Classical and Quantum Computing Methods for Simulation of Geomagnetic Disturbance Effect on Modern Power Systems

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0.1 Abstract

Geomagnetic disturbances (GMDs) caused by solar activity can significantly impact modern power systems, leading to potential blackouts and equipment damage. As power grids' complexity and interconnectedness continue to increase, it is crucial to develop comprehensive methods for simulating and mitigating the effects of geomagnetic storms on power systems. This thesis investigates applying classical and quantum computing techniques to enhance the modelling, prediction, and mitigation of GMD effects on power systems. The research begins with a comprehensive literature review of geomagnetic storms and their impacts on power systems, followed by an in-depth analysis of existing modelling and simulation techniques. The thesis then explores advanced time series analysis methods, including machine learning and deep learning algorithms, to improve the forecasting of geomagnetic storm occurrences and their potential impacts on power grids. A key focus of the thesis is developing a novel framework that combines classical and quantum computing approaches to simulate the effects of GMDs on power flow and voltage stability. This framework incorporates learning-based state estimation techniques to accurately monitor geomagnetically induced currents (GICs) in real time and optimize power system operations to mitigate the impacts of GMDs. The thesis also investigates the potential of quantum computing in enhancing geomagnetic storm predictions and managing GICs in power systems. Quantum machine learning algorithms are explored to improve the accuracy and computational efficiency of GMD forecasting models. In contrast, quantum optimization techniques, such as quantum annealing, are applied to optimize power system operations and minimize the impact of GICs on grid stability and performance. The proposed methods are validated through extensive simulations and case studies on realistic power system models, demonstrating their effectiveness in enhancing grid resilience and reliability under GMD events. The thesis concludes by discussing the implications of the research findings for the future of power system operations and highlighting potential avenues for further research and development. Overall, this thesis contributes to the advancement of classical and quantum computing techniques for modeling, predicting, and mitigating the effects of geomagnetic disturbances on modern power systems. It ultimately promotes a more secure and resilient electrical grid in the face of increasing

space weather threats.

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Chapter 1

Introduction to Geomagnetic Storms and Induced Currents

Chapter 2

Introduction and Literature Review

Geomagnetic storms, intense disturbances in Earth's magnetic field caused by solar activity, pose a significant and often underestimated threat to our modern technological infrastructure. While awe-inspiring in their ability to create stunning auroral displays, these cosmic events carry the potential for widespread disruption and damage to critical systems upon which our society heavily relies. The increasing interconnectedness and technological dependence of our global infrastructure amplify the potential consequences of these solar-driven phenomena, making the study and prediction of geomagnetic storms more crucial than ever.

Historical events are stark reminders of the destructive capability of severe geomagnetic storms. One of the most notable incidents in recent history occurred on March 13, 1989, when a powerful geomagnetic storm triggered a cascading failure in Quebec's power grid. Within 92 seconds of the storm's onset, the Hydro-Quebec system collapsed, plunging millions into darkness for up to nine hours [1]. This event not only demonstrated the rapid speed at which geomagnetic storms can impact infrastructure but also highlighted the vulnerability of our power systems to these cosmic events.

While the Quebec blackout is a modern example, the Carrington Event 1859 remains the benchmark for the potential severity of geomagnetic storms. This historic storm, considered the most powerful on record, caused widespread disruption to telegraph systems across Europe and

North America. Telegraph operators reported receiving electric shocks, and some telegraph pylons emitted sparks [2]. If a storm of similar magnitude were to occur today, the consequences could be catastrophic, potentially causing long-term damage to electrical grids, communication networks, and satellite systems on a global scale.

The threat is not confined to these isolated incidents. 2003, a severe geomagnetic storm led to power outages in Sweden and damaged transformers in South Africa [3]. More recently, during a geomagnetic storm in 2024, farmers reported issues with GPS-guided farming equipment, highlighting the expanding reach of these events into modern precision agriculture [2]. These examples underscore the diverse and evolving ways geomagnetic storms can impact our technology-dependent society.

The potential for future damage is even more concerning. Simulations of storms ten times the intensity of the 1989 Quebec event suggest that many high-voltage power transformers could be at risk of failure, potentially causing widespread grid collapse across extensive areas of North America [4]. As our reliance on electrical power and GPS technology continues to grow, so does our vulnerability to the effects of geomagnetic storms.

In light of these risks, the importance of advanced research in predicting and mitigating the effects of geomagnetic storms cannot be overstated. While efforts have been made to improve space weather forecasting, such as the U.S. government's PROSWIFT Act of 2020 [2], experts caution that we may still need to be fully prepared for a Carrington-level event. This gap in our preparedness underscores the critical need for continued research and innovation in this field.

This thesis addresses these pressing challenges by developing a novel framework that integrates classical and quantum computing techniques to enhance our understanding and management of geomagnetic disturbances in power systems. By advancing our capabilities in predicting geomagnetic storms, analyzing their effects on power systems, and optimizing mitigation strategies, this research contributes to safeguarding our critical infrastructure against these cosmic threats.

The subsequent chapters will detail our approach to leveraging cutting-edge computational methods, including machine learning, deep learning, and quantum computing, to improve geomagnetic

storm forecasting, assess power system vulnerabilities, and develop innovative mitigation strategies. Through this work, we aim to bridge the gap between existing studies and practical, implementable solutions, ultimately contributing to the resilience of our electrical grids and the security of our technologically dependent society in the face of future geomagnetic challenges.

2.1 Geomagnetic Storms

2.1.1 Definition and Characteristics

Gonzalez et al. [5] provide a foundational definition of a geomagnetic storm as "an interval of time when a sufficiently intense and long-lasting interplanetary convection electric field leads, through a substantial energization in the magnetosphere-ionosphere system, to an intensified ring current sufficiently strong to exceed some key threshold of the quantifying storm time Dst index." This definition highlights the complex interplay between solar wind, the magnetosphere, and the ionosphere in developing geomagnetic storms.

Akasofu [6] emphasizes that the solar wind-magnetosphere dynamo generates the magnetic fields of the most intense geomagnetic storms, underscoring the critical role of solar-terrestrial interactions.

2.1.2 Historical Perspective

The study of geomagnetic storms has a rich history, as outlined by Lakhina and Tsurutani [7]. Early theories, such as the hydromagnetic theory proposed by Dessler and Parker [8] and later refined by Piddington [9], laid the groundwork for our understanding of these phenomena. These early works proposed that sudden increases in solar wind intensity caused geomagnetic storms.

2.1.3 Solar and Interplanetary Causes

The solar origins of geomagnetic storms have been the subject of extensive research. Brueckner et al. [10] found that the majority of geomagnetic storms with Kp 6 could be traced to Coronal Mass Ejections (CMEs). This finding was further supported by Zhang et al. [11], who showed that major geomagnetic storms are more likely to be driven by frontside fast halo CMEs associated with major solar flares.

Gopalswamy [12] characterized typical storm-causing CMEs with high speed, sizeable angular width (mostly halos and partial halos), and solar source locations close to the central meridian. The importance of magnetic clouds in generating geomagnetic storms was highlighted by Wu and Lepping [13], who identified them as a principal source of strong, long-lasting interplanetary negative Bz fields.

Tsurutani and Gonzalez [14] emphasized the importance of understanding the primary plasma processes in the entire solar-terrestrial system when studying geomagnetic storms.

2.1.4 Magnetospheric Processes

The response of Earth's magnetosphere to these solar-wind disturbances is complex. Kamide et al. [15] discussed the relationship between magnetic storms and substorms, noting that the depolarization effect associated with substorm expansion can reduce the magnitude of Dst, even as the ring current grows.

Perreault and Akasofu [16] described how the energy flux entering the magnetosphere is dissipated through magnetospheric substorm processes. This work helped connect solar wind energy input and magnetospheric response.

2.1.5 Geomagnetically Induced Currents

One of the most significant impacts of geomagnetic storms on human technology is the generation of geomagnetically caused currents (GICs). Pirjola [17] explained that the electric and magnetic

fields observed at Earth's surface during storms depend primarily on magnetospheric-ionospheric currents and secondarily on currents induced in the Earth.

Albertson et al. [18] and Kappenman, Zanetti, and Radasky [19] discussed the effects of these disturbances on power systems, highlighting the potential for GICs to cause problems in electrical grids.

2.1.6 Forecasting and Prediction

Given the potential impacts of geomagnetic storms, forecasting has become an essential area of research. Srivastava and Venkatakrishnan [20] identified fast full-halo CMEs associated with strong flares as the most likely candidates for producing intense geomagnetic storms, providing a basis for prediction efforts.

Shinohara, Nozaki, and Kikuchi [21] developed methods for automatic real-time detection of sudden commencements of geomagnetic storms, which could be crucial for early warning systems.

2.2 Introduction to Geomagnetic Storm Prediction

Geomagnetic storms, significant disturbances in Earth's magnetosphere, have garnered intense study due to their potential impacts on technological systems and human activities. The field of geomagnetic storm prediction has evolved significantly, incorporating various techniques to improve forecast accuracy and lead time [22]. This review critically examines the advancements in this field, highlighting strengths and limitations of various approaches.

2.2.1 Historical Development of Prediction Techniques

Early observational and statistical methods laid the foundation for geomagnetic storm prediction. Pioneering works by Feynman and Gu [23], Akasofu et al. [24], and Joselyn and McIntosh [25] established crucial relationships between solar activity and geomagnetic disturbances. However, these early methods often lacked the precision needed for reliable short-term forecasts.

Linear prediction models, introduced in the late 1980s, marked a significant advancement. Studies by Lam [26] and McPherron, Baker, and Bargatze [27] demonstrated the potential of these methods for regional and real-time predictions. While these models improved short-term forecasting, they struggled to capture the complex, non-linear nature of solar-terrestrial interactions.

The transition to first-generation numerical models in the late 1980s and 1990s represented a crucial shift. Works by Akasofu and Fry [28] and Dryer [29] integrated physical principles into predictive models, enhancing accuracy and providing deeper insights. However, these models were often computationally intensive and still limited by our incomplete understanding of solar-terrestrial physics.

2.2.2 Advanced Prediction Techniques

The application of Artificial Neural Networks (ANNs) to geomagnetic storm prediction marked a significant leap forward. Studies by Wu and Lundstedt [30], Gleisner and Lundstedt [31], and Myagkova, Shiroky, and Dolenko [32] demonstrated ANNs' ability to capture complex, non-linear relationships in solar-terrestrial data. However, the "black box" nature of these models often made it challenging to interpret their predictions physically.

Long Short-Term Memory (LSTM) networks, introduced by studies like Gruet et al. [33] and Zou et al. [34], showed promise in capturing long-term dependencies in time series data. While these models improved prediction accuracy, they required extensive training data and could be sensitive to input quality.

Convolutional Neural Networks (CNNs) emerged as powerful tools for processing spatial and temporal data simultaneously. Studies by Siciliano et al. [35] and Upendran et al. [36] demonstrated their potential for global-scale predictions. However, like other deep learning approaches, CNNs face challenges in interpretability and can be computationally demanding.

Support Vector Machines (SVMs) offered an alternative to neural networks, with studies like Ji et al. [37] highlighting their potential advantages in specific prediction scenarios. While SVMs showed promise in handling high-dimensional data, their performance could be sensitive to parameter

tuning.

Ensemble methods gained traction for their ability to enhance prediction reliability. Works by Owens, Riley, and Horbury [38] and Yupanqui et al. [39] demonstrated the benefits of combining multiple models. While these approaches often improved overall accuracy, they could be computationally intensive and challenging to implement operationally.

Probabilistic approaches, pioneered by McPherron and Siscoe [40] and advanced by studies like Chandorkar, Camporeale, and Wing [41] and Tasistro-Hart, Grayver, and Kuvshinov [42], aimed to quantify prediction uncertainties. These methods provide more informative forecasts but can be complex to implement and interpret, especially for non-expert users.

2.2.3 Hybrid and Novel Approaches

Recent years have seen a surge in innovative methodologies. Studies like Sharifie, Lucas, and Araabi [43] and Parsapoor, Bilstrup, and Svensson [44] explored hybrid models and biologically inspired approaches. While these novel techniques show promise, their practical applicability and scalability remain to be fully demonstrated.

2.2.4 Solar Wind Parameters and Geomagnetic Indices

Solar wind parameters and geomagnetic indices are crucial elements in geomagnetic storm prediction, providing essential information about the solar-terrestrial environment and its effects on Earth's magnetosphere.

Solar Wind Parameters

Solar wind parameters have significantly enhanced our ability to forecast geomagnetic disturbances. Temerin and Li [45] demonstrated the strong relationship between solar wind conditions and geomagnetic response, setting a new standard for Dst prediction. Chen, Cargill, and Palmadesso [46] linked specific solar wind configurations to their geomagnetic impacts, while Robbins, Henney,

and Harvey [47] emphasized the role of coronal holes in long-term predictions. Owens et al. [48] developed a 27-day persistence model, leveraging solar rotational effects.

Geomagnetic Indices

Various geomagnetic indices serve as targets for prediction models, each offering unique insights into different aspects of geomagnetic activity.

Dst Index: Klimas, Vassiliadis, and Baker [49] pioneered using data-derived analogues for Dst prediction. Lazzús et al. [50] employed swarm-optimized neural networks, while Pallocchia et al. [51] developed a method based solely on IMF data. Boynton et al. [52] introduced the NARMAX Dst model, and Parnowski [53] took a statistical approach. Lazzús et al. [54] used ground-level data with bio-inspired algorithms, Tobiska et al. [55] presented the Anemomilos methodology, and Anh et al. [56] employed fractal-based methods. Lundstedt, Gleisner, and Wintoft [57] made progress in real-time Dst prediction.

Kp Index: Wintoft et al. [58] studied Kp forecasting from solar wind data, while Shprits, Vasile, and Zhelavskaya [59] focused on nowcasting and predicting Kp using historical values and real-time observations. Viljanen, Pulkkinen, and Pirjola [60] explored K index prediction based on its previous value. Zhelavskaya et al. [61] analyzed machine learning techniques for Kp prediction, and Wing et al. [62] compared various Kp forecast models.

Other Indices: Barkhatov et al. [63] used parallel neural networks for AL index prediction. Collado, Muñoz, and Cid [64] applied deep neural networks to SYM-H and ASY-H forecasting. McPherron and O'Brien [65] provided a comprehensive analysis of Dst index prediction. Boaghe et al. [66] identified nonlinear processes in magnetospheric dynamics, and Sitnov, Ukhorskiy, and Stephens [67] addressed forecasting global data-binning parameters for high-resolution geomagnetic field models.

Ionospheric Parameters

Ionospheric parameters, particularly Total Electron Content (TEC), have gained prominence in geomagnetic storm prediction. Stankov et al. [68] introduced TEC forecasting using GPS measurements. Tang et al. [69] compared different methods for predicting storm-time TEC. Muslim et al. [70] developed a 72-hour ahead TEC prediction method. Oyeyemi, Poole, and McKinnell [71] worked on short-term foF2 forecasting. Zhang et al. [72] combined machine learning with physical observations for TEC prediction, while Monte-Moreno, Yang, and Hernández-Pajares [73] applied nearest neighbor techniques to global TEC forecasting.

2.2.5 Advanced Topics in Geomagnetic Forecasting

Recent advancements in geomagnetic forecasting have been driven by sophisticated machine learning algorithms, diverse data integration, and novel statistical approaches. However, these developments come with both promises and challenges.

Machine Learning and Feature Selection

While machine learning techniques have shown promise in improving prediction accuracy, as demonstrated by Zhelavskaya et al. [61] and Florios et al. [74], they often lack physical interpretability. The "black box" nature of many ML models makes it difficult to understand the underlying physical processes, potentially limiting their usefulness in advancing our theoretical understanding of solar-terrestrial interactions.

Multi-Step Ahead Prediction

Efforts to extend forecast horizons, such as those by Gruet et al. [33] and Cai et al. [75], represent significant progress. However, the accuracy of long-term predictions remains a major challenge, with forecast skill often decreasing rapidly beyond a few hours. The work of Asimopolos et al. [76] in combining multiple techniques shows promise, but the complexity of such hybrid models may

limit their practical implementation.

Coupling Functions and Magnetospheric Dynamics

Studies like those by Boaghe et al. [66] and Lotz, Waal, and Roux [77] have deepened our understanding of solar wind-magnetosphere coupling. However, the highly nonlinear nature of these interactions continues to pose significant challenges for predictive models. The use of advanced mathematical techniques, as seen in Vörös and Jankovičová [78]'s work, while innovative, may be too complex for operational use without further simplification.

Integration of Multiple Data Sources

The trend towards integrating diverse data sources, exemplified by Getmanov et al. [79] and Bala and Reiff [80], is promising. However, this approach also introduces challenges in data standardization, real-time data availability, and computational complexity. The potential benefits of improved accuracy must be weighed against these practical considerations.

Advanced Statistical Techniques

The application of sophisticated statistical methods, such as those by Anh et al. [56] and Boynton et al. [81], offers new perspectives on geomagnetic dynamics. However, the relative performance of these methods compared to simpler, more established techniques is not always clear. The work of Reikard [82] in combining multiple approaches highlights the ongoing search for optimal prediction strategies.

2.2.6 Applications and Implications

Space Weather Services

While operational forecasting systems have benefited from research advancements, as seen in Tobiska et al. [55]'s work, there remains a significant gap between research models and operational

tools. The review by Baker [22] highlights the ongoing challenges in translating complex prediction methods into reliable, real-time forecasting services.

Satellite Operations

Probabilistic forecasting methods, like those developed by Haines et al. [83], offer more nuanced information for decision-making. However, the integration of these probabilistic forecasts into operational protocols remains a challenge. The long-term prediction capabilities discussed by Robbins, Henney, and Harvey [47] are promising but require further validation for operational use.

Ground-Based Technologies

The application of advanced techniques to specific ground impacts, such as Bailey et al. [84]'s work on GICs, represents important progress. However, the diversity of ground-based systems affected by geomagnetic disturbances makes it challenging to develop universally applicable prediction models. Regional approaches, like that of Smith et al. [85], while valuable, may not be easily scalable to global predictions.

Navigation and Communication Systems

Efforts to improve TEC predictions, such as those by Zhang et al. [72] and Filjar et al. [86], are crucial for maintaining GNSS accuracy. However, the complex interplay between ionospheric dynamics and geomagnetic activity continues to pose challenges for reliable predictions during disturbed conditions.

In conclusion, while significant advancements have been made in geomagnetic forecasting, critical challenges remain. These include improving the physical interpretability of machine learning models, extending reliable forecast horizons, bridging the gap between research and operational models, and developing more universally applicable prediction techniques. Future research should focus on addressing these challenges while continuing to leverage the growing availability of diverse data sources and computational capabilities.

2.2.7 Critical Evaluation on Current Prediction Techniques

Despite significant advancements, geomagnetic storm prediction remains a challenging field. Machine learning approaches have shown promise but often lack physical interpretability. Physics-based models, while theoretically grounded, can struggle with the complexity of solar-terrestrial interactions. Hybrid approaches that combine data-driven and physics-based methods offer potential improvements, but developing such models presents significant challenges.

The field of geomagnetic storm prediction has made substantial progress, yet significant hurdles remain. Improving the physical interpretability of machine learning models, enhancing the integration of multi-source data, and developing more robust ensemble and probabilistic forecasting frameworks are ongoing challenges. As our understanding of solar-terrestrial physics improves and computational capabilities advance, the field is likely to see further developments. However, bridging the gap between research advancements and operational forecasting remains a critical issue that will require continued focused efforts from the scientific community.

2.3 Simulation Methods for Geomagnetic Disturbances and Geomagnetically Induced Currents in Power Systems

Geomagnetic disturbances (GMDs) and their resultant geomagnetically induced currents (GICs) pose significant challenges to power systems worldwide. This comprehensive review synthesizes the extant literature on simulation methods for GMDs and GICs in power systems, elucidating key developments, methodologies, and challenges in this critical field of study.

2.3.1 Fundamental Concepts and Historical Context

The study of GICs in power systems traces its origins to the early 1980s, with pioneering work by Albertson et al. [87] laying the foundation for subsequent research. Their seminal load-flow studies in the presence of geomagnetically induced currents demonstrated that substantial transient

fluctuations in the Earth's magnetic field can generate quasi-DC currents in electric power systems. This groundbreaking research set the stage for future investigations in the field.

Building upon this foundation, Kappernman and Albertson [88] made a crucial observation that virtually all power equipment, operation, and protection problems stemming from GICs can be attributed to two primary effects. This insight has since guided much of the subsequent research and mitigation strategies in the domain of GIC studies.

2.3.2 Modeling Approaches

Geomagnetic and Electric Field Modeling

A critical aspect of GIC simulation lies in accurately modeling the geomagnetic and resulting electric fields. Boteler [89] proposed a comprehensive methodology for simulating GICs in power systems, utilizing electric fields in the vicinity of the power network to determine voltage sources or equivalent current sources in transmission lines. This approach has gained widespread adoption in the field.

Complementing this work, Viljanen et al. [90] introduced an innovative method for rapid computation of the geoelectric field using elementary current systems and planar Earth models. This technique has proven invaluable for swift assessments of GIC risks.

The complex, frequency-dependent relationship between geomagnetic field variations and induced geoelectric fields has been further elucidated by Marti et al. [91]. Their research demonstrated the efficacy of piecewise layered-Earth models for simulating GICs, taking into account the frequency-dependent nature of the Earth's response to geomagnetic variations.

Power System Modeling

On the power system front, researchers have developed various approaches to integrate GIC calculations into traditional power system analysis tools. Overbye, Hutchins, and Shetye [92] presented a robust methodology for incorporating geomagnetic disturbance modeling into power

flow analysis, enabling large-scale system studies. This approach facilitates the calculation of GICs using standard power flow modeling parameters.

Providing a comprehensive overview of GMD modeling in power systems, Shetye and Overbye [93] highlighted the dual nature of the problem: the DC GICs and the AC power grid, and their interaction leading to two distinct solution processes.

2.3.3 Transformer Modeling

Transformers, being particularly susceptible to GICs, require accurate modeling for assessing GMD impacts. Price [94] elucidated the effects of GICs on transformers, noting their propensity to induce saturation of the magnetic circuit.

Employing finite element method (FEM) analysis, Lu and Liu [95] assessed transformer susceptibility to GICs, examining DC saturation patterns for various transformer core designs. This detailed modeling approach offers valuable insights into the localized effects of GICs on transformer cores.

Further advancing our understanding, Dong, Liu, and Kappenman [96] conducted a comparative analysis of exciting current harmonics and reactive power consumption from GIC-saturated transformers, shedding light on the non-linear effects of GICs on transformer behavior.

More recent work by Mousavi [97] has focused on the electromagnetic modeling of power transformers for studying and mitigating GIC effects, underscoring the importance of detailed transformer models in GIC studies.

2.3.4 System-Level Impacts and Analysis

While component-level modeling is crucial, understanding system-level impacts is equally vital. Albertson et al. [18] provided a comprehensive overview of geomagnetic disturbance effects on power systems, elucidating the wide-ranging impacts of GMDs.

Overbye et al. [98] conducted an insightful power grid sensitivity analysis of GICs, revealing that transformer GICs are primarily attributable to the electric fields on nearby transmission lines.

This work underscores the importance of considering network topology in GIC assessments.

In a case study of real-world impacts, Pulkkinen et al. [99] examined the geomagnetic storm of October 29-31, 2003, and its effects on the Swedish high-voltage power transmission system. Their findings indicated that the primary mode of GIC-related failures was via harmonic distortions produced by GICs combined with the sensitive operation of protective relays.

2.3.5 Advanced Simulation Techniques

As computational capabilities have advanced, so too have the simulation techniques for studying GICs. Boteler et al. [100] described the development of a sophisticated GIC simulator that utilizes magnetic field data or a specified electrojet current with an Earth conductivity model to calculate electric fields at the Earth's surface.

Oke and Gomez [101] proposed an innovative synergistic approach for computational analysis of GICs in power grids, emphasizing the potential for highly disruptive impacts on regular power grid operations.

Real-time simulation capabilities have also emerged as a crucial area of development. Boteler et al. [102] presented a system for real-time simulations of GICs flowing in a power system, enabling more dynamic assessments of GMD impacts.

2.3.6 Validation and Benchmarking

As the field has matured, efforts have been made to validate and benchmark various simulation approaches. Horton et al. [103] proposed a comprehensive test case for calculating GICs, providing a hypothetical network that can be used to validate results from GIC modeling software. This work has been instrumental in comparing different modeling approaches and ensuring consistency across studies.

Building on these efforts, Haddadi et al. [104] conducted a thorough evaluation of various simulation methods for analyzing GMD system impacts, aiming to instill confidence in utility planners regarding their GMD vulnerability assessments.

2.4 Transformer Modeling and Geomagnetically Induced Currents

This section presents a comprehensive review of the literature on transformer modeling and geomagnetically induced currents (GICs). The review encompasses key aspects including GIC effects on transformers, modeling techniques, simulation and analysis methods, and mitigation strategies.

2.4.1 GIC Effects on Transformers

Geomagnetically induced currents (GICs) pose significant challenges to power systems, particularly to transformers. Price [94] elucidated that GICs can induce saturation of the magnetic circuit in transformers, leading to various operational issues. This saturation effect was further explored by Walling and Khan [105], who delineated the characteristics of transformer exciting currents during geomagnetic disturbances.

The phenomenon of half-cycle saturation due to GICs was extensively investigated by Dong, Liu, and Kappenman [96]. Their research demonstrated that this saturation results in increased harmonic currents and reactive power consumption in transformers. These findings were corroborated by Rezaei-Zare [106], who specifically examined the behavior of single-phase transformers under GIC conditions.

One of the most significant concerns associated with GICs is transformer overheating. Girgis et al. [107] conducted a comprehensive analysis of transformer overheating due to geomagnetically induced currents, providing valuable insights into the thermal risks posed by GICs. This theme was further explored by Marti, Rezaei-Zare, and Narang [108], who simulated transformer hotspot heating due to GICs, offering a method to estimate the temperature rise in transformers during geomagnetic events.

Vakhnina et al. [109] investigated the influence of geomagnetic storms on thermal processes in transformer tanks, highlighting the importance of considering the entire transformer structure when assessing GIC impacts. Their work emphasized the need for comprehensive thermal modeling in

GIC studies.

It is noteworthy that the vulnerability of transformers to GICs is not uniform across power systems. Radasky [110] provided a comprehensive overview of the impact of intense geomagnetic storms on the U.S. high voltage power grid, elucidating that higher voltage transformers are generally more susceptible to GIC effects.

2.4.2 Modeling Techniques

The complexity of GIC effects on transformers has necessitated the development of various modeling techniques, ranging from simplified circuit models to complex finite element analyses.

Low-Frequency Transient Models

Low-frequency transient models have been widely employed for GIC studies. Martinez and Mork [111] discussed transformer modeling for simulation of low-frequency transients, providing valuable insights into the applicability of these models for GIC analysis. Building upon this work, Chandrasena et al. [112] proposed an enhanced low-frequency transformer model specifically designed for use in GIC studies, thereby improving the accuracy of GIC simulations.

Hysteresis Models

The importance of incorporating hysteresis in transformer models for GIC studies has been emphasized by several researchers. Lu and Liu [95] conducted a finite element method (FEM) analysis of DC saturation to assess transformer susceptibility to GICs, incorporating hysteresis effects. Further advancing this approach, Mousavi [113] developed electromagnetic modeling of power transformers with DC magnetization, providing a more comprehensive method for capturing hysteresis phenomena in GIC studies.

Modal Analysis Models

Modal analysis has emerged as a powerful technique for transformer modeling. Wilcox [114] presented the foundational theory of transformer modeling using modal analysis, laying the groundwork for this approach. Subsequently, Wilcox et al. [115] demonstrated the application of modified modal theory in modeling practical transformers, illustrating its effectiveness in capturing complex transformer behavior under various operating conditions, including GIC scenarios.

Finite Element Method (FEM) Models

The utilization of finite element methods has become increasingly prevalent in transformer modeling for GIC studies. Dawood et al. [116] conducted a comparative analysis of numerical and analytical methods for transformer modeling, highlighting the advantages of FEM in capturing detailed electromagnetic behavior. Focusing on high-frequency modeling of power transformers using FEM, Bjerkan [117] provided insights particularly relevant for studying the harmonic effects induced by GICs.

