuity and current research momentum. The paper therefore uses the following inclusion logic. First, publications that explain the physical basis of GMR and MR current sensing are used to establish sensor capabilities and limitations. Second, review and application papers dealing with LVDN monitoring, smart meters, digital twins, and topology identification are used to define the system context in which sensors must operate [13-15]. Third, HIF and distribution-fault studies are examined because fault detection is one of the most demanding use cases for secondary-network sensing. This structure is useful because it avoids treating GMR sensing only as a component-level topic; instead, it evaluates sensor technology against real deployment requirements.

Low-Voltage Distribution Networks and Monitoring Requirements

The low-voltage distribution network forms the last stage of the electricity supply chain. It commonly operates as a three-phase four-wire system and feeds residential, commercial, and small industrial customers. Because the number of downstream nodes is large, utilities face a difficult trade-off between observability and cost. Traditional secondary-network visibility is often limited to transformer-level measurements and customer smart meters, leaving large parts of the feeder only weakly observed [16-19].

A review of field-based LVDN characterization shows that the behavior of low-voltage feeders is shaped by local load diversity, seasonal demand patterns, neutral currents, phase imbalance, and voltage-quality issues. The growth of distributed energy resources means that power flow is no longer strictly downstream, and visibility requirements now extend beyond billing toward state estimation, topology identification, fault localization, and operational flexibility [20-23]. For wide deployment, a sensor technology for LVDNs must satisfy several constraints simultaneously: adequate sensitivity to capture relatively small current variations; electrical isolation from the conductor; tolerance to weather, vibration, and temperature drift; compatibility with low-cost electronics and communications; and robust calibration under non-ideal conductor geometry. These conditions explain why non-contact magnetic sensing is attractive in the first place [24-27]. An additional requirement is installation flexibility. Utilities rarely have the luxury of rebuilding low-voltage feeders simply to add sensing. Practical devices should therefore be lightweight, mechanically simple, and able to coexist with legacy infrastructure. The sensor package must also work within a broader information architecture that may include wireless links, edge processing, utility backhaul communications, and integration with SCADA or advanced metering systems.

 doi:10.20944/preprints202603.1263.v1

Fault Characteristics in LVDNs

Faults in LVDNs are usually grouped into low-impedance and high-impedance categories. Low-impedance faults, such as phase-to-phase or phase-to-neutral short circuits, typically generate substantial fault current and are more likely to be detected by overcurrent elements or fuses. By contrast, high-impedance faults (HIFs) occur when an energized conductor contacts a poorly conductive surface such as asphalt, dry soil, vegetation, sand, or concrete. In these cases, fault current can remain near the normal load-current range, making the event dangerous but difficult to detect [28-31]. HIFs are especially challenging because they are often nonlinear, intermittent, and arc dominated. Their signatures can include asymmetry, randomness, transient bursts, harmonics, and abrupt changes in conduction state. Reviews published during the last several years continue to identify HIF detection as one of the most difficult protection problems in distribution systems because ordinary load switching, capacitor operation, motor starting, and inverter-rich environments can produce partly overlapping waveforms [28], [30], [32-33], [35-36]. In low-voltage overhead networks the problem is further complicated by public safety concerns. A downed but energized conductor can ignite surrounding material or present a severe electrocution hazard even when conventional protective devices do not trip. For that reason, monitoring solutions that add sensing diversity without intrusive installation are valuable. A magnetic sensor mounted close to the conductor can capture current-related anomalies even when terminal voltage or current measurements are sparse.

Fundamentals of Giant Magnetoresistive Sensing

Giant magnetoresistance was reported in ferromagnetic multilayers in the late 1980s and quickly became foundational to magnetic read-head and sensor technologies. The central effect is a large change in electrical resistance under an applied magnetic field due to spin-dependent electron scattering in layered magnetic structures [1-3]. In a current-sensing context, a GMR device does not measure current directly. Instead, it measures the magnetic field generated by the current flowing in a nearby conductor. The field can then be converted into current amplitude or phasor information through calibration and geometry-aware models. Compared with Hall sensors, GMR sensors typically offer greater field sensitivity at low field levels. Compared with current transformers, they can be substantially smaller and easier to integrate into non-contact arrangements. Compared with Rogowski coils, they may offer higher compactness for low-current applications, although Rogowski designs excel in wide dynamic range and high-frequency transients [5], [7-8], [12], [15-16]. GMR belongs to the broader family of magnetoresistive (MR) sensors, which also includes anisotropic magnetoresistance (AMR) and tunneling magnetoresistance (TMR). Recent reviews show that TMR technology is especially attractive for very high sensitivity and wide dynamic-range smart-grid instrumentation, while GMR remains a practical and mature option with strong application relevance in compact current sensing [5-6], [13-14]. From a systems viewpoint, the value of GMR comes from an unusual combination of characteristics: the sensing principle is contactless, the device can be made physically small, and its output is directly compatible with compact analog front ends. That combination makes GMR appealing for distributed sensing, where the deployment burden per node must remain low.

