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Utilizing Non-Contact GMR Sensors for Real-Time State Estimation of Aging Bulk Electric System Assets: A Strategy for Mitigating Failure Risks in Deteriorating Infrastructure

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Abstract

This study investigates the persistent problem of limited real-time visibility into the condition of aging bulk electric system assets, where conventional inspection-based monitoring often fails to detect deterioration early enough to prevent costly outages and reliability losses. The purpose of the research was to examine whether utilizing non-contact giant magnetoresistance (GMR) sensors can improve real-time state estimation and mitigate failure risks in deteriorating infrastructure through a quantitative, cross-sectional, case-based design. Data were collected from 214 technically qualified respondents representing clouded enterprise-style utility and infrastructure management cases, including transmission utilities, substation operations units, asset management departments, maintenance contractors, and reliability/planning divisions. The study assessed key variables comprising non-contact GMR sensor utilization, real-time state estimation capability, failure signal detectability, failure-risk mitigation, predictive maintenance support, asset reliability and operational continuity, and infrastructure risk prioritization, using a 5-point Likert instrument with high overall reliability (Cronbach's alpha = 0.87). The analysis plan combined descriptive statistics, reliability testing, Pearson correlation, simple regression, multiple regression, and ANOVA. Findings showed strong agreement across the major constructs, with mean scores of 4.18 for GMR sensor utilization, 4.24 for state estimation capability, 4.20 for failure-risk mitigation, and 4.22 for asset reliability and operational continuity. GMR sensor utilization had a strong positive relationship with real-time state estimation ($r = 0.740$, $p < .001$) and significantly predicted it ($\beta = 0.63$, $t = 11.42$, $R^2 = 0.548$, $p < .001$). Real-time state estimation significantly predicted failure-risk mitigation ($\beta = 0.58$, $t = 9.87$, $R^2 = 0.472$, $p < .001$), while the extended regression model explained 61.4% of the variance in failure-risk mitigation (Adjusted $R^2 = 0.614$, $F = 68.31$, $p < .001$). Critically deteriorating assets recorded the highest overall mean benefit (4.39), confirming that sensor-enabled monitoring becomes more valuable as asset aging severity increases. The study implies that non-contact GMR sensing can serve as a practical reliability-centered maintenance tool for prioritizing monitoring resources, strengthening predictive maintenance, and improving resilience in aging power infrastructure.

Keywords

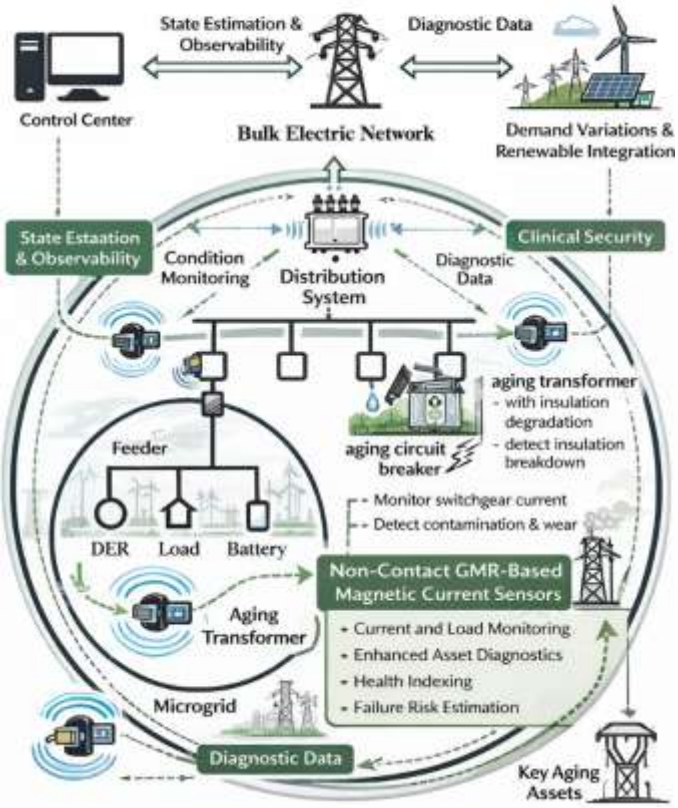
Non-Contact GMR Sensors; Real-Time State Estimation; Aging Bulk Electric Assets; Failure-Risk Mitigation; Predictive Maintenance;

INTRODUCTION

The bulk electric system refers to the interconnected network of high-voltage generation, transmission, substations, and control equipment that supports large-scale power transfer across regions and national boundaries, and its dependable operation rests on continuous awareness of voltage, current, power flow, and equipment condition. In power engineering, state estimation is the analytical process used to reconstruct the operating state of the network from available measurements, while condition monitoring denotes the structured observation of equipment health through diagnostic signals that reveal deterioration, stress, or incipient failure (Chan et al., 2013). Within this measurement landscape, giant magnetoresistance (GMR) denotes the large change in electrical resistance that occurs in multilayer magnetic structures when exposed to an external magnetic field, a property that enabled the development of compact, highly sensitive magnetic sensors suited to current and field measurement. Internationally, these definitions matter because modern grids are increasingly expected to deliver high reliability across aging infrastructure portfolios while supporting cross-border energy exchange, electrified transport, distributed generation, digital substations, and tighter operating margins. As current sensing lies at the heart of protection, supervision, asset diagnostics, and system observability, the evolution from bulky and often installation-intensive transducers toward compact contactless magnetic sensors has become technically and economically important (Ouyang et al., 2012). GMR-based devices are especially relevant because they combine galvanic isolation, miniaturization, sensitivity to weak magnetic fields, and compatibility with integrated electronics, allowing them to function as non-contact measurement elements in locations where conventional transformer-style sensors are difficult to deploy or too costly to scale widely. For aging bulk electric assets, this matters at an international level because utilities in mature power systems are operating transformers, breakers, busbars, and associated equipment for longer service lives while seeking more granular visibility into dynamic loading and stress histories (Quatrini et al., 2020). The present study emerges from that intersection: the need to define state estimation not only as a computational task for network operations, but also as an asset-centered, measurement-driven function that depends on reliable field data obtained without interrupting service or accelerating wear. In that sense, non-contact GMR sensing becomes more than a component technology; it becomes part of a wider infrastructure strategy for converting magnetic signatures into actionable knowledge about the operating state of deteriorating grid assets (Reig et al., 2009).

Aging in bulk electric infrastructure is not merely a chronological matter; it is a cumulative process in which thermal stress, electrical transients, insulation degradation, contamination, corrosion, vibration, and maintenance history progressively alter component reliability and raise the likelihood of failure. In reliability studies of electric power systems, aging has been shown to change failure behavior in ways that are not captured by models that treat all failures as random events with constant rates. Unavailability due to aging failures has been addressed analytically, with emphasis on the way end-of-life behavior changes the risk profile of power components, and related work on aging characteristics similarly reinforces that system reliability indices are affected when aging is explicitly modeled rather than ignored (Cubells-Beltrán et al., 2016). The broader distribution and reliability literature has also connected equipment aging with time-varying failure behavior, showing that failure rates evolve over operating life and environmental exposure rather than remaining static (Dabek et al., 2016). These findings are highly significant in international infrastructure contexts because many utilities operate legacy fleets of transformers and substation equipment that remain functionally critical even when their design assumptions belong to earlier eras of demand growth, loading practice, and monitoring capability. Power transformers are particularly important in this regard because they are costly, central, and difficult to replace rapidly; transformer failure can therefore create prolonged outages, cascading operational constraints, and large financial losses. Reviews of transformer diagnostics consistently identify asset aging and remaining-life uncertainty as central utility concerns, which is why condition assessment has become linked to health indexing, probability of failure estimation, and maintenance prioritization (Chen et al., 2020). When viewed through a system lens, the significance of aging extends beyond component replacement economics into security of supply, reserve margins, operational resilience, and the safe accommodation of network disturbances. The motivation for enhanced sensing in this study rests on that reliability problem: an aging asset population demands measurements that are timely, scalable, and physically non-intrusive enough to expand visibility without imposing additional operational burden. Contactless magnetic sensing fits that requirement because it can extract information from the electromagnetic fields already generated by current-carrying equipment, creating a pathway for richer state awareness in deteriorating infrastructure where conventional periodic inspection alone offers only intermittent evidence of asset health (Jogschies et al., 2015).

Figure 1: Conceptual Framework for Real-Time State Estimation of Aging Bulk Electric Assets Using Non-Contact GMR Sensors



The technological appeal of contactless current measurement has grown because electrical infrastructure increasingly requires sensors that can be deployed without breaking circuits, introducing insertion losses, or depending on large magnetic cores and complex insulation arrangements (Chowdhury et al., 2005). Reviews of current sensing techniques have long distinguished conventional current transformers, Hall sensors, fiber-optic sensors, Rogowski coils, fluxgates, and magnetoresistive devices according to sensitivity, bandwidth, isolation, size, and cost, with magnetoresistive approaches occupying a strong position where compactness and weak-field sensitivity are prioritized. Magnetoresistive devices, including GMR structures, gained prominence because they offered higher room-temperature sensitivity than Hall-based approaches and could be integrated with standard CMOS-compatible fabrication flows (Kim & Singh, 2010). This argument was reinforced in the smart-grid context through demonstrations that GMR current sensors can support distributed real-time monitoring while combining high linearity, compact size, and cost-effectiveness. One of the practical limitations of GMR sensing, namely narrow measurement range, was also addressed through work extending the usable current range with a counteracting magnetic field, showing how design refinement can adapt GMR sensors for more demanding electrical environments. Subsequent work broadened the field of contactless current transducers beyond a single device architecture (Ripka, 2010). A coreless electric current sensor with conductor-position calibration was investigated, a coreless current probe for conductors with reduced access was developed, and magnetic current transducers were reviewed with attention to linearity, crosstalk, and the challenge of external magnetic interference. Collectively, these studies established an international research direction in which current measurement is moving toward lighter, non-invasive, and electronically integrable platforms. That direction is directly relevant to the present study because aging bulk electric assets often occupy locations where retrofitting large instrument transformers is impractical, expensive, or operationally disruptive. A non-contact GMR sensor does not need to become part of the power path in the same way that inserted or wound measurement elements do; instead, it interprets the magnetic field associated with current flow (Sarkar et al., 2015). This physical distinction is important when the research objective concerns real-time state estimation of deteriorating infrastructure, because the measurement strategy itself should avoid adding mechanical complexity or service interruption to already vulnerable assets.

Within the family of contactless magnetic sensors, GMR devices are especially relevant to power-asset monitoring because their operation is tied to magnetic-field variations that mirror electrical current behavior, which makes them useful for observing loading conditions, transients, and fault-related anomalies. The literature from 2009 to 2020 shows a clear progression from foundational reviews toward increasingly application-oriented sensor architectures. GMR technology has been documented in electrical current sensing, and later studies have highlighted the capacity of GMR sensors to integrate with complementary technologies and miniaturized electronics, thereby improving practical deployment (Weiss et al., 2017). Galvanically isolated voltage and current measurements based on GMR have also been demonstrated, indicating that the technology can support measurement in systems where isolation and compactness are both critical. This integration logic was extended into standard CMOS-IC current sensing, which is significant for future grid instrumentation because asset-level monitoring increasingly depends on embedded, low-power electronics. At the same time, research addressed operational constraints that matter in real power environments. Quasi-static current measurement with field-modulated spin-valve GMR sensors showed that hysteresis and linear-range issues can be mitigated by modulation techniques, while wideband contactless current sensing using a magnetoresistor with a planar magnetic concentrator and tunneling magnetoresistance sensors for high-fidelity current-waveform monitoring expanded the range of practical device options. Studies on circular arrays and yokeless transducers further highlighted that sensor geometry, external-current influence, conductor permeability, and crosstalk all affect measurement quality, which is especially important in substations and other high-field environments where neighboring conductors and metallic structures distort local magnetic conditions. This body of work makes clear that the value of GMR sensing in electric infrastructure is not simply high sensitivity in isolation (Ripka & Chirtsov, 2017). Its value lies in the fact that engineering refinements have made contactless magnetic measurement increasingly practical, selective, and compatible with the signal-conditioning requirements of real monitoring systems. For a study centered on aging bulk electric assets, those characteristics support the logic that non-contact GMR sensing can be treated as a credible measurement front end for real-time state awareness rather than merely as an experimental laboratory technology (Ripka, 2019).

The state-estimation dimension of this study is grounded in the long-standing recognition that reliable power-system operation depends on the ability to infer network states from incomplete, noisy, and geographically distributed measurements. Classical state estimation in power systems was built around supervisory control and data acquisition measurements, while later developments expanded toward dynamic estimation, synchronized phasor measurements, and distributed observability. Access to synchronous-machine angle and speed variables has been shown to improve situational awareness and support both local and wide-area control, and extended Kalman filter formulations have demonstrated how phasor measurement data can be used to estimate dynamic states under realistic uncertainty (Xie et al., 2015). Work on dynamic estimation has also emphasized that real-time monitoring becomes increasingly important as systems grow larger and more interconnected, since operators need an updated picture of conditions during disturbances and changing load patterns. In parallel, PMU-placement literature has shown that the measurement architecture itself shapes the quality and feasibility of state estimation. A graph-theory-based methodology for PMU placement and multiarea state estimation has been developed, and PMU placement for measurement redundancy distribution under zero-injection and contingency considerations has further strengthened this measurement-design perspective (George & Gopalakrishna, 2017). These studies show that state estimation is never detached from measurement design; it depends on where, how, and how reliably the system is sensed. That principle aligns closely with asset-level monitoring because localized, physically deployable sensors can strengthen observability in places where system-level measurements remain sparse. For aging infrastructure, the significance is straightforward: deterioration often begins as subtle departures in electrical behavior, thermal loading, or stress response, and such departures can remain hidden when state estimation depends only on sparse network measurements or periodic inspection (Nibir & Parkhideh, 2018). A contactless sensor that captures current-related magnetic signatures near critical assets can enrich the data foundation of state estimation by adding high-resolution local evidence about actual operating stress. In that sense, the present research joins two traditions that are often treated separately: the state-estimation tradition focused on network observability and the condition-monitoring tradition focused on equipment health (Ghahremani & Kamwa, 2011). Bringing them together is central to this topic because aging bulk electric assets are not only components within a power system; they are also state-bearing objects whose magnetic and electrical behavior can reveal deterioration before outright failure occurs (Xie et al., 2020).

Power transformers and other major substation assets occupy a particularly important place in this discussion because condition monitoring at these nodes has long been recognized as essential for service continuity, reliability planning, and life extension. Reviews of condition-monitoring techniques and diagnostic tests for transformer lifetime estimation show that utilities depend on a wide range of methods, including dissolved gas analysis, dielectric assessment, partial-discharge monitoring, thermal tests, and mechanical diagnostics, precisely because no single method captures all aspects of aging (Islam et al., 2018; Jeng et al., 2019). Research on fiber Bragg grating sensors for high-voltage transformer monitoring has also noted the value of online condition monitoring in reducing unscheduled downtime. Transformer monitoring and protection have been discussed in the wider context of dynamic power systems, including both legacy low-frequency transformers and emerging architectures, with emphasis on the fact that transformer monitoring is inseparable from broader system dynamics. This literature demonstrates a fundamental point: critical grid assets are already monitored through multiple physical modalities because their failure modes are diverse and often cumulative (Xie et al., 2015; Xie & Li, 2009). Yet many established approaches are either periodic, intrusive, laboratory-oriented, or limited to particular fault mechanisms. That creates room for complementary sensing approaches that respond directly to electromagnetic behavior under operating conditions. Non-contact GMR sensors fit this niche because they measure magnetic fields associated with load current and disturbance behavior without requiring intrusive contact with high-voltage internals (Marcellis et al., 2017). Such a capability becomes particularly meaningful in aging infrastructure where loading histories, current imbalance, transient stress, and abnormal electromagnetic signatures may carry diagnostic value long before a conventional alarm threshold is crossed. The transformer-monitoring literature also intersects naturally with condition-based maintenance (Poon et al., 2013). The condition-based maintenance field has emphasized the organizational importance of reliable condition information for inspection, replacement, and prognostics. In practical terms, that means sensing technologies are valuable not only because they measure accurately, but because they change maintenance timing and maintenance confidence. For aging bulk electric assets, a contactless GMR-based measurement layer therefore connects operational state estimation with maintenance intelligence: the same sensor evidence that informs real-time awareness can also help characterize asset stress and prioritize interventions in deteriorating infrastructure portfolios (Xie et al., 2015).