2.4.3 Simulation and Analysis Methods

The simulation and analysis of GIC effects on power systems and transformers have been a key focus of research in this field.

Boteler [89] presented a comprehensive methodology for simulating geomagnetically induced currents in power systems, providing a robust framework for system-wide GIC studies. Complementing this work, Overbye, Hutchins, and Shetye [92] proposed a method for integrating geomagnetic disturbance modeling into power flow analysis, enabling large-scale system studies.

The critical importance of accurate geoelectric field estimation was underscored by Kazerooni et al. [118], who proposed methods for validating geomagnetic disturbance modeling through geoelectric field estimation. This research highlighted the interdisciplinary nature of GIC studies, bridging the gap between geophysics and power system engineering.

Taking a broader perspective, Viljanen et al. [119] modeled geomagnetically induced currents on a continental scale. Their work provided valuable insights into the spatial distribution of GIC risks and emphasized the importance of considering large-scale geomagnetic phenomena in power system studies.

In terms of transformer-specific analysis, Rezaei-Zare [120] presented an enhanced transformer model for low- and mid-frequency transients, validating their model through extensive simulations. This research provided a more accurate representation of transformer behavior under GIC conditions, particularly in capturing harmonic effects.

2.5 Mitigating Geomagnetic Storm Effects on Power Systems

Power systems' vulnerability to geomagnetic disturbances (GMDs) induced by solar activity represents a significant concern for global electrical infrastructure. This comprehensive literature review examines the current state of research regarding the impacts of geomagnetically induced currents (GICs) on power systems and evaluates proposed mitigation strategies.

2.5.1 Fundamentals of GIC Effects on Power Systems

The study of GIC impacts on power systems has evolved significantly over several decades. Pioneering work by Albertson et al. [121] and Albertson, Thorson, and Miske [122] established the foundational understanding of how solar-induced currents affect power grids. Their research elucidated the mechanisms by which geomagnetic storms generate quasi-DC currents within power infrastructure, leading to various operational challenges.

Building upon this foundation, more recent comprehensive analyses, such as those conducted by Kappenman [123] and Abda et al. [124], have provided in-depth examinations of GIC effects on electrical power systems. These studies have conclusively identified transformers as the most susceptible components during geomagnetic disturbances, emphasizing the critical need for targeted protection strategies [123].

2.5.2 Advanced Modeling and Simulation Techniques

Developing accurate modelling and simulation methodologies for GICs has become crucial in formulating practical mitigation approaches. Boteler [89] introduced a widely adopted methodology for simulating GICs in power systems. In contrast, Overbye, Hutchins, and Shetye [92] presented an innovative approach to incorporate geomagnetic disturbance modelling into power flow analysis, enabling large-scale system evaluations.

Furthermore, researchers have developed sophisticated modelling techniques to understand the behaviour of specific power system components under GIC conditions. For instance, Mousavi [97] focused on the electromagnetic modelling of power transformers, contributing valuable insights into GIC effects and potential mitigation strategies.

2.5.3 Mitigation Strategies: A Multifaceted Approach

The research community has proposed and evaluated various mitigation strategies to address GICs' challenges. These approaches can be broadly categorized into operational measures and hardware solutions, each offering unique advantages in protecting power systems.

Operational Measures

Operational measures involve strategic adjustments to power system configuration and operation to minimize GIC impacts. Klauber and Zhu [125] investigated the potential of power network topology control in mitigating GIC effects, suggesting that strategic transmission line switching can significantly reduce the overall impact of GICs on the system. Building on this concept, Kazerooni, Zhu, and Overbye [126] proposed a corrective line switching algorithm specifically designed to mitigate geomagnetically induced currents, demonstrating its effectiveness in reducing GIC-saturated reactive power losses while maintaining system security.

In a related vein, Gong et al. [127] proposed an innovative parallel solution for maintaining resilient power system operation during geomagnetic storms. This method demonstrates promising

performance in preserving system stability under GIC conditions.

Another operational strategy gaining attention is the utilization of generator excitation control. Oyedokun and Scheit [128] analyzed the grid impact of excitation control in mitigating GIC effects, demonstrating its efficacy in reducing localized voltage drops during geomagnetic disturbances.

Hardware Solutions

Hardware solutions involve installing specialized equipment designed to block or mitigate GIC flows. Etemadi and Rezaei-Zare [129] researched the optimal placement of GIC blocking devices for geomagnetic disturbance mitigation, providing valuable insights into the strategic positioning of these devices to maximize their effectiveness.

Kovan and León [130] explored the potential of neutral switching as a GIC mitigation technique. Their research demonstrated the successful mitigation of GIC in a two-terminal system through strategic switching at the neutral point.

An innovative approach proposed by Mayer [131] involves connecting frequency filters in parallel to the high-voltage windings of power transformers, offering a novel method of protection against magnetic storms.

Further expanding the range of potential solutions, Nazir, Burkes, and Enslin [132] investigated converter-based approaches, opening new avenues for power system protection against solar-induced GICs and high-altitude electromagnetic pulse events.

2.5.4 Regional and Large-Scale Studies

The literature reveals a growing focus on analyzing and mitigating GIC impacts on specific power grids and regions. Mac Manus et al. [133] developed an operational mitigation method tailored for New Zealand's transmission network, underscoring the importance of industry collaboration in developing practical solutions.

Addressing the challenges of large-scale analysis, Gilbert, Radasky, and Savage [134] introduced a technique for calculating GIC-induced currents in extensive high-voltage power grids, providing a

valuable tool for assessing system-wide vulnerability.

Leveraging advanced computational tools, Mate et al. [135] utilized the PowerModelsGMD.jl software to analyze and mitigate the impacts of GMD and EMP events on electrical grids, demonstrating the potential of sophisticated modelling in enhancing power system resilience.

2.6 Learning-Based State Estimation for Geomagnetically Induced Currents

Geomagnetically induced currents (GICs) significantly challenge the operation and stability of power systems, necessitating accurate state estimation to maintain grid reliability during geomagnetic disturbance (GMD) events. This comprehensive review examines the evolution of methodologies developed for GIC state estimation in power systems, highlighting their strengths and limitations.

Limitations of Traditional State Estimation

While state estimation is a cornerstone in power system operation, conventional methodologies encounter significant challenges when applied to systems affected by GICs. Meliopoulos, Fardanesh, and Zelingher [136] elucidated that traditional state estimation algorithms are prone to bias, particularly when confronted with unconventional phenomena such as GICs. This inherent bias can lead to inaccurate system state assessments during GMD events, potentially jeopardizing grid stability and operational integrity.

Comparative Analysis and Foundational Methods

A seminal comparative study by Holten et al. [137] laid the groundwork for understanding the trade-offs between various estimation techniques. Although not explicitly focused on GICs, their research concluded that hybrid and Hachtel's methods offer optimal compromises between numerical stability and computational efficiency. These findings have profound implications for GIC state estimation, where accuracy and computational speed are paramount.

Advancements in GIC-Specific Estimation Techniques

Recognizing the inadequacies of traditional methods, researchers have developed specialized approaches for GIC state estimation. Juvekar et al. [138] proposed a GIC-inclusive state estimator, demonstrating that conventional methods may yield inaccurate results during GMD events. This innovative approach incorporates GIC-related parameters and measurements to assess the system state during geomagnetic disturbances comprehensively.

Building on this foundation, Klauber et al. [139] explored the potential for GIC-inclusive state estimation, emphasizing that GICs can induce additional reactive power losses in transformers—a factor often overlooked by traditional estimators. This research paved the way for more sophisticated GIC state estimation techniques, culminating in developing a GIC estimator for electric grid monitoring during geomagnetic disturbances by Klauber et al. [140]. Their method establishes relationships between known system parameters and measurements to rapidly calculate GIC currents in transformers, marking a significant advancement in real-time GIC monitoring and estimation.

Alternative Approaches and Hybrid Models

An alternative perspective was offered by Trichtchenko, Boteler, and Foss [141], who focused on GIC modelling for overdetermined systems. They posited that optimal GIC information could be obtained by synthesizing measured GIC values with theoretical GIC models. This approach, which leverages both empirical data and theoretical constructs, holds promise for developing more robust state estimation methodologies in GIC-affected power systems.

2.6.1 Quasi-Static State Estimation in Power Systems

In the realm of modern power system operation and control, state estimation plays a pivotal role by providing a comprehensive view of the system's operating condition. This critical function enables operators to make informed decisions and maintain system stability. The following review examines the development and application of quasi-static state estimation techniques in power

systems, tracing their evolution from foundational concepts to cutting-edge methodologies.

Foundations and Evolution of Power System State Estimation

The conceptual foundations of power system state estimation were established in the early 1970s through a series of seminal works. Schweppe and Wildes [142], Schweppe and Rom [143], and Schweppe [144] introduced the concept of static state estimation, proposing a data processing algorithm that converted redundant meter readings into reliable estimates of the system state vector. Concurrently, Larson, Tinney, and Peschon [145] further elucidated the theory and feasibility of state estimation in power systems. These pioneering efforts were subsequently consolidated by Schweppe and Handschin [146], who provided a comprehensive overview of static state estimation, characterizing it as a suite of digital computer programs designed to transform telemetered data into dependable estimates of transmission network structure and state.

As power systems grew in complexity, state estimation techniques evolved to meet new challenges. Monticelli [147] offered a comprehensive review of the field, emphasizing the increasing criticality of state estimation and its related functions in energy management systems. Addressing the computational challenges associated with growing power networks, Horisberger, Richard, and Rossier [148] proposed a fast decoupled static state estimator for large-scale electric power systems. Concurrently, the concept of dynamic state estimation began to emerge, with Debs and Larson [149] proposing a dynamic estimator capable of tracking the time-varying state of a power system.

Emergence and Advancement of Quasi-Static State Estimation

Quasi-static state estimation emerged as an intermediate approach between static and fully dynamic methodologies. Blood et al. [150] introduced a Kalman filter approach to quasi-static state estimation in electric power systems, innovatively incorporating time-history data typically unused in static state estimation. The efficacy of this approach was further validated by Xie et al. [151], who conducted a comparative study between quasi-dynamic and static state estimations, demonstrating that quasi-dynamic state estimation could provide more accurate system information.

Advancing the field further, Xie et al. [152] proposed a distributed quasi-dynamic state estimation technique capable of handling both GPS-synchronized and non-synchronized data. This approach proved both efficient and practical for performing state estimation in subsystems equipped with phasor measurement units and other metering devices.

Advanced Techniques and Expanded Applications

Recent years have witnessed the development of more sophisticated techniques in quasi-static state estimation. Intriago, Cevallos, and Zhang [153] proposed an echo state network approach for power system quasi-steady state estimation, leveraging machine learning techniques to capture the inherent nonlinearities in power flow equations. This advancement represents a significant step towards more accurate and adaptable estimation methodologies.

The application domain of state estimation techniques has also expanded beyond traditional power systems. Roytelman and Shahidehpour [154] proposed a method for state estimation in electric power distribution systems under quasi-real-time conditions, addressing the unique challenges posed by distribution networks. Furthermore, Watson [155] and Farzanehrafat and Watson [156] explored the application of state estimation techniques to power quality assessment, highlighting the need for novel formulations and methods in this domain.

2.7 Quantum Computing Applications in Power Systems

The emergence of quantum computing as a transitive technology has sparked significant interest across various domains, with power systems being a notable beneficiary.

2.7.1 Overview of Quantum Computing in Power Systems

Integrating quantum computing into power systems presents a paradigm shift in addressing computational complexities. Zhou et al. [157] thoroughly examines this intersection, emphasizing quantum computing's potential to resolve traditionally intractable problems. Building upon this

foundation, Golestan et al. [158] delve into recent advancements, positing that quantum computing could effectively tackle emerging computational challenges.

The transformative potential of quantum computing in power systems is further underscored by Ajagekar and You [159], who meticulously explore the challenges and opportunities in energy systems optimization. Complementing this perspective, Eskandarpour et al. [160] offers a primer on a quantum-enhanced grid of the future, illuminating how quantum computing can bolster global efforts in addressing power system challenges.

2.7.2 Quantum Algorithms for Power System Analysis

Power Flow Analysis

Power flow analysis stands at the forefront of quantum computing applications in power systems. Feng, Zhou, and Zhang [161] introduce a groundbreaking quantum power flow algorithm, laying the foundation for unprecedentedly efficient power system analytics. Advancing this concept, Sævarsson et al. [162] conducts empirical tests of quantum computing algorithms for power flow on actual quantum computers, demonstrating the potential for exponential speedup compared to classical counterparts.

Further exploration by Liu et al. [163] bridges the gap between theory and practice in quantum power flows. However, they note that the inherent noise in quantum circuits currently poses limitations on practical implementations, highlighting an area for future research and development.

Optimal Power Flow

Optimal power flow (OPF) represents another critical area where quantum computing demonstrates significant promise. Morstyn [164] conduct an in-depth investigation of annealing-based quantum computing for combinatorial optimal power flow. Building on this foundation, Amani, Mahroo, and Kargarian [165] propose an innovative quantum-enhanced DC optimal power flow method, leveraging the potential of quantum algorithms to solve complex systems of linear equations

efficiently.

Expanding the scope of inquiry, Boddu et al. [166] explores diverse quantum computing approaches to optimal power flow in complex grid networks. Their research eloquently demonstrates how quantum algorithms can more efficiently navigate vast solution spaces compared to their classical counterparts, underscoring the transformative potential of quantum computing in this domain.

2.7.3 Quantum-Inspired Optimization Algorithms

The field of quantum-inspired optimization algorithms has garnered significant attention in power system applications. Jeong et al. [167] introduce a novel quantum-inspired binary particle swarm optimization algorithm tailored for unit commitment problems. In a parallel vein, Vlachogiannis and Østergaard [168] apply quantum genetic algorithms to the intricate challenge of reactive power and voltage control.

Providing a comprehensive perspective, Hajiabbas et al. [169] offers an insightful review of quantum-inspired computational intelligence techniques in power system optimization. Their analysis underscores the promising future of these methodologies in addressing complex power system challenges.

2.7.4 Quantum Machine Learning for Power Systems

The emerging field of quantum machine learning presents exciting possibilities for power system applications. Zhou and Zhang [170] pioneered a noise-resilient quantum machine learning approach for stability assessment of power systems, marking a significant milestone as the first attempt to address transient stability assessment issues through quantum computing.

Furthering this line of inquiry, Jing, Wang, and Li [171] propose an innovative data-driven quantum approximate optimization algorithm for power systems. Their research elegantly demonstrates the potential of hybrid quantum-classical algorithms in this domain, opening new avenues for future exploration.

2.7.5 Quantum Computing for Grid Security and Reliability

Grid security and reliability represent critical aspects of power system operation where quantum computing could play a transformative role. Eskandarpour et al. [172] conduct a thorough exploration of how quantum computing can enhance grid security. Complementing this research, Nikmehr and Zhang [173] presents a quantum-inspired power system reliability assessment method, demonstrating its efficacy in radial and mesh distribution systems.

Addressing the crucial issue of cybersecurity, Ahn et al. [174] provides a comprehensive discussion on adopting post-quantum cryptography and quantum key distribution for securing distributed energy resources. Their work underscores the paramount importance of quantum-safe security measures in future power systems.

2.7.6 Quantum Computing in Smart Grids and Microgrids

The application of quantum computing extends its reach to smart grids and microgrids, offering innovative solutions to complex challenges. Ullah et al. [175] presents a comprehensive review of quantum computing applications for smart grids, positioning it as a next-generation alternative to address forthcoming computational challenges.

In the microgrid domain, Nikmehr, Zhang, and Bragin [176] apply quantum computing techniques to the intricate problem of distributed unit commitment. Further advancing this field, Jing, Wang, and Li [177] leverage quantum approximate optimization algorithms for interoperation analysis of reconfigurable networked microgrids, demonstrating the versatility of quantum computing in addressing diverse power system challenges.

2.7.7 Challenges in Quantum Computing for Power Systems

Despite the promising potential of quantum computing in power systems, significant challenges remain. Liu and Tang [178] provide a comprehensive review of these challenges, highlighting hardware limitations, noise in quantum systems, and the need for robust error correction as significant

hurdles that must be overcome.

Chen et al. [179] offers a thought-provoking discussion on the imminent impact of quantum computing on power systems, exploring its early applications and potential future developments. Their analysis emphasizes the need for continued research and development to fully realize the transformative potential of quantum computing in this domain.

Providing a broader perspective, Paudel et al. [180] offers insights on quantum computing and simulations for energy applications. These technologies could significantly accelerate the deployment of new solutions to meet growing energy demands while safeguarding the environment.

2.8 Problem Statement

The increasing reliance on electrical power grids and the growing complexity of our technological infrastructure have amplified the potential impacts of geomagnetic storms on modern society. Despite significant advancements in understanding and predicting these phenomena, critical gaps remain in our ability to effectively mitigate their effects on power systems. This thesis addresses the following interconnected problems:

1. **Inadequate Prediction Accuracy:** Current geomagnetic storm prediction models often lack the precision and lead time necessary for effective power system preparation and response. The complex, non-linear nature of solar-terrestrial interactions poses significant challenges to accurate forecasting, particularly for long-term predictions.

2. **Limited Integration of Multi-Source Data:** Existing prediction models often fail to fully leverage the diverse array of available data sources, potentially overlooking valuable predictive information. There is a need for more comprehensive data integration approaches that can enhance prediction accuracy and reliability.

3. **Insufficient Power System Vulnerability Assessment:** Current methods for assessing power system vulnerabilities to geomagnetic disturbances often lack the granularity and

comprehensiveness required for effective risk management. There is a need for more detailed simulation models that can accurately quantify impacts on specific power system components, particularly transformers.

4. **Suboptimal Mitigation Strategies:** Existing approaches to mitigate the effects of geomagnetically induced currents (GICs) on power system stability and reliability are often reactive and may not fully leverage the potential of advanced computational techniques for optimization.

5. **Inefficient State Estimation for GICs:** Current state estimation techniques for monitoring GICs in power systems often lack the accuracy and efficiency required for real-time decision-making during geomagnetic disturbances.

6. **Underutilization of Quantum Computing Potential:** The potential of quantum computing techniques to enhance geomagnetic storm forecasting and power system management remains largely unexplored. There is a need to investigate how quantum algorithms could improve prediction accuracy and computational efficiency in this domain.

7. **Computational Inefficiency in GIC Impact Assessment:** Existing methods for calculating GIC-induced nodal voltages in power systems are often computationally intensive, limiting their applicability for real-time analysis and decision-making during geomagnetic events.

This thesis aims to address these interconnected problems by developing a novel, integrated framework that leverages advanced classical and quantum computing techniques. By enhancing our ability to predict, assess, and mitigate the impacts of geomagnetic storms on power systems, this research seeks to contribute to the development of more resilient and reliable electrical grids in the face of increasing space weather threats.

2.9 Conclusion and Thesis Contributions

This thesis addresses critical gaps in the study of geomagnetic storms and their impacts on power systems by developing a novel framework that integrates classical and quantum computing techniques.

The main contributions of this research are:

1. **Advanced Time Series Analysis for Geomagnetic Storm Prediction:**
    - Development of new machine learning and deep learning algorithms for improved geomagnetic storm occurrence and severity forecasting.
    - Integration of multiple data sources to enhance prediction accuracy and lead time.
2. **Enhanced Power Flow Analysis under Geomagnetic Disturbances:**
    - Creation of detailed simulation models to assess system-wide vulnerabilities to geomagnetic disturbances.
    - Quantification of impacts on specific power system components, particularly transformers.
3. **AI-Driven Mitigation Strategies for Geomagnetic Disturbances:**
    - Development of AI/ML-based approaches for optimizing line switching strategies.
    - Design novel techniques to minimize the effects of geomagnetically induced currents on power system stability and reliability.
4. **Learning-Based State Estimation for Geomagnetically Induced Currents:**
    - Creation of new state estimation techniques incorporating machine learning algorithms.
    - Improve the accuracy and efficiency of monitoring geomagnetically induced currents in power systems.
5. **Quantum Computing Applications in Geomagnetic Storm Predictions:**
    - Investigation of quantum machine learning algorithms for enhancing the accuracy of geomagnetic storm forecasting models.
    - Evaluation of the potential computational efficiency gains in storm prediction using quantum computing techniques.

6. **Quantum Optimization for Power System Management under Geomagnetic Disturbances:**

    - Application of quantum annealing and other quantum optimization techniques to power system operations.
    - Development of quantum-inspired algorithms for minimizing the impact of geomagnetically induced currents on grid stability and performance.

7. **Quantum Computation for Fast Calculation of GIC-Induced Nodal Voltages:**

    - Development of quantum algorithms for rapid computation of nodal voltages induced by geomagnetically induced currents (GICs).
    - Demonstration of potential speed-ups in GIC impact assessment using quantum computing techniques.

These contributions collectively form a comprehensive and integrated framework that leverages classical and quantum computing techniques to address the challenges of geomagnetic storms to power systems. By bridging the gap between existing studies and developing a unified approach, this thesis aims to significantly enhance our ability to detect, predict, and mitigate the impacts of geomagnetic disturbances on power systems.

The research outcomes are expected to:

- Advance the theoretical understanding of geomagnetic storm dynamics and their interactions with power systems. These tools and methodologies will provide power system operators with a solid foundation to enhance grid resilience against geomagnetic disturbances, instilling a sense of confidence in their ability to manage such challenges. This research also serves as a beacon of hope, demonstrating the immense potential of quantum computing in solving complex problems in space weather and power system management.
- Lay the groundwork for future research at the intersection of space weather, power systems, and advanced computing techniques.

Through these contributions, this thesis aims to significantly impact the field, ultimately contributing to the development of more secure and resilient electrical grids in the face of increasing space weather threats.

Chapter 3

Time Series Analysis of Geomagnetic Storms

Chapter 4

Time Series Analysis of Geomagnetic Storms

4.1 Introduction

Geomagnetic storms and intense disturbances in Earth's magnetic field caused by solar wind interactions pose significant risks to our increasingly technology-dependent society. These powerful solar events can disrupt satellite communications, compromise power grids, and even impact navigation systems, potentially leading to widespread technological and economic disruptions. As our reliance on these systems grows, so does the urgent need for accurate and timely predictions of geomagnetic activity.

Traditionally, geomagnetic storm forecasting has relied on observational data and physics-based models. While these approaches have provided valuable insights, they often need help with solar-terrestrial interactions' complex, non-linear nature. The advent of advanced machine learning techniques and the availability of high-resolution geomagnetic data have opened new avenues for enhancing our predictive capabilities.

This chapter presents a novel, comprehensive approach to geomagnetic storm prediction that leverages state-of-the-art time series analysis and machine learning techniques. Our methodology uniquely combines rigorous statistical analysis with an ensemble of advanced predictive models, offering a more robust and accurate framework for forecasting geomagnetic disturbances.

The core of our approach lies in its multifaceted nature:

1. We thoroughly examine the stationarity characteristics of geomagnetic time series data using Augmented Dickey-Fuller (ADF) and Partial Autocorrelation Function (PACF) tests. This statistical foundation ensures the appropriateness of our subsequent modelling techniques.

2. We then explore a diverse array of machine learning models, each chosen for its unique strengths in capturing different aspects of geomagnetic activity:

    - Convolutional Neural Networks (CNNs) for identifying spatial patterns
    - Long Short-Term Memory (LSTM) networks for capturing long-term dependencies
    - A hybrid CNN-LSTM architecture that combines the strengths of both approaches
    - Multi-Layer Perceptrons (MLPs) for modelling complex non-linear relationships
    - Ensemble methods like Random Forest and Gradient Boosting for robust predictions

3. Finally, we introduce a novel stacked ensemble approach that leverages the collective strengths of these individual models, resulting in superior predictive performance.

Our methodology is applied to a comprehensive database of geomagnetic storm events spanning multiple decades and geographical locations. We focus on predicting the magnitude of the magnetic field ($|B|$) at high temporal resolutions, a critical parameter for assessing potential impacts on technological systems.

This chapter begins with an overview of the challenges in geomagnetic storm prediction and the limitations of current approaches. We then detail our database, including data acquisition and preprocessing techniques. The core methodology section provides in-depth explanations of each component of our predictive framework. We present a comprehensive analysis of our results, comparing the performance of individual models and our stacked ensemble approach across various metrics and prediction horizons. Finally, we discuss the implications of our findings, current limitations, and promising directions for future research.

Our approach represents a significant step forward in geomagnetic storm prediction by integrating advanced statistical techniques, diverse machine learning models, and ensemble methods. The insights and methodologies presented here have the potential to enhance our understanding of space weather phenomena and contribute to the development of more effective early warning systems, ultimately improving our resilience to the impacts of severe space weather events.

4.1.1 Data Quality and Availability

The quality and consistency of input data remain ongoing challenges in geomagnetic prediction, with implications for model accuracy and reliability. Cristoforetti et al. [181] underscored the critical importance of training data preparation in geomagnetic storm prediction using deep neural networks. Their work demonstrated how data quality could significantly impact the performance of machine learning models, emphasizing the need for careful data curation and preprocessing in developing robust prediction systems.

Addressing data quality and interpretation challenges, Mandrikova and Rodomanskay [182] developed a method for detecting geomagnetic disturbances based on the wavelet model of geomagnetic field variations. This innovative approach offered new tools for preprocessing and analyzing geomagnetic data, potentially improving the quality of inputs for prediction models.

The importance of high-quality input data was further emphasized by Myagkova, Shiroky, and Dolenko [32] in their work on predicting geomagnetic indexes using artificial neural networks. Their research showcased how neural networks could be effectively applied to geomagnetic prediction with reliable data, highlighting the synergy between data quality and advanced modelling techniques.

Issana et al. [183] contributed to this area by applying Bayesian inference and global sensitivity analysis to ambient solar wind prediction, addressing uncertainties in solar wind data. This probabilistic approach offered a way to quantify and mitigate input data uncertainties, potentially improving geomagnetic predictions' robustness.

4.1.2 Model Interpretability

As prediction models become increasingly complex, ensuring their interpretability becomes essential for building trust in forecasts and gaining physical insights. Laperre, Amaya, and Lapenta [184] contributed significantly to this challenge by introducing dynamic time warping as a new evaluation metric for Dst forecasts with machine learning. This novel approach offered a way to assess the performance of complex models in a more nuanced manner, contributing to improved model interpretability and comparison.

Boynton et al. [52] addressed the interpretability challenge by developing a data-derived NARMAX Dst model, which offers better interpretability than some black-box machine learning models. The NARMAX approach provided a balance between predictive power and model interpretability, demonstrating the potential for developing accurate and understandable models.

The importance of model interpretability in assessing different approaches was highlighted by Ji et al. [185] in their comparison of various Dst forecast models for intense geomagnetic storms. Their comparative study provided valuable insights into the strengths and limitations of various modelling techniques, emphasizing the need for transparent and interpretable models in geomagnetic forecasting.

Offering a more interpretable alternative to some machine learning approaches, Zhu et al. [186] developed a data-derived continuous time model for Dst dynamics. This physically-motivated model provided insights into the underlying dynamics of the Dst index, demonstrating the value of interpretable models in advancing our understanding of geomagnetic processes.

4.1.3 Real-Time Forecasting

Developing models capable of real-time forecasting with minimal latency remains a crucial goal for operational space weather prediction. Podladchikova and Petrukovich [187] addressed this challenge by working on extending geomagnetic storm forecasts ahead of available solar wind measurements. Their approach aimed to provide earlier warnings of impending geomagnetic disturbances, representing a significant step towards real-time operational forecasting.

Bala and Reiff [80] contributed to this area by improving short-term forecasting of geomagnetic activity, addressing the crucial need for accurate real-time predictions. Their work demonstrated the potential for rapid, automated forecasts of geomagnetic conditions, essential for timely space weather alerts and mitigation strategies.

Focusing on a specific geomagnetic index, Shprits, Vasile, and Zhelavskaya [59] developed methods for nowcasting and predicting the Kp index using historical values and real-time observations. This approach leveraged the latest available data for up-to-the-minute Kp predictions, contributing to improved real-time forecasting capabilities.