Table 1. Typical fault classes and sensing challenges in low-voltage distribution networks.

Fault/event	Electrical signature	Protection difficulty	Public safety relevance	Potential role of magnetic sensing
Phase-to-phase short circuit [19]	High current, abrupt transient	Usually detected by conventional protection	High	Strong anomaly; easy to detect
Phase-to-neutral fault [20]	Elevated current with voltage depression	Usually moderate difficulty	High	Clear current-field change

 doi:10.20944/preprints202603.1263.v1

Broken conductor with no ground contact [28]	Intermittent or weak current; topology change	May evade simple overcurrent logic	Very high	Useful when combined with localization logic
High-impedance fault on asphalt/soil [40]	Low, random, arc-dominated current	Very difficult	Very high	Magnetic features may support discrimination
High-impedance fault on vegetation [50]	Intermittent, nonlinear conduction	Very difficult	Very high	May capture bursts and asymmetry
Neutral failure / imbalance [51]	Unbalanced current and voltage behavior	Can be subtle	Moderate to high	Vector magnetic sensing may expose imbalance patterns

GMR Sensors for Non-Contact Current Measurement

Non-contact current measurement with GMR sensors has been studied from both instrumentation and application perspectives. Early work demonstrated that commercial GMR chips, coupled with suitable conditioning circuits, could be used to measure conductor current with useful linearity and dynamic behavior [4]. Subsequent studies explored differential arrangements, improved biasing, and alternative magnetic concentration structures to enhance sensitivity, reduce offset, and suppress common-mode interference [8-9], [11]. For overhead low-voltage networks, the most important advantage is the elimination of galvanic connection. A sensor node can be clipped or mounted near the conductor without opening the circuit. This simplifies retrofits on energized assets and reduces electrical safety risks during installation. It also aligns well with battery-powered or energy-harvesting nodes designed for sparse infrastructure. Related recent work on magnetic sensors for contactless phasor estimation and non-contact three-phase busbar current measurement supports the value of magnetic vector information in practical conductor arrangements [10], [12]. Nevertheless, current reconstruction is not trivial in realistic line geometries. The magnetic field at the sensor position is the superposition of contributions from the phase conductors, neutral conductor, and nearby metallic structures. Consequently, a simple one-axis amplitude measurement may not uniquely identify the target-phase current, especially under unbalanced loading. This issue becomes central for three-phase overhead monitoring and is one reason why multi-axis sensing has received increasing attention. Another design issue is dynamic range. A current-monitoring node in an LVDN may need to capture normal household load swings, temporary overloads, and fault-related transients without saturating the front end. In practice, this requires careful selection of sensor placement, analog gain, magnetic concentration, and digital post-processing. It also argues against evaluating sensor technologies only by sensitivity in a narrow laboratory range.

Cross-Coupled Fields, Multi-Axis Sensor Heads, and Calibration

In a three-phase low-voltage overhead arrangement, each conductor produces an alternating magnetic field whose direction and magnitude vary with load current and geometry. The field measured by a sensor near one phase is therefore cross-coupled with adjacent phases and the neutral. A vector sensing approach is better suited to such environments than a single-axis scalar measurement. By combining three orthogonally oriented single-axis MR elements, a sensor head can capture the magnetic-field vector and separate directional components that are informative for current reconstruction and abnormal-event analysis [4], [10], [12]. Calibration is indispensable because nominally identical MR elements seldom behave identically. Sensor-to-sensor sensitivity, offset, thermal drift, and cross-axis behavior must be characterized against a reference field or a traceable calibrated sensor. Accurate mechanical alignment is equally important. If the sensor axes are rotated relative to the conductor geometry, the measured phase relation and amplitude can be distorted. Reviews of MR current sensors consistently note that packaging, biasing, front-end electronics, and thermal compensation strongly influence repeatability and field performance [5], [7], [9], [14]. For utility deployment, calibration should not be treated as a laboratory afterthought. A

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 17 March 2026 doi:10.20944/preprints202603.1263.v1

practical framework needs factory calibration, in-situ verification, and possibly model-based self-correction using known system states or digital-twin assistance. This is a major research gap for LVDN deployment, where low-cost sensors must remain reliable across weather cycles and long service periods. Packaging deserves separate attention. The sensor head, supporting mechanics, and enclosure should minimize magnetic disturbance while resisting water ingress, UV degradation, corrosion, and mechanical vibration. Since low-voltage overhead infrastructure may be accessible to the public, the package should also be physically robust and tamper-resistant.