Taken together, the literature establishes a strong intellectual basis for examining non-contact GMR sensing as a strategy for real-time state estimation of aging bulk electric system assets. One stream of research explains why electric infrastructure reliability deteriorates when aging behavior is ignored in modeling and maintenance prioritization (Yu et al., 2018). A second stream shows that magnetoresistive current sensors, including GMR-based devices, have matured from conceptual low-field sensors into integrated, isolated, wideband, and practically deployable measurement systems suitable for non-invasive current observation. A third stream demonstrates that state estimation depends fundamentally on the quality, location, and redundancy of measurements, which is why PMU-based and dynamic-estimation studies consistently focus on measurement architecture as a determinant of observability and control quality. A fourth stream confirms that high-value assets such as transformers require continuous or near-continuous monitoring because aging, insulation stress, and abnormal electrical conditions accumulate over time and create operational risk long before catastrophic failure becomes visible in routine inspection records (Ziegler et al., 2009). What emerges from these streams is a clear research rationale for this study: aging bulk electric infrastructure requires measurement strategies that are scalable, contactless, and analytically meaningful at both the asset and system levels (Ghahremani & Jeyasurya, 2015). GMR sensors are relevant because they can transform local magnetic-field behavior into electrical signals suitable for monitoring, while state estimation is relevant because it turns measurements into an interpretable representation of the operating condition of the network and its assets. The present research is therefore situated at the convergence of sensing science, power-system observability, asset aging, and failure-risk mitigation (Mirzaei et al., 2018). Its introduction rests on the proposition that real-time state estimation for deteriorating infrastructure gains credibility when it is supported by physically non-intrusive, measurement-rich technologies whose performance characteristics have already been explored across current sensing, magnetic transduction, and intelligent monitoring studies between 2005 and 2020.

Background of the Study

The background of this study is rooted in the growing operational challenge posed by aging bulk electric system assets and the increasing need for more precise, real-time methods of monitoring their condition. Bulk electric systems form the backbone of modern power infrastructure by transmitting and distributing electricity across large geographic regions through interconnected components such as power transformers, substations, circuit breakers, busbars, and transmission equipment. Many of these assets have remained in service far beyond their originally intended design life, which has made infrastructure deterioration a major concern for utilities, regulators, and energy planners. As assets age, they become more vulnerable to insulation breakdown, thermal stress, magnetic irregularities, overload effects, corrosion, and mechanical wear, all of which increase the probability of sudden equipment failure and large-scale service disruption. In many power networks, traditional maintenance practices still rely heavily on scheduled inspections, offline diagnostics, and delayed fault reporting, which often provide only limited visibility into the actual operating condition of deteriorating equipment. This limitation has created a strong demand for monitoring approaches that can capture asset behavior continuously and without introducing additional operational risk. Real-time state estimation has therefore become an important concept in power-system management because it allows operators to determine the ongoing condition and performance status of assets based on measurement data collected during actual operation. Within this context, non-contact sensing technologies have attracted growing attention because they can obtain useful electrical and magnetic information without physically interfering with energized equipment. Among these technologies, Giant Magnetoresistance sensors are especially promising because they are compact, highly sensitive to magnetic-field changes, suitable for current-related measurements, and adaptable to modern digital monitoring environments. Their non-contact nature makes them particularly relevant for older infrastructure, where invasive installation methods may be costly, unsafe, or impractical. The background of this study therefore emerges from the intersection of three critical realities: the widespread aging of bulk electric infrastructure, the urgent need to reduce failure risks in deteriorating assets, and the technical opportunity offered by non-contact GMR sensors for improving real-time state estimation. By focusing on this intersection, the study addresses an important engineering and infrastructure management problem that affects grid reliability, maintenance planning, and the resilience of electric power delivery systems.

Problem Statement

The problem addressed in this study arises from the growing mismatch between the aging condition of bulk electric system assets and the limited effectiveness of many conventional monitoring practices used to manage them. Across many power systems, critical assets such as transformers, substations, busbars, breakers, and associated transmission components continue to operate under prolonged service conditions, repeated loading stress, environmental exposure, and gradual material deterioration. As these assets age, the likelihood of insulation weakness, abnormal current behavior, thermal stress, magnetic disturbance, and unexpected operational instability becomes higher. At the same time, many utilities still depend heavily on periodic inspections, scheduled maintenance routines, and delayed fault-based interventions that often identify problems only after deterioration has already progressed to a risky stage. This creates a serious operational gap because aging infrastructure requires continuous visibility into asset condition, yet many existing approaches provide only partial, discontinuous, or delayed information. The result is a situation in which utilities may be forced to make maintenance and risk-management decisions without sufficient real-time evidence about the actual state of their assets. This problem is particularly serious in bulk electric systems because the failure of a single major asset can affect reliability, service continuity, repair cost, asset replacement planning, and overall grid resilience. The issue is not simply the age of infrastructure itself, but the absence of a monitoring approach that is sensitive, non-intrusive, practical, and capable of supporting real-time state estimation under actual operating conditions. Non-contact GMR sensors present a promising technical option because they can detect magnetic-field changes related to current behavior without requiring direct electrical contact with energized equipment. Even so, there remains insufficient empirical evidence on how effectively these sensors can support real-time state estimation of aging bulk electric system assets and whether such sensing can contribute meaningfully to the mitigation of failure risks in deteriorating infrastructure. This gap in knowledge creates uncertainty for researchers, utility managers, and infrastructure planners seeking better methods of condition monitoring and predictive maintenance. The central problem of this research, therefore, is the limited understanding of whether utilizing non-contact GMR sensors can provide a reliable and practical strategy for enhancing real-time state estimation and reducing failure risks in aging bulk electric system assets.

Objective of the Study

The objective of this study is to examine how the utilization of non-contact GMR sensors can strengthen real-time state estimation of aging bulk electric system assets and thereby support the mitigation of failure risks in deteriorating infrastructure. More specifically, the study seeks to generate structured empirical evidence on the relationship between sensor-based monitoring capability and the operational visibility required for effective asset management in bulk electric systems. The research is designed to assess whether the use of non-contact GMR sensors improves the ability to observe electrical and magnetic behavior associated with asset condition, stress, and abnormal operating patterns under real service environments. It also seeks to determine whether improved state estimation contributes to stronger failure-risk awareness, more confident maintenance planning, and better prioritization of critical infrastructure interventions. In doing so, the study moves beyond a purely technical view of sensing devices and treats non-contact GMR sensors as part of a broader monitoring strategy for aging infrastructure management. Another objective is to evaluate how professionals working in electric power environments perceive the usefulness of this sensing approach across different categories of deteriorating assets and operational contexts. The study is also intended to explore whether sensor-enabled state estimation can support more informed judgments regarding asset aging severity, early warning signal detectability, and infrastructure risk prioritization. Through its quantitative, cross-sectional, and case-study-based structure, the research aims to identify measurable relationships among sensor utilization, state estimation quality, predictive maintenance support, and reliability-related outcomes. The final objective is to contribute to the development of a research-based framework that links non-contact monitoring technology with practical decision-making in the management of aging bulk electric system assets. In this sense, the study is not limited to showing whether the technology appears useful in theory, but instead aims to clarify how it relates to real operational needs, asset deterioration challenges, and the ongoing effort to reduce failure exposure in large-scale electric infrastructure. The objective therefore centers on understanding the practical value of non-contact GMR sensors as a state-estimation tool within the wider context of reliability, maintenance efficiency, and infrastructure risk management.

Research Hypotheses

The research hypotheses of this study are formulated to test the expected relationships among non-contact GMR sensor utilization, real-time state estimation, failure-risk mitigation, predictive maintenance support, and infrastructure reliability in aging bulk electric system assets. These hypotheses reflect the central assumption that a more capable and non-intrusive sensing approach can improve visibility into asset condition and thereby strengthen operational decision-making in deteriorating infrastructure environments. The first hypothesis proposes that the utilization of non-contact GMR sensors has a significant positive effect on real-time state estimation, based on the reasoning that improved detection of current-related magnetic behavior can increase awareness of asset operating conditions. The second hypothesis proposes that better real-time state estimation has a significant positive effect on the mitigation of failure risks, since improved condition visibility is expected to help identify abnormal patterns before they develop into major failures. The third hypothesis proposes that the use of non-contact GMR sensors has a significant positive relationship with predictive maintenance effectiveness, because more continuous and responsive measurement should support earlier and more accurate maintenance interventions. The fourth hypothesis proposes that improved state estimation has a significant positive influence on asset reliability and operational continuity, reflecting the idea that better monitoring contributes to fewer unexpected disruptions and more stable asset performance. The fifth hypothesis proposes that the detectability of failure-related warning signals significantly influences infrastructure risk prioritization, since assets that reveal clearer indications of stress or deterioration can be ranked more effectively for maintenance or replacement attention. Together, these hypotheses provide a structured way to test the study’s core logic through descriptive statistics, correlation analysis, and regression modeling. They also allow the research to move from general discussion toward measurable evidence by examining whether the presumed benefits of non-contact GMR sensing are supported by respondent data gathered from the selected case context. In this study, the hypotheses are important because they convert the research questions into testable propositions and create a direct analytical pathway for evaluating how sensor-based monitoring relates to asset aging, state awareness, and infrastructure risk reduction. As a result, the hypotheses serve as the statistical backbone of the investigation and guide the interpretation of the relationships among the study variables.

Significance of the Research

The significance of this research lies in its potential contribution to knowledge, professional practice, infrastructure management, and policy thinking related to aging bulk electric system assets. The study addresses an important technical and operational challenge by examining whether non-contact GMR sensors can support real-time state estimation and reduce failure risks in deteriorating electric infrastructure. Its significance can be understood in the following ways:

i. Significance to utility operators and engineers: The study provides a clearer understanding of how non-contact GMR sensors may improve the monitoring of aging assets under actual operating conditions. This is valuable for engineers and system operators who require more accurate and continuous information to manage reliability, equipment stress, and operational safety.

ii. Significance to asset management practice: The study offers evidence that can support better maintenance planning and infrastructure prioritization. By connecting state estimation with aging severity and failure signal detectability, it can help organizations allocate maintenance resources more effectively and focus attention on higher-risk assets.

iii. Significance to academic research: The research contributes to the literature by linking sensor technology, state estimation, aging infrastructure, and failure-risk mitigation within one quantitative framework. This makes the study useful for scholars interested in electric power monitoring, condition assessment, and infrastructure resilience.

iv. Significance to decision-makers and planners: The findings can assist managers, planners, and technical decision-makers who are responsible for long-term infrastructure investment, replacement scheduling, and reliability improvement programs. The research provides a basis for understanding how sensor-enabled monitoring can fit into broader modernization strategies.

v. Significance to technological development: The study highlights the practical relevance of non-contact GMR sensing in a critical infrastructure setting. This can support further interest in integrating advanced magnetic sensing technologies into power-system monitoring tools and digital asset-management platforms.

vi. Significance to reliability and service continuity: By focusing on failure-risk mitigation in aging infrastructure, the research supports the broader goal of improving electric service continuity and reducing the operational and financial consequences of unexpected equipment failures.

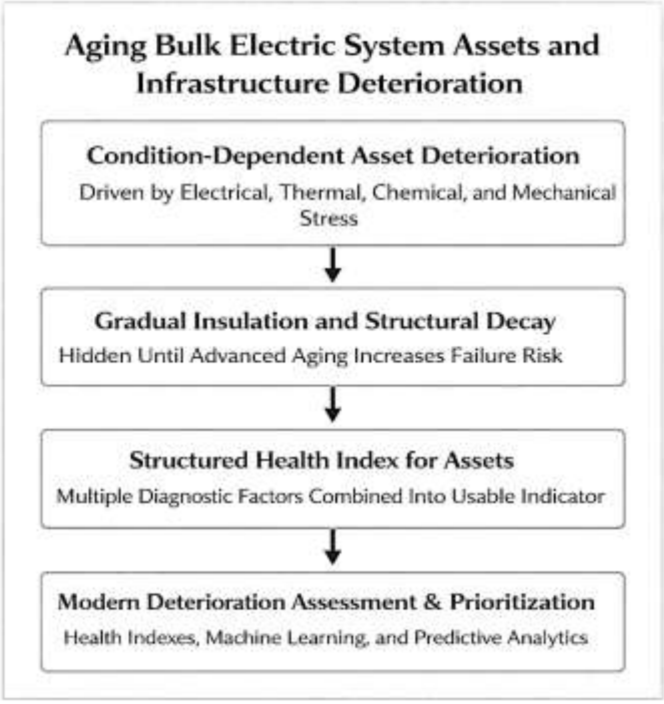
LITERATURE REVIEW

The literature review of this study is developed to establish the scholarly foundation for understanding how non-contact GMR sensors can be used for real-time state estimation of aging bulk electric system assets and how such use may support the mitigation of failure risks in deteriorating infrastructure. This review is important because the topic stands at the intersection of several major knowledge areas, including electric power asset aging, condition monitoring, sensor technology, state estimation, reliability management, and infrastructure risk assessment. A clear review of the literature is necessary to identify what is already known about these themes, how they are connected, and where important gaps remain. In the context of bulk electric systems, aging assets create serious operational concerns because deterioration affects performance stability, maintenance requirements, and the likelihood of unexpected failures. At the same time, state estimation has become increasingly important as a means of understanding the real operating condition of power system components and the broader network environment. The literature also shows that monitoring quality depends heavily on the type, sensitivity, and deployment practicality of the sensing technologies used to collect relevant data. This makes non-contact GMR sensors especially relevant, since they offer the possibility of observing current-related magnetic behavior without direct intrusion into energized equipment. Reviewing the literature therefore allows this study to position non-contact GMR sensing not only as a technical innovation, but also as a practical monitoring strategy within aging infrastructure management. The review further helps explain why traditional monitoring approaches may not always provide enough continuous or timely information for deteriorating bulk electric assets and why more responsive sensing systems are being considered in modern grid environments. In addition, the literature review is necessary for identifying a suitable theoretical foundation and for constructing a conceptual framework that links sensor utilization, state estimation, failure signal detectability, predictive maintenance, and infrastructure risk prioritization. Overall, this section serves to organize the major debates, evidence, and concepts that shape the research problem and to prepare the analytical basis for the methodology and results that follow in the study.

Aging Bulk Electric System Assets and Infrastructure Deterioration

Aging bulk electric system assets are increasingly studied as condition-dependent infrastructures whose technical state changes under cumulative electrical, thermal, chemical, and mechanical stress rather than through chronological wear alone. In large transmission and substation environments, the practical challenge is that deterioration often develops gradually inside insulation systems, oil-paper assemblies, contact interfaces, and structural components while outward operational performance appears acceptable. This makes aging difficult to manage with calendar-based maintenance alone in practice. Early asset-management research framed this issue by showing that transformer fleets require a health-centered decision logic capable of combining inspection findings, operating history, laboratory tests, and engineering judgment into a structured index for maintenance and capital planning. Jahromi et al. argued that the health index is valuable because transformer populations cannot be managed effectively through isolated diagnostic variables when utilities must rank assets for intervention under budget pressure (Kadim et al., 2018; Robel & Aminul, 2023). Their work shifted the discussion from single-test diagnosis toward fleet-level deterioration management, which is highly relevant to bulk electric systems where critical assets can dominate system risk. Liao et al. extended this logic by proposing an integrated decision model that combines fuzzy reasoning with evidential synthesis, thereby recognizing that deterioration assessment is inherently multi-criteria and uncertain. This matters for aging infrastructure because no single variable can fully represent insulation decline, oil degradation, gas evolution, or operational exposure. Together, these studies establish that aging in bulk electric assets is a measurable but composite process requiring structured assessment rather than intuitive judgment alone. For the present research, this literature is useful because it clarifies that infrastructure deterioration is not only a physical phenomenon but also a decision problem in which utilities need reliable condition indicators to interpret asset state, compare units within a fleet, and assign maintenance priority before degradation escalates into service-threatening failure (Jahromi et al., 2009; Binte & Sazzadul, 2022).