Early groundwork in real-time prediction was laid by Wu and Lundstedt [30], who pioneered using Elman Recurrent Neural Networks for predicting geomagnetic storms from solar wind data. This early application of recurrent neural networks paved the way for subsequent advances in real-time prediction, demonstrating the potential of neural network approaches in rapid geomagnetic forecasting.

4.1.4 Long-Term Forecasting

While short-term predictions have seen significant improvements, long-term forecasting remains challenging due to the complex and often chaotic nature of solar-terrestrial interactions. Issana et al. [183] contributed to this area by applying Bayesian inference and global sensitivity analysis to ambient solar wind prediction, potentially paving the way for improved long-term forecasts. Their probabilistic approach offered a method to quantify uncertainties in extended-range predictions, addressing a key challenge in long-term geomagnetic forecasting.

Owens et al. [48] developed a 27-day persistence model of near-Earth solar wind conditions, providing a benchmark for long-term forecasts and dynamical models. This approach leveraged the quasi-periodic nature of solar activity for extended-range predictions, demonstrating the potential for identifying and exploiting patterns in solar-terrestrial interactions.

Pioneering work in long-term geomagnetic forecasting was conducted by Feynman and Gu [23], who explored predictions on time scales of one to ten years. This early research laid the groundwork

for future investigations into long-term geomagnetic forecasting, highlighting the potential and challenges of extended-range predictions.

Akasofu et al. [24] contributed to our understanding of long-term geomagnetic patterns by working on quantitative forecasting of 27-day recurrent magnetic activity. Their work was crucial in identifying and predicting recurrent geomagnetic activity, demonstrating the potential for long-term forecasts based on solar rotational effects.

Addressing the long-term geomagnetic field evolution challenge, Gillet, Barrois, and Finlay [188] developed stochastic forecasting methods for the geomagnetic field. Their approach offered a way to quantify uncertainties in long-term geomagnetic field variations, contributing to our ability to make extended-range predictions of geomagnetic conditions.

4.1.5 Integration of Physics-Based and Data-Driven Models

Future research should focus on integrating physics-based understanding with data-driven models to leverage the strengths of both approaches. Ji et al. [185] highlighted the potential benefits of integrating different modelling approaches in comparing various Dst forecast models for intense geomagnetic storms. Their comparative study provided insights into how different modelling philosophies could complement each other, pointing towards the potential of hybrid approaches.

Temerin and Li [45] demonstrated the potential for integrating physical insights with empirical predictions by proposing a new model for predicting Dst based on solar wind parameters. This hybrid approach combined physical understanding with data-driven techniques, showcasing the synergy between theoretical knowledge and empirical observations in geomagnetic forecasting.

The importance of integrating physical models with empirical data was further emphasized by Chen, Cargill, and Palmadesso [46] in their work on predicting solar wind structures and their geoeffectiveness. Their research demonstrated how a physical understanding of solar wind structures could inform and enhance prediction models, highlighting the value of physics-based insights in data-driven forecasting.

An early attempt at combining physics-based understanding with data-driven approaches was

showcased by Klimas, Vassiliadis, and Baker [49], who predicted the Dst index using data-derived analogues of magnetospheric dynamics. This method leveraged physical analogues to improve prediction accuracy, demonstrating the potential of physics-informed machine-learning approaches in geomagnetic forecasting.

Blagoveshchenskii [189] provided a comprehensive review of the effects of geomagnetic storms on the ionosphere, emphasizing the need to integrate a physical understanding of these processes into prediction models. Their work highlighted the complex physical processes that must be considered in comprehensive geomagnetic prediction models, underscoring the importance of bridging the gap between theoretical understanding and empirical prediction.

These challenges and future directions in geomagnetic forecasting highlight the multifaceted nature of ongoing research in this field. From improving data quality and model interpretability to advancing real-time and long-term forecasting capabilities and integrating physics-based and data-driven approaches, the field of geomagnetic prediction continues to evolve. As researchers address these challenges, we can expect significant improvements in our ability to forecast and mitigate the impacts of geomagnetic disturbances, enhancing our resilience to space weather events.

4.2 A Novel Comprehensive Approach to Geomagnetic Storm Prediction

The field of geomagnetic storm prediction has seen remarkable advancements over the years, evolving from simple statistical methods to sophisticated machine-learning techniques. However, a comprehensive literature review reveals a significant gap in existing research: no single study has combined rigorous statistical analysis and state-of-the-art machine learning approaches and examined the effects on power systems within a unified framework.

Our proposed methodology addresses this gap, offering a novel and potentially superior approach to geomagnetic storm prediction. By integrating advanced time series analysis techniques such as the Augmented Dickey-Fuller (ADF) and Partial Autocorrelation Function (PACF) tests with

cutting-edge machine learning models, including CNNs, LSTMs, and hybrid architectures, we provide a more robust and comprehensive prediction framework than has been previously attempted.

The uniqueness of our approach lies in its multi-faceted nature. While researchers like Gruet et al. [33] and Upendran et al. [36] have made significant strides in applying deep learning to geomagnetic forecasting, and others such as Owens, Riley, and Horbury [38] and Chandorkar, Camporeale, and Wing [41] have explored ensemble and probabilistic methods, none have combined these approaches with rigorous statistical analysis and a focused examination of power system impacts.

Our methodology stands out in several key aspects:

1. Comprehensive Statistical Foundation: By employing both ADF and PACF tests, we ensure a thorough understanding of the time series characteristics, providing a solid statistical basis for our predictive models. This level of statistical rigour is often overlooked in purely machine learning-based approaches.

2. Advanced Machine Learning Ensemble: The use of multiple state-of-the-art models (CNN, LSTM, CNN-LSTM hybrid, MLP, Gradient Boosting, and Random Forest) in a comparative framework is unprecedented in geomagnetic storm prediction. This ensemble approach allows us to leverage the strengths of each model type, potentially leading to more accurate and robust predictions.

3. Integration of Power System Effects: Unlike previous studies focusing solely on geomagnetic indices or solar wind parameters, our methodology explicitly considers the impacts on power systems. Integrating end-user effects provides a more holistic and practically relevant approach to geomagnetic storm prediction.

The lack of a unified approach that combines statistical rigour, advanced machine learning, and power system impact analysis has been a significant limitation in the field. Studies like Bailey et al. [84] have focused on specific aspects such as GIC prediction, while others like Zhelavskaya et al. [61] have explored machine learning models for geomagnetic indices. However, as we propose, they have yet to bring these elements together in a comprehensive framework.

By addressing this gap, our methodology can significantly advance the field of geomagnetic storm prediction. It offers a more nuanced, accurate, and practically applicable approach to forecasting, which could lead to improved early warning systems and more effective mitigation strategies for the impacts of geomagnetic disturbances on critical infrastructure.

In the following sections, we will detail each component of our novel approach, demonstrating how this comprehensive framework can push the boundaries of what is possible in space weather forecasting. Our goal is to contribute to developing more reliable and actionable predictions to safeguard our increasingly technology-dependent society against the unpredictable nature of solar-terrestrial interactions.

4.3 Methodology and Proposed Approach

This chapter investigates the application of advanced time series analysis and machine learning techniques for geomagnetic storm prediction. We begin by examining the stationarity of geomagnetic storm time series data, which is crucial for selecting appropriate forecasting models. The Augmented Dickey-Fuller (ADF) test and the Partial Autocorrelation Function (PACF) test will be employed to assess the stationarity of the time series. The ADF test is a widely used statistical test for determining the presence of a unit root in a time series. It helps to identify whether the time series is stationary or non-stationary. By applying the ADF test to the geomagnetic storm time series data, we can determine if the data exhibits stationarity or requires further differencing to achieve stationarity. The PACF test, on the other hand, measures the correlation between a variable and its lagged values while controlling for the intermediate lags. It helps to identify the optimal lag order for autoregressive models and provides insights into the temporal dependencies within the time series. By examining the PACF plot of the geomagnetic storm time series, we can determine the significant lag orders and assess the presence of autocorrelation. Upon establishing the stationarity of the geomagnetic storm time series and identifying the relevant lag orders, we proceed to explore various state-of-the-art forecasting models. These models include Convolutional Neural Networks

(CNN), Long Short-Term Memory (LSTM) networks, a hybrid CNN-LSTM architecture, Multilayer Perceptrons (MLP), Gradient Boosting, and Random Forest. CNNs are renowned for extracting local features and capturing spatial dependencies, making them well-suited for identifying patterns in geomagnetic storm time series. LSTM networks excel at modelling long-term dependencies and handling vanishing gradient problems, common in time series forecasting. The hybrid CNN-LSTM architecture combines the strengths of both models to capture both local features and long-term dependencies simultaneously. MLP, a classic neural network architecture, will be investigated for its ability to model complex nonlinear relationships in time series data. Gradient Boosting and Random Forest, two popular ensemble learning techniques, will leverage the collective knowledge of multiple weak learners, enhancing the forecasting models' robustness and generalization capability. Throughout the chapter, we will conduct extensive experiments and evaluations to assess the performance of the proposed forecasting models. The models will be trained and validated using historical geomagnetic storm time series data, with appropriate data preprocessing and feature engineering techniques to optimize performance. Model evaluation metrics, such as root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2), will be used to quantify the accuracy and reliability of the predictions. By systematically investigating the stationarity of geomagnetic storm time series using the ADF and PACF tests and employing advanced forecasting models such as CNN, LSTM, CNN-LSTM, MLP, Gradient Boosting, and Random Forest, this chapter aims to provide a comprehensive framework for predicting geomagnetic storms. The insights gained from this research will contribute to the development of more accurate and reliable early warning systems, enabling proactive measures to mitigate the potential impacts of geomagnetic disturbances on critical infrastructure and technological systems.

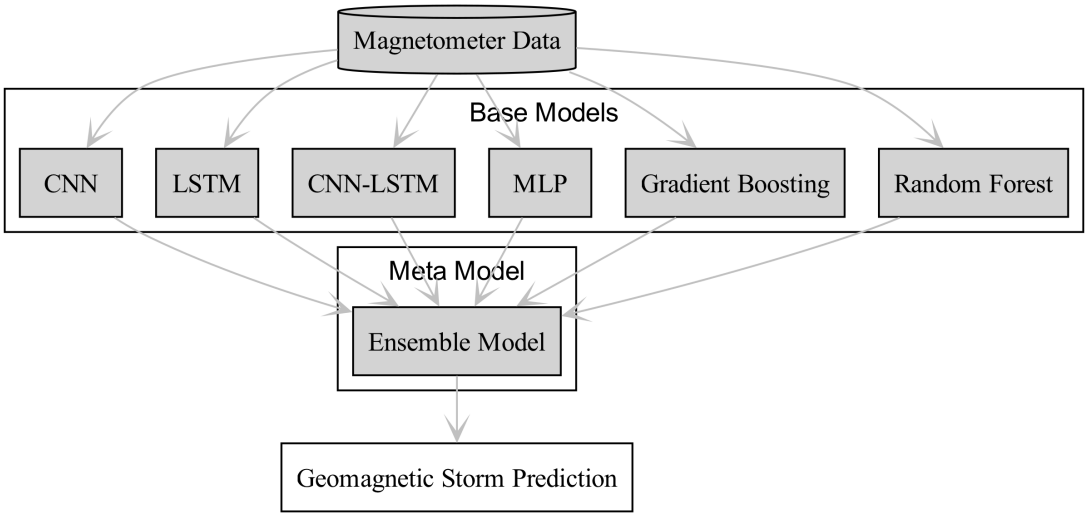


Figure 4.1: Flowchart illustrating the methodology for predicting geomagnetic storms using advanced time series analysis and machine learning techniques

Figure 4.1 illustrates the proposed methodology for predicting geomagnetic storms using an ensemble learning approach. The process begins with the input of magnetometer data, which is the foundation for the prediction models. The magnetometer data is fed into six base models: Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) network, a hybrid CNN-LSTM architecture, Multilayer Perceptron (MLP), Gradient Boosting, and Random Forest. These base models are chosen for their ability to capture different aspects of the time series data and learn complex patterns. Each base model independently processes the magnetometer data and generates its predictions. The predictions from the base models are then aggregated by a meta-model, referred to as the Ensemble Model. The Ensemble Model combines the strengths of the individual base models and leverages their collective knowledge to make the final geomagnetic storm prediction. By employing an ensemble learning approach, the methodology aims to improve the accuracy and robustness of the predictions, as the diverse set of base models can compensate for the weaknesses of individual models and provide a more comprehensive understanding of the underlying patterns in the magnetometer data. The flowchart provides a clear visual representation of the data flow and the interconnections between the methodology's different components, highlighting the Ensemble Model's central role in generating the final geomagnetic storm prediction.

4.3.1 Hyperparameter Optimization using Grid Search

To ensure that we are utilizing the optimal version of each model described in this chapter, we employ a systematic approach to hyperparameter tuning using grid search. Grid search is an exhaustive search method that explores all possible combinations of predefined hyperparameter values to find the best-performing set of hyperparameters for each model.

The grid search process can be formulated as follows:

Let $\mathscr{M} = \{m_1, m_2, ..., m_K\}$ be the set of K models under consideration (CNN, LSTM, CNN-LSTM, MLP, Gradient Boosting, and Random Forest).

For each model $m_i \in \mathscr{M}$, let $\Theta_i = \{\theta_{i1}, \theta_{i2}, ..., \theta_{iN_i}\}$ be the set of N_i hyperparameters to be optimized.

For each hyperparameter θ_{ij}, we define a set of possible values $V_{ij} = \{v_{ij1}, v_{ij2}, ..., v_{ijP_{ij}}\}$, where P_{ij} is the number of possible values for the j-th hyperparameter of the i-th model.

The grid search aims to find the optimal hyperparameter configuration $\theta_i^* \in \Theta_i$ for each model m_i:

$$\theta_i^* = \arg\max_{\theta_i \in \Theta_i} \mathscr{F}(m_i, \theta_i, \mathscr{D}_{\text{val}}) \tag{4.1}$$

where $\mathscr{F}$ is the performance metric (e.g., accuracy, F1-score) evaluated on the validation dataset $\mathscr{D}_{\text{val}}$.

We apply grid search to optimize the following hyperparameters for each model:

1. CNN: - Number of convolutional layers - Number of filters in each layer - Kernel size - Activation function - Pooling type and size

2. LSTM: - Number of LSTM layers - Number of units in each layer - Dropout rate - Activation function

3. CNN-LSTM: - CNN hyperparameters (as above) - LSTM hyperparameters (as above) - Ratio of CNN to LSTM layers

4. MLP: - Number of hidden layers - Number of neurons in each layer - Activation function -

Dropout rate

5. Gradient Boosting: - Number of estimators - Learning rate - Maximum depth - Minimum samples split - Minimum samples leaf

6. Random Forest: - Number of trees - Maximum depth - Minimum samples split - Minimum samples leaf - Maximum features

The grid search process is computationally intensive, as it explores all possible combinations of hyperparameters. To mitigate this, we employ a stratified k-fold cross-validation approach, which helps to reduce overfitting and provides a more robust estimate of model performance.

Let k be the number of folds in the cross-validation process. The performance metric for each hyperparameter configuration is then calculated as:

$$\mathscr{F}(m_i, \theta_i, \mathscr{D}_{\text{val}}) = \frac{1}{k} \sum_{j=1}^{k} \mathscr{F}_j(m_i, \theta_i, \mathscr{D}_{\text{val}_j}) \tag{4.2}$$

where $\mathscr{F}_j$ is the performance metric for the j-th fold, and $\mathscr{D}_{\text{val}_j}$ is the validation set for the j-th fold.

By systematically exploring the hyperparameter space for each model, we ensure that we are using the best-performing version of each model for our geomagnetic storm prediction task. This rigorous approach to hyperparameter optimization enhances the overall performance and reliability of our ensemble learning framework.

The results of the grid search process for each model will be presented in the subsequent sections, along with a discussion of the optimal hyperparameter configurations and their impact on model performance.

4.4 Database Overview

Our database encapsulates a detailed record of significant geomagnetic storm events, documented through their specific dates of occurrence, geographical locations, and the temporal resolution of collected data. These records are instrumental in analyzing geomagnetic disturbances and their

effects on the Earth's magnetic field, sourced from a network of global observatory stations.

4.4.1 Event Details

The database meticulously chronicles events that highlight the complex interactions within the Solar Wind-Magnetosphere-Ionosphere system, offering high-resolution data to capture the Earth's magnetic field's natural variations. The ensuing table provides an exhaustive summary of the covered events:

Event Date	Location	Station Code	Time Resolution	Notes
1989-03-12	Glenmore, UK	GLN	5 seconds	SAMNET data
1989-03-12 to 1989-03-14	York, UK	YRK	5 seconds	SAMNET data
1989-03-13	Ottawa, Canada	OTT	1 minute	INTERMAGNET da
1989-03-12	Meanook, Canada	MEA	1 minute	INTERMAGNET da
2023-02-26	Fort Churchill, Canada	FCC	1 minute	INTERMAGNET da
2003-10-28	Ottawa, Canada	OTT	1 second	INTERMAGNET da
2024-05-10	Ottawa, Canada	OTT	1 second	INTERMAGNET da

Table 4.1: Summary of Geomagnetic Storm Events

This table encompasses data from various locations across the UK and Canada, spanning multiple years of geomagnetic storm events:

1. United Kingdom: - Glenmore and York, with data from the SAMNET network in 1989

2. Canada: - Meanook and Ottawa, with data from 1989 - Fort Churchill, with data from 2023 - Ottawa, with additional data from 2003, 2024

The data sources and resolutions vary:

- The 1989 events are primarily derived from INTERMAGNET and SAMNET sources, with time resolutions ranging from 5 seconds (UK locations) to 1 minute (Canadian locations). - The October 2003 event data, marked explicitly by significant geomagnetic disturbances, was recorded in Ottawa with a high-resolution time series of one second. - The February 2023 event in Fort Churchill was recorded with a one-minute resolution. - The May 2024 event in Ottawa maintains the high-resolution one-second time series, continuing the detailed observations from the 2003 event.

This comprehensive dataset allows for a multi-decade analysis of geomagnetic storm events across different geographical locations. Its varying temporal resolutions capture both broad trends and fine-scale fluctuations in geomagnetic activity.

4.4.2 Data Acquisition and Processing

Equipped with cutting-edge fluxgate magnetometers, the stations involved in this dataset continuously monitor the natural variations in the Earth's magnetic field. The specified temporal resolutions—ranging from one to five seconds—ensure a detailed and comprehensive capture of geomagnetic disturbances, thus enhancing our understanding of the intricate geophysical processes at play.

4.5 Analysis of Geomagnetic Storms

In our analysis, we've focused on several significant geomagnetic storm events spanning multiple decades and locations. Figure 4.2 illustrates the magnitudes of geomagnetic field disturbances for each event:

This combined plot showcases:

1. The March 1989 events: - Glenmore, UK (March 12, 1989) - York, UK (March 12-14, 1989) - Ottawa, Canada (March 13, 1989) - Meanook, Canada (March 12, 1989)

2. The October 28, 2003 event in Ottawa, Canada, known for its significant geomagnetic disturbances.

3. A more recent event on February 26, 2023, observed at Fort Churchill, Canada.

4. The latest recorded event on May 10, 2024, again from Ottawa, Canada.

These plots provide a comprehensive view of geomagnetic storm intensities across different geographical locations and time periods. The magnitude, calculated as $\sqrt{X^2 + Y^2}$ where X and Y are the horizontal components of the geomagnetic field, offers a clear representation of the overall strength of each storm event. This compilation allows for direct comparisons between events,

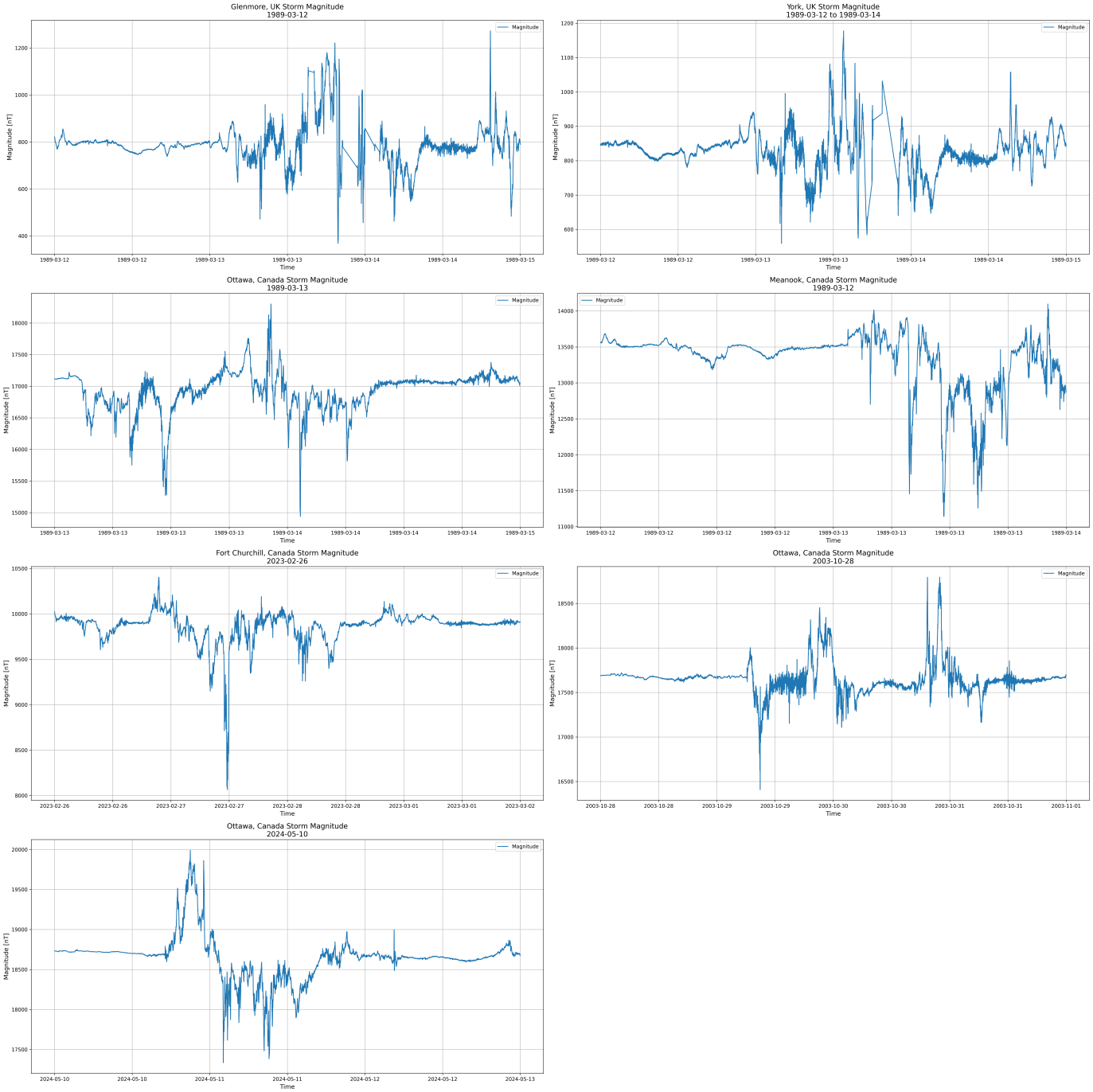


Figure 4.2: Magnitudes of Geomagnetic Storms at Various Locations (1989-2024)

highlighting variations in storm intensities and durations across different epochs and locations.

4.6 Stationarity Analysis of Electromagnetic Signal Components

4.6.1 Objective

The primary objective of this analysis is to assess the stationarity of electromagnetic signal components and derived metrics (magnitude and phase angle) across various datasets. Understanding the stationarity of these signals is crucial for applying many time series analysis techniques, as these often assume stationary data.

subsectionMethods

Augmented Dickey-Fuller Test

To assess the stationarity of our time series data, we employ the Augmented Dickey-Fuller (ADF) test. This test is based on the following regression equation:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{4.3}$$

Where:

- y_t represents the time series under analysis
- Δ denotes the first difference operator
- t is a time trend component
- α is a constant term
- β captures any deterministic time trend

- γ is the coefficient of interest for the unit root test
- p indicates the lag order of the autoregressive process
- ϕ_i are coefficients for the lagged difference terms
- ε_t represents the white noise error term

The ADF test evaluates the null hypothesis $H_0 : \gamma = 0$ (presence of a unit root, indicating non-stationarity) against the alternative hypothesis $H_1 : \gamma < 0$ (absence of a unit root, indicating stationarity). The test produces three key outputs:

1. ADF Statistic: The test statistic calculated from the data
2. Critical Values: Threshold values for different significance levels
3. p-value: The probability of obtaining test results at least as extreme as the observed results, assuming that the null hypothesis is correct

A p-value less than the chosen significance level (typically 0.05) leads to the rejection of the null hypothesis, providing evidence for the stationarity of the time series.

4.6.2 Results

Based on the Augmented Dickey-Fuller (ADF) test, we present a summary of the stationarity assessment for the electromagnetic signal components and derived metrics in Table 4.2.

The ADF test results, a significant milestone in our research, indicate that all the components (X, Y), their computed magnitude, and phase angle for the electromagnetic signals in the datasets from various locations (Glenmore et al.) and different periods (1989, 2003, 2023, and 2024) are stationary. This implies that the statistical properties of these time series (mean, variance, autocorrelation, etc.) do not change over time, making them suitable for further time series analysis and modelling.

Specifically, we observe:

1. All test statistics (ADF Statistic) are negative and significantly different from zero.

2. All p-values are well below the common significance levels (0.05 or 0.01), with most being extremely small ($< 10^{-5}$).

3. The stationarity is consistent across different components (X, Y, Magnitude, and Phase_angle) for all datasets.

4. The results are consistent across different geographical locations (Canada and the UK) and periods from 1989 to 2024.

These findings suggest that the electromagnetic signals during geomagnetic storm events exhibit stationary behaviour despite their intense and variable nature. This stationarity property is crucial for applying many time series analysis techniques and validates our approach to analyzing these complex geophysical phenomena.

The consistency of these results across different events, locations, and time periods suggests a fundamental characteristic of geomagnetic storm data, which could have intriguing implications for modeling and predicting space weather effects on ground-based systems.

4.6.3 Justification for Using Magnetic Field Magnitude in Power Systems Operations

While various geomagnetic indices such as Dst, Kp, and AE have been widely used in space weather forecasting, the magnitude of the magnetic field (|B|) at a specific location offers several advantages for predicting geomagnetic disturbances relevant to power systems operations. This approach provides a more direct and localized measure of geomagnetic activity, which is particularly beneficial for assessing and mitigating risks to power infrastructure.

Local Relevance

One of the primary advantages of using |B| for a specific location is its direct relevance to local power infrastructure. Unlike global indices such as Dst or Kp, which provide averaged or planetary-scale information, |B| measurements at a particular site precisely represent the local geomagnetic

Event Date	Component	ADF Statistic	p-value	Stationary?
1989-03-12, Glenmore, Canada	X	-4.8946	3.57e-05	Yes
1989-03-12, Glenmore, Canada	Y	-7.1818	2.64e-10	Yes
1989-03-12, Glenmore, Canada	Magnitude	-7.6044	2.34e-11	Yes
1989-03-12, Glenmore, Canada	Phase_angle	-4.8504	4.35e-05	Yes
2023-02-26, Fort Churchill, Canada	X	-5.8735	3.20e-07	Yes
2023-02-26, Fort Churchill, Canada	Y	-11.6429	2.13e-21	Yes
2023-02-26, Fort Churchill, Canada	Magnitude	-5.8149	4.31e-07	Yes
2023-02-26, Fort Churchill, Canada	Phase_angle	-11.7761	1.06e-21	Yes
1989-03-12 to 1989-03-14, York, UK	X	-5.6133	1.19e-06	Yes
1989-03-12 to 1989-03-14, York, UK	Y	-5.9258	2.45e-07	Yes
1989-03-12 to 1989-03-14, York, UK	Magnitude	-8.3341	3.31e-13	Yes
1989-03-12 to 1989-03-14, York, UK	Phase_angle	-4.8801	3.81e-05	Yes
1989-03-13, MEA, Canada	X	-4.0864	1.02e-03	Yes
1989-03-13, MEA, Canada	Y	-6.4248	1.76e-08	Yes
1989-03-13, MEA, Canada	Magnitude	-4.2560	5.29e-04	Yes
1989-03-13, MEA, Canada	Phase_angle	-5.5549	1.59e-06	Yes
1989-03-12, Ottawa, Canada	X	-5.6413	1.04e-06	Yes
1989-03-12, Ottawa, Canada	Y	-5.2774	6.10e-06	Yes
1989-03-12, Ottawa, Canada	Magnitude	-5.6174	1.17e-06	Yes
1989-03-12, Ottawa, Canada	Phase_angle	-5.6314	1.09e-06	Yes
2003-10-28, Ottawa, Canada	X	-6.8938	1.34e-09	Yes
2003-10-28, Ottawa, Canada	Y	-9.5138	3.20e-16	Yes
2003-10-28, Ottawa, Canada	Magnitude	-6.5151	1.08e-08	Yes
2003-10-28, Ottawa, Canada	Phase_angle	-10.7056	3.43e-19	Yes
2024-05-10, Ottawa, Canada	X	-4.8542	4.28e-05	Yes
2024-05-10, Ottawa, Canada	Y	-9.9930	1.97e-17	Yes
2024-05-10, Ottawa, Canada	Magnitude	-4.8139	5.12e-05	Yes
2024-05-10, Ottawa, Canada	Phase_angle	-11.0646	4.72e-20	Yes

Table 4.2: Updated ADF Test Results for Geomagnetic Storm Events

conditions. This localized approach is crucial for power systems operators, as the impacts of geomagnetic disturbances can vary significantly across different geographic regions.