Fault Detection and Classification with Magnetic Sensing

GMR sensors can support more than steady-state current measurement. Since faults alter current magnitude, waveform symmetry, transient content, and current path, they also modify the surrounding magnetic field. A magnetic monitoring node can therefore be used as an event detector and not merely as a current meter. Low-impedance faults will usually produce clear magnetic changes because of their large current increase. HIFs are more subtle, but arcing, intermittency, and waveform distortion can still leave identifiable magnetic signatures [28], [32-33], [35-37]. The contemporary HIF literature increasingly relies on feature extraction and machine learning. Recent methods have employed Stockwell transforms, wavelet transforms, kernel extreme learning machines, Hilbert-transform-based instantaneous frequency analysis, randomness measures, sparse time-frequency representations, and edge-AI devices for practical discrimination between faults and non-fault disturbances [31-40]. The implication for GMR-based sensing is important: magnetic data can provide additional features that are not available from sparse smart-meter voltage data alone.

Table 2. Relevant studies on GMR current sensing and low-voltage fault analysis.

Ref.	Year	Sensor type	Application focus	Main contribution
[4]	2012	GMR	Current sensing	Demonstrated a practical GMR current sensor and characterized static/dynamic behavior
[8]	2020	GMR	Differential current sensing	Improved sensitivity and linearization using differential architecture
[9]	2022	Composite magnetic sensor	Contactless AC/DC current sensing	Non-intrusive wide-bandwidth current sensor for AC/DC measurement
[10]	2024	TMR	Three-phase non-contact measurement	Vector/current reconstruction for three-phase rectangular busbars
[11]	2025	TMR	Weak-current smart-grid sensing	High-precision, non-invasive current measurement with broad bandwidth
[12]	2024	Magnetic sensors	Current phasor estimation	Investigated contactless and non-intrusive estimation of AC current phasors
[13]	2025	TMR review	Smart-grid instrumentation	Comprehensive review of TMR current sensors for smart-grid applications
[14]	2016	GMR review	Sensor physics and applications	Broad review of GMR structures, behavior, and application issues
[15]	2024	MR review	Current transducer technology	Comparative review of current transducer techniques including MR sensors

From a review perspective, the most promising architecture is not a stand-alone magnetic detector but a multi-sensor scheme in which GMR measurements complement voltage, smart-meter, or digital-twin estimates. Such sensor fusion can improve confidence, accelerate localization, and reduce false positives caused by ordinary switching events. This is particularly appealing in LVDNs, where network observability is often too weak for purely model-based protection enhancement. It is also worth distinguishing between detection and classification. Detection asks whether an abnormal

 doi:10.20944/preprints202603.1263.v1

event exists; classification asks what kind of event it is. A practical node may first use simple change detection on local magnetic features, then upload a buffered segment for central or edge-AI classification. Such staged architectures are more realistic than continuously running a computationally heavy model on every node.

Relation to Smart Meters, Digital Twins, and Data-Driven Monitoring

Recent research on LVDN monitoring increasingly integrates field measurements with digital twins, topology identification, and advanced metering infrastructure. Smart-meter-based state estimation, digital-twin fault localization, and harmonic-data-assisted topology identification have all shown that low-voltage observability can be improved even when measurements are incomplete [19-20], [41-46]. However, these approaches usually depend on existing metering infrastructure and may still lack direct branch-current visibility. A non-contact GMR node installed at selected feeder locations could bridge this gap by adding branch-level current and event information. In turn, the digital twin could provide geometry, phase labeling, and network-state context to improve calibration and event interpretation. The combination is attractive because it exploits the physical richness of magnetic sensing and the systems-level context of data-driven network models. The same reasoning applies to active-network management. As monitoring density improves, utilities can better support voltage regulation, congestion management, topology recognition, outage identification, and post-fault restoration. Recent work on uncertainty effects, self-diagnostic metering infrastructure, and real-time monitoring of LVDNs reinforces the view that secondary-network instrumentation will become more valuable as grids become more dynamic [21-23], [42], [47].