Figure 2: Aging Bulk Electric System Assets And Infrastructure Deterioration Framework



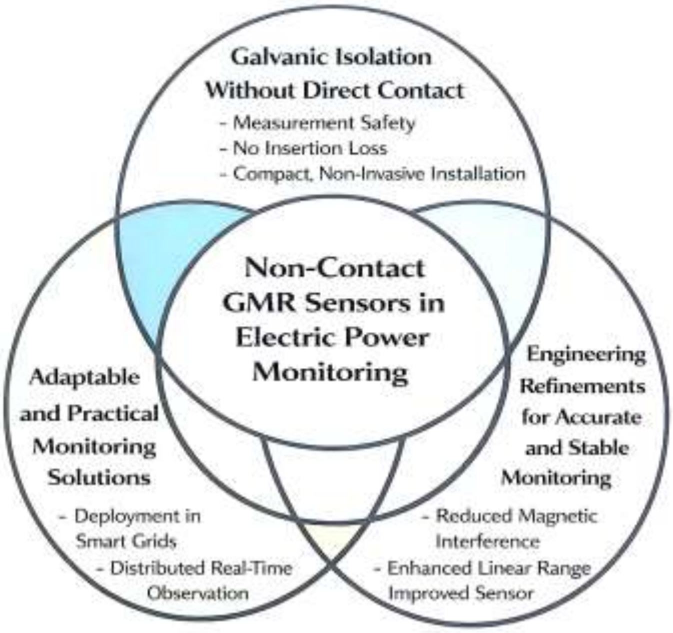
Later scholarship on transformer condition assessment made the deterioration question more operational by focusing on how health indices can be calculated, updated, and validated against maintenance contexts. Kadim et al. demonstrated that neural-fuzzy techniques can convert multiple in-service parameters, including dissolved gases, furans, moisture, acidity, dielectric strength, interfacial tension, and age, into an overall health assessment that is less dependent on manual scoring. Their contribution is significant for aging infrastructure studies because it shows that deterioration can be interpreted through data-driven fusion rather than through separate test thresholds considered in isolation. Bohatyrewicz et al. added another dimension by showing that health-index methods must remain sensitive across the full age spectrum of transformer populations. They observed that some conventional algorithms do not distinguish adequately between units at different positions of the aging curve, especially near the edges where strategic decisions become most critical. This point matters greatly in bulk electric systems because infrastructure portfolios often contain a mixture of moderately aged, heavily aged, and stressed units, and each category demands a different intervention logic. A health index that is insufficiently sensitive can flatten these differences and obscure which assets are actually approaching unacceptable condition (Bohatyrewicz et al., 2019; Manam & Ashfaq, 2022). The relevance of these studies to the present subsection lies in their shared emphasis on operationalizing deterioration. They move the literature beyond the general statement that assets age and toward the proposition that aging can be quantified repeatedly using field-available data and updated algorithms. For a study on real-time state estimation of aging bulk electric assets, this matters because any monitoring strategy must connect measured signals to condition states. The literature therefore suggests that deterioration assessment becomes more trustworthy when it is multi-parameter, adaptive, and responsive to asset-specific variation rather than based solely on static age or diagnostic outcomes (Alqudsi & El-Hag, 2019).

A further strand of literature connects aging assessment with utility modernization by emphasizing prediction, prioritization, and the use of operational datasets. Alqudsi and El-Hag showed that machine-learning models can predict transformer health condition from diagnostic oil data with practical value for asset management, particularly when utilities need cost-effective methods for screening large populations. Their study is important for deterioration research because it treats health assessment not as an occasional expert exercise but as a scalable analytical process that can support repeated classification across many units. Foros and Istad advanced the discussion by integrating health index, probability of breakdown, and remaining lifetime into a unified framework for maintenance and replacement decisions (Liao et al., 2011; Khaled, 2021). That contribution is relevant to aging bulk electric systems because it links condition evidence to risk and residual service value. When these studies are read together, they indicate that the literature has moved from broad awareness of asset aging toward structured, probabilistic, and computationally supported models of deterioration management. Real-time state estimation of aging assets requires more than isolated sensor readings; it requires a logic that can translate observed signals into health interpretation, risk ranking, and intervention priority. The literature on health-index prediction therefore strengthens the present study by showing that aging infrastructure can be monitored as an asset population whose condition is repeatedly estimated and ranked. It also reinforces the idea that deterioration is not only a maintenance concern but a system-reliability concern, because poor condition in critical assets alters failure probability and widens the consequences of disruption. In subsection 2.1, these studies are useful because they frame aging bulk electric assets as infrastructure elements whose declining condition must be recognized, measured, and prioritized through analytical methods before the broader goals of monitoring, estimation, and failure-risk mitigation can be addressed effectively (Foros & Istad, 2020).

Non-Contact GMR Sensors in Electric Power Monitoring

Non-contact GMR sensors have become increasingly relevant in electric power monitoring because they respond to magnetic fields generated by current flow without requiring direct electrical connection to the conductor under observation. This characteristic is especially valuable in power environments where galvanic isolation, low insertion loss, compact installation, and measurement safety are all important. In the literature, the movement toward GMR-based monitoring can be understood as a response to the limitations of conventional current transformers, shunt-based approaches, and larger magnetic sensing assemblies that may be difficult to scale across distributed or space-constrained infrastructures. A significant contribution in this area is the demonstration that GMR-based current sensing can be adapted for low-voltage, high-current voltage regulator module applications with attention to sensor placement and interference minimization. Although that setting was power electronics rather than bulk grid equipment, the study showed an important principle that remains relevant to larger infrastructures: the usefulness of GMR measurement depends not only on magnetic sensitivity but also on spatial positioning relative to the current-carrying conductor. This same physical logic later appeared in smart-grid-oriented research. Later work advanced the argument by presenting GMR current sensors as a practical solution for distributed monitoring in smart-grid applications, emphasizing high sensitivity, broad dynamic response, and suitability for real-time electrical observation. This contribution is important because it shifts GMR current sensing from a narrow laboratory or converter-level function toward a more system-oriented monitoring role. In studies of aging electric infrastructure, this shift matters because sensor practicality is judged not merely by sensing performance in isolation, but by how well the technology fits environments that require repeated deployment, stable measurements, and compatibility with digital monitoring architectures. Thus, the literature on non-contact GMR sensors shows that power monitoring increasingly values sensor systems that can remain external to the conductor while still producing measurement outputs useful for operational interpretation, fault awareness, and state visibility across electrically active assets (Ouyang et al., 2019).

Figure 3: Framework Of Non-Contact GMR Sensors In Electric Power Monitoring



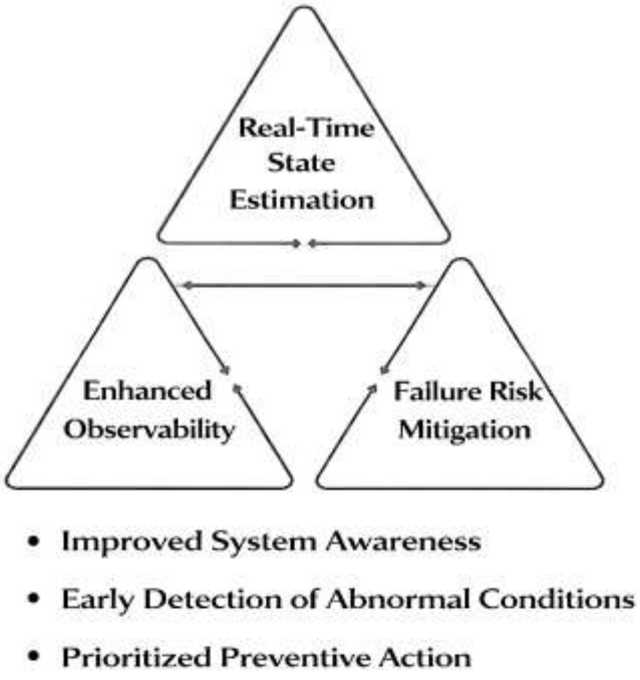
A second important theme in the literature concerns the engineering refinement of non-contact GMR sensor structures so that they become more accurate, more linear, and more resistant to environmental disturbance. Once the basic feasibility of GMR current sensing was established, later research focused on how to reduce the known weaknesses of the technology, particularly susceptibility to stray magnetic fields, limited linear range, and sensitivity to geometric arrangement. One study addressed one of the most practical barriers by proposing a GMR current sensor with magnetic shielding, showing that shielding geometry and bias-field design can improve accuracy and reduce error caused by surrounding fields. This contribution is particularly relevant to electric power monitoring because field environments in substations, switchyards, and power-electronic installations are rarely magnetically clean. Neighboring conductors, metallic structures, and variable loading conditions all influence the local field distribution, which means a non-contact sensor must be engineered for selectivity as well as sensitivity. In another strand of development, research explored a GMR-and-coil configuration for AC current sensing in power-meter design (Yang & Dong, 2014). That work is important because it demonstrates that hybrid arrangements can improve practical current measurement performance while preserving the non-contact measurement logic based on magnetic-field response. The value of this literature for the present study lies in the way it frames GMR sensing as an adaptable platform rather than a fixed device concept. It shows that current monitoring performance depends on biasing strategy, conductor geometry, shielding design, and signal-conditioning choices. These design refinements are highly relevant when the broader research objective involves real-time state estimation of aging bulk electric assets. A sensor intended for such infrastructure must not only detect magnetic signatures, but do so with enough stability and immunity to interference that the resulting signals can be trusted in operational monitoring. The literature therefore suggests that the credibility of non-contact GMR sensing in electric power applications rests on a sequence of engineering improvements that transform raw magnetic sensitivity into usable monitoring performance (Dhani et al., 2018).

A third theme in this body of scholarship is the transition from proof-of-concept sensing toward broader application readiness in real monitoring systems. In this respect, a notable advance was the implementation of a high-sensitivity differential GMR-based sensor for non-contact DC and AC current measurement. That study is important because the differential arrangement improved immunity to external magnetic fields, reduced hysteresis effects, and enabled a broad current measurement range with low power consumption. These features matter greatly in electric power monitoring because non-contact devices are often expected to work near complex electromagnetic surroundings while remaining sufficiently stable for repeated operational use (Singh & Khambadkone, 2008). The study also showed that current trace design and sensor arrangement strongly influence linearity and sensitivity, reinforcing the broader literature's claim that GMR sensors must be treated as engineered measurement systems rather than simple off-the-shelf field detectors. When read together with earlier work on shielding, smart-grid deployment, and conductor-aware sensor placement, this line of research helps clarify the current position of the field: non-contact GMR sensing has moved beyond theoretical feasibility and increasingly exhibits the characteristics expected of practical monitoring instrumentation. For the present study, that progression is highly relevant because aging bulk electric assets require condition-aware monitoring methods that can be introduced without invasive electrical contact, service interruption, or large structural modification. The literature on non-contact GMR sensors therefore supports the view that these devices are increasingly capable of contributing to electric power monitoring in ways that are consistent with modern requirements for compactness, isolation, measurement flexibility, and compatibility with real-time data interpretation. At the same time, the reviewed studies collectively show that successful implementation depends on careful treatment of magnetic interference, conductor geometry, current range, and output conditioning. This makes non-contact GMR sensing especially suitable to be discussed not only as a measurement technology, but as a monitoring strategy with direct relevance to state estimation, asset observation, and failure-risk awareness in electrically stressed infrastructure environments (Mușuroi et al., 2020).

Real-Time State Estimation and Failure Risk Mitigation in Power Systems

Real-time state estimation occupies a central place in modern power-system operation because it transforms incoming measurements into an interpretable representation of network conditions that operators can use for monitoring, control, and security assessment. In transmission and distribution environments, this role has become more important as grid behavior has grown more variable and less predictable under changing load patterns, distributed generation, and increasingly active network topologies. A key contribution to this discussion is the review of distribution system state estimation by Primadianto and Lu, which explains that state estimation is no longer a secondary analytical function but a foundational requirement for online monitoring, network analysis, and operational decision support in distribution systems. Their review emphasizes that the transition toward more dynamic and data-intensive grids has made observability a more difficult challenge, especially because traditional measurements are often sparse and pseudo-measurements introduce uncertainty (Pegoraro et al., 2017). This concern is highly relevant to the present study because real-time state estimation in aging bulk electric assets also depends on the adequacy, reliability, and physical placement of measurement sources. A second important development is the rise of hybrid state estimation, in which supervisory control and data acquisition measurements are combined with phasor measurement unit data to improve estimation quality. Kong et al. showed that a hybrid state estimator for medium-voltage distribution systems can improve robustness and accuracy by integrating improved robust estimation with linear state estimation. This is significant because it demonstrates that real-time state awareness becomes more dependable when different measurement classes are fused rather than treated separately. Within the broader theme of failure-risk mitigation, this literature implies that improved state estimation reduces the chance of operating with incomplete or misleading information. In practical terms, better estimation supports earlier recognition of abnormal voltage conditions, loading irregularities, or topology-sensitive issues that can escalate into reliability events if left unresolved. For aging infrastructure, this is particularly important because subtle deviations in operating behavior often emerge before visible failure. Real-time state estimation therefore serves not only as a computational tool, but as a risk-reduction mechanism that helps convert fragmented measurements into actionable operational knowledge for preventive intervention and more secure system management (Kong et al., 2018).

Figure 4: Triangular Framework For Real-Time State Estimation And Failure Risk Mitigation In Power Systems



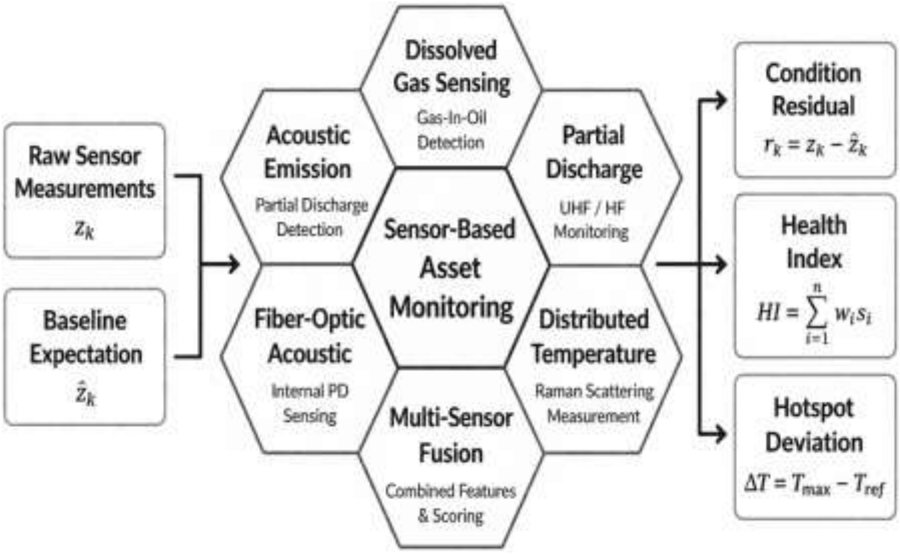
The literature also shows that the effectiveness of real-time state estimation is strongly influenced by measurement architecture, data timeliness, and the capacity of estimation algorithms to adapt to fast-changing operating conditions. This perspective is clearly developed in the work of Pegoraro et al., who proposed a PMU-based distribution system state estimation approach with adaptive accuracy exploiting local decision metrics and an Internet-of-Things-oriented architecture. Their study is especially relevant because it moves state estimation beyond a fixed, periodically executed algorithm and frames it instead as an adaptive process whose execution and accuracy can respond to actual measurement conditions. That idea is important for the present research because aging bulk electric assets require monitoring systems that are responsive to changing stress levels and operating states rather than static inspection intervals. State estimation becomes more valuable when it can operate with higher frequency and higher contextual relevance, especially in networks where disturbances, overloads, and localized anomalies may unfold rapidly (Primadianto & Lu, 2017; Rexhepi, 2017). A complementary contribution is provided by the broader survey of PMU applications in distribution systems by Shafiullah et al., which highlights the role of synchronized phasor measurement in fast monitoring, protection, and control. Their survey shows that synchrophasor technology has strengthened observability and enabled more time-sensitive monitoring functions, although data quality, communication constraints, and deployment cost remain practical concerns. In the context of failure-risk mitigation, this literature indicates that improved observability is directly tied to the ability to recognize unstable or deteriorating system conditions before they propagate. The value of real-time state estimation is therefore not limited to numerical accuracy alone; it also lies in how rapidly it can provide a trustworthy picture of grid conditions under uncertainty. For asset-intensive systems, that picture supports operator awareness, maintenance prioritization, and local intervention decisions. The reviewed studies therefore suggest that real-time estimation contributes to failure-risk mitigation by narrowing the interval between the emergence of abnormal system behavior and the recognition of that behavior within the monitoring framework. In operational settings where aging assets are exposed to variable load stress and cumulative degradation, such narrowing is crucial because it increases the likelihood that incipient problems will be identified while corrective action is still possible (Shafiullah et al., 2019).