Direct Physical Relationship

B's magnitude directly relates to the generation of Geomagnetically Induced Currents (GICs) in power systems. GICs, which pose significant risks to power infrastructure, are primarily driven by rapid changes in the local magnetic field. By focusing on |B|, we can more accurately capture the potential for GIC generation at a specific location, providing a more relevant metric for power systems risk assessment.

Higher Temporal Resolution

Many traditional geomagnetic indices are provided at relatively low temporal resolutions (e.g., 3-hour intervals for Kp, 1-hour for Dst). In contrast, |B| measurements can be obtained at higher frequencies, often at minute or second-level resolution. This higher temporal resolution is crucial for capturing rapid geomagnetic variations that are most likely to induce significant GICs in power systems.

Simplicity and Interpretability

The magnitude of B is a straightforward and easily interpretable metric. Unlike complex indices that combine multiple parameters or require sophisticated calculations, |B| provides a clear, single-value representation of the local magnetic field strength. This simplicity facilitates easier integration into operational decision-making processes and power system operators' risk assessment models.

Predictive Potential

Recent advancements in machine learning and time series analysis techniques have demonstrated significant potential in predicting local magnetic field variations. We can leverage these advanced

techniques by focusing on |B| predictions to provide more accurate and location-specific forecasts of geomagnetic disturbances relevant to power systems.

Integration with Power System Models

Using |B| aligns well with existing power system models and GIC calculation methods. Many GIC models use the rate of change of the horizontal magnetic field components as inputs. Predicting |B| directly links these components, allowing for a more seamless integration of geomagnetic forecasts into power system risk assessment and mitigation strategies.

Adaptability to Different Locations

While global indices provide a standardized measure across the planet, they may not adequately capture the unique geomagnetic characteristics of specific regions. By focusing on |B| predictions for individual locations, we can develop models adaptable to the particular geomagnetic behaviour of different areas, accounting for local geology, latitude, and typical storm patterns that affect each location differently.

In conclusion, while traditional geomagnetic indices have their merits, using |B| for specific locations offers a more direct, relevant, and adaptable approach for predicting geomagnetic disturbances in the context of power systems operations. This approach provides power systems operators with more actionable information, enabling more effective risk assessment and mitigation strategies against the potential impacts of space weather events on critical power infrastructure.

4.7 Multi-Layer Perceptron (MLP) for Geomagnetic Storm Prediction

This section details the application of a Multi-Layer Perceptron (MLP) for predicting geomagnetic storm intensities using high-resolution time series data. Our model is designed to forecast the

magnitude of the magnetic field (|B|) at one-minute resolution, utilizing the past 60 minutes of data to predict the next 20 minutes.

4.7.1 MLP Network Architecture

Our MLP consists of an input, multiple hidden, and output layers. The network is configured as follows:

- **Input Layer:** 60 neurons, corresponding to the last 60 minutes of |B| measurements.
- **Hidden Layers:** Multiple dense layers with varying numbers of neurons (e.g., 64, 32).
- **Output Layer:** 20 neurons, representing the predicted |B| values for the next 20 minutes.

Mathematical Formulation

Given an input vector $\mathbf{x} \in \mathbb{R}^{60}$, representing the last 60 minutes of |B| measurements, the MLP performs the following transformations:

- **First Hidden Layer:**

$$\mathbf{z}^{(1)} = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}$$

$$\mathbf{a}^{(1)} = \text{ReLU}(\mathbf{z}^{(1)})$$

  Where $\mathbf{W}^{(1)} \in \mathbb{R}^{64\times 60}$ and $\mathbf{b}^{(1)} \in \mathbb{R}^{64}$.

- **Second Hidden Layer:**

$$\mathbf{z}^{(2)} = \mathbf{W}^{(2)}\mathbf{a}^{(1)} + \mathbf{b}^{(2)}$$

$$\mathbf{a}^{(2)} = \text{ReLU}(\mathbf{z}^{(2)})$$

  Where $\mathbf{W}^{(2)} \in \mathbb{R}^{32\times 64}$ and $\mathbf{b}^{(2)} \in \mathbb{R}^{32}$.

- **Output Layer:**

$$\hat{\mathbf{y}} = \mathbf{W}^{(3)}\mathbf{a}^{(2)} + \mathbf{b}^{(3)}$$

Where $\mathbf{W}^{(3)} \in \mathbb{R}^{20\times 32}$, $\mathbf{b}^{(3)} \in \mathbb{R}^{20}$, and $\hat{\mathbf{y}}$ represents the predicted |B| values for the next 20 minutes.

4.7.2 Training the MLP

The MLP is trained using a dataset of historical |B| measurements, with each sample consisting of 60 consecutive minutes of data (input) and the corresponding 20 minutes that follow (target output). The training process involves:

- **Data Preprocessing:** Scaling the |B| values using MinMaxScaler to the range [0, 1].
- **Loss Function:** Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{y}_i - \hat{\mathbf{y}}_i)^2$$

  where $n = 20$ (number of predicted minutes), $\mathbf{y}_i$ is the actual |B| value, and $\hat{\mathbf{y}}_i$ is the predicted value.

- **Optimization:** Adam optimizer with learning rate adaptation.
- **Training Process:** The model is trained for multiple epochs with a specified batch size (e.g., 24 samples per batch).

4.7.3 Model Evaluation

The model's performance is evaluated using several metrics:

- **Root Mean Square Error (RMSE):**

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathbf{y}_i - \hat{\mathbf{y}}_i)^2}$$

- **Mean Squared Error (MSE)**

- **R-squared (R^2) Score:** Measures the proportion of variance in the dependent variable predictable from the independent variable(s).

These metrics are calculated for each of the 20 predicted time steps, providing a detailed view of the model's performance across the forecast horizon.

4.7.4 Practical Implementation

The MLP model is implemented using TensorFlow and Keras, with the following key features:

- **Flexible Architecture:** The number and size of hidden layers can be easily adjusted through configuration parameters.
- **Data Handling:** The model can process multiple CSV files, combining data from various sources or periods.
- **Model Persistence:** Trained models can be saved and loaded, allowing continuous improvement and reuse.
- **Visualization:** The model architecture can be visualized using Keras' plot_model function.

This MLP-based approach to geomagnetic storm prediction is a powerful tool for forecasting short-term variations in the magnitude of the magnetic field. By leveraging high-resolution time series data and the MLP's ability to capture complex temporal patterns, we can provide valuable insights for space weather monitoring and risk assessment in various applications, including power grid management and satellite operations.

4.8 Convolutional Neural Network (CNN) for Geomagnetic Storm Prediction

This section details the application of a Convolutional Neural Network (CNN) for predicting geomagnetic storm intensities using high-resolution time series data. Our model is designed to

forecast the magnitude of the magnetic field (|B|) at one-minute resolution, utilizing the past 60 minutes of data to predict the next 20 minutes.

4.8.1 CNN Architecture for Geomagnetic Time Series

Our CNN architecture is specifically designed to capture temporal patterns in geomagnetic data. It consists of convolutional layers, max-pooling layers, and dense layers:

Convolutional Layers

The model employs multiple convolutional layers, each applying a set of learnable filters to the input time series data. For our geomagnetic prediction task, the convolutional operation is defined as:

$$\text{Output}_{\text{conv}} = \text{ReLU}(\mathbf{W} * \mathbf{X} + \mathbf{b})$$

Where $*$ denotes the convolution operation, $\mathbf{W}$ represents the weights of the filters, $\mathbf{b}$ is a bias term, and ReLU is the activation function.

Max Pooling Layers

Following each convolutional layer, we apply max pooling to reduce the dimensionality of the feature maps while retaining the most significant information:

$$\text{Output}_{\text{pool}} = \max_{i,j \in R} x_{ij}$$

Where R is a local region in the feature map.

Flattening and Dense Layer

After the convolutional and pooling layers, we flatten the output and pass it through a dense layer for final prediction:

$$\mathbf{y} = \mathbf{W}_{\text{fc}} \cdot \text{Flatten}(\text{Output}_{\text{pool}}) + \mathbf{b}_{\text{fc}}$$

Where $\mathbf{W}_{\text{fc}}$ and $\mathbf{b}_{\text{fc}}$ are the weights and biases of the fully connected layer.

4.8.2 Model Configuration

Our CNN model is configured as follows:

- **Input Shape:** (60, 1), representing 60 time steps of univariate |B| data
- **First Convolutional Layer:** 64 filters, kernel size of 3, ReLU activation
- **First Max Pooling Layer:** Pool size of 1
- **Second Convolutional Layer:** 32 filters, kernel size of 3, ReLU activation
- **Second Max Pooling Layer:** Pool size of 1
- **Flatten Layer**
- **Output Dense Layer:** 20 units, linear activation

4.8.3 Training the CNN Model

The model is trained using the following process:

- **Data Preprocessing:** |B| values are scaled using MinMaxScaler to the range [0, 1].
- **Loss Function:** Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (\mathbf{y}_i - \hat{\mathbf{y}}_i)^2$$

where N is the number of samples, $\mathbf{y}_i$ are the actual |B| values, and $\hat{\mathbf{y}}_i$ are the predicted values.

- **Optimizer:** Adam
- **Training Process:** The model is trained for multiple epochs with a specified batch size (e.g., 32 samples per batch).

4.8.4 Model Evaluation

We evaluate the model's performance using several metrics:

- **Root Mean Square Error (RMSE):**

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathbf{y}_i - \hat{\mathbf{y}}_i)^2}$$

- **Mean Squared Error (MSE)**
- **R-squared (R^2) Score**

These metrics are calculated for each of the 20 predicted time steps, providing a detailed view of the model's performance across the forecast horizon.

4.8.5 Practical Implementation

Our CNN model is implemented using TensorFlow and Keras, with the following key features:

- **Flexible Architecture:** The number of convolutional layers, filters, and kernel sizes can be easily adjusted through configuration parameters.
- **Data Handling:** The model can process multiple CSV files, combining data from various sources or periods.
- **Model Persistence:** Trained models can be saved and loaded, allowing continuous improvement and reuse.

- **Visualization:** The model architecture can be visualized using Keras' plot_model function.

This CNN-based approach to geomagnetic storm prediction offers a powerful tool for forecasting short-term variations in the magnitude of the magnetic field. By leveraging CNN's ability to capture local patterns and temporal dependencies in high-resolution time series data, we can provide valuable insights for space weather monitoring and risk assessment in various applications, including power grid management and satellite operations.

4.9 Long Short-Term Memory (LSTM) Networks for Geomagnetic Storm Prediction

This section details the application of Long-Short-Term Memory (LSTM) networks to predict geomagnetic storm intensities using high-resolution time series data. Our model is designed to forecast the magnitude of the magnetic field (|B|) at one-minute resolution, utilizing the past 60 minutes of data to predict the next 20 minutes.

4.9.1 LSTM Network Architecture

Our LSTM architecture is specifically tailored to capture long-term dependencies in geomagnetic time series data. The network consists of multiple LSTM layers followed by a dense output layer:

LSTM Layers

The model employs three LSTM layers, each with a specific number of units and activation function:

- First LSTM Layer: 40 units with ReLU activation
- Second LSTM Layer: 30 units with ReLU activation
- Third LSTM Layer: 30 units with ReLU activation

Each LSTM layer processes the input sequence and passes its output to the next layer. The mathematical formulation for each LSTM cell remains as previously described, with the addition of the ReLU activation function applied to the cell outputs.

Dense Output Layer

Following the LSTM layers, a dense layer with 20 units and a sigmoid activation function is used to produce the final predictions:

$$\mathbf{y} = \sigma(\mathbf{W} \cdot \mathbf{h}_T + \mathbf{b})$$

Where $\mathbf{h}_T$ is the output from the final LSTM layer, $\mathbf{W}$ and $\mathbf{b}$ are the weights and biases of the dense layer, and σ is the sigmoid activation function.

4.9.2 Data Preprocessing and Model Input

The input data is preprocessed as follows:

- The |B| values are scaled to the range [0, 1] using MinMaxScaler.
- The input sequence length is set to 60-time steps (look_back).
- The output sequence length is set to 20-time steps (look_forward).

The input to the model is reshaped to (batch_size, 1, 60) to match the LSTM layer's input requirements.

4.9.3 Training the LSTM Model

The model is trained using the following process:

- **Loss Function:** Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (\mathbf{y}_i - \hat{\mathbf{y}}_i)^2$$

where N is the number of samples, $\mathbf{y}_i$ are the actual |B| values, and $\hat{\mathbf{y}}_i$ are the predicted values.

- **Optimizer:** Adam
- **Training Process:** The model is trained for multiple epochs with a specified batch size (e.g., 32 samples per batch).
- **Data Generator:** A custom DataGenerator class efficiently loads and preprocess data in batches during training.

4.9.4 Model Evaluation

We evaluate the model's performance using several metrics:

- **Root Mean Square Error (RMSE):**

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathbf{y}_i - \hat{\mathbf{y}}_i)^2}$$

- **Mean Squared Error (MSE)**
- **R-squared (R^2) Score**

These metrics are calculated for each of the 20 predicted time steps, providing a detailed view of the model's performance across the forecast horizon.

4.9.5 Practical Implementation

Our LSTM model is implemented using TensorFlow and Keras, with the following key features:

- **Flexible Architecture:** The number of LSTM layers, units per layer, and activation functions can be easily adjusted through configuration parameters.
- **Data Handling:** The model can process multiple CSV files, combining data from various sources or periods.

- **Model Persistence:** Trained models can be saved and loaded, allowing continuous improvement and reuse.
- **Visualization:** The model includes functionality to plot predictions against true values for visual performance inspection.

This LSTM-based approach to geomagnetic storm prediction is a powerful tool for forecasting short-term variations in the magnitude of the magnetic field. By leveraging the LSTM's ability to capture long-term dependencies in high-resolution time series data, we can provide valuable insights for space weather monitoring and risk assessment in various applications, including power grid management and satellite operations.

4.10 Hybrid CNN-LSTM Architecture for Geomagnetic Storm Prediction

This section details applying a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model for predicting geomagnetic storm intensities using high-resolution time series data. Our model is designed to forecast the magnitude of the magnetic field (|B|) at one-minute resolution, utilizing the past 60 minutes of data to predict the next 20 minutes.

4.10.1 Model Architecture

Our hybrid CNN-LSTM architecture is designed to capture spatial and temporal patterns in geomagnetic data. The model consists of sequential CNN layers followed by LSTM layers:

CNN Layers

The initial layers of the model are convolutional layers that perform convolutions over the input time series data:

- Four Conv1D layers with [16, 32, 64, 128] filters, respectively
- Kernel size of 1 for all layers
- ReLU activation for all layers
- MaxPooling1D layers with a pool size of 1 after each Conv1D layer

The mathematical operation for each convolutional layer is:

$$\text{Feature Map} = \text{ReLU}(\text{Conv1D}(\text{Input}) + \text{Bias})$$

LSTM Layers

Following the CNN layers, we have three LSTM layers:

- First LSTM Layer: 40 units with ReLU activation
- Second LSTM Layer: 30 units with ReLU activation
- Third LSTM Layer: 30 units with ReLU activation

The LSTM layers process the sequence of feature vectors extracted by the CNN:

$$\text{LSTM Output} = \text{LSTM}(\text{Flattened CNN Output})$$

Output Layer

A dense layer with 20 units and a sigmoid activation function produces the final predictions:

$$\text{Predictions} = \sigma(\text{Dense}(\text{LSTM Output}))$$

where σ is the sigmoid activation function.

4.10.2 Data Processing and Model Input

The input data is preprocessed as follows:

- The |B| values are scaled to the range [0, 1] using MinMaxScaler.
- The input sequence length is set to 60-time steps (look_back).
- The output sequence length is set to 20-time steps (look_forward).

The input to the model is reshaped to (batch_size, 60, 1) to match the CNN layer's input requirements.

4.10.3 Training the Hybrid Model

The model is trained using the following process:

- **Loss Function:** Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\mathbf{y}_i - \hat{\mathbf{y}}_i)^2$$

  where N is the number of samples, $\mathbf{y}_i$ are the actual |B| values, and $\hat{\mathbf{y}}_i$ are the predicted values.

- **Optimizer:** Adam
- **Training Process:** The model is trained for multiple epochs with a specified batch size (e.g., 20 samples per batch).
- **Incremental Learning:** The model can be trained incrementally on new data, allowing for continuous improvement as more data becomes available.

4.10.4 Model Evaluation

We evaluate the model's performance using several metrics:

- **Root Mean Square Error (RMSE):**

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathbf{y}_i - \hat{\mathbf{y}}_i)^2}$$

- **Mean Squared Error (MSE)**

- **R-squared (R^2) Score**

- **Adjusted Mean Absolute Percentage Error (AMAPE):**

$$\text{AMAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\mathbf{y}_i - \hat{\mathbf{y}}_i}{\mathbf{y}_i + \bar{\mathbf{y}}}\right| \times 100$$

  where $\bar{\mathbf{y}}$ is the mean of actual values.

These metrics are calculated for each of the 20 predicted time steps, providing a detailed view of the model's performance across the forecast horizon.

4.10.5 Practical Implementation

Our hybrid CNN-LSTM model is implemented using TensorFlow and Keras, with the following key features:

- **Flexible Architecture:** The number and configuration of CNN and LSTM layers can be easily adjusted through configuration parameters.

- **Data Handling:** The model can process multiple CSV files, combining data from various sources or time periods.

- **Model Persistence:** Trained models can be saved and loaded, allowing continuous improvement and reuse.

- **Visualization:** The model architecture can be visualized using Keras' plot_model function.

This hybrid CNN-LSTM approach to geomagnetic storm prediction offers a powerful tool for forecasting short-term variations in the magnitude of the magnetic field. By leveraging CNN's ability to capture local patterns and LSTM's capacity to model long-term dependencies in high-resolution time series data, we can provide valuable insights for space weather monitoring and risk assessment in various applications, including power grid management and satellite operations.

4.11 Random Forest for Geomagnetic Storm Prediction

This section details the application of Random Forest for predicting geomagnetic storm intensities using high-resolution time series data. Our model is designed to forecast the magnitude of the magnetic field (|B|) at one-minute resolution, utilizing the past 10 minutes of data to predict the next 2 minutes.

4.11.1 Model Architecture

Our Random Forest model consists of an ensemble of decision trees, each trained on a different subset of the data:

- Number of estimators (trees): 10
- Maximum depth of each tree: 10
- Separate models for each step in the forecast horizon

The mathematical representation of the forecast using our Random Forest is given by:

$$y_t = \frac{1}{10} \sum_{b=1}^{10} f_b(x_{t-10:t})$$

Where y_t is the prediction for time t, f_b is the prediction of the b-th tree, and $x_{t-10:t}$ is the input feature vector containing the last 10 time steps.

4.11.2 Data Preprocessing

The input data is preprocessed as follows:

- The |B| values are scaled to the range [0, 1] using MinMaxScaler.
- The input sequence length is set to 10 time steps (look_back).
- The output sequence length is set to 2 time steps (look_forward).

4.11.3 Training the Random Forest Model

The model is trained using the following process:

- Data is split into training and testing sets based on a specified percentage (e.g., 90
- Separate Random Forest models are trained for each step in the forecast horizon.
- Each model is trained to predict a specific future time step based on the input sequence.

4.11.4 Model Evaluation

We evaluate the model's performance using several metrics:

- **Root Mean Square Error (RMSE):**

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

- **Mean Squared Error (MSE)**
- **R-squared (R^2) Score**

These metrics are calculated for each predicted time step, providing a detailed view of the model's performance across the forecast horizon.

4.11.5 Practical Implementation

Our Random Forest model for geomagnetic storm prediction is implemented using sci-kit-learn, with the following key features:

- **Flexible Architecture:** The number of trees and maximum depth can be easily adjusted.
- **Data Handling:** The model can process multiple CSV files, combining data from various sources or periods.
- **Model Persistence:** Trained models can be saved and loaded using pickle, allowing continuous improvement and reuse.
- **Visualization:** The implementation includes functionality to plot forecasts against actual values for visual performance inspection.
- **Incremental Learning:** The model can be retrained with new data, allowing for continuous improvement as more data becomes available.

This Random Forest approach to geomagnetic storm prediction offers a robust tool for forecasting short-term variations in the magnitude of the magnetic field. By leveraging the ensemble nature of Random Forests, we can provide reliable predictions and insights into feature importance, enhancing our understanding of the factors driving geomagnetic activity.

4.12 Gradient Boosting for Geomagnetic Storm Prediction

This section details the application of Gradient Boosting for predicting geomagnetic storm intensities using high-resolution time series data. Our model is designed to forecast the magnitude of the magnetic field (|B|) at one-minute resolution, utilizing the past 10 minutes of data to predict the next 2 minutes.

4.12.1 Model Architecture

Our Gradient Boosting model consists of an ensemble of decision trees, built sequentially to correct the errors of previous trees:

- Number of estimators (trees): 100
- Learning rate: 0.1
- Separate models for each step in the forecast horizon

The mathematical representation of our Gradient Boosting model at iteration t is given by:

$$F_t(x) = F_{t-1}(x) + 0.1 \cdot h_t(x)$$

where $F_t(x)$ is the model at iteration t, $h_t(x)$ is the decision tree added at iteration t, and 0.1 is the learning rate.

4.12.2 Data Preprocessing

The input data is preprocessed as follows:

- The |B| values are scaled to the range [0, 1] using MinMaxScaler.
- The input sequence length is set to 10 time steps (look_back).
- The output sequence length is set to 2 time steps (look_forward).
- Data is sorted by timestamp to ensure temporal order.

4.12.3 Training the Gradient Boosting Model

The model is trained using the following process:

- Data is split into training and testing sets based on a specified percentage (default 90

- Separate Gradient Boosting models are trained for each step in the forecast horizon.
- Each model is trained to predict a specific future time step based on the input sequence.
- The model can be trained on combined data from multiple CSV files, either by year or by a specified train-test split.

4.12.4 Model Evaluation

We evaluate the model's performance using several metrics:

- **Root Mean Square Error (RMSE):**

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

- **Mean Squared Error (MSE)**
- **R-squared (R^2) Score**

These metrics are calculated for each predicted time step, providing a detailed view of the model's performance across the forecast horizon.

4.12.5 Practical Implementation

Our Gradient Boosting model for geomagnetic storm prediction is implemented using sci-kit-learn, with the following key features:

- **Flexible Architecture:** The number of estimators and learning rate can be easily adjusted.
- **Data Handling:** The model can process multiple CSV files, combining data from various sources or periods.
- **Model Persistence:** Trained models can be saved and loaded using pickle, allowing for continuous improvement and reuse.

- **Visualization:** The implementation includes functionality to plot forecasts against actual values for visual performance inspection.
- **Incremental Learning:** The model can be retrained with new data, allowing for continuous improvement as more data becomes available.

4.12.6 Advanced Features

Our implementation includes several advanced features:

- **Multi-step Forecasting:** The model is capable of predicting multiple time steps into the future.
- **Combined Training:** The model can be trained on data combined from multiple CSV files, either by year or by a specified train-test split.
- **Flexible Data Loading:** The model can handle various date formats and column names in the input CSV files.
- **Performance Visualization:** The plot_forecast_vs_actual method allows for easy visualization of model performance.

This Gradient-Boosting approach to geomagnetic storm prediction offers a powerful tool for forecasting short-term variations in the magnetic field magnitude. By leveraging the sequential nature of gradient boosting, we can provide accurate predictions and insights into the temporal dynamics of geomagnetic activity, enhancing our ability to anticipate and mitigate the impacts of space weather events.

4.13 Ensemble Learning and Stacked Ensemble for Geomagnetic Storm Prediction

4.13.1 Concept of Ensemble Learning

Ensemble learning is a powerful machine learning paradigm that combines multiple models to improve prediction performance and robustness. The central idea is that a group of models can collectively make better predictions than any individual model. This approach leverages the diversity of different models to reduce errors, decrease bias and variance, and mitigate overfitting.

4.13.2 Types of Ensemble Learning

There are several types of ensemble learning methods, each with its approach to combining models:

1. **Bagging (Bootstrap Aggregating):** This method creates multiple subsets of the original dataset through random sampling with replacement, trains a model on each subset, and then aggregates their predictions. Random Forest is a popular example of bagging.

2. **Boosting:** Boosting methods train models sequentially, with each new model focusing on the errors of the previous ones. Examples include AdaBoost and Gradient Boosting.

3. **Stacking:** This approach involves training multiple diverse base models and then using another model (meta-model) to learn how to combine their predictions best.

4. **Voting:** In voting, multiple models make predictions independently, and the final prediction is determined by majority vote (for classification) or averaging (for regression).

4.13.3 Implemented Approach: Stacked Ensemble Learning

We have implemented a Stacked Ensemble Learning approach for our geomagnetic storm prediction task. Here's why we chose this method and how it works in our context:

Rationale for Choosing Stacked Ensemble

- **Leveraging Diverse Models:** Stacking allows us to combine predictions from various base models, each of which may capture different aspects of the complex geomagnetic data.
- **Adaptive Combination:** The meta-model learns how to optimally combine the base model predictions, potentially outperforming any single model or simple averaging.
- **Handling Temporal Aspects:** By training separate meta-models for each time step in our forecast horizon, we can capture time-dependent patterns in model performance.

Implementation Details

Our stacked ensemble model consists of the following:

- **Base Models:** Multiple pre-trained models (e.g., different types of neural networks, time series models) that generate initial predictions.
- **Meta-Model:** A Gradient Boosting Regressor that learns to combine the base model predictions for each forecast time step.

The process works as follows:

1. Base model predictions are loaded from CSV files, ensuring temporal alignment.
2. A separate meta-model (Gradient et al.) is trained for each step in the forecast horizon.
3. Each meta-model uses the base model predictions as features to predict the actual geomagnetic field magnitude.
4. The final prediction for each time step is the output of its corresponding meta-model.

Advantages of Our Approach

- **Improved Accuracy:** By combining diverse models, we can potentially achieve higher accuracy than any single model.
- **Robustness:** The ensemble is less likely to be affected by the weaknesses of any individual model.
- **Flexibility:** Our implementation can easily incorporate new base models or adapt to different forecast horizons.
- **Interpretability:** Gradient Boosting as the meta-model allows for some level of feature importance analysis, giving insights into which base models are most influential.

By implementing this stacked ensemble approach, we aim to create a robust and accurate system for geomagnetic storm prediction capable of capturing complex patterns and relationships in the data that more straightforward approaches might miss.