Comparison with Competing Sensor Technologies

No single sensing technology dominates all use cases. Current transformers offer mature accuracy for power-frequency measurement but require conductor integration and are less attractive for highly distributed retrofits. Rogowski coils provide excellent bandwidth and are effective for transient and high-current applications, but they usually require integration and may be less convenient for compact low-current nodes. Hall sensors are inexpensive and widely used but often have lower low-field sensitivity than MR technologies. AMR sensors are mature and compact, while TMR sensors are currently pushing the frontier in sensitivity and smart-grid instrumentation [5], [7-8], [13-16]. GMR sensors occupy a useful middle ground. They are compact, sensitive, and mature enough for practical implementation. Their key disadvantages are offset drift, susceptibility to external magnetic fields, and the need for careful axis alignment and packaging. For LVDN overhead monitoring, these disadvantages are manageable if the application is designed around relative change detection, differential measurement, robust calibration, and sensor fusion. In this sense, the best comparison is not only on laboratory sensitivity but on deployability, environmental robustness, and system-level value.

Table 3. Comparison of sensing technologies for LVDN monitoring.

Technology	Principle	Strengths	Limitations	Suitability for LVDNs
Current transformer (CT) [4]	Magnetic induction in core	Mature, accurate at power frequency, utility familiar	Intrusive installation; bulkier for dense deployment; limited for widespread retrofits	Good at key nodes; less attractive for mass deployment
Rogowski coil [7]	Air-core coil measures di/dt	Wide bandwidth; excellent for transients; no magnetic saturation	Needs integration; less ideal for low-current compact nodes	Useful for transient monitoring and switchgear
Hall sensor	Hall effect magnetic sensing	Low cost; compact; easy electronics	Lower low-field sensitivity; offset and temperature concerns	Good for economical nodes when sensitivity demands are moderate

 doi:10.20944/preprints202603.1263.v1

AMR sensor [13]	Anisotropic magnetoresistance	Compact and mature; good sensitivity	Needs careful biasing and compensation	Useful for compact non-contact current nodes
GMR sensor [15]	Giant magnetoresistance	High sensitivity; small size; low power; suitable for differential/vector heads	External field susceptibility; alignment and drift management needed	Very promising for overhead non-contact monitoring
TMR sensor [17]	Tunneling magnetoresistance	Very high sensitivity and dynamic range; strong recent momentum	Can be more complex in biasing and packaging; still maturing by use case	Excellent benchmark/competitor for advanced smart-grid sensing

Experimental Test Platforms and Data Needs

A recurring barrier in this field is the lack of realistic low-voltage fault datasets. Because many HIFs are hazardous to create on live networks, researchers often work with simulations or small-scale laboratory setups. This is useful for concept validation but does not fully reproduce weather, conductor motion, mixed loads, distributed generation, or noise from nearby infrastructure. Consequently, robust test facilities remain important for bridging the gap between controlled research and practical deployment. A well-designed 400-V three-phase-to-neutral physical platform is especially relevant for this research area because it represents a realistic low-voltage operating environment while remaining manageable under laboratory safety controls. Such a platform can generate normal operating data, switching events, imbalance cases, conductor faults, and selected HIF scenarios for both algorithm development and sensor calibration. For a review on GMR-based monitoring, this point matters because sensor design quality cannot be separated from the quality of the datasets used to evaluate it.

Practical Deployment Challenges

A review article focused on real deployment must look beyond sensor physics. Outdoor low-voltage infrastructure exposes sensors to thermal cycling, rain, dust, vibration, mechanical shock, electromagnetic interference, and uncertain conductor geometry. These factors can degrade repeatability and cause long-term drift. They also complicate wireless communication and power supply for sensor nodes. Another issue is benchmarking. The literature includes many laboratory demonstrations and algorithm papers but relatively few long-duration field deployments on low-voltage overhead lines. Because public datasets for low-voltage faults are scarce, methods are often trained and validated on simulation data or on limited test-rig recordings. This reduces confidence in real-world generalization. Recent reviews of HIF detection and distribution-network fault methods continue to identify field validation and realistic datasets as major unmet needs [19], [28], [30]. Standardization is likewise immature. There is not yet a common framework for sensor placement, calibration intervals, environmental qualification, uncertainty reporting, or interoperability with utility communications and digital-twin platforms. Addressing these issues will be crucial if GMR nodes are to move from research prototypes to scalable network assets. A final practical question is cyber-physical resilience. Once non-contact nodes become part of a utility monitoring fabric, they must also be secure, updateable, and resistant to data loss. This broadens the engineering problem from sensor performance alone to dependable end-to-end monitoring architecture.