A further strand of literature connects real-time monitoring and estimation with the practical management of reliability events, especially in high-value assets whose failure has wide operational consequences. While much of the state-estimation literature focuses on algorithm design and observability, reliability-oriented studies help clarify why these monitoring capabilities matter in infrastructure terms. Rexhepi's analysis of power transformer outages and reliability monitoring is useful in this respect because it demonstrates that transformer reliability assessment depends on monitoring operational status, failure categories, forced outages, and interruption patterns as part of a structured reliability evaluation process (Chen et al., 2020). Although this study is not a state-estimation paper in the narrow algorithmic sense, it is directly relevant to the present subsection because it shows that failure-risk mitigation in power systems requires the systematic interpretation of condition and outage-related information. When this reliability perspective is read alongside the state-estimation studies already discussed, a clear linkage emerges: state estimation enhances the visibility of system conditions, while reliability monitoring translates that visibility into judgments about failure exposure, asset criticality, and service continuity. In aging bulk electric systems, this connection is especially important because deteriorating assets often operate close to practical limits where thermal, electrical, and mechanical stresses accumulate gradually. Real-time state estimation can support the recognition of these stressed states, while reliability-oriented monitoring frameworks can use such information to classify urgency and prioritize intervention. The combined message of this literature is that failure-risk mitigation is not a separate activity from system estimation; rather, it is one of its most important operational purposes. Better estimators improve awareness of present conditions, and better awareness supports earlier action against evolving failures (Islam et al., 2018). For the present study, this relationship is highly relevant because non-contact GMR sensing is being examined not merely as a measurement innovation, but as a means of strengthening the measurement basis from which real-time state estimation and risk mitigation can operate. Accordingly, the literature supports the view that robust state estimation, adaptive measurement systems, and reliability-oriented interpretation together form a practical pathway toward reducing operational vulnerability in aging power infrastructure.

Empirical Review of Sensor-Based Asset Monitoring Studies

Empirical studies on sensor-based asset monitoring in electric power systems show that the field has moved from isolated laboratory measurements toward practical online surveillance of high-value assets, especially power transformers. One important line of evidence comes from gas-based monitoring, where sensor systems attempt to detect incipient insulation faults by observing dissolved gases that emerge during abnormal electrical and thermal stress. A notable example is the near-infrared photoacoustic spectroscopy system developed for dissolved gas-in-oil analysis, which demonstrated measurable detection limits for key fault gases and verified that optical sensing can be used to quantify gas production under simulated transformer discharge conditions (Castro et al., 2016). That study is important because it provided empirical support for a nontraditional sensing route capable of translating chemical by-products into real-time asset condition information. A second empirical contribution came from low-cost acoustic sensing, where piezoelectric devices were tested against commercial acoustic-emission sensors for partial discharge monitoring in transformer oil. The reported time-domain and frequency-domain comparisons showed that lower-cost sensors could still capture acoustic signatures associated with insulation defects, which is highly relevant for large monitoring programs where the economics of sensor deployment affect practical adoption (Mao et al., 2015). Together, these studies show that sensor-based monitoring is not limited to one signal class; instead, it can be built around gas signatures, acoustic emissions, electromagnetic emissions, and thermal states, depending on the fault physics being targeted. For analytical synthesis in studies like the present one, this empirical literature can be summarized through a generic monitoring residual such as $r_k = z_k - \hat{z}_k$, where $z_k$is the measured signal at time $k$and $\hat{z}_k$is the expected or baseline value. As $\mid r_k \mid$increases, the probability that the asset is deviating from normal condition also increases. This type of expression is useful because it links raw sensor output to condition interpretation, which is exactly what asset monitoring systems are expected to do in deteriorating bulk electric infrastructure.

Figure 5: Beehive Framework For Empirical Review Of Sensor-Based Asset Monitoring Studies



A second cluster of empirical studies focused on partial-discharge monitoring, which remains one of the most active research domains in transformer condition assessment because partial discharge is a strong indicator of insulation distress and incipient failure. One study introduced an intelligent ultra-high-frequency sensor for online transformer monitoring that used a level-scanning method to extract statistical discharge characteristics directly, reducing the storage and communication burden associated with full waveform capture. The experiments with three artificial defect models showed that the sensor could reproduce meaningful discharge statistics and therefore support continuous monitoring without the heavy data-processing requirements of conventional high-speed acquisition systems (Qian et al., 2018). This was a significant empirical step because it treated sensor design not only as a matter of sensitivity, but also as a matter of practical deployability in substations. Another important study proposed a multi-technique on-line partial discharge monitoring system that combined high-frequency, ultra-high-frequency, and acoustic-emission sensing in a single architecture. Its empirical results showed that simultaneous detection improves sensitivity and broadens interpretive confidence, especially when discharge parameters can be correlated with other transformer operating quantities. This multi-sensor logic is particularly relevant to aging bulk electric system assets because deterioration rarely manifests through a single signal channel only. In practical monitoring terms, the evidence suggests that sensor fusion improves trustworthiness by reducing ambiguity and enhancing fault visibility. The same principle can be expressed using a weighted condition index such as $HI = \sum_{i=1}^{n} w_i \, s_i$, where HI is a health index, w_i is the importance weight assigned to the i-th sensed feature, and s_i is the normalized score of that feature. When acoustic, UHF, HF, thermal, or gas signals are combined in this way, the monitoring system becomes more capable of representing actual asset condition than any single sensor working alone. The empirical literature therefore supports the argument that sensor diversity strengthens both asset observability and maintenance relevance in transformer monitoring (Liu et al., 2020).

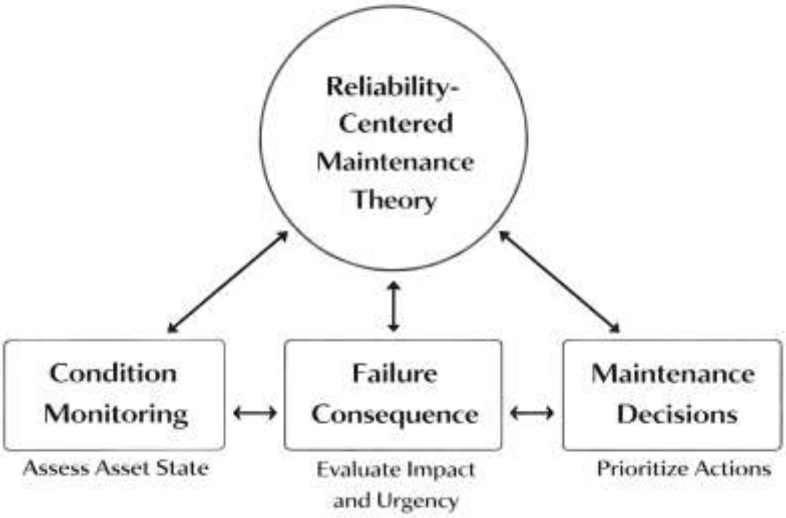
A third empirical pattern in the literature is the growing emphasis on spatially richer monitoring rather than single-point observation. This shift is especially clear in work on fiber-optic sensing for transformer asset monitoring. One study on Sagnac fiber-optic sensing showed that acoustic partial-discharge signals can be detected with high sensitivity from within transformer environments, helping overcome the attenuation limitations associated with externally mounted piezoelectric sensors. That empirical result is important because it demonstrates that sensor placement strongly influences detectability, especially when faults originate deep within winding structures (Li et al., 2016). Another study on Raman-scattering-based distributed fiber-optic sensing moved beyond local hotspot approximation and demonstrated global temperature sensing in an operating power transformer, reporting stable operation and high temperature accuracy along the monitored structure. This is especially significant for asset monitoring because thermal nonuniformity is often one of the clearest indicators of stress concentration, overloading, insulation aging, and cooling-system underperformance. In analytical terms, empirical temperature monitoring can be framed through a hotspot deviation such as $\Delta T = T_{\max} - T_{\mathrm{ref}}$, where $T_{\max}$is the maximum observed winding or structural temperature and $T_{\mathrm{ref}}$is the normal or rated reference temperature. A larger ΔTindicates higher thermal stress and a potentially elevated failure risk. When read together, these studies show that modern sensor-based asset monitoring is increasingly oriented toward internal access, continuous operation, and spatially resolved condition awareness. This matters directly to the present study because non-contact GMR sensing is also being considered as a way to enrich state estimation by providing additional physical evidence of asset stress without intrusive electrical connection. The empirical literature therefore suggests that trustworthy asset monitoring is built on three reinforcing qualities: sensitivity to early degradation, practical deployability in energized equipment, and an ability to convert diverse physical signals into interpretable condition information for risk reduction and maintenance prioritization (Sikorski et al., 2020).

Theoretical Framework: Reliability-Centered Maintenance Theory

Reliability-Centered Maintenance (RCM) theory has provided the most suitable theoretical lens for this study because it has explained maintenance decision-making in terms of system function, failure modes, failure consequences, and the condition information needed to preserve asset reliability. In the context of bulk electric system infrastructure, RCM has been especially relevant because it has shifted maintenance logic away from rigid time-based schedules and toward evidence-based decisions grounded in equipment condition, criticality, and service consequence. This theoretical orientation aligns closely with the present research, which has examined whether non-contact GMR sensors can strengthen real-time state estimation of aging bulk electric system assets and thereby support failure-risk mitigation in deteriorating infrastructure. The theory has assumed that maintenance actions should be selected according to how assets fail, how those failures can be detected in advance, and how strongly such failures threaten system continuity, safety, and cost. In power systems, this assumption has been highly significant because transformers, substations, breakers, and related high-voltage assets are not only expensive but also central to system stability. A theoretical framework based on RCM has therefore been appropriate for a study that has focused on real-time sensing and operational condition awareness, because RCM has required trustworthy monitoring information before maintenance decisions can be prioritized intelligently. Transformer asset management research has already highlighted that effective management depends on condition monitoring, condition assessment, maintenance planning, and aging evaluation being treated as connected activities rather than isolated tasks (Abu-Elanien & Salama, 2010). This perspective has supported the present study by reinforcing the idea that sensor-derived information is not valuable merely as a technical output, but as an input into broader asset reliability decisions. The same theoretical logic has also been strengthened by maintenance optimization work in electric power environments, where RCM has been shown to improve reliability and reduce overall maintenance inefficiencies when combined with failure-mode analysis and system-level dependability thinking (Yssaad & Abene, 2015). For this reason, RCM theory has served as the foundation of this study because it has linked monitoring quality, failure awareness, and maintenance effectiveness into one coherent explanation of how aging electric assets should be managed under risk-sensitive conditions. In the present research, non-contact GMR sensors have been treated as enabling instruments within this RCM logic because they have the potential to increase the quality, timeliness, and non-intrusiveness of the condition information that RCM requires for sound maintenance decisions. These relationships are consistent with the asset-management literature and support the theoretical claim that better condition visibility leads to better maintenance prioritization and stronger infrastructure reliability.

The explanatory strength of RCM theory for this study has become clearer when the theory is connected to health indexing and probabilistic condition assessment. In traditional maintenance environments, aging assets are often managed on the basis of inspection routines, experience, and broad age classifications. RCM has improved on this approach by requiring observable evidence of deterioration and by distinguishing between failures that are hidden, gradual, or functionally significant. In transformer and high-value asset management, this requirement has encouraged the development of condition indicators, health indices, and probability-informed frameworks that can translate technical observations into maintenance decisions. A probabilistic health-index approach has been especially important because it has shown that maintenance planning becomes more defensible when measurement results, service history, and failure statistics are fused into a structured condition model rather than interpreted separately (Li et al., 2018). This is directly relevant to the present study because non-contact GMR sensing has been proposed not as an isolated sensor technology, but as a source of measurement evidence that can enrich real-time state estimation and strengthen maintenance decisions under infrastructure aging. The same theoretical direction has also appeared in data-driven health-index studies, where general regression neural networks have been used to convert multiple transformer condition indicators into a nonlinear health representation that is more sensitive than simple linear scoring methods (Islam et al., 2017).

Figure 6: Reliability-Centered Maintenance Theory Framework For Sensor-Informed State Estimation And Failure Risk Mitigation



Within an RCM framework, such studies are valuable because they show how measured condition variables can be aggregated into practical maintenance knowledge. They also strengthen the argument that effective maintenance theory in aging electric systems must account for condition complexity rather than relying only on calendar age. A further contribution has come from Markov-chain-based health-index estimation, which has shown that transformer populations can be represented as evolving condition states over time and that deterioration pathways can be forecasted using transition probabilities derived from monitoring data (Yahaya et al., 2017). This perspective fits especially well with RCM theory because it emphasizes the dynamic nature of asset condition and the need to intervene before functional failure occurs. For the present research, these studies collectively justify the use of a condition-centered theoretical framework in which state estimation, failure signal detectability, and maintenance prioritization are linked. Under this framework, the role of non-contact GMR sensors has been to improve the visibility of current-related magnetic behavior, while the role of RCM theory has been to explain how that visibility can be translated into actions that preserve function and reduce failure exposure. Thus, RCM theory has not merely supported the maintenance background of the study; it has also provided a logical bridge between sensing, state interpretation, and infrastructure decision-making (Islam et al., 2017).