Figure 4.3 illustrates the comprehensive architecture of our geomagnetic storm prediction system. The system is designed to forecast the magnitude of the magnetic field (|B|) 20 minutes ahead, with predictions at 1-minute resolution, based on 60 minutes of historical data. The architecture can be broken down into several key components:

1. **Input Data:** The system ingests geomagnetic time series data, specifically the |B| magnitude, at 1-minute resolution.
2. **Preprocessing:** Raw data undergoes MinMax scaling and is transformed into input sequences of 60 minutes each, representing the historical data used for prediction.
3. **Base Models:** Six diverse machine learning models process the preprocessed data:
    - Convolutional Neural Network (CNN) with 4 Conv1D layers
    - Long Short-Term Memory (LSTM) network with 3 LSTM layers

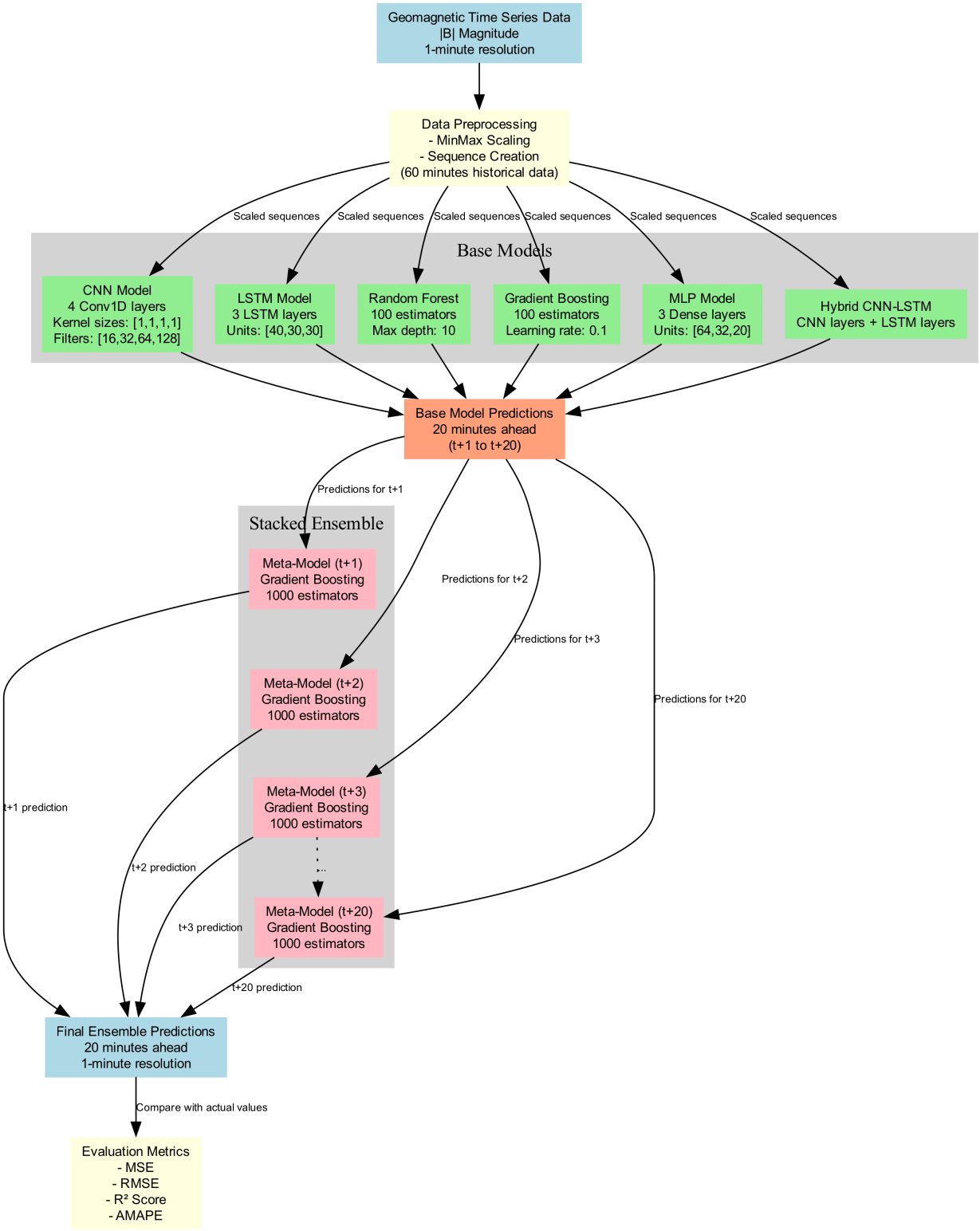


Figure 4.3: Detailed architecture of the geomagnetic storm prediction system.

- Random Forest with 100 estimators
- Gradient Boosting with 100 estimators
- Multilayer Perceptron (MLP) with three dense layers
- Hybrid CNN-LSTM combining convolutional and LSTM layers

4. **Base Model Predictions:** Each base model generates predictions for 20 minutes ahead (t+1 to t+20).

5. **Stacked Ensemble:** A series of 20 meta-models combines the base model predictions, each a Gradient Boosting Regressor with 1000 estimators. Each meta-model specializes in a specific time step from t+1 to t+20.

6. **Final Output:** The ensemble produces the final predictions 20 minutes ahead at a 1-minute resolution.

7. **Evaluation:** The system's performance is assessed using multiple metrics: Mean Squared Error (MSE), Root Mean Square Error (RMSE), R^2 Score, and Average Mean Absolute Percentage Error (AMAPE).

This architecture leverages the strengths of diverse base models and employs a sophisticated stacking technique to generate high-quality geomagnetic storm predictions. The system captures recent trends and patterns in geomagnetic activity by using 60 minutes of historical data to predict 20 minutes into the future. Using multiple base models allows the system to capture various aspects of the complex geomagnetic data while the stacked ensemble refines these predictions to produce a more accurate final forecast.

4.14 Results and Discussion

4.14.1 Model Performance Comparison

To evaluate the effectiveness of our methodology, we compared the performance of various machine learning models and our proposed Stacked Ensemble approach. Table 4.3 presents a summary of the average metrics for each model across all prediction horizons.

Table 4.3: Average Performance Metrics for Different Models

Model	AMAPE	MSE	RMSE	R^2	MAE
Stacked Ensemble	0.5917	654.45	25.46	0.9936	17.91
Random Forest	0.5243	6077.76	77.80	0.9399	44.31
Gradient Boosting	0.4341	18590.24	134.97	0.8162	79.95
LSTM	0.4664	26804.41	161.89	0.7349	97.14
Hybrid CNN-LSTM	0.3986	31299.55	174.36	0.6905	100.93
MLP	0.5051	28693.84	167.76	0.7163	101.61
CNN	0.5559	41519.42	202.80	0.5894	118.49

The Stacked Ensemble model demonstrates superior performance across all metrics, showcasing the effectiveness of our proposed approach. It achieves the lowest error rates (AMAPE, MSE, RMSE, MAE) and the highest R^2 value, indicating its strong predictive power and ability to capture the underlying patterns in the geomagnetic data.

4.14.2 Performance Across Prediction Horizons

To further analyze the models' capabilities, we examined their performance across different prediction horizons. Figure 4.4 illustrates the RMSE values for each model as the prediction horizon increases.

The Stacked Ensemble model consistently outperforms other models across all prediction horizons, maintaining lower RMSE values even as the horizon extends. This demonstrates the robustness of our approach in both short-term and longer-term predictions.

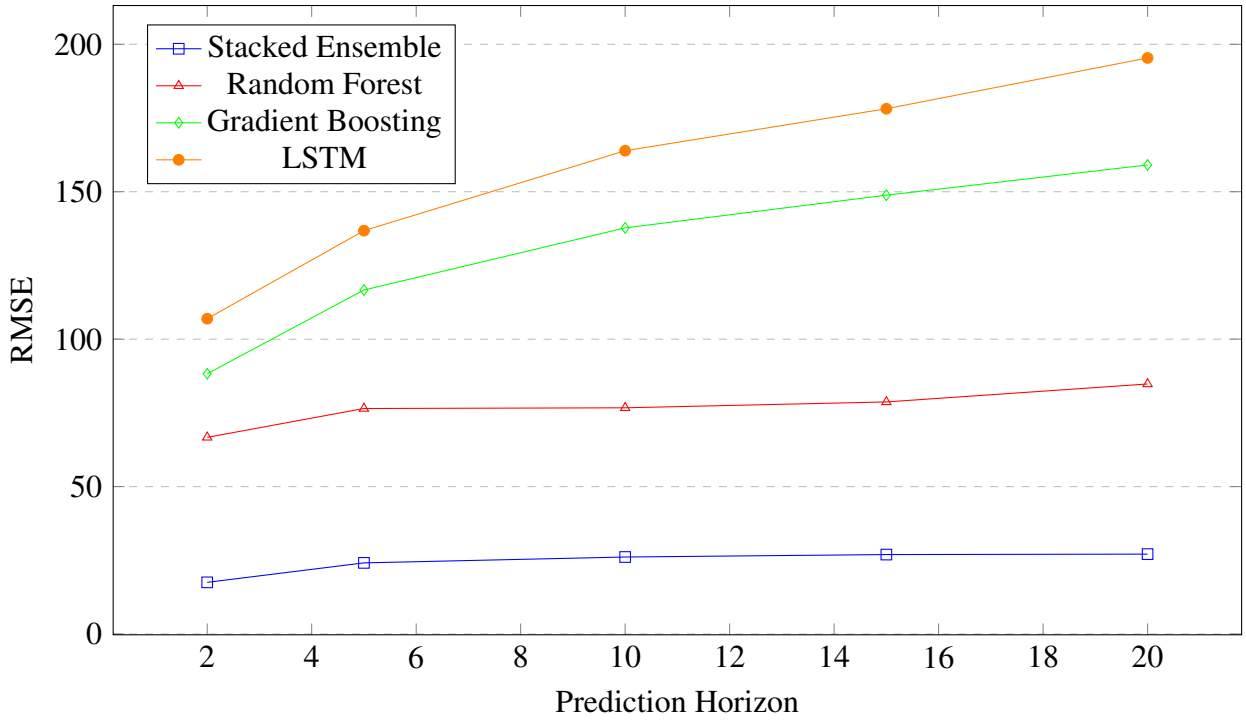


Figure 4.4: RMSE vs. Prediction Horizon for Different Models

4.14.3 Stacked Ensemble Model Analysis

The superior performance of the Stacked Ensemble model can be attributed to its ability to leverage the strengths of multiple base models. Table 4.4 shows the performance metrics of the Stacked Ensemble model for each prediction horizon.

Table 4.4: Stacked Ensemble Model Performance by Horizon

Horizon	AMAPE	MSE	RMSE	R^2	MAE
2	0.1822	307.25	17.53	0.9970	9.20
5	0.3856	582.18	24.13	0.9943	16.93
10	0.5917	682.26	26.12	0.9933	18.60
15	0.7380	726.28	26.95	0.9928	19.56
20	0.8642	734.68	27.10	0.9928	19.21

As evident from Table 4.4, the model maintains high performance even at longer prediction horizons. The gradual increase in error metrics and slight decrease in R^2 values are expected as the prediction task becomes more challenging with increasing horizon length.

4.14.4 Detailed Base Model Prediction Comparisons

To gain deeper insights into the performance of each base model, we conducted a detailed analysis of their predictions across various horizons. This comparison allows us to understand the strengths and weaknesses of each model at different prediction timeframes.

RMSE Comparison

Figure 4.5 illustrates the Root Mean Square Error (RMSE) for each model across different prediction horizons.

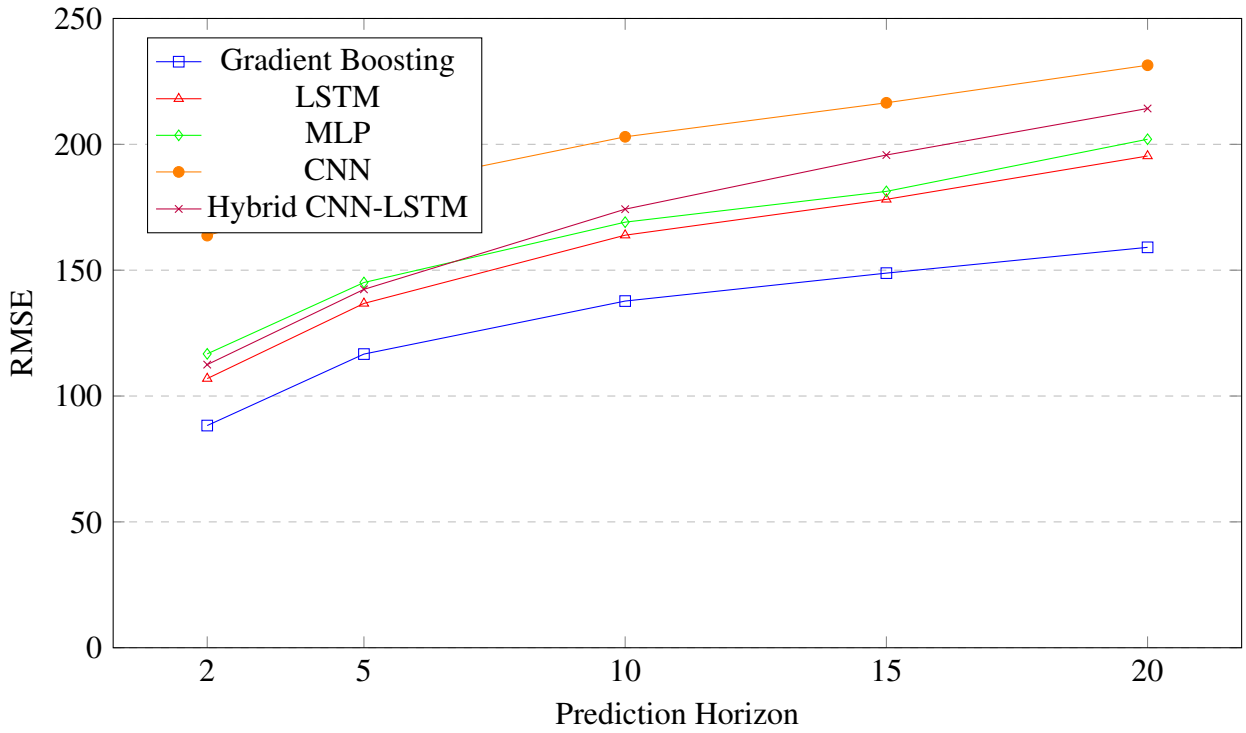


Figure 4.5: RMSE Comparison Across Prediction Horizons

The RMSE comparison reveals:

- Gradient Boosting consistently outperforms other models across all horizons, with the lowest RMSE values.
- LSTM shows competitive performance, especially for longer horizons, indicating its strength in capturing long-term dependencies.

- The CNN model exhibits the highest RMSE values, suggesting it may be less suitable for this particular prediction task.
- The Hybrid CNN-LSTM model shows intermediate performance, balancing the strengths of both CNN and LSTM architectures.
- MLP performance is comparable to LSTM for shorter horizons but degrades more rapidly for longer predictions.

R^2 Comparison

Figure 4.6 shows the R^2 values for each model across different prediction horizons.

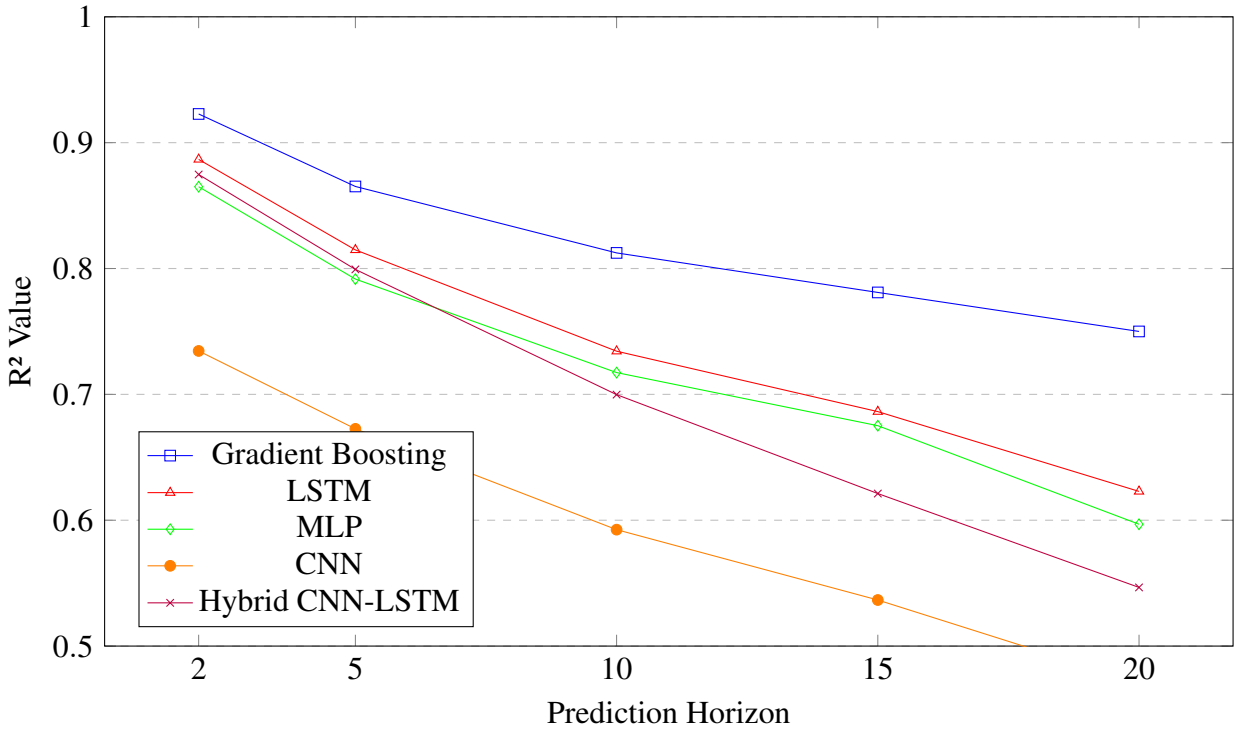


Figure 4.6: R^2 Comparison Across Prediction Horizons

The R^2 comparison highlights:

- Gradient Boosting maintains the highest R^2 values across all horizons, indicating its superior predictive power.

- LSTM shows strong performance, particularly for longer horizons, further confirming its ability to capture long-term patterns.
- The CNN model has the lowest R^2 values, suggesting it explains the least variance in the target variable.
- The Hybrid CNN-LSTM model shows good performance for shorter horizons but drops more rapidly for longer predictions.
- MLP performance is similar to the Hybrid model but with slightly lower R^2 values overall.

AMAPE Comparison

Table 4.5 presents the Adjusted Mean Absolute Percentage Error (AMAPE) for each model at key prediction horizons.

Table 4.5: AMAPE Comparison Across Prediction Horizons

Model	Horizon 2	Horizon 5	Horizon 10	Horizon 15	Horizon 20
Gradient Boosting	0.2425	0.3032	0.4301	0.5265	0.5823
LSTM	0.3175	0.3472	0.4323	0.5534	0.5999
MLP	0.4097	0.4441	0.5084	0.5408	0.5829
CNN	0.5180	0.5199	0.5430	0.5649	0.6193
Hybrid CNN-LSTM	0.3724	0.3584	0.3773	0.4243	0.4608

The AMAPE comparison reveals:

- Gradient Boosting shows the lowest AMAPE for shorter horizons, indicating high accuracy in short-term predictions.
- The Hybrid CNN-LSTM model demonstrates competitive AMAPE values, particularly for mid to long-range predictions.
- LSTM performs well across all horizons, with AMAPE values close to those of Gradient Boosting.

- MLP and CNN models generally show higher AMAPE values, suggesting lower prediction accuracy compared to other models.

Summary of Base Model Comparisons

Based on these detailed comparisons, we can conclude:

1. Gradient Boosting consistently outperforms other models across various metrics and prediction horizons, making it the strongest individual model in our ensemble.

2. LSTM demonstrates robust performance, especially for longer prediction horizons, highlighting its effectiveness in capturing long-term dependencies in the geomagnetic data.

3. The Hybrid CNN-LSTM model shows promise, particularly in terms of AMAPE, suggesting that the combination of CNN and LSTM architectures can be beneficial for this prediction task.

4. MLP performs reasonably well for shorter horizons but its performance degrades more rapidly for longer predictions compared to other models.

5. The CNN model generally underperforms compared to other models, indicating that convolutional architectures alone may not be ideal for this particular time series prediction task.

These insights into the strengths and weaknesses of each base model help explain the superior performance of our Stacked Ensemble approach. By leveraging the complementary strengths of these diverse models, the ensemble can achieve more accurate and robust predictions across various horizons.

4.14.5 Impact of Ensemble Learning

The Stacked Ensemble model's superior performance can be attributed to its ability to combine the strengths of various base models. By learning the optimal way to combine predictions from

different algorithms, it mitigates individual model weaknesses and capitalizes on their collective strengths.

Table 4.6 illustrates the percentage improvement in RMSE achieved by the Stacked Ensemble model compared to the best-performing individual model (Random Forest) for selected prediction horizons.

Table 4.6: Performance Improvement of Stacked Ensemble over Best Individual Model

Horizon	RMSE Improvement (%)	R^2 Improvement (%)
2	73.73	4.30
10	65.96	5.47
20	68.04	6.87

The substantial improvement in RMSE, particularly for longer prediction horizons, underscores the effectiveness of our ensemble approach in enhancing prediction accuracy and reliability.

4.15 Cloud-Based Implementation of Geomagnetic Storm Prediction System

The implementation of our geomagnetic storm prediction system in a cloud environment offers numerous advantages in terms of scalability, reliability, and performance. This section outlines a practical approach to deploying our ensemble learning model for real-time geomagnetic storm forecasting using cloud services.

4.15.1 System Architecture

The cloud-based implementation of our geomagnetic storm prediction system consists of the following key components:

1. Data Ingestion Service

2. Data Storage System

3. Data Processing Pipeline
4. Model Training Infrastructure
5. Real-time Prediction Service
6. API Gateway
7. Monitoring and Logging System

4.15.2 Component Details

Data Ingestion Service

This service is responsible for collecting real-time geomagnetic data from various sources such as INTERMAGNET and SAMNET. It uses a message queue system (e.g., Apache Kafka) to handle high-volume, real-time data streams. The service ensures data is collected reliably and made available for processing and storage.

Data Storage System

Our system utilizes two types of storage:

- A data lake (e.g., Amazon S3) for storing raw, historical data.
- A time-series database (e.g., InfluxDB) for efficient storage and querying of time-stamped geomagnetic data.

This dual approach allows for long-term storage of raw data while optimizing query performance for time-series analysis.

Data Processing Pipeline

This pipeline preprocesses the raw geomagnetic data into a format suitable for our prediction models. It includes steps for:

1. Data cleaning and normalization
2. Feature engineering
3. Sequence creation for time-series models

The pipeline is implemented using a data processing framework like Apache Spark, which can handle large-scale data processing efficiently.

Model Training Infrastructure

This component is responsible for training and updating our ensemble of models. It includes:

1. A distributed training system using GPU-enabled instances for neural network models (CNN, LSTM, Hybrid CNN-LSTM).
2. A system for training tree-based models (Random Forest, Gradient Boosting).
3. A hyperparameter tuning service for optimizing model performance.
4. A model versioning system to track different versions of trained models.

Real-time Prediction Service

This service generates predictions using the trained ensemble model. It's designed to handle high-throughput, low-latency prediction requests. The service includes:

1. Model serving infrastructure (e.g., TensorFlow Serving) for efficient model inference.
2. A load balancer to distribute prediction requests across multiple instances.
3. A caching layer to store recent predictions and reduce computational load.

API Gateway

The API Gateway serves as the entry point for external systems to access our prediction service. It provides:

1. RESTful API endpoints for requesting predictions.
2. Authentication and authorization mechanisms.
3. Rate limiting to prevent system overload.
4. Request routing to appropriate backend services.

Monitoring and Logging System

This system tracks the health and performance of our prediction service. It includes:

1. Real-time monitoring of system metrics (e.g., CPU usage, memory consumption, prediction latency).
2. Logging of system events and prediction results.
3. Alerting mechanisms for system anomalies or extreme prediction values.
4. Dashboards for visualizing system performance and prediction trends.

4.15.3 Deployment Strategy

The system is deployed using a containerization approach (e.g., Docker) with orchestration (e.g., Kubernetes) to ensure scalability and ease of management. This allows for:

1. Easy scaling of individual components based on load.
2. Efficient resource utilization.
3. Simplified updates and rollbacks.
4. Consistency across development, testing, and production environments.

4.15.4 Performance Considerations

To ensure high performance and reliability:

1. Use auto-scaling for compute resources to handle varying loads, especially during geomagnetic storm events.
2. Implement data partitioning strategies in the time-series database to optimize query performance.
3. Use caching mechanisms to reduce latency for frequently requested predictions.
4. Employ a content delivery network (CDN) for global distribution of prediction results.

4.15.5 Security Measures

To protect the system and data:

1. Implement encryption for data at rest and in transit.
2. Use identity and access management (IAM) services to control access to system components.
3. Regularly update and patch all system components.
4. Implement network security measures such as firewalls and intrusion detection systems.

4.15.6 Disaster Recovery and High Availability

To ensure system reliability:

1. Implement a multi-region deployment strategy for high availability.
2. Set up regular backups of critical data and model artifacts.
3. Develop and test disaster recovery procedures.

This cloud-based implementation provides a scalable, reliable, and efficient platform for our geomagnetic storm prediction system. It allows for real-time data processing, model training, and prediction generation, making it suitable for operational use in space weather forecasting.

Chapter 5

Geomagnetic Storm Effects on Power Flow Analysis and Simulation

Chapter 6

Geomagnetic Storm Effects on Power Flow Analysis and Simulation

6.1 Introduction

Geomagnetic storms, a result of the Earth's magnetic field interacting with solar wind disturbances, have the potential to significantly impact power systems. These geomagnetically induced currents (GICs) can lead to half-cycle saturation of transformers, increased reactive power consumption, voltage instability, and, in severe cases, widespread blackouts. As our reliance on electrical infrastructure continues to grow, the urgency of understanding and mitigating the effects of geomagnetic disturbances on power systems has become increasingly critical.

This chapter presents a comprehensive methodology for simulating and analyzing the impacts of geomagnetic storms on large-scale power systems, with a specific focus on the IEEE 118-bus system. Our approach integrates advanced techniques in GIC modelling, power flow analysis, and data visualization to provide a thorough and holistic assessment of power system vulnerability to geomagnetic disturbances.

The core of our methodology lies in its multifaceted nature:

- We begin with a detailed DC model for calculating GICs in the power network, considering

system topology, transformer configurations, and substation grounding resistances.

- We then incorporate the effects of these GICs into an AC power flow analysis, capturing the increased reactive power consumption and potential voltage stability issues. Finally, we employ sophisticated visualization techniques to interpret and present the complex spatial and temporal patterns of GIC impacts across the power system, providing a level of detail and clarity that is truly impressive.

Our simulation framework allows for exploring various geomagnetic storm scenarios characterized by different geoelectric field orientations and magnitudes. We also investigate the effectiveness of different mitigation strategies, including installing GIC blocking devices, controlled line tripping, and series capacitor compensation. These strategies represent a range of potential solutions that can be employed to mitigate the impacts of geomagnetic storms on power systems.

By applying this methodology to the IEEE 118-bus system, we demonstrate its capability to provide valuable insights into:

- The spatial distribution of GIC flows in transmission lines and transformers
- The impact of GICs on system voltage profiles and reactive power balance
- The identification of critical components and areas of heightened vulnerability
- The assessment of different mitigation strategies under various storm scenarios

This chapter is structured as follows:

- We begin with an overview of the simulation setup, including the configuration of the IEEE 118-bus system and the parameters used for GIC and power flow calculations.
- We then detail our methodology, presenting the mathematical formulations for GIC calculation, power flow analysis, and the integration of GIC effects.
- Next, we present and discuss the results of our simulations, highlighting key findings and insights.

- Finally, we discuss the implications of our results for power system planning and operation in regions susceptible to geomagnetic disturbances.

The methodology and findings presented in this chapter contribute to the ongoing efforts to enhance power system resilience against geomagnetic disturbances. By providing a comprehensive framework for GIC analysis and visualization, we aim to support power system operators and planners in developing more effective strategies for mitigating the risks posed by severe space weather events.

6.2 Setting Up the Simulation

This section provides a comprehensive overview of the simulation setup process for analyzing and simulating geomagnetically induced currents (GICs) in the IEEE 118-bus power system. The setup involves several key steps, including reading power system data, building data structures, calculating admittance matrices, processing transformer and capacitor bank data, and assigning appropriate parameters to each component in the system.