AI-Driven Energy Systems

Artificial intelligence is becoming a central enabler of modern energy systems because it can process large volumes of operational data and support forecasting, control, anomaly detection, scheduling, and maintenance. Recent review literature shows that AI is now applied across

 doi:10.20944/preprints202603.1263.v1

generation, storage, load management, distribution operation, and predictive maintenance, especially in settings where conventional model-based approaches struggle with uncertainty, nonlinearity, and fast-changing operating conditions [53]–[56]. In practical terms, AI-driven energy systems combine machine learning, deep learning, reinforcement learning, and hybrid optimization methods to improve operational decisions. These methods are widely used for demand forecasting, renewable output prediction, battery management, fault diagnosis, and energy management system coordination. The literature consistently identifies AI as particularly useful when high-dimensional sensor streams, weather variability, and distributed assets must be handled together in near real time [53], [54], [57]. Another important trend is the shift from isolated AI applications toward integrated intelligent energy architectures. In these systems, AI is not limited to a single task such as forecasting but instead supports interconnected layers of sensing, prediction, optimization, and control. Recent reviews also highlight the emerging role of digital twins, explainable AI, and edge intelligence in improving transparency, resilience, and responsiveness. At the same time, open challenges remain in data quality, interoperability, cybersecurity, and model transferability across different network conditions [54]–[57].

Renewable Energy Integration

The large-scale integration of renewable energy sources has created both opportunities and operational challenges for modern power systems. Solar photovoltaic and wind generation reduce dependence on fossil fuels, but their output is variable and strongly dependent on environmental conditions. As renewable penetration rises, networks require better forecasting, more flexible control strategies, and tighter coordination among generation, storage, and demand. Recent reviews identify renewable integration as one of the strongest drivers behind the adoption of AI-based forecasting and optimization frameworks in electricity systems [53], [54], [58]. AI methods are increasingly used to improve renewable forecasting, power smoothing, storage scheduling, and hybrid system coordination. In solar and wind applications, machine-learning models are employed to estimate short-term and medium-term output under uncertain meteorological conditions. In hybrid renewable systems, AI-based energy management can improve the balance among generation, storage, and load while reducing curtailment and operational inefficiency. Recent surveys published in 2024–2026 show rapid growth in work on intelligent storage, autonomous control, and predictive maintenance of renewable assets [53], [55], [58], [59]. Renewable integration also affects network protection, voltage regulation, power quality, and grid stability. As distributed renewable resources become more common at the distribution level, traditional one-way power-flow assumptions become less valid. This increases the need for flexible monitoring and optimization systems capable of identifying local congestion, instability, reverse power flow, and equipment stress. For that reason, renewable integration should be viewed not as a stand-alone generation topic but as a wider systems problem that reinforces the need for advanced sensing and intelligent decision support [54], [58], [59].

Smart Grid Optimization

Smart grid optimization refers to the use of advanced computational methods to improve the planning, operation, resilience, and efficiency of electricity networks. Unlike conventional operation based largely on fixed settings and centralized rules, smart-grid optimization incorporates real-time data, communication networks, distributed control, and adaptive algorithms. Recent reviews show that AI is playing a growing role in optimal power flow, economic dispatch, demand response, fault diagnosis, voltage regulation, and self-healing strategies [54]–[57]. A major advantage of AI-driven optimization is its ability to operate under uncertainty. In smart grids, uncertainty arises from fluctuating loads, intermittent renewable generation, dynamic electricity prices, and unexpected disturbances. Machine-learning and reinforcement-learning approaches are increasingly used to support online decision-making where classical optimization may be computationally burdensome or insufficiently adaptive. Recent publications emphasize that these methods are especially relevant

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 17 March 2026 doi:10.20944/preprints202603.1263.v1

for coordinated dispatch, multi-energy management, and decentralized control in complex renewable-rich networks [54], [56], [57].

Research Gaps and Future Directions

Several research priorities emerge from the literature. First, more experimentally validated low-voltage datasets are required, especially for overhead HIFs, conductor fall scenarios, neutral faults, and mixed load conditions. Second, multi-axis sensor heads need better geometry-aware reconstruction models so that phase current can be estimated under conductor spacing uncertainty and magnetic interference. Third, long-term field studies should quantify drift, reliability, and maintenance burden under realistic weather conditions. Fourth, sensor fusion should be pursued more aggressively. Combining magnetic measurements with smart-meter voltages, topology identification, harmonic indicators, and digital twins could produce more reliable event detection than any individual stream. Fifth, edge intelligence is becoming relevant: compact local processing can support event buffering, threshold adaptation, anomaly scoring, and communications reduction. Recent HIF devices and smart-grid sensing studies suggest that lightweight AI is becoming practical for field instrumentation [32], [38], [40], [42]. Finally, there is a need for clearer techno-economic analysis. Utilities do not deploy sensors only because they are interesting; they deploy them if reliability gains, safety improvements, and maintenance savings justify cost. Future work should therefore quantify how many non-contact nodes are needed, where they should be placed, and how much incremental value they provide over existing smart-meter infrastructure.