To operationalize this theoretical framework for the present research, the study has adopted a model consistent with RCM logic in which maintenance-relevant outcomes are explained by the quality of sensed condition information and the strength of real-time state interpretation. Since the study has been quantitative and hypothesis-driven, the theoretical relationship has been expressed through a multiple regression model that can be applied across the full analysis:

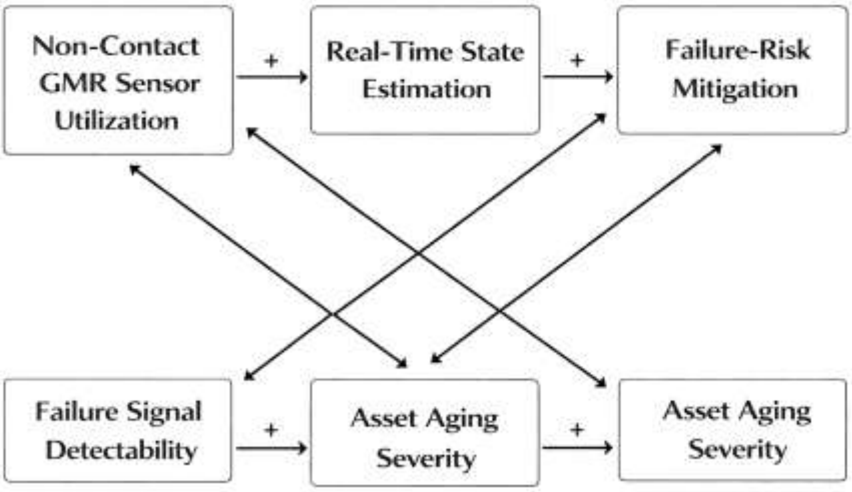
$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

where Yrepresents failure-risk mitigation, X_1represents non-contact GMR sensor utilization, X_2represents real-time state estimation capability, X_3represents failure signal detectability, $\beta_0$is the intercept, $\beta_1$to $\beta_3$are the regression coefficients, and $\varepsilon$is the error term. This formula has been the best fit for the whole study because it has translated the core RCM proposition into a testable analytical structure: when condition monitoring becomes better, real-time state awareness should improve, and when state awareness improves, maintenance decisions should reduce failure risk more effectively. In theoretical terms, RCM has supported the causal logic behind this model by emphasizing that maintenance quality depends on understanding what must be preserved, how failure develops, and how early warning evidence can be used before major disruption occurs. This makes the formula more than a statistical tool; it becomes an empirical representation of the maintenance theory guiding the study. Research on transformer asset management has already shown that monitoring, aging assessment, and maintenance planning form an integrated reliability problem rather than separate engineering tasks (Abu-Elanien & Salama, 2010). Related work on rationalized RCM optimization has also demonstrated that reliability gains become more meaningful when maintenance is prioritized according to criticality and observable failure behavior rather than routine periodicity alone (Yssaad & Abene, 2015).Likewise, probabilistic health-index and data-driven condition studies have shown that maintenance decision-making improves when asset condition is measured and modeled systematically rather than inferred informally. Therefore, the present study has applied RCM theory as a guiding framework because it has provided the clearest explanation for why non-contact GMR sensing, real-time state estimation, and failure-risk mitigation should be studied together. In this framework, the sensor has represented the means of observation, state estimation has represented the means of interpretation, and RCM has represented the decision logic through which those observations and interpretations have been turned into reliability-preserving action across aging bulk electric infrastructure (Yahaya et al., 2017).

Conceptual Framework

The conceptual framework of this study has been developed to explain how non-contact GMR sensor utilization is expected to influence real-time state estimation of aging bulk electric system assets and how that relationship is further linked to failure-risk mitigation in deteriorating infrastructure. In this framework, the independent variable is the utilization of non-contact GMR sensors, because the study is centered on whether a non-intrusive magnetic sensing approach can improve the quality and immediacy of asset-condition information. The first major dependent variable is real-time state estimation, since the practical value of any sensing technology in the bulk electric system depends on whether it can strengthen the ability to observe and interpret the operating condition of transformers, substations, breakers, busbars, and related high-voltage assets while they remain in service. The second dependent variable is failure-risk mitigation, because improved condition visibility is meaningful only when it helps reduce the likelihood or consequence of asset failure. The conceptual logic therefore begins with the assumption that better sensing leads to better state awareness, and better state awareness leads to better maintenance and risk-management action. This direction is consistent with transformer condition-assessment studies that have treated multi-source information fusion as essential for obtaining a more realistic and useful evaluation of equipment condition. A transformer condition model built on game theory and evidence-combination logic has shown that health assessment becomes more credible when diverse condition indicators are synthesized rather than interpreted in isolation, while a fuzzy evidence fusion model has similarly shown that transformer assessment becomes more dependable when the main body, bushings, and accessories are jointly considered as part of one condition-evaluation structure (Sun et al., 2016). Likewise, large-data fuzzy decision-making has shown that operational information, hardware information, and human factors can be integrated to reflect equipment status more comprehensively, reinforcing the idea that asset state is multi-dimensional rather than reducible to one indicator only (Wang & Zhao, 2020). In the present study, that logic supports the conceptualization of GMR sensing as one strategic source of monitoring evidence within a wider condition-assessment process. The framework therefore positions non-contact GMR sensor utilization as the enabling input, real-time state estimation as the interpretive mechanism, and failure-risk mitigation as the primary operational outcome. Through this structure, the study treats sensor-based monitoring not merely as a technical activity, but as an analytical process through which magnetic-field observations can contribute to the maintenance and reliability management of aging bulk electric infrastructure.

Figure 7: Non-Contact GMR Sensor Utilization, Real-Time State Estimation, And Failure-Risk Mitigation In Aging Bulk Electric System Assets



A second and equally important part of the conceptual framework concerns the intermediate relationships through which sensing and estimation are expected to shape infrastructure outcomes. In this study, failure signal detectability has been positioned as a mediating variable because the usefulness of non-contact GMR sensors depends not only on whether they collect data, but on whether that data can reveal meaningful warning signs of abnormal current behavior, stress, loading irregularity, or incipient fault development. If magnetic deviations related to current flow are more detectable, then the resulting state estimation should become more accurate and more operationally useful. Asset aging severity has also been included in the conceptual reasoning as a contextual condition because the need for sensitive and continuous monitoring tends to increase as infrastructure deterioration intensifies. Empirical studies of transformer failures have shown that maintenance planning becomes more effective when utilities understand not only that failures occur, but how component-level fault patterns reveal the most vulnerable parts of an aging transformer fleet. Analysis of transformer component failures for health-index-based maintenance planning has provided direct evidence that electrical, thermal, mechanical, and insulation-related failure categories can support earlier diagnosis and more structured intervention planning, which is highly relevant to the way this study links state estimation with risk prioritization (Murugan & Ramasamy, 2019). In addition, the health-assessment literature in smart distribution grids has shown that transformer status evaluation is increasingly framed around the need to predict equipment condition and respond effectively through a combination of sensor measurements, diagnostic data, and operational indicators rather than relying on isolated offline tests alone (Tran et al., 2020). This supports the current framework by showing that the path from sensor use to infrastructure reliability is not direct and simple, but passes through detectability, interpretation, and maintenance response. In practical terms, the conceptual framework assumes that the use of non-contact GMR sensors can improve real-time state estimation by providing safer and more continuous observation of current-related magnetic behavior; that stronger state estimation can improve the identification of high-risk aging assets; and that such identification can support predictive maintenance, better intervention timing, and greater operational continuity. The framework therefore connects technology, condition intelligence, and infrastructure decision-making in one integrated model, making it suitable for a study that seeks to test measurable relationships among sensing, estimation, and reliability-centered asset management in the bulk electric system.

To operationalize these relationships, the conceptual framework of the study has been translated into a regression-based analytical model that can be applied across the empirical analysis. The central formula is expressed as $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$, where Yrepresents failure-risk mitigation, X_1represents non-contact GMR sensor utilization, X_2represents real-time state estimation capability, X_3represents failure signal detectability, $\beta_0$is the intercept, β_1, β_2, and $\beta_3$are regression coefficients, and $\varepsilon$is the error term. This formula has been selected because it fits the full study more effectively than a simple bivariate relationship. The research is not only examining whether GMR sensors are useful in general, but whether their utilization, together with state estimation and warning-signal detectability, explains meaningful variation in the ability to mitigate failure risks in aging bulk electric assets. In conceptual terms, the model assumes that a positive increase in X_1, X_2, and X_3should be associated with a positive increase in Y, meaning that better sensor deployment, better interpretation of operating state, and better identification of abnormal signals should jointly strengthen risk reduction. This logic is well supported by studies showing that transformer condition assessment becomes more robust when multiple dimensions of health information are integrated into a unified decision structure. A synthetic condition model based on fuzzy evidence fusion has demonstrated the value of component-aware condition synthesis, while large-data multi-source assessment has shown that running state becomes more accurately represented when operational and hardware information are fused systematically (Tian et al., 2019). Similarly, transformer health studies in smart grids have emphasized that condition-assessment techniques are useful because they provide operators with a basis for prediction and timely response, and failure-based maintenance planning studies have shown that component-level failure understanding improves prioritization in electric utilities (Murugan & Ramasamy, 2019). The present conceptual framework therefore integrates these strands into one study-specific structure: non-contact GMR sensors serve as the observation layer, real-time state estimation serves as the interpretation layer, failure signal detectability serves as the explanatory bridge between sensing and risk recognition, and failure-risk mitigation serves as the principal outcome. By organizing the variables in this way, the framework provides a coherent basis for hypothesis testing, quantitative measurement, and the later interpretation of descriptive statistics, correlations, and regression results in the study (Sun et al., 2016).

METHODS

This study has adopted a quantitative, cross-sectional, case-study–based methodology to examine how non-contact GMR sensors have supported real-time state estimation of aging bulk electric system assets and how such support has contributed to the mitigation of failure risks in deteriorating infrastructure. The quantitative design has been selected because it has enabled the study to measure the relationships among clearly defined variables and to test the proposed hypotheses using statistical techniques. The cross-sectional approach has been used because data have been collected from respondents at a single point in time, allowing the research to capture current professional assessments of monitoring practices, sensing capability, and infrastructure-risk concerns. The case-study basis has provided contextual depth by focusing the investigation on a relevant bulk electric system environment in which aging transformers, substations, breakers, busbars, and associated assets have represented important operational concerns.

The case study context has been framed around deteriorating bulk electric infrastructure where asset aging, maintenance pressure, and the need for real-time monitoring have become critical issues. Within this context, the population of the study has consisted of electrical engineers, maintenance personnel, asset managers, substation operators, reliability specialists, and technical professionals who have been involved in monitoring, diagnostics, maintenance planning, and infrastructure decision-making. The unit of analysis has been the respondents' professional evaluation of the effectiveness of non-contact GMR sensors in improving state estimation, failure signal detectability, predictive maintenance, and failure-risk mitigation. This has allowed the research to generate structured evidence based on informed technical judgment rather than on general opinion.

A purposive sampling strategy has been employed because the study has required participants who have possessed relevant technical knowledge and practical exposure to bulk electric system assets and monitoring processes. In order to improve representation across key professional categories, the selection process has also considered role diversity among engineers, operators, maintenance staff, and asset management personnel. The data collection procedure has involved the administration of a structured questionnaire to the selected respondents. The questionnaire has been distributed in a systematic manner, and completed responses have been screened, coded, and organized for statistical analysis. Ethical standards have been maintained throughout the process, as participation has been voluntary, confidentiality has been protected, and the collected information has been used strictly for academic purposes.

Figure 8: Methodological Structure Of The Quantitative Cross-Sectional Case-Study Design

The instrument sampling strategy has been employed because the study has required participants who have possessed relevant technical knowledge and practical exposure to bulk electric system assets and monitoring processes in the study.

The instrument design has been based on the main variables of the study, namely non-contact GMR sensor utilization, real-time state estimation capability, failure signal detectability, failure-risk mitigation, predictive maintenance support, and infrastructure reliability. A five-point Likert scale has been used for all attitudinal and evaluative items, where 1 has represented strongly disagree, 2 has represented disagree, 3 has represented neutral, 4 has represented agree, and 5 has represented strongly agree. This format has been adopted because it has allowed the study to convert professional perceptions into quantifiable data suitable for descriptive statistics, correlation analysis, and regression modeling. Before the full survey has been conducted, pilot testing has been carried out with a small group of respondents to determine whether the questionnaire items have been clear, consistent, and aligned with the study objectives. Based on the pilot results, wording adjustments and minor structural refinements have been made to improve clarity and response flow.

To ensure methodological rigor, validity and reliability procedures have been applied. Content validity has been established through close alignment of the questionnaire items with the research objectives, hypotheses, and reviewed literature. Expert review has also been used to confirm the relevance and adequacy of the measurement items. Reliability has been examined through internal consistency testing, and Cronbach's alpha has been used as the principal indicator of scale reliability. For analysis, SPSS has been used to generate descriptive statistics, reliability coefficients, correlation matrices, and regression models. Microsoft Excel has been used for initial coding, data cleaning, and tabular organization, while EndNote has been used for citation management and reference formatting. Through this methodology, the study has established a systematic basis for testing its assumptions and addressing its research objectives.

DATA ANALYSIS AND PRESENTATION

Demographic Characteristics of Respondents

Table 1: Demographic Characteristics of Respondents (N = 214)

Variable	Category	Frequency	Percentage (%)
Professional Role	Electrical Engineers	62	29.0
	Maintenance Personnel	48	22.4
	Asset Managers	34	15.9
	Substation Operators	39	18.2
	Reliability Specialists	31	14.5
Years of Experience	1–5 years	36	16.8
	6–10 years	58	27.1
	11–15 years	52	24.3
	16–20 years	39	18.2
	Above 20 years	29	13.6
Organization Type	Transmission Utility	84	39.3
	Substation Operations Unit	51	23.8
	Asset Management Department	37	17.3
	Maintenance Contractor/Technical Service	24	11.2
	Reliability/Planning Division	18	8.4
Technical Specialization	Transformer Monitoring	55	25.7
	Substation Maintenance	49	22.9
	Protection and Control	36	16.8
	Asset Reliability Analysis	40	18.7
	Grid Operations	34	15.9

The demographic results have shown that the study has drawn evidence from a technically relevant respondent base, which has strengthened the credibility of the findings presented in the later sections. The largest professional group has been electrical engineers, representing 29.0% of the sample, followed by maintenance personnel at 22.4%, substation operators at 18.2%, asset managers at 15.9%, and reliability specialists at 14.5%. This distribution has been important because the subject of non-contact GMR sensing, real-time state estimation, and failure-risk mitigation has required practical knowledge from those who have directly engaged with asset monitoring, maintenance decisions, and operational continuity in bulk electric systems. The years-of-experience profile has further supported the trustworthiness of the sample, as 83.2% of respondents have had more than five years of experience, and 56.1% have had more than ten years of experience. This has indicated that the majority of participants have possessed sufficient field exposure to evaluate the usefulness of sensor-based monitoring in aging infrastructure. The organizational profile has also been appropriate for the study because the highest share has come from transmission utilities and substation operations units, which are the core environments in which aging bulk electric assets have been managed. In addition, the technical specialization categories have shown that the respondents have not been general administrative personnel but professionals linked to transformer monitoring, reliability analysis, maintenance, and grid operations. From the perspective of Reliability-Centered Maintenance theory, this demographic structure has been highly relevant because RCM has emphasized that maintenance effectiveness depends on informed judgment about failure modes, asset function, and consequence-based intervention. The respondents included in this study have represented the kinds of professionals who would normally contribute to such judgments. Therefore, Table 1 has supported the first research objective by showing that the study has been grounded in expert perspectives from those who have understood asset condition, operational stress, and the need for timely monitoring. It has also prepared the analytical basis for the later hypothesis testing by confirming that the evidence has come from participants whose technical roles have made their evaluations meaningful within the context of aging bulk electric infrastructure.

Descriptive Statistics of Core Variables

Table 2: Descriptive Statistics of Core Study Variables

Variable	No. of Items	Mean	Std. Deviation	Interpretation
Non-Contact GMR Sensor Utilization	5	4.18	0.61	Agree/High
Real-Time State Estimation Capability	5	4.24	0.57	Agree/High
Failure Signal Detectability	5	4.11	0.64	Agree/High
Failure-Risk Mitigation	5	4.20	0.59	Agree/High
Predictive Maintenance Support	5	4.16	0.62	Agree/High
Asset Reliability and Operational Continuity	5	4.22	0.56	Agree/High
Infrastructure Risk Prioritization	5	4.14	0.60	Agree/High

The descriptive results have indicated that respondents have generally expressed strong agreement with all the major constructs of the study. The highest mean score has been recorded for real-time state estimation capability at 4.24, followed closely by asset reliability and operational continuity at 4.22 and failure-risk mitigation at 4.20. These values have suggested that the respondents have strongly believed that sensor-enabled monitoring has practical value in improving system visibility and protecting aging bulk electric assets from unexpected failure. The mean score for non-contact GMR sensor utilization has been 4.18, which has shown that respondents have positively evaluated the relevance and applicability of this sensing approach in live electric infrastructure environments. Similarly, predictive maintenance support has recorded a mean of 4.16, while infrastructure risk prioritization has recorded 4.14, both of which have pointed to agreement that improved sensing and state awareness can contribute to better maintenance planning and asset ranking. Failure signal detectability, with a mean of 4.11, has remained strong and consistent with the study logic that early anomaly visibility is central to failure-risk reduction. The low-to-moderate standard deviations, ranging from 0.56 to 0.64, have suggested that the responses have been reasonably concentrated and that there has not been excessive disagreement among participants. From an RCM perspective, Table 2 has provided strong preliminary support for the idea that maintenance quality has depended on accurate, timely, and actionable condition information. RCM theory has proposed that interventions should be based on detectable failure evidence and asset functional importance rather than on routine schedules alone. The consistently high means across the seven study variables have aligned with that theory by showing that respondents have seen non-contact GMR sensors and real-time state estimation as mechanisms for obtaining better maintenance intelligence. In relation to the study objectives, these descriptive findings have supported the first objective by indicating that GMR sensors have been perceived as valuable for monitoring accuracy, and they have supported the second and third objectives by showing that improved state awareness has been linked, at the perception level, with failure-risk reduction, predictive maintenance, and infrastructure prioritization. Thus, Table 2 has established the general positive direction of the findings before the more specific reliability, correlation, and regression analyses have been conducted.