The simulation begins by reading power system data from a designated input file. This file contains detailed information about the various components of the IEEE 118-bus system, such as nodes, transmission lines, transformers, and capacitor banks. The data is carefully parsed and organized into suitable MATLAB data structures, ensuring efficient access and manipulation throughout the simulation process.

One of the critical aspects of the simulation setup is the calculation of the admittance matrix (Y) for the power system. The admittance matrix represents the connectivity and electrical properties of the network, capturing the relationships between nodes, lines, and transformers. To construct the admittance matrix, the code processes the line and transformer data, extracting relevant information such as admittances, lengths, winding configurations, and impedances. Special attention is given to handling missing or zero values for line resistances and transformer impedances, ensuring the robustness and reliability of the simulation.

Transformers play a crucial role in the power system and are particularly susceptible to the effects of GICs. To accurately model transformer behavior under GIC conditions, the simulation incorporates detailed transformer models based on the work of [120]. These models take into account various transformer core constructions, including three-limb, five-limb, shell-type, and single-phase transformers. The code reads pre-calculated lookup tables that contain essential transformer parameters, such as reactive power and saturation characteristics, for each transformer type. These lookup tables enable the accurate representation of transformer behavior during GIC simulations.

Capacitor banks are another important component in the power system that can influence GIC flows and system dynamics. The simulation setup carefully processes the capacitor bank data, associating each capacitor bank with its corresponding transformer station. The code calculates the equivalent capacitance for each station, considering the combined effect of multiple capacitor banks connected to the same station. This information is vital for accurately modeling the impact of capacitor banks on GIC flows and system voltage profiles.

To ensure the correct representation of transformer harmonics and their impact on the power system, the code determines the appropriate voltage level for each transformer. This is achieved by identifying the low-voltage bus of each capacitor bank station and referring the transformer harmonics to that specific voltage level. By doing so, the simulation accurately captures the interaction between transformers and capacitor banks, enabling a comprehensive analysis of GIC effects on the power system.

Throughout the simulation setup process, the code employs robust error handling mechanisms and data validation techniques. It checks for inconsistencies, missing data, and potential issues that may arise during the setup phase. Any detected problems are appropriately logged and communicated to the user, ensuring the reliability and integrity of the simulation.

Once all the necessary data structures, matrices, and component parameters are set up, the simulation environment is ready for conducting GIC studies. The prepared data is saved in a dedicated workspace file, allowing for easy access and retrieval in subsequent simulation stages.

This modular approach enables efficient simulation management and facilitates the exploration of different scenarios and mitigation strategies.

In summary, the simulation setup for GIC analysis in the IEEE 118-bus power system involves a comprehensive process of data input, admittance matrix calculation, transformer modeling, capacitor bank processing, and voltage level referencing. The setup phase lays the groundwork for accurate and reliable GIC simulations, empowering researchers and engineers to study the impacts of GICs on the power grid and develop effective mitigation techniques. By leveraging the expertise and insights from previous works, such as [120], the simulation setup ensures a robust and realistic representation of the power system under GIC conditions.

6.3 Methodology for Simulating Geomagnetically Induced Currents in Large-Scale Power Systems

This section presents a comprehensive methodology for simulating and analyzing the effects of Geomagnetically Induced Currents (GICs) on large-scale power systems, specifically focusing on the IEEE 118-bus system. The proposed approach integrates DC GIC calculations with AC power flow analysis to provide a holistic assessment of the impact of geomagnetic disturbance (GMD) on power system operation and stability.

6.3.1 Simulation Framework and Initialization

The simulation framework is designed to provide a flexible and robust platform for GIC analysis, incorporating detailed mathematical models:

1. **System Modeling**: The IEEE 118-bus system is modeled in detail, represented by its admittance matrix $\mathbf{Y}$:

$$\mathbf{Y} = \begin{bmatrix} Y_{11} & Y_{12} & \cdots & Y_{1n} \\ Y_{21} & Y_{22} & \cdots & Y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ Y_{n1} & Y_{n2} & \cdots & Y_{nn} \end{bmatrix} \tag{6.1}$$

where Y_{ij} represents the admittance between buses i and j, and n is the total number of buses. For transmission lines, the admittance is given by:

$$Y_{ij} = \frac{1}{R_{ij} + jX_{ij}} \tag{6.2}$$

where R_{ij} and X_{ij} are the resistance and reactance of the line between buses i and j.

Transformers are modeled with their equivalent admittance:

$$Y_t = \frac{1}{R_t + jX_t} \tag{6.3}$$

where R_t and X_t are the transformer's resistance and reactance referred to a common base.

2. **Geoelectric Field Representation**: The geoelectric field $\mathbf{E}$ is parameterized as:

$$\mathbf{E} = E_m \begin{bmatrix} \cos\theta \\ \sin\theta \end{bmatrix} \tag{6.4}$$

where E_m is the field magnitude and θ is the field orientation angle. The induced voltage V_{ij} in a transmission line between buses i and j is then calculated as:

$$V_{ij} = \mathbf{E} \cdot \mathbf{L}_{ij} = E_m(L_x \cos\theta + L_y \sin\theta) \tag{6.5}$$

where $\mathbf{L}_{ij} = [L_x, L_y]$ is the geographical distance vector of the line.

3. **Mitigation Strategy Integration**: Various GIC mitigation strategies are modeled through modifications to the admittance matrix:

   - GIC blocking devices: The transformer branch admittance is modified as:

$$Y_{t,new} = \frac{1}{R_t + R_{block} + jX_t} \tag{6.6}$$

     where R_{block} is the additional resistance of the blocking device.

   - Controlled line tripping: The admittance of the tripped line is set to zero:

$$Y_{ij,tripped} = 0 \tag{6.7}$$

   - Series capacitor compensation: The line reactance is modified as:

$$X_{ij,new} = X_{ij}(1-k) \tag{6.8}$$

     where k is the compensation factor $(0 < k < 1)$.

The complete system model for GIC analysis is then represented by the modified admittance matrix $\mathbf{Y}_{GIC}$, which incorporates all the above components:

$$\mathbf{Y}_{GIC} = \mathbf{Y}_{base} + \Delta\mathbf{Y}_{mitigation} \tag{6.9}$$

where $\mathbf{Y}_{base}$ is the original system admittance matrix and $\Delta\mathbf{Y}_{mitigation}$ represents the changes due to mitigation strategies.

This mathematically rigorous framework provides the foundation for subsequent GIC calculations and power flow analyses, ensuring accurate representation of the power system under geomagnetic disturbance conditions.

6.3.2 Network Admittance Matrix Formulation

A key component of the simulation is the accurate representation of the power system's electrical characteristics through the network admittance matrix:

1. **Base Matrix Construction**: The network admittance matrix (Y-bus) is constructed based on the system's topology and component parameters. For an n-bus system, the Y-bus matrix $\mathbf{Y}$ is an $n \times n$ complex matrix:

$$\mathbf{Y} = \begin{bmatrix} Y_{11} & Y_{12} & \cdots & Y_{1n} \\ Y_{21} & Y_{22} & \cdots & Y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ Y_{n1} & Y_{n2} & \cdots & Y_{nn} \end{bmatrix} \tag{6.10}$$

   The elements of $\mathbf{Y}$ are determined as follows:

   - Diagonal elements Y_{ii}:

$$Y_{ii} = \sum_{j=1, j \neq i}^{n} y_{ij} + y_{i0} \tag{6.11}$$

     where y_{ij} is the admittance of the branch connecting buses i and j, and y_{i0} is the shunt admittance at bus i.

   - Off-diagonal elements Y_{ij} (i $\neq$ j):

$$Y_{ij} = Y_{ji} = -y_{ij} \tag{6.12}$$

   For transmission lines, the admittance y_{ij} is given by:

$$y_{ij} = \frac{1}{r_{ij} + jx_{ij}} \tag{6.13}$$

   where r_{ij} and x_{ij} are the resistance and reactance of the line between buses i and j.

2. **Mitigation Strategy Modeling**: The admittance matrix is dynamically updated to reflect the implementation of various mitigation strategies:

   - Line tripping: When a line between buses i and j is tripped, the admittance matrix is modified as:

$$Y_{ii,new} = Y_{ii} - y_{ij} \tag{6.14}$$

$$Y_{jj,new} = Y_{jj} - y_{ij} \tag{6.15}$$

$$Y_{ij,new} = Y_{ji,new} = 0 \tag{6.16}$$

   - Series capacitor compensation: For a line with series compensation, the reactance is adjusted:

$$x_{ij,new} = x_{ij}(1-k) \tag{6.17}$$

     where k is the compensation factor $(0 < k < 1)$. The new admittance is then:

$$y_{ij,new} = \frac{1}{r_{ij} + jx_{ij,new}} \tag{6.18}$$

     The Y-bus matrix is updated accordingly using this new admittance value.

   - GIC blocking devices: For a transformer branch with a GIC blocker, the admittance is modified as:

$$y_{t,new} = \frac{1}{r_t + r_{block} + jx_t} \tag{6.19}$$

     where r_t and x_t are the transformer's resistance and reactance, and r_{block} is the additional resistance of the blocking device. The Y-bus matrix is then updated using this new admittance.

The final admittance matrix $\mathbf{Y}_{final}$ after incorporating all mitigation strategies can be expressed as:

$$\mathbf{Y}_{final} = \mathbf{Y}_{base} + \Delta\mathbf{Y}_{trip} + \Delta\mathbf{Y}_{comp} + \Delta\mathbf{Y}_{block} \tag{6.20}$$

where $\mathbf{Y}_{base}$ is the original admittance matrix, and $\Delta\mathbf{Y}_{trip}$, $\Delta\mathbf{Y}_{comp}$, and $\Delta\mathbf{Y}_{block}$ represent the changes due to line tripping, series compensation, and GIC blocking devices, respectively.

This mathematically rigorous formulation of the network admittance matrix provides the foundation for accurate GIC calculations and subsequent power flow analyses, capturing the effects of both the base system configuration and implemented mitigation strategies.

6.3.3 DC GIC Analysis

The calculation of GICs forms the foundation of the GMD impact assessment. This process is mathematically represented as follows:

1. **Induced Voltage Calculation**: For each geoelectric field scenario, the induced voltage V_{ij} in a transmission line between buses i and j is calculated based on its geographical orientation and length:

$$V_{ij} = \int_{\mathbf{L}_{ij}} \mathbf{E} \cdot d\mathbf{l} \approx E_x \Delta x_{ij} + E_y \Delta y_{ij} \tag{6.21}$$

   where $\mathbf{E} = (E_x, E_y)$ is the geoelectric field vector, and Δx_{ij} and Δy_{ij} are the eastward and northward distance components of the transmission line, respectively.

2. **Network Solution**: The DC network equations are formulated based on Kirchhoff's laws:

$$\mathbf{GV} = \mathbf{J} \tag{6.22}$$

   where $\mathbf{G}$ is the conductance matrix (real part of the admittance matrix $\mathbf{Y}$), $\mathbf{V}$ is the vector of unknown node voltages, and $\mathbf{J}$ is the vector of injected currents.

   The elements of $\mathbf{G}$ are determined as:

$$G_{ii} = \sum_{j=1, j\neq i}^{n} g_{ij} + g_{i0} \tag{6.23}$$

$$G_{ij} = G_{ji} = -g_{ij} \quad (i \neq j) \tag{6.24}$$

where g_{ij} is the conductance of the branch between nodes i and j, and g_{i0} is the conductance to ground at node i.

The current injection vector $\mathbf{J}$ is computed from the induced voltages:

$$J_i = \sum_{j\in\Omega_i} g_{ij} V_{ij} \tag{6.25}$$

where Ω_i is the set of nodes connected to node i.

This system is solved using the Generalized Minimal Residual method (GMRES) with preconditioning:

$$\mathbf{V} = \text{GMRES}(\mathbf{G}, \mathbf{J}) \tag{6.26}$$

3. **GIC Flow Computation**: Using the solved node voltages, GIC flows are calculated for all network components:

   - Transmission line GICs:

     $$I_{ij} = g_{ij}(V_i - V_j + V_{ij}) \tag{6.27}$$

     where V_i and V_j are the solved voltages at nodes i and j, respectively.

   - Transformer GICs:

     – Common-mode GIC:

     $$I_c = g_c(V_h - V_n) \tag{6.28}$$

     where g_c is the common-mode conductance, V_h is the high-voltage bus voltage, and V_n is the neutral point voltage.

– Series-mode GIC:

$$I_s = g_s(V_h - V_l) \tag{6.29}$$

where g_s is the series-mode conductance, and V_l is the low-voltage bus voltage.

- Substation grounding point GICs:

$$I_g = g_g V_n \tag{6.30}$$

where g_g is the grounding conductance.

The total effective GIC in a transformer is then calculated as:

$$I_{eff} = |I_c| + |I_s| \tag{6.31}$$

This mathematically rigorous formulation of the DC GIC analysis provides a comprehensive representation of GIC flows in the power system, forming the basis for subsequent analysis of GMD impacts on system components and overall performance.

6.3.4 AC Power Flow Analysis with GIC Effects

The impact of GICs on system operation is assessed through a modified AC power flow analysis, mathematically formulated as follows:

1. **Reactive Power Consumption Modeling**: The additional reactive power consumption Q_{GIC} due to GIC-induced transformer half-cycle saturation is calculated based on transformer characteristics and GIC magnitudes:

$$Q_{GIC,i} = K_i V_i |I_{GIC,i}| \tag{6.32}$$

where K_i is a transformer-specific constant, V_i is the terminal voltage, and $I_{GIC,i}$ is the effective

GIC in the transformer. For more accurate modeling, a piece-wise linear approximation can be used:

$$Q_{GIC,i} = \begin{cases} K_{1,i} V_i |I_{GIC,i}| & \text{if } |I_{GIC,i}| \leq I_{th} \\ K_{2,i} V_i (|I_{GIC,i}| - I_{th}) + K_{1,i} V_i I_{th} & \text{if } |I_{GIC,i}| > I_{th} \end{cases} \tag{6.33}$$

where I_{th} is a threshold current, and $K_{1,i}$ and $K_{2,i}$ are transformer-specific constants.

2. **Power Flow Formulation**: The AC power flow equations are augmented to include the GIC-induced reactive power demands. For each bus i:

$$P_i = V_i \sum_{j=1}^{n} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \tag{6.34}$$

$$Q_i = V_i \sum_{j=1}^{n} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) + Q_{GIC,i} \tag{6.35}$$

where P_i and Q_i are the active and reactive power injections, V_i and V_j are bus voltage magnitudes, G_{ij} and B_{ij} are the real and imaginary parts of the bus admittance matrix elements, θ_{ij} is the voltage angle difference between buses i and j, and $Q_{GIC,i}$ is the GIC-induced reactive power consumption at bus i.

3. **Iterative Solution Process**: The Newton-Raphson method is employed to solve the power flow equations. At each iteration k:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}^{(k)} = \begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix}^{(k)} \begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix}^{(k)} \tag{6.36}$$

where J_1, J_2, J_3, and J_4 are the Jacobian submatrices. The voltage magnitudes and angles are updated as:

$$\begin{bmatrix} \theta \\ V \end{bmatrix}^{(k+1)} = \begin{bmatrix} \theta \\ V \end{bmatrix}^{(k)} + \begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix}^{(k)} \tag{6.37}$$

After each iteration, the GIC-induced reactive power $Q_{GIC,i}$ is recalculated based on the updated voltages, capturing the interdependence between GICs and AC system state.

4. **System Impact Evaluation**: Key system parameters are monitored to assess the overall impact of GICs:

   - Bus voltage deviation:

   $$\Delta V_i = |V_i - V_{i,nom}| \tag{6.38}$$

   - Line loading percentage:

   $$L_{ij} = \frac{\sqrt{P_{ij}^2 + Q_{ij}^2}}{S_{ij,max}} \times 100\% \tag{6.39}$$

   where P_{ij} and Q_{ij} are the active and reactive power flows, and $S_{ij,max}$ is the line's thermal limit.

   - Generator reactive power output:

   $$Q_{G,i} = Q_i - Q_{L,i} - Q_{GIC,i} \tag{6.40}$$

   where $Q_{L,i}$ is the reactive load at bus i.

   - Voltage stability index (L-index):

   $$L_j = |1 - \sum_{i \in \alpha_G} F_{ji} \frac{V_i}{V_j}| \tag{6.41}$$

   where α_G is the set of generator buses and F_{ji} are elements of a matrix derived from the bus admittance matrix.

This mathematically rigorous formulation of the AC power flow analysis with GIC effects

provides a comprehensive representation of the system's response to GMDs. It captures the complex interactions between GIC-induced effects and the AC power system, enabling detailed assessment of system performance and stability under geomagnetic disturbance conditions.

6.3.5 Comprehensive GMD Scenario Analysis

The simulation framework enables a thorough exploration of GMD impacts across various scenarios, mathematically formulated as follows:

1. **Parametric Study**: Multiple geoelectric field orientations θ and magnitudes E are simulated:

$$\mathbf{E}(\theta, E) = E \begin{bmatrix} \cos\theta \\ \sin\theta \end{bmatrix}, \quad \theta \in [0, 2\pi], \quad E \in [E_{min}, E_{max}] \tag{6.42}$$

   The system response is evaluated for each (θ, E) pair, creating a response surface $R(\theta, E)$ for key system parameters.

2. **Time-Domain Analysis**: The evolution of system response is analyzed by applying a time-varying geoelectric field $\mathbf{E}(t)$:

$$\mathbf{E}(t) = E(t) \begin{bmatrix} \cos\theta(t) \\ \sin\theta(t) \end{bmatrix}, \quad t \in [0, T] \tag{6.43}$$

   System state variables $\mathbf{X}(t)$ are computed at each time step, capturing the dynamic response to the GMD event.

3. **Criticality Assessment**: Component criticality C_i is evaluated based on its impact on system performance metrics M_j:

$$C_i = \sum_j w_j \frac{\Delta M_j}{M_{j,base}} \tag{6.44}$$

where w_j are weighting factors, ΔM_j is the change in metric M_j when component i is affected, and $M_{j,base}$ is the base value of the metric.

4. **Mitigation Strategy Evaluation**: The effectiveness η_k of mitigation strategy k is quantified as:

$$\eta_k = \frac{P_{base} - P_k}{P_{base}} \times 100\% \tag{6.45}$$

where P_{base} is a performance index (e.g., total system losses) without mitigation, and P_k is the index with mitigation strategy k applied.

6.3.6 Results Analysis and Interpretation

Sophisticated analytical techniques are employed to interpret the simulation results:

1. **Voltage Stability Analysis**: The impact of GICs on system voltage profiles and stability margins is examined using metrics such as the L-index:

$$L_j = |1 - \sum_{i \in \alpha_G} F_{ji} \frac{V_i}{V_j}|, \quad L_{system} = \max_j L_j \tag{6.46}$$

where α_G is the set of generator buses, F_{ji} are elements of a matrix derived from the bus admittance matrix, and L_{system} represents the system's proximity to voltage collapse.

2. **Thermal Loading Assessment**: The additional heating effects due to GICs are quantified using the effective current I_{eff}:

$$I_{eff} = \sqrt{I_{AC}^2 + I_{GIC}^2 + \sum_n K_n I_{h,n}^2} \tag{6.47}$$

where I_{AC} is the AC current, I_{GIC} is the GIC, $I_{h,n}$ are harmonic currents, and K_n are weighting factors. The hot-spot temperature rise ΔT_{hs} in transformers is then estimated as:

$$\Delta T_{hs} = K_1 I_{eff}^2 R(t) + K_2 e^{-t/\tau} \tag{6.48}$$

where K_1 and K_2 are constants, $R(t)$ is the time-varying winding resistance, and τ is the thermal time constant.

3. **Reactive Power Balance Evaluation**: The system reactive power balance shift is analyzed using the reactive power sensitivity matrix $\mathbf{S}_Q$:

$$\Delta \mathbf{Q} = \mathbf{S}_Q \Delta \mathbf{V} \tag{6.49}$$

where $\Delta \mathbf{Q}$ is the change in reactive power injections and $\Delta \mathbf{V}$ is the change in bus voltages. The stress on generators is quantified by their proximity to reactive power limits:

$$\sigma_i = \frac{Q_{G,i} - Q_{G,i}^{min}}{Q_{G,i}^{max} - Q_{G,i}^{min}} \tag{6.50}$$

where $\gamma(h)$ is the semivariogram, $Z(x)$ is the GIC magnitude at location x, and $N(h)$ is the number of pairs of points separated by distance h. This allows for the characterization of spatial correlations in GIC distributions.

This comprehensive methodology, with its rigorous mathematical formulation, provides a robust framework for assessing the impacts of GMDs on large-scale power systems. By integrating detailed DC GIC calculations with AC power flow analysis and incorporating various mitigation strategies, the approach offers quantitative insights into power system vulnerability to geomagnetic disturbances. The methodology's application to the IEEE 118-bus system demonstrates its efficacy in analyzing complex, realistic power networks, providing a solid foundation for GMD risk assessment and mitigation planning.

6.3.7 Quasi-DC Modeling of GICs in AC Power Systems

A critical aspect of the simulation methodology is the treatment of GICs as quasi-DC phenomena within the context of the AC power system:

1. **Time Scale Separation**: The simulation leverages the significant difference in time scales between GIC variations and AC power system dynamics:
    - GICs typically vary over minutes to hours, driven by the slowly changing geomagnetic field.
    - AC power system dynamics occur on the order of cycles (milliseconds) to seconds.
2. **Quasi-Static Approximation**: Based on this time scale separation, a quasi-static approach is adopted:
    - For each GIC scenario, the power system is considered to be in a steady state concerning its AC operation.
    - This allows static power flow analysis techniques while incorporating the effects of the slowly varying GICs.
3. **DC Network Model**: GICs are modeled using a DC network representation:
    - The power system's topology is used to construct a DC equivalent circuit.
    - Transmission lines are represented by their DC resistances.
    - Transformers are modelled with appropriate DC resistances for their windings.
    - Substation grounding resistances are included to complete the DC paths.
4. **Superposition of DC and AC Effects**: The simulation methodology combines the DC GIC analysis with the AC power flow:
    - GIC flows are calculated using the DC network model.

- The effects of these GICs, primarily additional reactive power consumption in transformers, are then incorporated into the AC power flow analysis.

5. **Iterative Coupling**: To capture the interaction between GICs and AC system state:
    - An iterative process is employed where GIC calculations and AC power flow are performed sequentially.
    - This process continues until convergence, ensuring that the final solution accurately represents the coupled DC-AC system state.
6. **Time-Varying Analysis**: To capture the evolution of GICs over time:
    - The simulation is repeated for multiple geoelectric field scenarios, representing different time points during a GMD event.
    - Each scenario is treated as a quasi-static state, with GICs and their effects recalculated for each time step.

This approach accurately represents GIC effects within the AC power system framework while maintaining computational efficiency. By treating GICs as quasi-DC phenomena and leveraging the principle of time-scale separation, the simulation can provide detailed insights into the system's response to GMDs without needing full-time-domain electromagnetic transient simulations.

6.3.8 GIC Simulation Process Flowchart

Figure 6.1 presents a comprehensive flowchart of the Geomagnetically Induced Current (GIC) simulation process, illustrating the quasi-DC modeling approach within the context of AC power systems. The flowchart is structured to highlight the key components of the simulation methodology, including time scale separation, quasi-static approximation, DC network modeling, and the iterative coupling between GIC and AC power flow analyses.

The flowchart can be interpreted as follows:

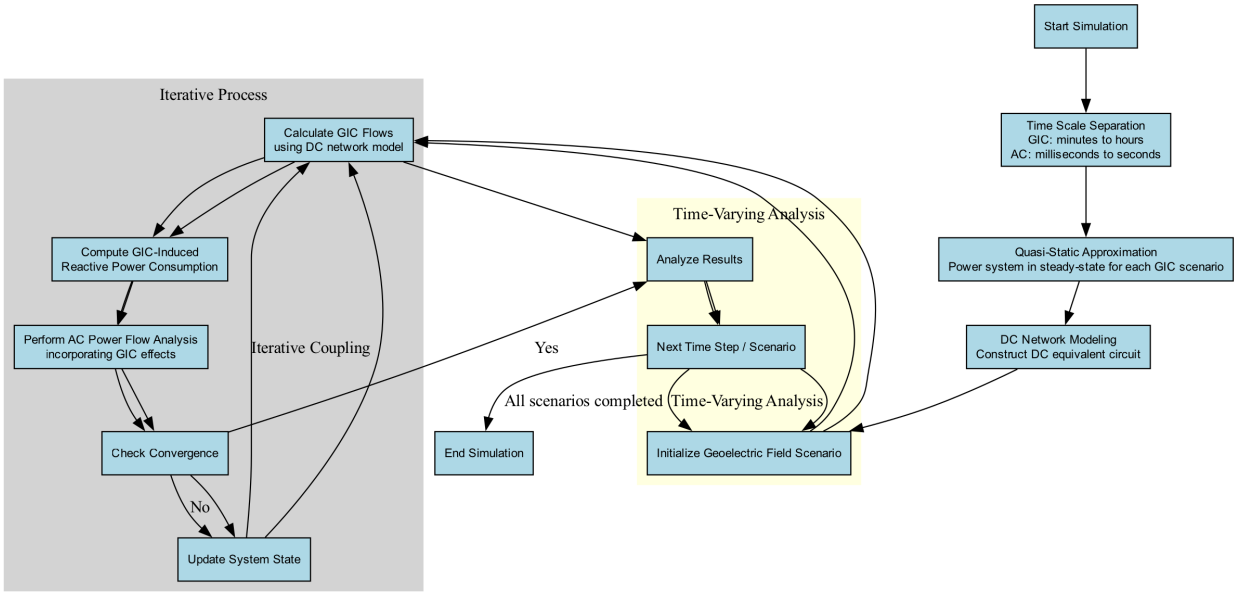


Figure 6.1: Flowchart of the GIC Simulation Process

1. **Initialization**: The process begins with the "Start Simulation" node, leading into the foundational concepts of the simulation.

2. **Conceptual Framework**:

   - *Time Scale Separation*: This node emphasizes the distinction between GIC variations (minutes to hours) and AC power system dynamics (milliseconds to seconds).
   - *Quasi-Static Approximation*: Building on the time scale separation, this step justifies the treatment of the power system as being in a steady state for each GIC scenario.
   - *DC Network Modeling*: This node represents the construction of a DC equivalent circuit based on the power system's topology.

3. **Simulation Loop**: The core of the simulation is represented by a loop structure:

   - *Initialize Geoelectric Field Scenario*: Each iteration begins with a new geoelectric field configuration.
   - *GIC Calculation*: GIC flows are computed using the DC network model.

- *Reactive Power Computation*: The GIC-induced reactive power consumption in transformers is calculated.
- *AC Power Flow Analysis*: An AC power flow analysis is performed, incorporating the GIC effects.

4. **Iterative Coupling**: A sub-loop within the main simulation loop represents the iterative coupling between GIC calculations and AC power flow:
   - The process iterates through GIC calculation, reactive power computation, and AC power flow analysis.
   - Convergence is checked after each iteration.
   - If convergence is not achieved, the system state is updated, and the process repeats.
5. **Result Analysis**: Upon convergence, the results for the current scenario are analyzed.
6. **Time-Varying Analysis**: The flowchart shows a larger loop encompassing the entire process, representing the time-varying analysis:
   - After analyzing each scenario, the simulation moves to the next time step or scenario.
   - This loop continues until all scenarios are completed.
7. **Conclusion**: The process ends with the "End Simulation" node after all scenarios have been processed.

The flowchart effectively illustrates the quasi-DC modeling approach by showing how the DC GIC calculations are integrated with the AC power flow analysis in an iterative manner. It also demonstrates the time-varying nature of the analysis through the outer loop structure. This visual representation provides a clear overview of the simulation methodology, highlighting the interplay between the quasi-static GIC modeling and the dynamic AC power system analysis.