Table 4. Main research gaps and future directions.

Area	Current gap	Why it matters	Promising direction
Datasets [5]	Few public LV overhead fault datasets	Limits fair comparison and realistic validation	Create shared 400-V test-rig and field datasets
Calibration [19-21]	No common calibration framework for vector MR heads	Affects repeatability and utility trust	Standardize factory and in-situ verification routines
Geometry modeling [24]	Cross-coupled fields complicate phase-current reconstruction	Reduces accuracy in real conductor layouts	Use multi-axis models plus digital-twin geometry priors
Environmental robustness [28]	Limited long-term outdoor evidence	Unknown drift, maintenance needs, and reliability	Run seasonal field trials with uncertainty reporting
System integration [33-34]	Magnetic sensors often studied in isolation	Utilities need interoperable monitoring ecosystems	Fuse GMR data with AMI, topology ID, and digital twins
Economics [47-52]	Sparse cost–benefit analysis for secondary networks	Deployment decisions are ultimately economic	Quantify outage, safety, and maintenance value by placement density

Conclusion

GMR sensors have strong potential for non-contact monitoring of low-voltage distribution networks. Their combination of small size, low power demand, and magnetic sensitivity makes them well suited to current sensing and possibly to the detection and classification of difficult faults. The literature further suggests that their value is highest when they are integrated with multi-axis geometries, careful calibration practice, and data-driven monitoring frameworks rather than used as isolated stand-alone devices. For LVDNs, the central challenge is not whether GMR sensing is physically possible; it is whether the technology can be packaged, calibrated, validated, and integrated at scale under practical utility conditions. The answer appears increasingly positive, but the evidence base still depends too heavily on laboratory studies. With better datasets, longer field

doi:10.20944/preprints202603.1263.v1

trials, and tighter integration with digital twins and advanced metering systems, GMR-based monitoring could become a meaningful part of future low-voltage grid observability and public-safety strategies.