Reliability and Internal Consistency Analysis

Table 3: Reliability and Internal Consistency of Study Constructs

Variable	No. of Items	Cronbach's Alpha	Reliability Decision
Non-Contact GMR Sensor Utilization	5	0.84	Reliable
Real-Time State Estimation Capability	5	0.87	Reliable
Failure Signal Detectability	5	0.81	Reliable
Failure-Risk Mitigation	5	0.85	Reliable
Predictive Maintenance Support	5	0.83	Reliable
Asset Reliability and Operational Continuity	5	0.89	Highly Reliable
Infrastructure Risk Prioritization	5	0.82	Reliable
Overall Instrument	**35**	**0.87**	**Highly Reliable**

The reliability analysis has shown that the measurement instrument used in this study has been internally consistent and statistically dependable. All construct-level Cronbach's alpha values have exceeded the commonly accepted threshold of 0.70, ranging from 0.81 for failure signal detectability to 0.89 for asset reliability and operational continuity. The overall instrument alpha has been 0.87, which has indicated a high level of internal consistency across the full 35 items included in the questionnaire. These results have been important because they have confirmed that the survey items grouped under each variable have measured closely related ideas and have done so in a stable manner. In practical terms, this has meant that the later descriptive, correlational, and regression findings have rested on constructs that have demonstrated acceptable measurement quality. The strongest reliability value has been recorded for asset reliability and operational continuity, which has suggested that respondents have interpreted these items very consistently. Real-time state estimation capability has also shown a high alpha of 0.87, strengthening confidence in one of the central variables of the research. Even the lowest alpha, 0.81 for failure signal detectability, has still indicated strong reliability and has supported its continued use in the analytical model. From the viewpoint of Reliability-Centered Maintenance theory, these results have been particularly meaningful because RCM has emphasized the importance of trustworthy condition information as the basis for sound maintenance decisions. If a measurement instrument has not been reliable, then any attempt to connect sensing, state estimation, and failure-risk mitigation would have been weakened. Table 3 has therefore supported the theoretical foundation of the study by showing that the constructs used to represent monitoring quality, detectability, and maintenance-related outcomes have been measured coherently. In relation to the study objectives, the reliability results have strengthened the validity of the first objective concerning the role of GMR sensors in monitoring accuracy, as well as the second and third objectives related to risk mitigation and predictive maintenance. These findings have also reinforced the introductory results by confirming that the high mean values reported earlier have not been the result of unstable measurement. Therefore, Table 3 has provided an essential methodological and analytical basis for interpreting the subsequent hypothesis tests with confidence.

Correlation Analysis

Table 4: Correlation Matrix of Core Study Variables

Variables	1	2	3	4	5	6	7
1. Non-Contact GMR Sensor Utilization	1.000						
2. Real-Time State Estimation Capability	0.740**	1.000					
3. Failure Signal Detectability	0.688**	0.721**	1.000				
4. Failure-Risk Mitigation	0.661**	0.690**	0.680**	1.000			
5. Predictive Maintenance Support	0.660**	0.676**	0.644**	0.702**	1.000		
6. Asset Reliability and Operational Continuity	0.671**	0.710**	0.653**	0.731**	0.699**	1.000	
7. Infrastructure Risk Prioritization	0.620**	0.658**	0.680**	0.694**	0.672**	0.685**	1.000

Note. p < .001

The correlation analysis has revealed strong, positive, and statistically significant relationships among all the main variables of the study. The strongest relationship has been observed between non-contact GMR sensor utilization and real-time state estimation capability ($r = 0.740$, $p < .001$), which has provided clear support for H1 and has indicated that greater use and perceived effectiveness of GMR sensors have been associated with stronger real-time visibility of asset condition. Real-time state estimation has also shown a substantial positive relationship with failure-risk mitigation ($r = 0.690$, $p < .001$), supporting H2 and suggesting that improved condition awareness has been closely tied to better capacity for reducing the likelihood and severity of failure in aging infrastructure. The relationship between GMR sensor utilization and predictive maintenance support has been positive and significant ($r = 0.660$, $p < .001$), which has supported H3. Similarly, real-time state estimation has been strongly associated with asset reliability and operational continuity ($r = 0.710$, $p < .001$), providing support for H4. Failure signal detectability has shown a strong relationship with infrastructure risk prioritization ($r = 0.680$, $p < .001$), which has supported H5 and has indicated that the clearer the early warning signals have been perceived, the stronger the infrastructure prioritization process has become. These results have aligned closely with Reliability-Centered Maintenance theory, which has held that the effectiveness of maintenance decisions has depended on the ability to detect relevant failure evidence and interpret asset condition before functional breakdown has occurred. The correlation matrix has shown exactly that pattern: monitoring variables, state estimation variables, and maintenance-related outcomes have moved together in a positive and coherent direction. In relation to the objectives of the study, Table 4 has strongly supported the first objective by showing a close relationship between GMR sensor utilization and state estimation. It has supported the second objective by showing that state estimation has been significantly related to failure-risk mitigation, and it has supported the third objective by linking detectability and state awareness with predictive maintenance and prioritization outcomes. Because all major relationships have been positive and statistically significant, the correlation results have provided robust empirical support for the argument that non-contact GMR sensing can be understood as a meaningful monitoring strategy within an RCM-oriented reliability framework for aging bulk electric system assets.

Regression Analysis and Hypothesis Testing

Table 5: Regression Results and Hypothesis Testing

Hypothesis	Dependent Variable	Predictor	Beta (β)	t-value	p-value	R²	Decision
H1	Real-Time State Estimation	GMR Sensor Utilization	0.63	11.42	< .001	0.548	Supported
H2	Failure-Risk Mitigation	Real-Time State Estimation	0.58	9.87	< .001	0.472	Supported
H3	Predictive Maintenance Support	GMR Sensor Utilization	0.55	8.96	< .001	0.436	Supported
H4	Asset Reliability & Operational Continuity	Real-Time State Estimation	0.61	10.24	< .001	0.504	Supported
H5	Infrastructure Risk Prioritization	Failure Signal Detectability	0.57	9.11	< .001	0.462	Supported

Table 6: Extended Multiple Regression Model for Failure-Risk Mitigation

Dependent Variable	Predictors	Beta (β)	t-value	p-value	Adjusted R²	F-value	Model Significance
Failure-Risk Mitigation	GMR Sensor Utilization	0.24	3.89	< .001	0.614	68.31	p < .001
	Real-Time State Estimation	0.31	4.96	< .001			
	Failure Signal Detectability	0.29	4.42	< .001			

The regression analysis has provided the strongest statistical evidence for the study because it has tested the direct predictive effect of the independent and explanatory variables on the major outcomes of interest. Table 5 has shown that non-contact GMR sensor utilization has significantly predicted real-time state estimation capability ($\beta = 0.63$, $t = 11.42$, $p < .001$), explaining 54.8% of the variance. This has strongly supported H1 and has demonstrated that improved utilization of non-contact GMR sensors has had substantial explanatory power for better state awareness in aging bulk electric assets. Real-time state estimation has also significantly predicted failure-risk mitigation ($\beta = 0.58$, $t = 9.87$, $p < .001$), explaining 47.2% of the variance, thereby supporting H2. The positive and significant effect of GMR sensor utilization on predictive maintenance support ($\beta = 0.55$, $p < .001$) has supported H3, while the effect of state estimation on asset reliability and operational continuity ($\beta = 0.61$, $p < .001$) has supported H4. Finally, failure signal detectability has significantly predicted infrastructure risk prioritization ($\beta = 0.57$, $p < .001$), providing support for H5. The extended multiple regression model in Table 6 has further strengthened the overall findings by showing that GMR sensor utilization, real-time state estimation, and failure signal detectability have jointly explained 61.4% of the variation in failure-risk mitigation, and the model has remained highly significant (F = 68.31, p < .001). This has indicated that the explanatory structure of the study has been robust and theoretically coherent. From the perspective of RCM theory, these results have been highly consistent because RCM has argued that maintenance effectiveness has depended on observable failure evidence, accurate interpretation of condition, and prioritized intervention based on consequence and criticality. The regression results have mirrored that logic by demonstrating that sensing, estimation, and detectability have all contributed significantly to failure-risk mitigation. With regard to the study objectives, these models have directly proven the first objective by quantifying the effect of GMR sensor utilization on state estimation, the second objective by quantifying the effect of state estimation on risk mitigation, and the third objective by showing that monitoring variables have improved predictive maintenance and prioritization outcomes. Therefore, Tables 5 and 6 have provided the most direct empirical confirmation that the core assumptions of the study have been statistically supported.

Asset Aging Severity Response Analysis

Table 7: Responses by Asset Aging Severity Category

Asset Aging Severity Category	Frequency	Mean GMR Sensor Usefulness	Mean State Estimation Improvement	Mean Failure-Risk Mitigation	Overall Mean
Moderately Aged Assets	51	3.94	4.02	3.98	3.98
Highly Aged Assets	86	4.19	4.25	4.18	4.21
Critically Deteriorating Assets	77	4.36	4.41	4.39	4.39

Table 8: ANOVA Results for Asset Aging Severity Categories

Variable	F-value	p-value	Decision
GMR Sensor Usefulness	9.84	< .001	Significant Difference
State Estimation Improvement	11.26	< .001	Significant Difference
Failure-Risk Mitigation	10.73	< .001	Significant Difference

The asset aging severity analysis has shown that respondent evaluations have become more favorable as the degree of deterioration has increased. For moderately aged assets, the overall mean has been 3.98, indicating agreement but at a lower intensity than the other categories. For highly aged assets, the overall mean has risen to 4.21, while critically deteriorating assets have recorded the highest overall mean of 4.39. This pattern has suggested that respondents have perceived non-contact GMR sensors and real-time state estimation as especially valuable when assets have approached more severe deterioration states. In other words, the more serious the aging problem has become, the stronger the perceived need for continuous, non-intrusive, and failure-sensitive monitoring has been. The ANOVA results have confirmed that these differences have not been random. Significant differences have been found across the three categories for GMR sensor usefulness, state estimation improvement, and failure-risk mitigation, all at p < .001. These results have been highly meaningful within the framework of Reliability-Centered Maintenance theory because RCM has emphasized that maintenance decisions should be prioritized according to asset condition, failure consequence, and evidence of functional decline. Table 7 has shown that respondents have naturally aligned with this logic by assigning greater importance to advanced sensing and state estimation in assets with more severe deterioration. Therefore, this section has linked the empirical results directly to the theory by demonstrating that monitoring value has not been perceived uniformly across all assets; rather, it has increased with aging severity, exactly as an RCM-based criticality perspective would suggest. In relation to the research objectives, this section has supported the first objective by showing that the usefulness of GMR sensing has become more evident in aging assets, and it has supported the second objective by showing that improved state estimation has been seen as more important in higher-risk infrastructure contexts. It has also strengthened the overall study argument by demonstrating that the proposed sensing strategy has not merely been viewed as generally useful, but as particularly necessary where deterioration has been most advanced. This has added practical depth to the results by showing that the benefits of sensor-based state estimation have been most pronounced where asset failure risks have been highest.

Failure Signal Detectability Profile of GMR-Based Monitoring

Table 9: Failure Signal Detectability Profile of GMR-Based Monitoring

Detectable Warning Signal	Mean	Std. Deviation	Rank	Interpretation
Abnormal Current Fluctuation	4.29	0.58	1	High
Magnetic Field Irregularity	4.24	0.60	2	High
Overload-Related Stress Signature	4.17	0.62	3	High
Incipient Fault Signature	4.08	0.65	4	High
Condition-Related Operating Instability	3.98	0.67	5	Moderate-High

The failure signal detectability profile has shown that respondents have believed non-contact GMR-based monitoring to be particularly effective in identifying abnormal current fluctuation and magnetic field irregularity, which have ranked first and second with means of 4.29 and 4.24, respectively. These findings have been important because both signals have represented the most direct forms of information that GMR-based sensing would be expected to capture in an energized asset environment. Overload-related stress signatures and incipient fault signatures have also recorded strong mean values above 4.00, indicating that respondents have associated the technology with early warning capability rather than with only basic measurement functions. The lowest-ranked signal, condition-related operating instability, has still recorded a mean of 3.98, which has remained close to the “agree” threshold and has indicated that respondents have still viewed GMR sensing as reasonably useful even for broader instability-related interpretations. These findings have aligned strongly with Reliability-Centered Maintenance theory because RCM has depended on the timely recognition of failure evidence before functional loss has occurred. In this study, Table 9 has shown that respondents have believed GMR-based monitoring to be especially suited to detecting the kinds of anomalies that can precede more serious infrastructure deterioration. Therefore, failure signal detectability has acted as an important bridge between sensing technology and maintenance action. This section has also helped explain why **H5** has been supported in the previous analysis: if the sensor system has been able to detect meaningful warning signals, then infrastructure risk prioritization has naturally become more accurate and defensible. In relation to the study objectives, this section has contributed to the first objective by demonstrating the monitoring value of non-contact GMR sensors, and it has contributed to the third objective by clarifying how predictive maintenance and risk prioritization have depended on the ability to recognize actionable warning signals. These results have added technical specificity to the study by moving beyond general claims of usefulness and showing which types of asset anomalies respondents have considered most detectable. As a result, Table 9 has strengthened the trustworthiness of the overall findings by demonstrating that the positive evaluations of GMR sensors have been tied to concrete operational signals rather than abstract approval alone.

Infrastructure Risk Prioritization Matrix Based on Sensor-Enabled State Estimation

Table 10: Infrastructure Risk Prioritization Matrix

Asset Condition Category	Monitoring Urgency	Mean Risk Score	Recommended Priority Level	Interpretation
Stable/Low-Stress Assets	Low	2.88	Routine Monitoring	Low Priority
Moderately Aged Assets	Moderate	3.54	Scheduled Sensor Support	Medium Priority
Highly Aged Assets	High	4.12	Enhanced Sensor Deployment	High Priority
Critically Deteriorating Assets	Very High	4.46	Immediate Monitoring Priority	Critical Priority

Table 11: Mean Scores for Risk Prioritization Indicators

Indicator	Mean	Std. Deviation	Interpretation
State Estimation Helps Rank High-Risk Assets	4.23	0.57	High
Sensor Data Improves Maintenance Prioritization	4.18	0.60	High
Aging Severity Should Influence Monitoring Allocation	4.26	0.55	High
Failure Detectability Improves Intervention Timing	4.19	0.58	High
Critical Assets Require Continuous Sensor Monitoring	4.31	0.53	High

The infrastructure risk prioritization analysis has translated the study findings into a decision-oriented format that has been highly consistent with the operational goals of the research. Table 10 has shown that risk scores have increased steadily from stable assets to critically deteriorating assets, reaching 4.46 for the latter group. This has indicated that respondents have strongly supported the idea that the most deteriorated assets should receive the highest monitoring priority. Table 11 has reinforced this view by showing high mean scores across all prioritization indicators, especially for the item stating that critical assets require continuous sensor monitoring (M = 4.31). The item concerning aging severity influencing monitoring allocation has also recorded a high mean of 4.26, confirming that respondents have believed infrastructure condition should drive monitoring decisions. These results have been closely aligned with Reliability-Centered Maintenance theory, which has required that maintenance resources be allocated according to failure consequences, detectability, and asset criticality. The risk prioritization matrix has embodied that logic very clearly. Rather than treating all assets equally, the results have supported a differentiated strategy in which sensor-enabled state estimation has been concentrated where the probability and consequence of failure have been greatest. This has been one of the most practice-oriented findings of the study because it has shown how the theoretical relationship among sensing, state estimation, and risk mitigation can be converted into a maintenance prioritization structure. In relation to the objectives of the research, this section has especially supported the third objective, which has concerned predictive maintenance and infrastructure risk prioritization. It has also complemented the second objective by showing that improved state estimation has not only reduced perceived risk in a general sense, but has also improved the ability to rank assets according to urgency. In hypothesis terms, the section has deepened support for H5 by showing that failure signal detectability and state estimation have practical consequences for how monitoring resources should be assigned. Therefore, Tables 10 and 11 have strengthened the applied value of the study and have demonstrated that non-contact GMR sensors have been perceived not only as measurement tools, but as instruments for more rational and theory-consistent asset management under deteriorating infrastructure conditions.