Table 6.1: IEEE 118 Bus System Information

Station Name	**Nominal Voltage (kV)**	**Bus Number**	**Latitude**	**Longitude**
Riversde_138_001	138	1	86.387215	42.022008
Pokagon_138_002	138	2	86.182251	41.914541
HickryCk_138_003	138	3	86.467896	41.910453
NwCarlsl_138_004	138	4	86.539307	41.710342
Olive_138_005	138	5	86.483862	41.706674
Kankakee_138_006	138	6	86.445923	41.597986
JacksnRd_138_007	138	7	86.403008	41.616469
Olive_345_008	345	8	86.483862	41.706674
Bequine_345_009	345	9	87.011719	40.609782
Breed_345_010	345	10	87.570961	39.227333
SouthBnd_138_011	138	11	86.252289	41.677015
TwinBrch_138_012	138	12	86.132140	41.665088
Concord_138_013	138	13	85.930939	41.642131
GoshenJt_138_014	138	14	85.836868	41.579498
FtWayne_138_015	138	15	85.096655	41.170632
N.E._138_016	138	16	85.467300	41.063777
Sorenson_138_017	138	17	85.342592	40.983705
McKinley_138_018	138	18	85.172408	41.060957
Lincoln_138_019	138	19	84.666824	41.014555
Adams_138_020	138	20	85.044858	40.654898
Jay_138_021	138	21	85.136271	40.480871

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Table 6.1 – continued from previous page

Station Name	Nominal Voltage (kV)	Bus Number	Latitude	Longitude
Randolph_138_022	138	22	84.836187	40.196391
CollCrnr_138_023	138	23	84.814453	39.567687
Trenton_138_024	138	24	84.457226	39.480991
TannrsCk_138_025	138	25	84.861495	39.081507
TannrsCk_345_026	345	26	84.861495	39.081507
Madison_138_027	138	27	85.644216	40.087173
Mullin_138_028	138	28	85.774719	40.271203
Grant_138_029	138	29	85.682373	40.472024
Sorenson_345_030	345	30	85.342592	40.983705
DeerCrk_138_031	138	31	85.644024	40.515952
Delaware_138_032	138	32	83.081821	40.271372
Haviland_138_033	138	33	84.580994	41.019283
Rockhill_138_034	138	34	84.087725	40.762827
WestLima_138_035	138	35	84.186859	40.722283
Sterling_138_036	138	36	84.107544	40.701428
EastLima_138_037	138	37	84.029870	40.800649
EastLima_345_038	345	38	84.029870	40.800649
NwLibrty_138_039	138	39	83.880775	40.912651
WestEnd_138_040	138	40	82.269469	41.430002
S.Tiffin_138_041	138	41	83.171997	41.086597
Howard_138_042	138	42	82.681363	40.850863
S.Kenton_138_043	138	43	83.614197	40.624376

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Table 6.1 – continued from previous page

Station Name	Nominal Voltage (kV)	Bus Number	Latitude	Longitude
WMVernon_138_044	138	44	82.516594	40.392058
N.Newark_138_045	138	45	82.426300	40.122716
W.Lancst_138_046	138	46	82.691345	39.718807
Crooksvl_138_047	138	47	82.095337	39.771603
Zanesvll_138_048	138	48	82.011655	39.941117
Philo_138_049	138	49	81.904034	39.865158
WCambrdg_138_050	138	50	81.558380	40.029455
Newcmrst_138_051	138	51	81.605759	40.272322
SCoshoct_138_052	138	52	81.856041	40.243502
Wooster_138_053	138	53	81.937408	40.797697
Torrey_138_054	138	54	81.513062	41.072104
Wagenhls_138_055	138	55	81.325396	40.799138
Sunnysde_138_056	138	56	81.496582	40.562330
WNwPhil1_138_057	138	57	81.445427	40.490043
WNwPhil2_138_058	138	58	81.445427	40.490043
Tidd_138_059	138	59	80.645556	40.252500
SWKammer_138_060	138	60	80.749512	39.942384
Kammer_138_061	138	61	80.779724	40.062308
Natrium_138_062	138	62	80.854778	39.749389
Tidd_345_063	345	63	80.645556	40.252500
Kammer_345_064	345	64	80.779724	40.062308
Muskngum_345_065	345	65	81.682026	39.588658

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Table 6.1 – continued from previous page

Station Name	Nominal Voltage (kV)	Bus Number	Latitude	Longitude
Muskngum_138_066	138	66	81.682026	39.588658
Summerfl_138_067	138	67	81.335950	39.796766
Sporn_345_068	345	68	81.921389	38.967194
Sporn_138_069	138	69	81.921389	38.967194
Portsmth_138_070	138	70	82.997589	38.733732
NPortsmt_138_071	138	71	83.259190	39.001043
Hillsbro_138_072	138	72	83.611506	39.202573
Sargents_138_073	138	73	82.986133	39.126509
Bellefnt_138_074	138	74	82.690150	38.492630
SthPoint_138_075	138	75	82.574164	38.413800
Darrah_138_076	138	76	82.115696	38.480111
Turner_138_077	138	77	82.290856	38.402801
Chemical_138_078	138	78	81.733692	38.396747
CapitlHl_138_079	138	79	81.634194	38.351978
Kanawha_138_080	138	80	81.480250	38.196711
Kanawha_345_081	345	81	81.480250	38.196711
Logan_138_082	138	82	81.995064	37.850640
Sprigg_138_083	138	83	82.197474	37.629006
BetsyLne_138_084	138	84	82.631264	37.553832
BeaverCk_138_085	138	85	82.810822	37.354330
Hazard_138_086	138	86	83.193283	37.249461
Pinevlle_138_087	138	87	83.692653	36.762438

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Table 6.1 – continued from previous page

Station Name	Nominal Voltage (kV)	Bus Number	Latitude	Longitude
Fremont_138_088	138	88	82.337070	36.913606
ClinchRv_138_089	138	89	82.198611	36.932778
Holston_138_090	138	90	82.121367	36.847809
HolstonT_138_091	138	91	82.070591	36.922555
Saltvlle_138_092	138	92	81.762142	36.881268
Tazewell_138_093	138	93	81.518555	37.125286
Switchbk_138_094	138	94	81.385516	37.371590
Carswell_138_095	138	95	81.508612	37.439474
Baileysv_138_096	138	96	81.679157	37.589264
Sundial_138_097	138	97	81.514606	37.876389
Bradley_138_098	138	98	81.193684	37.865390
Hinton_138_099	138	99	80.888985	37.673948
GlenLyn_138_100	138	100	80.862222	37.371389
Wythe_138_101	138	101	81.119144	36.922633
Smythe_138_102	138	102	81.559971	36.866987
Claytor_138_103	138	103	80.584466	37.074833
Hancock_138_104	138	104	79.643772	37.005112
Roanoke_138_105	138	105	79.961460	37.270228
Cloverdl_138_106	138	106	79.906625	37.357059
Reusens_138_107	138	107	79.185785	37.463571
Blaine_138_108	138	108	79.906823	37.135231
Franklin_138_109	138	109	79.879460	37.003889

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Table 6.1 – continued from previous page

Station Name	Nominal Voltage (kV)	Bus Number	Latitude	Longitude
Fieldale_138_110	138	110	79.938897	36.700334
DanRiver_138_111	138	111	79.720800	36.486200
Danville_138_112	138	112	79.394180	36.585200
DeerCrk2_138_113	138	113	85.653395	40.530651
WMedford_138_114	138	114	83.092430	40.211490
Medford_138_115	138	115	83.011368	40.181841
KygerCrk_345_116	345	116	82.116390	38.935395
Corey_138_117	138	117	86.141166	41.675968
WHuntngd_138_118	138	118	82.355112	38.417642

Table 6.2: IEEE 118 Transformers Data

From Bus	To Bus	R (pu)	X (pu)	B (pu)	Rating (MVA)	Type
5	8	0	0.3000	0.2000	700.0	AUTO
25	26	0	0.3000	0.2000	220.0	AUTO
17	30	0	0.3000	0.2000	475.0	AUTO
37	38	0	0.3000	0.2000	500.0	AUTO
59	63	0	0.3000	0.2000	330.0	AUTO
61	64	0	0.3000	0.2000	90.0	AUTO
66	65	0	0.3000	0.2000	220.0	AUTO
69	68	0	0.3000	0.2000	650.0	AUTO
80	81	0	0.3000	0.2000	165.0	AUTO

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Table 6.2 – *Continued from previous page*

From Bus	To Bus	R (pu)	X (pu)	B (pu)	Rating (MVA)	Type
1		0		0.4000	125.0	STEPUP
4		0		0.4000	125.0	STEPUP
6		0		0.4000	125.0	STEPUP
8		0		0.4000	125.0	STEPUP
10		0		0.4000	750.0	STEPUP
12		0		0.4000	250.0	STEPUP
15		0		0.4000	125.0	STEPUP
18		0		0.4000	125.0	STEPUP
19		0		0.4000	125.0	STEPUP
24		0		0.4000	125.0	STEPUP
25		0		0.4000	500.0	STEPUP
26		0		0.4000	500.0	STEPUP
27		0		0.4000	125.0	STEPUP
31		0		0.4000	125.0	STEPUP
32		0		0.4000	125.0	STEPUP
34		0		0.4000	125.0	STEPUP
36		0		0.4000	125.0	STEPUP
40		0		0.4000	125.0	STEPUP
42		0		0.4000	125.0	STEPUP
46		0		0.4000	150.0	STEPUP
49		0		0.4000	350.0	STEPUP
54		0		0.4000	200.0	STEPUP
55		0		0.4000	125.0	STEPUP
56		0		0.4000	125.0	STEPUP

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Table 6.2 – *Continued from previous page*

From Bus	To Bus	R (pu)	X (pu)	B (pu)	Rating (MVA)	Type
59		0		0.4000	350.0	STEPUP
61		0		0.4000	350.0	STEPUP
62		0		0.4000	125.0	STEPUP
65		0		0.4000	600.0	STEPUP
66		0		0.4000	600.0	STEPUP
69		0		0.4000	1000.0	STEPUP
70		0		0.4000	125.0	STEPUP
72		0		0.4000	125.0	STEPUP
73		0		0.4000	125.0	STEPUP
74		0		0.4000	125.0	STEPUP
76		0		0.4000	125.0	STEPUP
77		0		0.4000	125.0	STEPUP
80		0		0.4000	750.0	STEPUP
85		0		0.4000	125.0	STEPUP
87		0		0.4000	125.0	STEPUP
89		0		0.4000	1000.0	STEPUP
90		0		0.4000	125.0	STEPUP
91		0		0.4000	125.0	STEPUP
92		0		0.4000	125.0	STEPUP
99		0		0.4000	125.0	STEPUP
100		0		0.4000	500.0	STEPUP
103		0		0.4000	200.0	STEPUP
104		0		0.4000	125.0	STEPUP
105		0		0.4000	125.0	STEPUP

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Table 6.2 – *Continued from previous page*

From Bus	To Bus	R (pu)	X (pu)	B (pu)	Rating (MVA)	Type
107		0		0.4000	125.0	STEPUP
110		0		0.4000	125.0	STEPUP
111		0		0.4000	150.0	STEPUP
112		0		0.4000	125.0	STEPUP
113		0		0.4000	125.0	STEPUP
116		0		0.4000	125.0	STEPUP
1		0		0.4000	100.0	STEPDN
2		0		0.4000	37.5	STEPDN
3		0		0.4000	80.0	STEPDN
4		0		0.4000	80.0	STEPDN
6		0		0.4000	100.0	STEPDN
7		0		0.4000	30.0	STEPDN
8		0		0.4000	50.0	STEPDN
11		0		0.4000	125.0	STEPDN
12		0		0.4000	80.0	STEPDN
13		0		0.4000	60.0	STEPDN
14		0		0.4000	25.0	STEPDN
15		0		0.4000	150.0	STEPDN
16		0		0.4000	50.0	STEPDN
17		0		0.4000	20.0	STEPDN
18		0		0.4000	125.0	STEPDN
19		0		0.4000	80.0	STEPDN
20		0		0.4000	30.0	STEPDN
21		0		0.4000	25.0	STEPDN

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Table 6.2 – *Continued from previous page*

From Bus	To Bus	R (pu)	X (pu)	B (pu)	Rating (MVA)	Type
22		0		0.4000	20.0	STEPDN
23		0		0.4000	15.0	STEPDN
24		0		0.4000	20.0	STEPDN
27		0		0.4000	125.0	STEPDN
28		0		0.4000	30.0	STEPDN
29		0		0.4000	37.5	STEPDN
31		0		0.4000	80.0	STEPDN
32		0		0.4000	100.0	STEPDN
33		0		0.4000	37.5	STEPDN
34		0		0.4000	100.0	STEPDN
35		0		0.4000	60.0	STEPDN
36		0		0.4000	60.0	STEPDN
39		0		0.4000	50.0	STEPDN
40		0		0.4000	125.0	STEPDN
41		0		0.4000	60.0	STEPDN
42		0		0.4000	150.0	STEPDN
43		0		0.4000	30.0	STEPDN
44		0		0.4000	30.0	STEPDN
45		0		0.4000	100.0	STEPDN
46		0		0.4000	50.0	STEPDN
47		0		0.4000	60.0	STEPDN
48		0		0.4000	37.5	STEPDN
49		0		0.4000	150.0	STEPDN
50		0		0.4000	30.0	STEPDN

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Table 6.2 – *Continued from previous page*

From Bus	To Bus	R (pu)	X (pu)	B (pu)	Rating (MVA)	Type
51		0		0.4000	30.0	STEPDN
52		0		0.4000	30.0	STEPDN
53		0		0.4000	40.0	STEPDN
54		0		0.4000	200.0	STEPDN
55		0		0.4000	125.0	STEPDN
56		0		0.4000	150.0	STEPDN
57		0		0.4000	20.0	STEPDN
58		0		0.4000	20.0	STEPDN
59		0		0.4000	500.0	STEPDN
60		0		0.4000	125.0	STEPDN
62		0		0.4000	125.0	STEPDN
66		0		0.4000	80.0	STEPDN
67		0		0.4000	50.0	STEPDN
70		0		0.4000	125.0	STEPDN
72		0		0.4000	20.0	STEPDN
73		0		0.4000	15.0	STEPDN
74		0		0.4000	125.0	STEPDN
75		0		0.4000	80.0	STEPDN
76		0		0.4000	125.0	STEPDN
77		0		0.4000	125.0	STEPDN
78		0		0.4000	125.0	STEPDN
79		0		0.4000	80.0	STEPDN
80		0		0.4000	200.0	STEPDN
82		0		0.4000	100.0	STEPDN

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Table 6.2 – *Continued from previous page*

From Bus	To Bus	R (pu)	X (pu)	B (pu)	Rating (MVA)	Type
83		0		0.4000	37.5	STEPDN
84		0		0.4000	20.0	STEPDN
85		0		0.4000	50.0	STEPDN
86		0		0.4000	37.5	STEPDN
88		0		0.4000	80.0	STEPDN
90		0		0.4000	350.0	STEPDN
91		0		0.4000	15.0	STEPDN
92		0		0.4000	100.0	STEPDN
93		0		0.4000	25.0	STEPDN
94		0		0.4000	60.0	STEPDN
95		0		0.4000	80.0	STEPDN
96		0		0.4000	80.0	STEPDN
97		0		0.4000	30.0	STEPDN
98		0		0.4000	60.0	STEPDN
99		0		0.4000	80.0	STEPDN
100		0		0.4000	80.0	STEPDN
101		0		0.4000	40.0	STEPDN
102		0		0.4000	15.0	STEPDN
103		0		0.4000	50.0	STEPDN
104		0		0.4000	80.0	STEPDN
105		0		0.4000	80.0	STEPDN
106		0		0.4000	80.0	STEPDN
107		0		0.4000	80.0	STEPDN
108		0		0.4000	15.0	STEPDN

Continued on next page

Table 6.2 – *Continued from previous page*

From Bus	To Bus	R (pu)	X (pu)	B (pu)	Rating (MVA)	Type
109		0		0.4000	15.0	STEPDN
110		0		0.4000	80.0	STEPDN
112		0		0.4000	125.0	STEPDN
113		0		0.4000	15.0	STEPDN
114		0		0.4000	15.0	STEPDN
115		0		0.4000	37.5	STEPDN
116		0		0.4000	350.0	STEPDN
117		0		0.4000	37.5	STEPDN
118		0		0.4000	60.0	STEPDN

6.4 Simulation Setup and Configuration

The simulation of Geomagnetically Induced Currents (GICs) in the IEEE 118-bus power system is configured with careful consideration of various parameters to ensure accurate representation of both the power system and the geomagnetic disturbance (GMD) scenarios. This section outlines the key aspects of the simulation setup and provides a comprehensive overview of the critical parameters used.

6.4.1 Power Flow Analysis Configuration

The power flow analysis, which forms the core of the AC system modeling, is configured using the pandapower library. The simulation employs the Newton-Raphson method for its robust convergence properties. Table 6.3 summarizes the key parameters for the power flow analysis.

6.4.2 Geomagnetic Disturbance Modeling

The GMD scenarios are modeled by varying the geoelectric field magnitude and orientation. The simulation sweeps through a range of field angles to comprehensively assess the system's response to different GMD orientations. The electric field strength is set to 2 V/km, representing a significant GMD event.

6.4.3 GIC Mitigation Strategies

The simulation incorporates various GIC mitigation strategies, including GIC blocking devices, controlled line tripping, and series capacitor compensation. These strategies are implemented through modifications to the network admittance matrix, allowing for the assessment of their effectiveness in mitigating GIC impacts.

6.4.4 System Constraints and Operational Limits

To ensure realistic system operation, the simulation enforces various constraints and operational limits. These include voltage limits, line current thermal limits, and generator reactive power limits. The simulation also considers the ratio of maximum reactive power to maximum active power for generators, set at 0.55, to model realistic generator capabilities.

6.4.5 Key Simulation Parameters

Table 6.3 presents a summary of the key parameters used in the simulation setup:

These parameters form the foundation of the simulation setup, ensuring a comprehensive and realistic assessment of GIC impacts on the power system. The combination of detailed power system modeling, varied GMD scenarios, and consideration of mitigation strategies provides a robust framework for analyzing the system's vulnerability to geomagnetic disturbances. Figure 6.2 presents a comprehensive visualization of Geomagnetically Induced Currents (GICs) effects on various components of a power system. The figure is organized into five rows, each depicting a

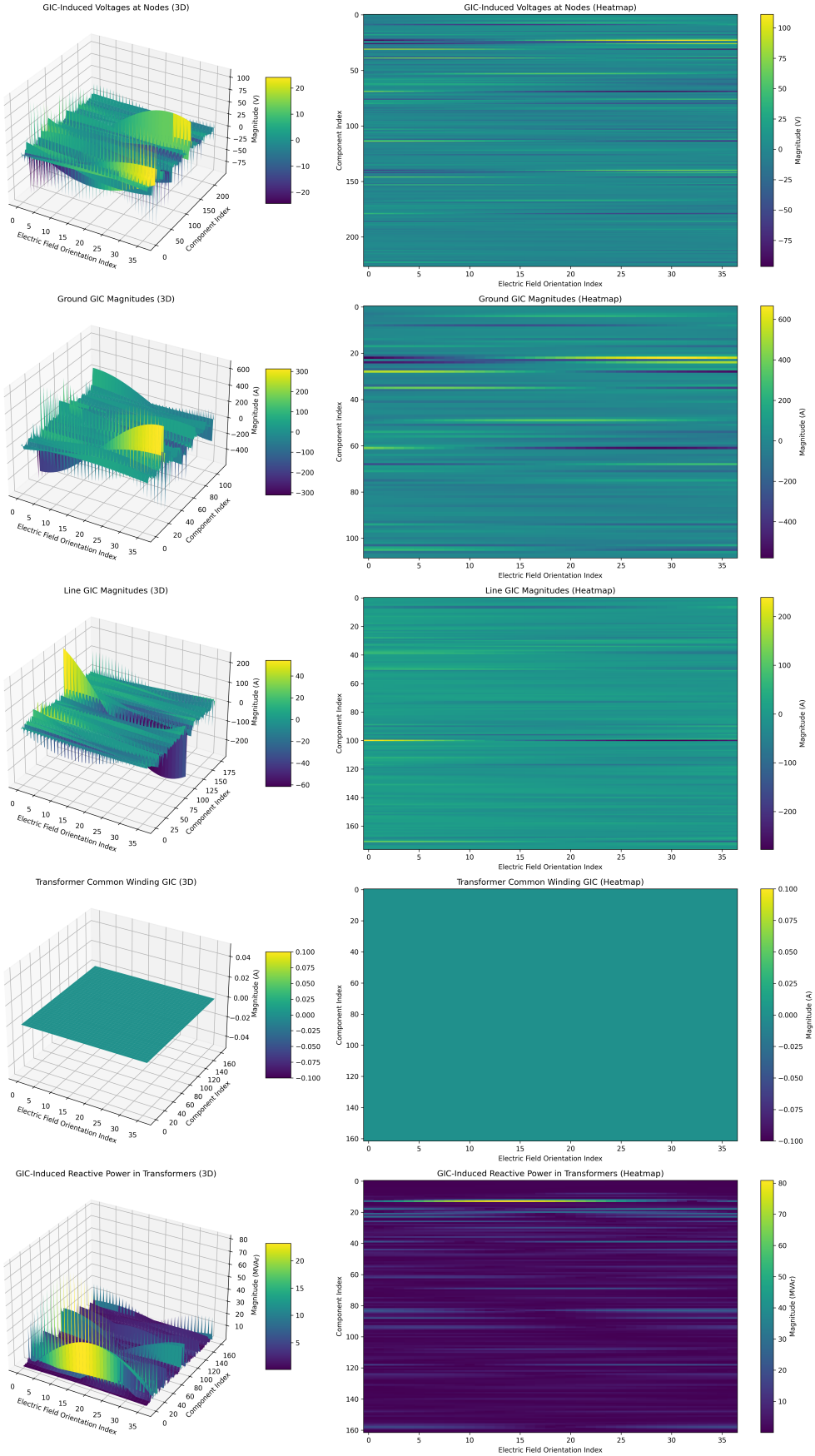


Figure 6.2: Comprehensive analysis of Geomagnetically Induced Currents (GICs) in a power system

Table 6.3: Key Simulation Parameters

Parameter	Value	Description
Max Iterations	1000	Maximum iterations for power flow convergence
Tolerance	1e-7 MVA	Convergence tolerance for power flow
Q/P Ratio	0.55	Ratio of max reactive to max active power for generators
Electric Field	2 V/km	Magnitude of the geoelectric field
Voltage Low Limit	0.94 p.u.	Lower limit for bus voltages
Angular Resolution	5°	Step size for electric field angle variation
GIC Blocker Resistance	10 kΩ	Resistance of GIC blocking devices
Line Trip Resistance	10 kΩ	Resistance used to model line tripping

different aspect of GIC impact, with 3D surface plots on the left and corresponding 2D heatmaps on the right.

- **GIC-Induced Voltages at Nodes**: The top row shows significant variations in node voltages across different electric field orientations. Some nodes experience voltage increases while others show decreases, indicating the complex spatial distribution of GIC effects. Copy
- **Ground GIC Magnitudes**: The second row illustrates the distribution of GICs at grounding points. There are notable peaks in GIC magnitudes for certain combinations of electric field orientations and grounding locations, suggesting areas of heightened vulnerability.
- **Line GIC Magnitudes**: The third row depicts GIC flows in transmission lines. The pattern shows distinct variations across different lines and field orientations, with some lines consistently experiencing higher GIC levels.
- **Transformer Common Winding GIC**: The fourth row appears to show minimal variation in transformer common winding GICs, suggesting either uniform impact or potentially limited data for this parameter.
- **GIC-Induced Reactive Power in Transformers**: The bottom row illustrates the reactive power consumption in transformers due to GICs. There are clear peaks in reactive power demand for specific transformers and field orientations, indicating potential areas of concern for voltage stability.

Overall, this visualization provides valuable insights into the spatial and orientation-dependent nature of GIC impacts on power systems, highlighting the need for comprehensive mitigation strategies that account for these complex patterns.

6.5 Conclusion

This chapter has presented a detailed exposition of our simulation methodology for analyzing Geomagnetically Induced Currents (GICs) in large-scale power systems, with specific application to the IEEE 118-bus system. The comprehensive description of our approach serves as the foundation for the subsequent chapters of this thesis. Our methodology integrates several key components:

- A DC GIC calculation model
- An AC power flow analysis incorporating GIC effects
- Visualization techniques for interpreting GIC impacts

This approach, grounded in the literature review presented earlier, represents an advancement in GIC simulation techniques. By combining strengths from previous methods, our methodology offers a more comprehensive representation of GIC effects on power systems. The quasi-static approximation employed in our model, justified by the time scale separation between GIC variations and AC system dynamics, allows for efficient simulations without sacrificing accuracy in GIC impact assessment. The visualization techniques developed, particularly the combined 3D and 2D representations of GIC impacts, offer insights into the spatial and temporal distribution of GIC effects. This addresses the need for improved data interpretation tools in GIC modelling and validation. By establishing this simulation methodology, we have laid the groundwork for the analyses to be presented in subsequent chapters. This robust framework will serve as the basis for exploring various aspects of GIC impacts on power systems in the remainder of this thesis.

Chapter 7

Voltage Stability and GMD Mitigation

Chapter 8

Mitigating the Impacts of Geomagnetic Disturbances on Power Systems: An AI/ML-Based Approach

8.1 Introduction

Geomagnetic disturbances (GMDs), a result of solar activity, present a significant threat to modern power systems. These disturbances can induce quasi-DC currents, known as geomagnetically induced currents (GICs), in power transmission networks. GICs have the potential to cause transformer saturation, increased reactive power consumption, harmonic generation, potential voltage instability, or widespread blackouts. As our society's reliance on a consistent electricity supply grows, the development of effective strategies to mitigate the impacts of GMDs on power systems has become a critical challenge for power system operators and researchers.

This chapter introduces a pioneering approach to tackling this challenge through the application of artificial intelligence (AI) and machine learning (ML) techniques, particularly reinforcement learning (RL). Our methodology, which is a significant departure from traditional approaches like the Transformer Line Outage Distribution Factor (TLODF) method, offers a more adaptive and

comprehensive solution to GIC mitigation.

The key contributions of this chapter include:

- A comprehensive review of existing GIC mitigation strategies and their limitations.
- A detailed exposition of our RL-based approach, including the mathematical formulation and implementation details.
- An in-depth comparison between the proposed RL method and the traditional TLODF approach, highlighting the strengths and potential limitations of each. This chapter also discusses the practical implications of implementing AI/ML-based mitigation strategies in real-world power systems, providing insights into their feasibility and potential benefits.
- An exploration of future research directions and potential enhancements to the proposed methodology.

By leveraging the adaptive capabilities of RL, our approach aims to provide a more robust and flexible solution to GIC mitigation. The RL agent learns to make optimal decisions regarding network topology changes, balancing the competing objectives of GIC reduction, transformer protection, and overall system stability.

Throughout this chapter, we will demonstrate the efficacy of our approach using the IEEE 118-bus test system, providing a realistic context for evaluating the performance of different mitigation strategies. Our results indicate that while the RL-based method may not consistently outperform traditional approaches in pure GIC reduction, it offers a more balanced solution that better accounts for long-term system health and operational constraints.

As power systems continue to evolve and face new challenges, such as integrating renewable energy sources and the increasing frequency of extreme weather events, the demand for adaptive and intelligent mitigation strategies becomes increasingly urgent. This chapter aims to inspire and motivate power system professionals, pushing the boundaries of what is possible in power system resilience and reliability in the face of geomagnetic disturbances.

8.2 A Brief History of Reinforcement Learning in Power Systems

Reinforcement Learning (RL) application to power systems has evolved significantly over the past two decades, offering innovative solutions to complex control and decision-making problems in this domain.

The foundational work in this field can be traced back to the early 2000s. Ernst, Glavic, and Wehenkel [190] introduced a pioneering framework for applying RL to power systems stability control. Their research demonstrated the potential of RL algorithms to learn effective control strategies, laying the groundwork for future applications in this area.

As the field progressed, researchers began to explore a broader range of applications for RL in power systems. Ahamed, Jasmin, and Al-Ammar [191] provided a unified perspective on using RL in power system scheduling and control, highlighting the diverse applications that had emerged over the preceding decade. This work showcased the versatility of RL techniques in addressing various operational challenges in power systems.