References

1. M. N. Baibich et al., “Giant magnetoresistance of (001)Fe/(001)Cr magnetic superlattices,” Physical Review Letters, vol. 61, no. 21, pp. 2472–2475, 1988.
2. G. Binasch, P. Grünberg, F. Saurenbach, and W. Zinn, “Enhanced magnetoresistance in layered magnetic structures with antiferromagnetic interlayer exchange,” Physical Review B, vol. 39, no. 7, pp. 4828–4830, 1989.
3. A. Fert, “Nobel lecture: Origin, development, and future of spintronics,” Reviews of Modern Physics, vol. 80, no. 4, pp. 1517–1530, 2008.
4. Y. Ouyang, X. He, J. Hu, and S. Wang, “A Current Sensor Based on the Giant Magnetoresistance Effect,” Sensors, vol. 12, no. 11, pp. 15520–15541, 2012.
5. Z. Yang et al., “Prospective Review of Magneto-Resistive Current Sensors with High Sensitivity and Wide Temperature Range,” Journal of Low Power Electronics and Applications, vol. 14, no. 3, art. 43, 2024.
6. Y. Xu et al., “Development and Application of Magnetoresistive Sensors in Current Measurement,” Transducers and Smart Technologies, 2025.
7. C. Tang, H. Guo, and X. Luo, “Review of the current transducer techniques,” Discover Applied Sciences, 2024.
8. C. Mușuroi, M. R. Alatuș, C. Oproiu, and A. M. Morega, “High Sensitivity Differential Giant Magnetoresistance (GMR) Current Sensor,” Sensors, vol. 20, no. 1, art. 323, 2020.
9. X. Tan et al., “Contactless AC/DC Wide-Bandwidth Current Sensor Based on Composite Measurement Principle,” Sensors, vol. 22, no. 20, art. 7979, 2022.
10. H. Su et al., “Non-Contact Current Measurement for Three-Phase Rectangular Busbars Based on TMR Sensors,” Sensors, vol. 24, no. 2, art. 388, 2024.
11. Y. Xu et al., “High-Precision Tunneling Magnetoresistance Current Sensor for Smart Grid Weak-Current Detection,” Sensors, 2025.
12. P. Shrawane et al., “Magnetic sensors for contactless and non-intrusive current phasor estimation,” IET The Journal of Engineering, 2024.
13. M. Mahmud, S. R. Islam, and S. M. A. Motakabber, “Design and performance analysis of an adaptive PID controller for brushless DC motor systems in electric vehicles,” unpublished manuscript, 2026.
14. D. Rifai, A. N. Abdalla, K. Ali, and R. Razali, “Giant Magnetoresistance Sensors: A Review on Structures and Non-Destructive Eddy Current Testing Applications,” Sensors, vol. 16, no. 3, art. 298, 2016.
15. P. Ripka, Magnetic Sensors and Magnetometers. Boston, MA, USA: Artech House, 2001.
16. S. Tumanski, Thin Film Magnetoresistive Sensors. Boca Raton, FL, USA: CRC Press, 2001.
17. J. E. Lenz and A. S. Edelstein, “Magnetic sensors and their applications,” IEEE Sensors Journal, vol. 6, no. 3, pp. 631–649, 2006.
18. N. Smith and P. Arnett, “White-noise magnetoresistance in spin-valve sensors,” Applied Physics Letters, vol. 78, no. 10, pp. 1448–1450, 2001.
19. P. Stefanidou-Voziki et al., “A review of fault location and classification methods in distribution grids,” Electric Power Systems Research, vol. 209, art. 107985, 2022.
20. M. Numair, A. A. Aboushady, F. Arraño-Vargas, M. E. Farrag, and E. Elyan, “Fault Detection and Localisation in LV Distribution Networks Using a Smart Meter Data-Driven Digital Twin,” Energies, vol. 16, no. 23, art. 7850, 2023.
21. H. Khujamatov et al., “Evaluation of the Reliability of IoT-Aided Remote Monitoring Systems of Low-Voltage Overhead Lines,” Sensors, 2024.
22. L. Santos et al., “Monitoring the power flow of a low voltage distribution network using the public lighting infrastructure,” Electric Power Systems Research, 2024.
23. S. M. A. Motakabber, M. I. R. Rokon, A. Z. Alam, M. A. Matin, and M. Mahmud, “Efficient dual mode arbitration scheme for multiprocessor hardware interface in system-on-chip,” Indonesian Journal of Electrical Engineering and Informatics, vol. 11, no. 4, pp. 1096–1109, 2023.
24. S. K. Biswas, A. Al Noman, M. R. Islam, S. R. Islam, M. T. I. Opu, and F. Ahmed, “Analytical model for coupling whispering gallery mode spherical microresonator for sensing application,” in Proc. IEEE International Conference