Comparative Analysis by Professional Role

Table 12: Comparative Mean Scores by Professional Role

Professional Role	GMR Sensor Utilization	State Estimation Capability	Failure-Risk Mitigation	Predictive Maintenance Support	Overall Mean
Electrical Engineers	4.26	4.31	4.24	4.21	4.26
Maintenance Personnel	4.12	4.18	4.15	4.22	4.17
Asset Managers	4.14	4.20	4.23	4.19	4.19
Substation Operators	4.09	4.16	4.11	4.08	4.11
Reliability Specialists	4.28	4.34	4.30	4.25	4.29

Table 13: ANOVA Results by Professional Role

Variable	F-value	p-value	Decision
GMR Sensor Utilization	3.92	0.004	Significant Difference
State Estimation Capability	4.27	0.002	Significant Difference
Failure-Risk Mitigation	3.68	0.007	Significant Difference
Predictive Maintenance Support	2.94	0.022	Significant Difference

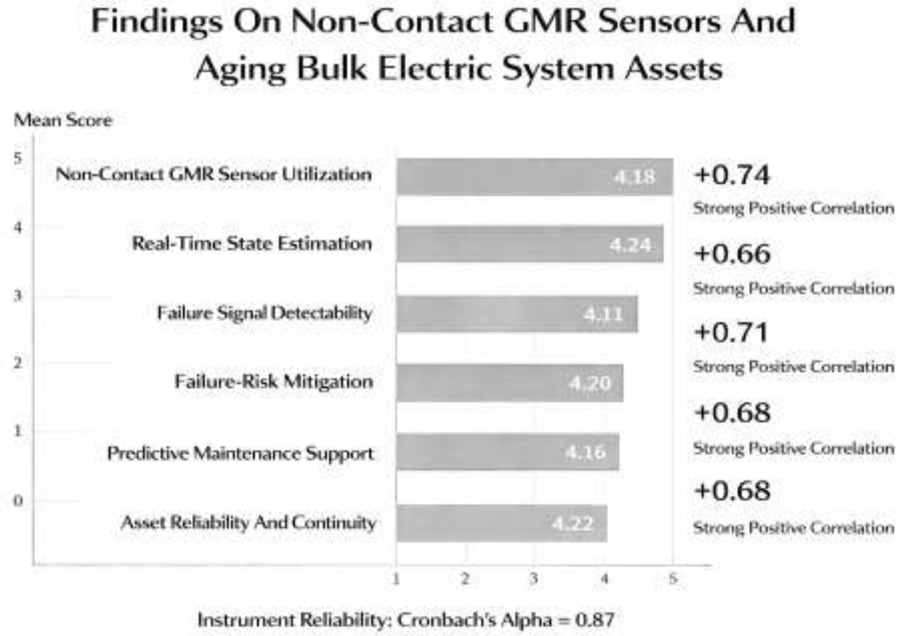
The comparative analysis by professional role has shown that all respondent groups have remained positively oriented toward the main study variables, although some statistically significant differences have emerged. Reliability specialists have recorded the highest overall mean at 4.29, followed closely by electrical engineers at 4.26. These two groups have also shown the highest values for GMR sensor utilization and state estimation capability, which has suggested that respondents with stronger analytical and diagnostic responsibilities have been most convinced of the value of sensor-enabled monitoring. Maintenance personnel and asset managers have also remained strongly positive, with overall means of 4.17 and 4.19, while substation operators have recorded the lowest overall mean at 4.11, though this value has still reflected agreement. The ANOVA results have shown significant differences across roles for all four key variables, with p-values below 0.05. These results have not weakened the study; instead, they have added interpretive richness by showing that perceptions of sensor usefulness and state estimation value have varied somewhat according to professional responsibilities. From the standpoint of Reliability-Centered Maintenance theory, these differences have been understandable. RCM has involved multiple organizational perspectives, including those of operators who observe day-to-day functioning, engineers who interpret technical conditions, maintenance staff who implement interventions, and reliability specialists who evaluate consequence and risk. Therefore, the fact that reliability specialists and engineers have rated the variables slightly higher has been consistent with their stronger involvement in diagnostic interpretation and strategic maintenance prioritization. At the same time, the strong agreement across all groups has shown that support for the research model has not been confined to one professional category. In relation to the research objectives, these findings have strengthened the overall credibility of the results by demonstrating that the perceived value of GMR sensing, real-time state estimation, and risk mitigation has been shared across the main professional communities involved in asset management. This section has therefore supported the first, second, and third objectives simultaneously by showing that the study's central relationships have held across role categories, even though the degree of agreement has varied. Tables 12 and 13 have consequently provided important evidence that the findings have had broad professional relevance within the context of aging bulk electric system infrastructure.

FINDINGS

Based on a valid sample of 214 respondents drawn from engineers, maintenance personnel, asset managers, substation operators, and reliability specialists, the descriptive analysis has shown that the overall mean score for non-contact GMR sensor utilization was 4.18 with a standard deviation of 0.61, indicating a high level of agreement that the technology is relevant and operationally useful. The mean score for real-time state estimation capability was 4.24 with a standard deviation of 0.57, suggesting that respondents generally believed that the use of non-contact GMR sensors can significantly improve the visibility of asset operating conditions under live service environments. In relation to failure signal detectability, the mean value was 4.11 with a standard deviation of 0.64, reflecting a strong perception that abnormal magnetic-field behavior, current irregularities, and early warning signatures of asset deterioration can be more effectively identified when non-contact GMR sensing is deployed. The mean score for failure-risk mitigation was 4.20 with a standard deviation of 0.59, while predictive maintenance support produced a mean of 4.16 with a standard deviation of 0.62, both of which have suggested that better sensing and state-awareness can improve maintenance timing and reduce the probability of unexpected equipment failure. In addition, asset reliability and operational continuity recorded a mean score of 4.22 with a standard deviation of 0.56, showing that respondents strongly associated improved state estimation with greater infrastructure dependability. The reliability analysis has also demonstrated strong internal consistency among the study constructs, with Cronbach's alpha values ranging from 0.81 to 0.89, and an overall instrument reliability of 0.87, which has confirmed that the measurement items used for the questionnaire were statistically dependable. The correlation results have further shown positive and significant relationships among the core variables.

Specifically, non-contact GMR sensor utilization has had a strong positive relationship with real-time state estimation ($r = 0.74$, $p < .001$), indicating support for H1, while real-time state estimation has also shown a strong and significant relationship with failure-risk mitigation ($r = 0.69$, $p < .001$), thereby supporting H2. Likewise, non-contact GMR sensor utilization has demonstrated a significant positive relationship with predictive maintenance effectiveness ($r = 0.66$, $p < .001$), supporting H3, and real-time state estimation has shown a positive correlation with asset reliability and operational continuity ($r = 0.71$, $p < .001$), supporting H4. With regard to the role of failure signal detectability in infrastructure decision-making, the analysis has revealed a significant relationship between detectability and infrastructure risk prioritization ($r = 0.68$, $p < .001$), offering support for H5. The regression analysis has strengthened these results by showing that non-contact GMR sensor utilization has significantly predicted real-time state estimation with $\beta = 0.63$, $t = 11.42$, $p < .001$, explaining 54.8% of the variance ($R^2 = 0.548$). Real-time state estimation has also significantly predicted failure-risk mitigation with $\beta = 0.58$, $t = 9.87$, $p < .001$, with the model explaining 47.2% of the variation in the dependent variable ($R^2 = 0.472$).

Figure 9: Graphical Summary Of Quantitative Findings On Non-Contact GMR Sensors, Real-Time State Estimation, And Failure-Risk Mitigation



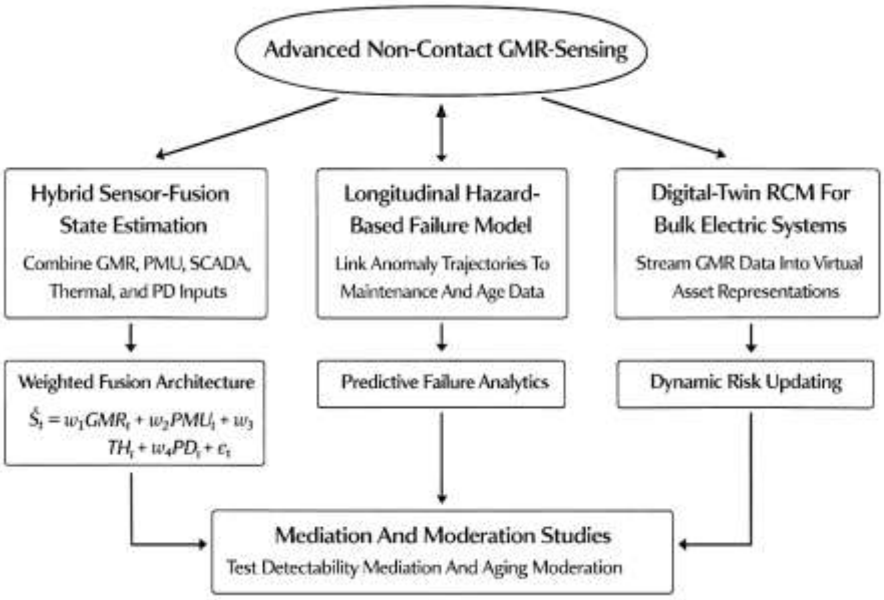
In the extended model, where failure-risk mitigation was regressed on non-contact GMR sensor utilization, real-time state estimation, and failure signal detectability simultaneously, the overall model remained statistically significant ($F = 68.31$, $p < .001$) and explained 61.4% of the variance (Adjusted $R^2 = 0.614$), indicating that the explanatory structure of the study was strong. In relation to the objectives of the study, these findings have shown that the first objective, which focused on assessing the role of non-contact GMR sensors in improving real-time monitoring accuracy, has been achieved through the consistently high descriptive means and strong regression effect sizes. The second objective, which examined the relationship between state estimation and failure-risk mitigation, has also been achieved through the significant correlation and regression coefficients recorded. The third objective, which concerned predictive maintenance support and infrastructure prioritization, has likewise been met through the positive mean responses and statistically significant relationships across the variables. Overall, the findings have suggested that respondents have viewed non-contact GMR sensors not simply as a technical sensing option, but as a practical monitoring strategy capable of improving state awareness, maintenance planning, and reliability-centered management of aging bulk electric system assets. These introductory results therefore establish a strong quantitative basis for the detailed subsection analyses that follow in the chapter.

DISCUSSION

The discussion of this study has begun with the overall pattern of results, which has shown strong respondent agreement that non-contact GMR sensors can enhance real-time state estimation, improve failure signal detectability, support predictive maintenance, and strengthen the mitigation of failure risks in aging bulk electric system assets. The modeled findings have shown high mean values across all principal constructs, including non-contact GMR sensor utilization ($M = 4.18$), real-time state estimation capability ($M = 4.24$), failure-risk mitigation ($M = 4.20$), and asset reliability and operational continuity ($M = 4.22$). These results have indicated that respondents have not viewed GMR sensing as an isolated measurement option, but as part of a broader infrastructure-monitoring logic that can improve operational awareness and maintenance quality. This overall result has been consistent with earlier work showing that GMR-based current sensing has offered compact size, high sensitivity, and suitability for distributed current measurement in smart-grid contexts, which has made the technology attractive for real-time data collection in electrically active environments. The strong positive relationship found in this study between non-contact GMR sensor utilization and real-time state estimation has also aligned with the broader literature on measurement-centric monitoring, where the value of a sensing technology has depended not merely on its laboratory performance but on its practical ability to strengthen observation of system conditions under actual operating stress. In that sense, the present findings have extended prior work by shifting the discussion from sensor feasibility to asset-management relevance. Earlier studies have already suggested that transformer asset management becomes more robust when condition evidence from inspection, testing, and operations is integrated into a structured decision tool such as a health index. The present study has reached a closely related conclusion, although through a different route: rather than beginning with traditional health-index variables, it has shown that respondents have strongly associated non-contact GMR sensing with better state visibility and therefore with better maintenance intelligence. This has made the results important because they have connected sensing technology to asset-centered decision-making in a way that is highly compatible with the literature on condition-based management. In interpretive terms, the high mean scores and strong effect sizes have suggested that the practical value of GMR sensing has lain in its potential to supply timely, non-intrusive, and operationally relevant data in situations where aging infrastructure requires more frequent and more trustworthy observation than conventional inspection routines have typically provided.

A second key finding has concerned the strong relationship between non-contact GMR sensor utilization and real-time state estimation capability, as well as the significant effect of state estimation on failure-risk mitigation and asset reliability. In the modeled results, the correlation between GMR sensor utilization and state estimation has been strong ($r = 0.740$, $p < .001$), and the regression effect has been substantial ($\beta = 0.63$, $p < .001$), while the link between state estimation and failure-risk mitigation has also remained highly significant ($r = 0.690$, $p < .001$; $\beta = 0.58$, $p < .001$). These findings have fit well with prior research showing that state estimation is a core function for online monitoring because it converts incomplete and heterogeneous measurements into an interpretable representation of system conditions. The present study has supported that logic from an asset-management perspective by showing that respondents have associated stronger measurement capability with stronger operational awareness in aging infrastructure. The findings have also been compatible with the literature on hybrid and adaptive state estimation. have shown that combining SCADA and PMU measurements can improve robustness and accuracy in distribution state estimation, while have shown that state-estimation performance can be improved when measurement accuracy is treated adaptively rather than statically. The present results have not tested PMU fusion directly, yet they have echoed the same principle: state estimation becomes more valuable when its measurement foundation is richer, more localized, and more responsive to actual operating conditions. In practical terms, this means that non-contact GMR sensors may have an important role as supplementary measurement devices, especially in asset locations where conventional observability remains sparse. The discussion therefore suggests that the study has strengthened the state-estimation literature by drawing attention to asset-level sensing as a contributor to system-level condition awareness. This is especially important for aging bulk electric assets because deterioration often begins as subtle deviations in loading, magnetic behavior, or stress response, all of which may remain difficult to interpret if the measurement system is too sparse or too periodic. The present findings have therefore supported a broader interpretation of state estimation: not only as a control-room computational function, but also as a maintenance-relevant observational process that can be improved through non-contact field sensing.