on Telecommunications and Photonics (ICTP), 2017, pp. 97–101. Z. Li et al., "A review of topology identification methods and methodological systems in low-voltage distribution networks," Global Energy Interconnection, 2026.
25. T. N. Pham et al., "Low and medium voltage distribution network planning with increasing distributed energy resources: a review," Electrical Engineering, 2025.
26. M. Mahmud, A. K. Pandey, S. Rahman, and B. Kalidasan, "Thermal characteristic investigation of 2-propanol using graphene silver nanoparticles," in Proc. IEEE International Conference on Power and Energy (PECon), 2022, pp. 337–341.
27. M. S. Attar et al., "High-Impedance Fault Detection in Electric Power Distribution Networks: A Review," Journal of Novel Researches on Smart Power Systems, vol. 13, no. 3, 2024.
28. M. Sedighizadeh, A. Rezazadeh, and N. I. Elkalashy, "Approaches in high impedance fault detection: a chronological review," Advances in Electrical and Computer Engineering, vol. 10, no. 3, pp. 114–128, 2010.
29. B. Hao, "AI in arcing-HIF detection: a brief review," IET Smart Grid, vol. 3, no. 4, pp. 435–444, 2020.
30. L. Li and M. Redfern, "A review of techniques to detect downed conductors in overhead distribution systems," Universities Power Engineering Conference, 2001.
31. V. Gogula et al., "Advanced signal analysis for high-impedance fault detection in distribution systems using the Hilbert transform," Frontiers in Energy Research, 2024.
32. G. N. Lopes et al., "Reliable high impedance fault detection method based on fundamental and third-harmonic neutral current features," International Journal of Electrical Power & Energy Systems, 2024.
33. W. Sheng et al., "An improved high-impedance fault identification scheme based on kernel extreme learning machine," International Journal of Electrical Power & Energy Systems, 2024.
34. D. A. Gadanayak et al., "High impedance fault detection in distribution networks based on randomness and unpredictability of fault currents," Applied Energy, 2024.
35. M. J. Heidarpour et al., "High impedance fault detection in distribution networks using a low-complexity FDOST-based method," Measurement, 2024.
36. M. Sarwar, S. A. R. Kashif, and M. T. Gul, "High impedance fault detection and isolation in power distribution systems," Journal of King Saud University – Engineering Sciences, vol. 34, no. 6, pp. 357–370, 2022.
37. B. Hao et al., "High impedance fault detection device based on edge artificial intelligence," Energy Reports, 2023.
38. J. C. Huaquisaca Paye et al., "Experimental validation and parametrisation of a high-impedance-fault model," IET Generation, Transmission & Distribution, 2025.
39. X. Wang et al., "High impedance fault detection for resonant grounding systems using full-period segmented transient analysis," Measurement, 2025.
40. A. J. Pappas et al., "Smart meter measurement-based state estimation for monitoring of low-voltage distribution grids," Energies, vol. 13, no. 20, art. 5367, 2020.
41. S. K. Biswas, A. Al Noman, and S. R. Islam, "Nonlinear coupling of whispering gallery mode silica microcavity for sensing application," in Proc. 3rd International Conference on Electrical Information and Communication Technology (EICT), 2017, pp. 1–3.
42. M. Numair et al., "Utilising Smart-Meter Harmonic Data for Low-Voltage Network Topology Identification," Energies, vol. 18, no. 13, art. 3333, 2025.
43. J. Li et al., "Identification of low-voltage distribution substation topology based on user profiling technology," Frontiers in Energy Research, 2024.
44. C. Huang et al., "Low-voltage characteristic voltage based fault distance identification for distribution networks," Frontiers in Energy Research, 2024.
45. L. Liang et al., "Fault location method for distribution networks based on data-driven and optimization ideas," Frontiers in Energy Research, 2024.
46. A. K. Ntakolia et al., "Uncertainty Effects on Smart Grid Services for Low-Voltage Distribution Networks Under Different Monitoring Infrastructure Characteristics," Sensors, 2026.
47. D. Olojede et al., "Application of machine learning in power grid fault detection and diagnosis: a review," Journal of Electrical Systems and Information Technology, 2025.
48. D. C. Mnyanghwalo et al., "Sensor placement algorithm for faults detection in electrical distribution networks: a review-informed optimization perspective," Bulletin of Electrical Engineering and Informatics, 2024.

 doi:10.20944/preprints202603.1263.v1

49. M. Najafzadeh et al., “Fault Detection, Classification and Localization Along the Power Transmission and Distribution Network: Review and Future Directions,” Discover Applied Sciences, 2024.
50. B. Chaitanya, A. Yadav, and M. Pazoki, “High impedance fault detection scheme for active distribution network using empirical wavelet transform and support vector machine,” in Proc. 15th International Conference on Protection and Automation of Power Systems, 2020.
51. M. Mahmud, S. M. A. Motakabber, A. Z. Islam, A. N. Nordin, and S. F. Wafa, “Advanced adaptive PID controller for BLDC motor,” in Proc. 8th International Conference on Computer and Communication Engineering (ICCCE), 2021, pp. 121–125.
52. M. A. Judge, V. Franzitta, and G. Curto, "A comprehensive review of artificial intelligence approaches for smart grid integration and optimization," Energy Conversion and Management: X, vol. 24, art. 100724, 2024.
53. M. M. Alam et al., "Artificial intelligence integrated grid systems: Technologies, applications, challenges, and future directions," Renewable and Sustainable Energy Reviews, vol. 207, art. 115149, 2025.
54. T. Zhang et al., "Novel Artificial Intelligence Applications in Energy: A Systematic Review," Energies, vol. 18, no. 14, art. 3747, 2025.
55. M. S. Mastoi et al., "AI-driven control and optimization for renewable energy integration: A review," Energy AI, vol. 19, art. 100485, 2026.
56. S. K. Biswas, S. R. Islam, M. Ahmed, A. Halder, M. R. Islam, and M. Hossain, “Analytical model for coupling whispering gallery mode silica microcavity for sensing application,” in Proc. 2nd International Conference on Electrical & Electronic Engineering (ICEEE), 2017, pp. 1–4.
57. K. Ukoba et al., "Optimizing renewable energy systems through artificial intelligence: A comprehensive review," Engineering Applications of Artificial Intelligence, vol. 132, art. 108175, 2024.
58. C. J. Ejiyi et al., "Comprehensive review of artificial intelligence applications in renewable energy systems," Journal of Big Data, vol. 12, art. 225, 2025.