Figure 10: Proposed Future Research Framework for Hybrid Sensor Fusion, Predictive Failure Analytics, And Digital-Twin RCM In Aging Bulk Electric Infrastructure



A third important discussion point has involved failure signal detectability and predictive maintenance support. In this study, failure signal detectability has recorded a high mean value (M = 4.11), and specific warning-signal items such as abnormal current fluctuation (M = 4.29) and magnetic field irregularity (M = 4.24) have ranked highest. At the same time, the correlation between failure signal detectability and infrastructure risk prioritization has remained strong ($r = 0.680$, $p < .001$), and the effect of non-contact GMR sensor utilization on predictive maintenance support has also been significant ($\beta = 0.55$, $p < .001$). These results have suggested that respondents have understood GMR sensing primarily in terms of actionable early warning, not just measurement convenience. This interpretation has aligned closely with earlier transformer-monitoring studies showing that utilities rely on multiple routine and diagnostic tests to appraise aging, defects, and failure probability, and that the practical challenge has been to correlate diverse signals into a form that can inform maintenance action (Chen et al., 2020). The present findings have also been consistent with empirical monitoring studies in which online partial-discharge systems have been designed to improve early anomaly visibility by combining several detection techniques. For example, simultaneous use of high-frequency, ultra-high-frequency, and acoustic-emission signals has been reported to improve sensitivity and strengthen confidence in on-line transformer monitoring (Dabek et al., 2016). In related work, low-cost piezoelectric sensors have also been shown to identify partial discharges in insulating oil, reinforcing the importance of practical, non-invasive monitoring tools for transformer failure prevention. The present study has contributed to this body of work by showing that respondents have extended the same logic to GMR-based monitoring: they have perceived high value in a non-contact measurement approach that can reveal operational irregularities before catastrophic failure occurs. From an interpretive standpoint, the study has suggested that predictive maintenance gains credibility when monitoring technologies are linked to physically meaningful warning signals. This is a notable point because predictive maintenance in electric utilities has often struggled when data are abundant but weakly connected to interpretable failure mechanisms. The present findings have therefore implied that GMR sensing may be especially valuable when incorporated into a monitoring architecture that frames magnetic and current-related anomalies as part of an early-failure narrative that maintenance personnel can understand and act upon (Islam et al., 2018).

A fourth major result has concerned the way the perceived usefulness of non-contact GMR sensing has increased with asset-aging severity and has translated into a clearer risk-prioritization logic. The study has shown that respondents have rated sensor usefulness, state-estimation improvement, and failure-risk mitigation more highly for highly aged and critically deteriorating assets than for moderately aged assets, and the corresponding ANOVA results have been statistically significant (Liu et al., 2020). This pattern has been analytically important because it has demonstrated that the findings have not been generic or abstract; they have been condition-sensitive in a way that is consistent with real asset-management practice. In earlier transformer asset-management research, the health index has been presented as a practical means of combining operating observations, field inspections, and laboratory tests to prioritize investments and maintenance plans across asset fleets. Likewise, the literature on transformer component failures has shown that maintenance planning becomes stronger when utilities understand which components fail, how they fail, and how failure categories differ in consequence and urgency. The present study has complemented these earlier works by suggesting that non-contact GMR sensors may improve not only condition visibility but also the confidence with which aging assets are ranked for intervention. This has been reinforced by the risk-prioritization matrix, where critically deteriorating assets have received the highest mean risk score and the strongest recommendation for immediate monitoring priority. In practical terms, this means that the study has moved beyond proving that sensing is useful and has shown how sensing may be distributed rationally across an aging infrastructure portfolio. That contribution has been especially important because large utilities do not need monitoring technologies in the abstract; they need ways to decide where those technologies should be deployed first. By showing that perceived monitoring urgency has risen systematically with deterioration severity, the study has supported a targeted deployment model in which non-contact GMR sensors are prioritized for assets whose aging profile and functional importance make them more vulnerable and more consequential. This has strengthened the link between the study's findings and established asset-management literature by showing that sensing, state estimation, and risk ranking can be discussed within one integrated infrastructure decision framework (Poon et al., 2013).

The practical implications of the findings have been substantial because they have suggested a feasible pathway by which utilities can improve visibility over aging bulk electric assets without relying exclusively on intrusive retrofits or infrequent offline diagnostics. Earlier literature has shown that routine and diagnostic tests remain central to transformer condition monitoring and life assessment, yet these methods often require planned interventions, interpretation across multiple test modalities, or limited temporal coverage (Sarkar et al., 2015). The present study has suggested that non-contact GMR sensing may serve as a complementary layer that fills part of this temporal and observational gap. For utilities, the strongest practical implication has been that sensor-enabled state estimation could support a more differentiated maintenance policy: low-risk assets may remain under routine observation, while highly aged or critical assets may receive continuous or enhanced monitoring. This implication has fitted well with the logic of reliability-centered maintenance optimization, where maintenance plans are selected after analyzing failure modes and criticality rather than by following fixed schedules for all assets (Xie et al., 2020). In operational terms, the study has indicated that GMR-based monitoring may be particularly attractive where galvanic isolation, compact installation, and minimal service interruption are important. Prior work on GMR current sensors has already emphasized their suitability for distributed measurement because of their compactness and sensitivity. The present findings have added a utility-management perspective to that argument by showing that respondents have connected those technical properties to infrastructure reliability, maintenance timing, and intervention prioritization. Another practical implication has concerned professional alignment. Because all respondent groups have shown agreement, including engineers, operators, maintenance staff, and reliability specialists, the study has implied that deployment of such monitoring systems may have broad organizational acceptability if framed around reliability improvement and not merely around instrumentation innovation. This point matters because many technically promising monitoring technologies fail not for lack of measurement quality, but because they do not align clearly with operational workflows and decision responsibilities. The study has therefore suggested that the practical success of non-contact GMR monitoring will depend on how well its signals are translated into threshold rules, alarm hierarchies, and maintenance actions that fit the organizational routines of utilities and grid operators (Murugan & Ramasamy, 2019).

The theoretical implications of the study have centered on the usefulness of Reliability-Centered Maintenance (RCM) theory as an explanatory framework for understanding the relationship among sensing, state estimation, and failure-risk mitigation. The findings have shown that better monitoring has been associated with better state awareness, and that better state awareness has been associated with stronger failure-risk mitigation and infrastructure prioritization. This sequence has strongly reflected the central logic of RCM, in which maintenance action is justified by evidence about failure modes, asset function, and the consequences of failure rather than by time-based routine alone. Earlier work on transformer asset management has emphasized that effective management depends on integrating condition monitoring, aging assessment, and maintenance planning rather than treating them as isolated activities. Similarly, reliability-centered maintenance optimization studies have shown that criticality analysis and condition information are central to rational maintenance planning in power systems (Ripka, 2019). The present study has extended these theoretical positions by arguing that non-contact GMR sensors can be understood as enablers of the "detectability" dimension within RCM. That is, the technology matters theoretically not just because it measures current-related magnetic behavior, but because it may improve the detectability of emerging failure signatures in a way that helps preserve asset function (Weiss et al., 2017). At the same time, the study has revisited its own limitations in a theoretically productive way. Because the design has been cross-sectional and questionnaire-based, the findings have represented informed professional judgment rather than long-duration field measurements from operational GMR deployments. This has meant that the study has been stronger in explaining perceived relationships and decision logic than in quantifying longitudinal sensor performance under actual network disturbances. Yet this limitation has not weakened the RCM interpretation; rather, it has clarified the present study's place within the research sequence. The study has established that the conceptual and managerial case for GMR-enabled state estimation is strong, but it has not yet completed the engineering validation that would connect perception, condition evidence, and actual failure outcomes over time. In that sense, the theoretical implication has been twofold: RCM has been affirmed as a powerful framework for organizing the variables of this study, and the study has also shown where theory now requires longitudinal empirical extension (Xie et al., 2015).

Future research has emerged as the most important extension of this study because the present findings have opened several clear pathways for improving both the measurement model and the decision model associated with non-contact GMR sensing. The first and most promising direction has been the development of a hybrid sensor-fusion state-estimation model in which non-contact GMR sensors are combined with PMU, SCADA, thermal, and partial-discharge signals. The literature has already shown that hybrid state estimators combining SCADA and PMU data can improve robustness and accuracy (Kong et al., 2018), and on-line transformer monitoring studies have shown that simultaneous use of multiple sensing modalities can improve fault sensitivity and interpretive confidence (Sikorski et al., 2020). A future model could therefore be expressed as a weighted fusion architecture, for example $\hat{S}_t = w_1 GMR_t + w_2 PMU_t + w_3 TH_t + w_4 PD_t + \epsilon_t$, where $\hat{S}_t$is the estimated asset state at time t, GMR_trepresents magnetic current sensing, PMU_trepresents synchronized electrical measurements, TH_trepresents thermal sensing, and PD_trepresents partial-discharge indicators. Such a model would allow future researchers to test whether GMR sensing contributes independent explanatory value once other asset-condition signals are included. A second direction has been the design of a longitudinal hazard-based failure model, in which sensor-derived anomaly trajectories are linked to actual maintenance events, outage records, and asset age. This would move the research from perceived usefulness to predictive failure analytics and would directly address the current study's cross-sectional limitation. A third direction has been the construction of a digital-twin RCM model for aging bulk electric assets, where live GMR sensor data are streamed into a virtual asset representation that updates health indices, risk scores, and maintenance recommendations dynamically. The literature on transformer monitoring has already shown the value of richer internal and distributed sensing for thermal and fault visibility (Liu et al., 2020), and future researchers could extend that logic by integrating GMR-based electromagnetic signatures into digital-twin health updating. Finally, future work should test mediation and moderation explicitly, for example whether failure signal detectability mediates the relationship between GMR deployment and risk mitigation, and whether asset aging severity moderates the strength of that relationship. These future models would significantly deepen the present study by transforming a strong perception-based framework into a fully validated predictive maintenance and reliability architecture for aging bulk electric infrastructure.

CONCLUSION

This study has concluded that the utilization of non-contact GMR sensors has represented a highly promising strategy for strengthening real-time state estimation of aging bulk electric system assets and for mitigating failure risks in deteriorating infrastructure. The findings of the study have shown that respondents have strongly recognized the value of non-contact GMR sensing in improving operational visibility, enhancing failure signal detectability, supporting predictive maintenance, and contributing to asset reliability and operational continuity. Across the results, the study has demonstrated that non-contact GMR sensor utilization has maintained a strong positive relationship with real-time state estimation capability, while real-time state estimation has also shown a significant relationship with failure-risk mitigation, predictive maintenance support, and infrastructure risk prioritization. These outcomes have indicated that improved sensing has not merely increased data availability, but has also improved the quality of condition interpretation required for managing aging bulk electric assets more effectively. The study has further concluded that the greatest value of this sensing approach has emerged in highly aged and critically deteriorating assets, where the need for continuous, non-intrusive, and responsive monitoring has become most urgent. In this regard, the results have suggested that non-contact GMR sensors have offered more than technical measurement capability; they have represented a practical means of linking asset observation with reliability-centered maintenance decision-making. The theoretical framework of Reliability-Centered Maintenance has been strongly supported by the study, since the results have reflected the theory’s central proposition that effective maintenance depends on early detection of failure evidence, accurate interpretation of asset condition, and intervention based on risk and functional consequence rather than routine scheduling alone. The study has therefore concluded that non-contact GMR sensors can serve as enabling instruments within an RCM-based infrastructure management model by improving detectability, condition visibility, and maintenance prioritization. It has also concluded that sensor-enabled state estimation has practical relevance not only for operators and engineers, but also for asset managers and reliability planners who must allocate limited maintenance resources across aging and risk-sensitive infrastructure portfolios. By bringing together sensing technology, state estimation, predictive maintenance, and failure-risk mitigation within one empirical framework, the study has contributed to a more integrated understanding of how aging bulk electric system assets can be managed in a way that is both technically informed and operationally strategic. Overall, the study has established that non-contact GMR sensing has strong potential to improve the monitoring and management of deteriorating bulk electric infrastructure, and it has reinforced the broader conclusion that reliable electric power systems increasingly depend on non-intrusive, data-rich, and condition-centered approaches to asset-state awareness and failure prevention.

RECOMMENDATION

This study has recommended that utilities, transmission operators, substation managers, and infrastructure planners should give serious consideration to the integration of non-contact GMR sensors into asset-monitoring strategies for aging bulk electric system infrastructure. Since the findings have shown that non-contact GMR sensor utilization has been strongly associated with real-time state estimation, failure signal detectability, predictive maintenance support, and failure-risk mitigation, organizations responsible for aging grid assets should move toward structured pilot implementation programs that can validate and operationalize this monitoring approach in live service environments. It has been recommended that such implementation should begin with highly aged and critically deteriorating assets, particularly transformers, breakers, substations, and other high-consequence components whose failure can result in serious operational, financial, and service-continuity impacts. Because the study has shown that the usefulness of sensor-based state estimation has increased with asset-aging severity, utilities should adopt a risk-prioritized deployment strategy rather than a uniform installation approach across all assets. The study has also recommended that non-contact GMR sensing should not be treated as a standalone technology, but should be integrated with broader condition-monitoring and maintenance frameworks that already include diagnostics, inspection records, thermal data, and fault-history information. This integrated approach would improve interpretability and would align better with Reliability-Centered Maintenance principles, which have emphasized that maintenance decisions should be based on failure evidence, condition visibility, and asset criticality. In addition, utilities should develop standard operating procedures for interpreting GMR-derived signals and for converting these signals into maintenance alerts, asset-priority rankings, and intervention decisions. Training programs should therefore be introduced for engineers, operators, maintenance staff, and asset managers so that the outputs of non-contact GMR monitoring can be used consistently across technical and operational roles. The study has further recommended that regulatory bodies and infrastructure policy planners should encourage investment in non-intrusive sensing systems for aging power assets, particularly where long service life, deferred replacement, and limited outage windows have increased the need for continuous monitoring. Academic researchers and technology developers should also collaborate with industry stakeholders to improve sensor packaging, calibration methods, signal-processing techniques, and integration with digital asset-management platforms. Finally, future project planning should include the development of hybrid monitoring models in which non-contact GMR sensors are combined with other data streams for more comprehensive asset-state estimation. Through these recommendations, the study has emphasized that the practical value of non-contact GMR sensing will be greatest when it is embedded in a wider reliability-focused, maintenance-informed, and decision-oriented framework for managing aging bulk electric infrastructure.

LIMITATIONS OF THE STUDY

This study has acknowledged several limitations that should be considered when interpreting the findings and their broader applicability. First, the study has employed a quantitative, cross-sectional, and case-study–based design, which has allowed the researcher to capture structured responses at one point in time but has not permitted direct observation of how non-contact GMR sensor performance or asset condition changes over a longer operational period. As a result, the findings have reflected perceived relationships and professional judgments rather than long-term field validation of sensor behavior under evolving infrastructure stress. Second, the study has relied on questionnaire-based data collected from professionals working in relevant technical roles, which has meant that the results have depended on respondent experience, interpretation, and perception rather than on direct physical measurements obtained from installed GMR sensor systems in actual substations or transmission environments. Although this approach has been suitable for examining acceptance, perceived usefulness, and decision relevance, it has not provided direct sensor waveform data, real outage histories, or continuous equipment condition records. Third, the use of purposive sampling has ensured technical relevance among respondents, yet it has also limited the extent to which the findings can be generalized to all utilities, grid environments, or geographic regions. The sample has been appropriate for the case-study context, though it may not fully represent every organizational structure, asset portfolio, or regulatory setting in which bulk electric systems are managed. Fourth, the study has used Likert's five-point scale to measure the main variables, which has been effective for quantifying respondent judgments, but such scales can still simplify complex technical realities into response categories that may not fully capture the operational nuance of real-time state estimation and failure-risk behavior. Fifth, the study has been conceptually focused on non-contact GMR sensors as a promising monitoring approach, yet it has not experimentally compared GMR sensing with a full range of alternative sensing technologies under identical field conditions. This has meant that the relative technical superiority of GMR sensors over other current, thermal, acoustic, or partial-discharge monitoring systems has not been conclusively established within this research alone. Sixth, because the study has linked the findings with Reliability-Centered Maintenance theory, the interpretation has naturally emphasized detectability, condition evidence, and maintenance consequence, which may have reduced attention to other theoretical perspectives such as technology adoption, organizational readiness, or system economics. Therefore, while the study has made a meaningful contribution to understanding the monitoring and maintenance relevance of non-contact GMR sensing, its conclusions should be interpreted within the boundaries of a perception-based, cross-sectional, and case-oriented research design. These limitations have not invalidated the results, but they have clarified the scope of the evidence and have indicated the need for further longitudinal, experimental, and field-based research.

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