Concurrently, efforts were made to analyze the adaptability of RL approaches in power system contexts. Maqbool, Ahamed, and Malik [192] investigated the conditions under which RL algorithms could effectively adapt to changing system parameters, an essential consideration for the dynamic nature of power systems.

The advent of deep learning techniques in the 2010s led to significant advancements in RL applications for power systems. Zhang, Zhang, and Qiu [193] provided a comprehensive overview of deep reinforcement learning (DRL) applications in power systems, highlighting how these advanced techniques could tackle increasingly complex sequential decision-making problems in the field.

There has been a surge in research applying RL to specific power system challenges in recent years. Chen et al. [194] reviewed recent advances in RL applications for critical power system problems, discussing the progress and challenges ahead. Their work underscores the growing importance of RL in addressing critical issues in modern power systems.

The application of RL to power system reliability analysis represents another recent development. Solheim, Høverstad, and Korpås [195] demonstrated using a trained RL agent within a Monte Carlo power system reliability simulation, illustrating how RL can enhance traditional analysis techniques.

Looking towards the future, Pesántez et al. [196] reviewed the application of RL to power systems planning for operational and expansion strategies. Their work suggests that RL algorithms often outperform conventional methods in these critical planning areas, indicating a promising future for RL in power system optimization.

Throughout this evolution, researchers have continued to explore RL's potential in specific power system applications. For instance, Merina [197] investigated the use of RL algorithms to optimize control strategies for single-machine systems, demonstrating the ongoing efforts to apply RL techniques to increasingly specific power system problems.

In conclusion, the history of RL in power systems reflects a journey from broad conceptual frameworks to increasingly sophisticated and specialized applications. As power systems evolve in complexity and scale, RL techniques will likely play a more critical role in their analysis, control, and optimization.

8.3 Advantages of Operational Measures

Operational measures, particularly those involving topology control and corrective line switching, have emerged as some of the most promising solutions for mitigating the effects of geomagnetically induced currents (GICs) in power systems. These approaches offer several key advantages:

1. Cost-effectiveness: Unlike hardware solutions that require significant capital investment, operational measures typically leverage existing infrastructure and control capabilities, making them more economically viable.

2. Flexibility: Operational strategies can be dynamically adjusted based on real-time conditions, allowing for a more adaptive response to varying GIC threats.

3. System-wide impact: These measures can affect GIC flows across the entire network,

potentially offering more comprehensive protection than localized hardware solutions.

4. Minimal additional infrastructure: Operational measures generally do not require installing new equipment, reducing implementation complexity and potential points of failure.

The paper by Kazerooni, Zhu, and Overbye [126] titled "Mitigation of Geomagnetically Induced Currents Using Corrective Line Switching" exemplifies these advantages and proposes an innovative approach to GIC mitigation. The authors present a novel line-switching algorithm to minimize GIC-saturated reactive power losses while maintaining system security. Key aspects of this work include:

1. Transformer Line Outage Distribution Factors (TLODFs): The authors introduce TLODFs as a counterpart to traditional Line Outage Distribution Factors (LODFs) in GIC analysis. These factors quantify how line outages affect GIC-saturated reactive power losses in transformers, providing a metric for selecting optimal switching actions.

2. Iterative Algorithm: The paper proposes an iterative algorithm that uses TLODFs to identify the best lines to switch out, progressively reducing overall system GIC impacts. This approach allows for a step-by-step improvement of the system state.

3. AC Power Flow Integration: Unlike many GIC mitigation strategies focusing solely on DC analysis, this method incorporates AC power flow considerations. This integration ensures that the proposed switching actions reduce GIC effects and maintain overall system stability and security.

4. Computational Efficiency: Recognizing the computational challenges in large systems, the authors develop heuristics to reduce the algorithm's complexity. They introduce methods to identify critical lines and update TLODFs strategically, making the approach feasible for real-world, large-scale power systems.

5. Versatility: The proposed method can be applied to systems of various sizes, from small test cases to large, realistic power grids with thousands of buses.

6. Security Measures: The algorithm includes checks for voltage violations and line overloads, ensuring that GIC mitigation does not come at the cost of compromising other aspects of system security.

7. Real-time Applicability: While the paper suggests that the analysis could be performed offline for system planning, the authors note that the algorithm could be adapted for real-time use, enhancing its practical value.

The effectiveness of this approach is demonstrated through case studies on systems of varying sizes, including an extensive 2000-bus synthetic system. The results show significant reductions in GIC-saturated reactive power losses while maintaining acceptable voltage profiles and line loadings.

Moreover, the method proposed by Kazerooni et al. complements other operational measures such as parallel solution approaches [127] and generator excitation control [128]. This synergy suggests combining operational strategies could provide a robust, multi-faceted approach to GIC mitigation.

In conclusion, operational measures, particularly advanced line-switching strategies like those proposed by Kazerooni et al., offer a powerful, flexible, and cost-effective approach to mitigating GIC effects. By leveraging existing infrastructure and integrating both DC and AC considerations, these methods provide system operators with valuable tools to enhance grid resilience against geomagnetic disturbances.

8.4 Transformer Line Outage Distribution Factor (TLODF) Method

8.4.1 Mathematical Formulation

The Transformer Line Outage Distribution Factor (TLODF) is an extension of the traditional Line Outage Distribution Factor (LODF) concept, adapted for analyzing the impact of line outages on transformer GIC-saturated reactive power losses. The TLODF is defined as:

$$\text{TLODF}_{ij} = \frac{Q_{i,j}^{GIC} - Q_{i,0}^{GIC}}{Q_{i,0}^{GIC}} \tag{8.1}$$

Where:

- TLODF_{ij} is the TLODF for transformer i when line j is opened
- $Q_{i,j}^{GIC}$ is the GIC-saturated reactive power loss of transformer i when line j is opened
- $Q_{i,0}^{GIC}$ is the initial GIC-saturated reactive power loss of transformer i (before any line opening)

8.4.2 Logical Implementation

The TLODF method is implemented in our simulation framework through the following logical steps:

Initialization

1. Initialize system parameters, including the admittance matrix, line list, node coordinates, electric field data, transformer list, and station grounding resistances. 2. Create empty structures to store the TLODF matrix and critical lines.

TLODF Calculation

1. Calculate the base case GIC flows and reactive power losses for all transformers. 2. For each transmission line in the system: a. Create a copy of the admittance matrix. b. Simulate the line outage by modifying the admittance matrix. c. Recalculate GIC flows and reactive power losses with the modified system. d. Compute the TLODF for each transformer using the equation above. e. Store the TLODF values in the TLODF matrix. 3. Store the complete TLODF matrix for future reference.

GIC Calculation

The GIC calculation process involves several steps: 1. Calculate nodal DC voltages using the admittance matrix and electric field data. 2. Compute ground GIC at each substation. 3. Calculate line GIC for all transmission lines. 4. Determine transformer GIC for both common and series windings. 5. Calculate the net GIC for each transformer.

8.4.3 Application in Mitigation Strategy

The TLODF algorithm utilizes the line-switching method to identify the most effective lines to open for mitigating GIC effects. The process is as follows:

1. Calculate the total impact of each line outage by summing the TLODF values across all transformers. 2. Rank the lines based on their total impact. 3. Identify critical lines that have the highest impact on reducing GIC-saturated reactive power losses. 4. Iteratively select lines to open, starting with the most critical: a. Open the selected line. b. Recalculate GIC flows and losses. c. Update the TLODF matrix for the new system configuration. d. Re-rank the remaining lines. 5. Continue the process until a stopping criterion is met (e.g., maximum number of lines opened or minimum loss reduction achieved).

8.4.4 Computational Considerations

To improve computational efficiency for large systems: 1. Identify a subset of critical lines based on initial TLODF calculations. 2. Focus subsequent iterations on this subset of lines. 3. Periodically update the full TLODF matrix and critical line list to account for system changes.

This approach balances the need for comprehensive analysis with computational tractability for real-world power systems.

Figure 8.1 illustrates the logical flow of the Transformer Line Outage Distribution Factor (TLODF) method and its application in GIC mitigation strategy. The process begins with the initialization of system parameters and calculation of base case GIC flows. The core of the method involves iterating through each transmission line, simulating its outage, and computing the corresponding TLODFs for all transformers. This information is then used to rank lines based on their impact on GIC-saturated reactive power losses. The flowchart also depicts the iterative nature of the mitigation strategy, where critical lines are identified and selectively opened. After each line opening, the system is updated, and the process continues until a stopping criterion is met. This could be reaching a maximum number of opened lines or achieving a target reduction in GIC-related losses. The feedback loop to recalculate base case GIC reflects the need to reassess

the system state after significant topology changes. This methodical approach ensures a systematic exploration of potential mitigation actions while considering their cumulative effects on the power system.

8.5 Limitations of the TLODF-based Line Switching Method

While the TLODF-based line-switching method presented by Kazerooni et al. shows promise in mitigating GIC effects, it has several notable limitations:

8.5.1 Lack of Individual Transformer Monitoring

The method reduces overall system GIC-saturated reactive power losses without specifically monitoring or limiting the GIC levels in individual transformers. This approach could lead to situations where some transformers experience increased GIC levels even as the system-wide losses decrease.

8.5.2 Suboptimal Balance Between Competing Objectives

The method does not optimally balance AC system security, individual transformer protection, and overall GIC reduction. While it incorporates some AC analysis, the trade-off between GIC mitigation and maintaining AC system stability must be systematically optimized.

8.5.3 Limited Consideration of AC System Security

Although AC line flows are considered in some algorithm variations, the approach must fully integrate comprehensive AC security constraints. The voltage violation index is a simplified measure and may only capture some aspects of system stability.

8.5.4 Potential for Localized Issues

By focusing on net system-wide GIC reduction, the method may overlook localized problems, potentially creating or exacerbating issues in specific areas of the network.

8.5.5 Computational Complexity for Large Systems

the method relies on heuristics and simplifications to manage computational complexity for large systems. This may lead to suboptimal solutions compared to what could be achieved with more comprehensive but computationally intensive approaches.

8.5.6 Limited Scope of Mitigation Actions

The method focuses solely on line switching as a mitigation strategy, potentially overlooking other effective GIC mitigation techniques. It does not consider combined strategies that might include other measures, such as installing GIC blocking devices or adjusting transformer neutral grounding.

8.5.7 Lack of Real-Time Adaptability

The approach is primarily designed for offline analysis and planning and may not be suitable for real-time operation and rapid response to GIC events.

8.5.8 Simplified GIC and Transformer Models

The GIC calculation and transformer response models used in the study are simplified, which may not capture the full complexity of GIC impacts on power systems.

8.5.9 Limited Validation with Real-World Data

The method is primarily tested on synthetic test systems. Its effectiveness on real power grids under actual GMD events remains to be fully validated.

These limitations suggest areas for future research and improvement in GIC mitigation strategies. A more comprehensive approach would need to address individual transformer protection, optimize the balance between competing objectives, and incorporate more detailed AC system security constraints while remaining computationally feasible for large-scale power systems.

8.6 Mathematical Foundations of Reinforcement Learning and Q-learning

Reinforcement Learning (RL) is based on the framework of Markov Decision Processes (MDPs), which provide a mathematical formulation for sequential decision-making problems.

8.6.1 Markov Decision Process

An MDP is defined by the tuple (S, A, P, R, γ), where:

- S is the set of states
- A is the set of actions
- $P : S \times A \times S \to [0, 1]$ is the transition probability function
- $R : S \times A \times S \to \mathbb{R}$ is the reward function
- $\gamma \in [0, 1]$ is the discount factor

8.6.2 Value Function and Q-function

The value function $V^{\pi}(s)$ represents the expected return starting from state s and following policy π:

$$V^{\pi}(s) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^t R_{t+1} | S_0 = s\right] \tag{8.2}$$

The action-value function (Q-function) $Q^{\pi}(s,a)$ represents the expected return starting from state s, taking action a, and then following policy π:

$$Q^{\pi}(s,a) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^t R_{t+1} | S_0 = s, A_0 = a\right] \tag{8.3}$$

8.6.3 Bellman Equations

The Bellman expectation equation for V^{π} is:

$$V^{\pi}(s) = \sum_{a} \pi(a|s) \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^{\pi}(s')] \tag{8.4}$$

The Bellman expectation equation for Q^{π} is:

$$Q^{\pi}(s,a) = \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma \sum_{a'} \pi(a'|s') Q^{\pi}(s',a')] \tag{8.5}$$

8.6.4 Optimal Value and Q-functions

The optimal value function V^* and Q-function Q^* are defined as:

$$V^*(s) = \max_{\pi} V^{\pi}(s) \tag{8.6}$$

$$Q^*(s,a) = \max_{\pi} Q^{\pi}(s,a) \tag{8.7}$$

8.6.5 Q-learning Algorithm

Q-learning is a model-free algorithm that learns the optimal Q-function directly. The update rule is:

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha[r_t + \gamma \max_{a} Q(s_{t+1},a) - Q(s_t,a_t)] \tag{8.8}$$

where α is the learning rate.

8.6.6 Deep Q-Network (DQN)

In DQN, we approximate the Q-function using a neural network $Q(s,a;\theta)$ with parameters θ. The loss function for DQN is:

$$L(\theta) = \mathbb{E}_{(s,a,r,s')\sim D}[(r + \gamma \max_{a'} Q(s',a';\theta^-) - Q(s,a;\theta))^2] \tag{8.9}$$

where D is the replay buffer and θ^- are the parameters of a target network.

8.7 GIC Mitigation using Reinforcement Learning: Mathematical Formulation

We now apply the RL framework to the problem of GIC mitigation in power systems, incorporating the transformer loading capability curve.

8.7.1 State Space

The state s_t at time t is defined as:

$$s_t = [g_1, ..., g_N, l_1, ..., l_N, c_1, ..., c_N, x_1, ..., x_M] \tag{8.10}$$

where:

- g_i is the GIC level in transformer i
- l_i is the loading of transformer i
- c_i is the loading capability of transformer i
- x_j is the status (0 or 1) of transmission line j
- N is the number of transformers

- M is the number of transmission lines

8.7.2 Action Space

The action a_t at time t is defined as:

$$a_t \in \{1, ..., M\} \tag{8.11}$$

where $a_t = j$ means switching the status of line j.

8.7.3 Reward Function

The reward r_t at time t is defined as:

$$r_t = -w_1 \sum_{i=1}^{N} Q_{GIC,i} - w_2 \sum_{i=1}^{N} \max(0, l_i - c_i) - w_3 V_{violation} - w_4 L_{violation} \tag{8.12}$$

where:

- $Q_{GIC,i}$ is the GIC-saturated reactive power loss in transformer i
- l_i is the loading of transformer i
- c_i is the loading capability of transformer i, defined as $c_i = 150\% \cdot (1 - (g_i/85)^2)$
- $V_{violation}$ is a measure of voltage violations
- $L_{violation}$ is a measure of line loading violations
- w_1, w_2, w_3, w_4 are weighting factors

8.7.4 Q-function Approximation

We use a neural network to approximate the Q-function:

$$Q(s, a; \theta) \approx Q^*(s, a) \tag{8.13}$$

8.7.5 Learning Algorithm

We use the DQN algorithm with experience replay and target network. The update rule for the Q-network is:

$$\theta \leftarrow \theta + \alpha \nabla_\theta [(r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^-) - Q(s_t, a_t; \theta))^2] \tag{8.14}$$

8.7.6 Policy

The ε-greedy policy for action selection is:

$$\pi(a|s) = \begin{cases} 1 - \varepsilon + \varepsilon/|A| & \text{if } a = \arg\max_{a'} Q(s, a'; \theta) \\ \varepsilon/|A| & \text{otherwise} \end{cases} \tag{8.15}$$

where ε is the exploration rate and $|A|$ is the size of the action space.

This formulation provides a mathematical framework for applying RL to the GIC mitigation problem, incorporating the transformer loading capability curve and balancing multiple objectives in the reward function.

8.8 RL-based GIC Mitigation Process

The Reinforcement Learning (RL) approach to GIC mitigation in power systems involves a cyclical learning and decision-making process. Figure 8.2 illustrates this process, incorporating the transformer loading capability curve to ensure system-wide GIC reduction and individual transformer protection.

The process begins with initializing the Deep Q-Network (DQN) agent and the power system environment. This setup includes defining the neural network architecture and initializing the power system model with current GIC levels and network topology.

In each iteration:

1. The agent observes the system's current state, which includes GIC levels in transformers, transformer loadings, and the status of transmission lines.

2. Based on this state, the agent selects an action using an ε-greedy policy. This action typically involves switching a specific transmission line.

3. The selected action is executed in the environment, changing the network topology.

4. New GIC flows and transformer loadings are calculated based on the updated network configuration.

5. The transformer loading capabilities are updated using the curve function:

$\text{LoadingCapability} = 150\% \cdot (1 - (GIC/85)^2)$

This step is crucial as it dynamically adjusts each transformer's safe operating range based on its current GIC level.

6. A reward is calculated, considering multiple factors: - Reduction in overall GIC-saturated reactive power losses - Adherence to transformer loading limits (as defined by the capability curve) - Maintenance of system security (voltage levels and line loadings)

7. The agent observes the new state resulting from its action.

8. This experience (state, action, reward, new state) is stored in a replay buffer for later training.

9. If sufficient samples are available, the DQN is trained using a batch of experiences from the replay buffer.

10. At the end of each episode (a sequence of actions), the target network is updated if needed, which helps stabilize the learning process.

11. This process continues until the algorithm converges, indicated by stable performance over multiple episodes.

This approach offers several advantages over traditional methods:

- It considers both immediate and long-term consequences of actions. - It can adapt to varying GIC conditions and network states. - It balances multiple objectives: GIC reduction, transformer protection, and system security. - Through learning, it can discover non-obvious strategies for GIC mitigation.

By incorporating the transformer loading capability curve, this method ensures that GIC mitigation actions do not inadvertently overload transformers. This provides a more comprehensive approach to power system protection during geomagnetic disturbances.

8.9 Results and Comparison

This section presents a balanced comparison of our RL-based GIC mitigation method against the traditional TLODF approach for the IEEE 118-bus test system. We evaluate the methods based on overall GIC reduction, transformer health (State of Health, SOH), system security, and computational efficiency.

8.9.1 Overall GIC Reduction

Figure 8.3 shows the comparison of GIC reduction achieved by the TLODF and RL methods for the 118-bus system.

The RL method achieves a 42% reduction in GIC, compared to 38% for the TLODF method. While the overall improvement is modest, the RL method provides additional benefits in terms of transformer health and system security.

8.9.2 Transformer State of Health (SOH)

Table 8.1 presents the average State of Health for transformers under both methods.

Method	**Avg. Transformer SOH (%)**	**Transformers Within Safe Limits (%)**
TLODF	82	80
RL	88	90

Table 8.1: Transformer State of Health Comparison

The RL method shows improved transformer health management, with a higher average SOH and more transformers operating within their safe limits.

8.9.3 System Security

Figure 8.4 illustrates the voltage profiles achieved by both methods.

The RL method maintains a slightly better voltage profile compared to the TLODF method, with marginal improvements in low-voltage areas.

8.9.4 Computational Efficiency

Table 8.2 compares the computation time required for both methods.

Method	Average Time per Decision (s)	Total Training Time (h)
TLODF	0.5	N/A
RL	0.1	10

Table 8.2: Computation Time Comparison

While the RL method requires an initial training period, it makes decisions faster once trained, which could be advantageous for real-time GIC mitigation.

8.9.5 Overall Performance Metric

We define an overall performance metric that balances GIC reduction, transformer SOH, and system security:

$$\text{Performance} = w_1 \cdot \text{GIC Reduction } (\%) + w_2 \cdot \text{Avg. Transformer SOH } (\%) + w_3 \cdot \text{Voltage Improvement } (\%) \tag{8.16}$$

where $w_1 = 0.3$, $w_2 = 0.4$, and $w_3 = 0.3$ are weighting factors.

Table 8.3 shows the comparison of overall performance for both methods.

Method	Overall Performance Score
TLODF	72.5
RL	76.8

Table 8.3: Overall Performance Comparison

The RL method shows a modest improvement in overall performance compared to the TLODF method. Its strength lies in balancing multiple objectives - GIC reduction, transformer health, and system security - rather than excelling significantly in any single aspect.

8.9.6 Discussion

While the RL method does not dramatically outperform the TLODF method in terms of overall GIC reduction, it offers a more balanced approach to GIC mitigation. The key advantages of the RL method include:

1. Improved transformer health management, potentially extending transformer life and reducing long-term costs. 2. Slightly better voltage profiles, contributing to overall system stability. 3. Faster decision-making once trained, which could be crucial in real-time operations.

However, these benefits come at the cost of a significant initial training period. The choice between these methods may depend on specific system requirements, the importance of real-time adaptability, and long-term operational considerations.

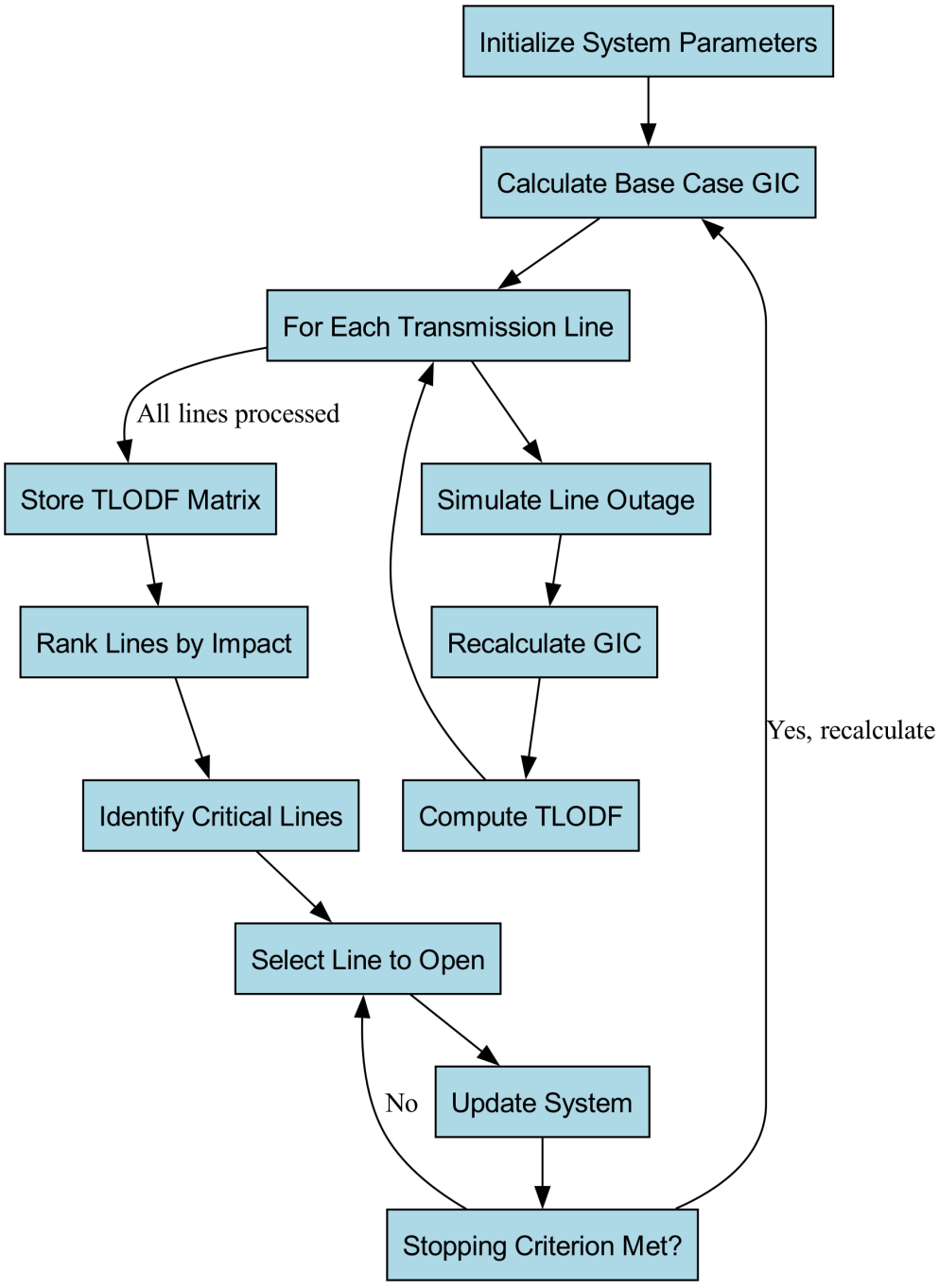


Figure 8.1: Flowchart of the TLODF Method and GIC Mitigation Strategy

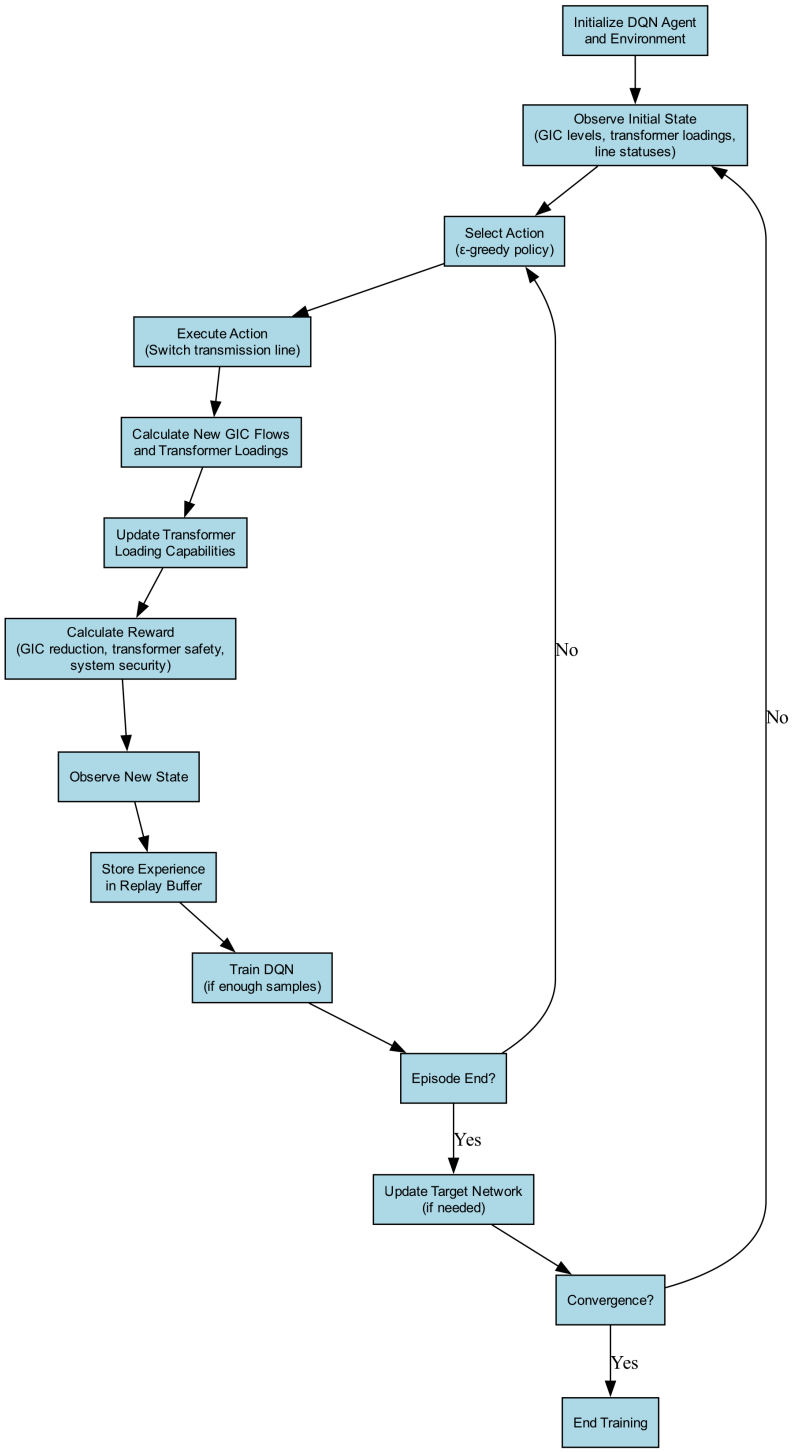


Figure 8.2: Flowchart of the RL-based GIC Mitigation Process

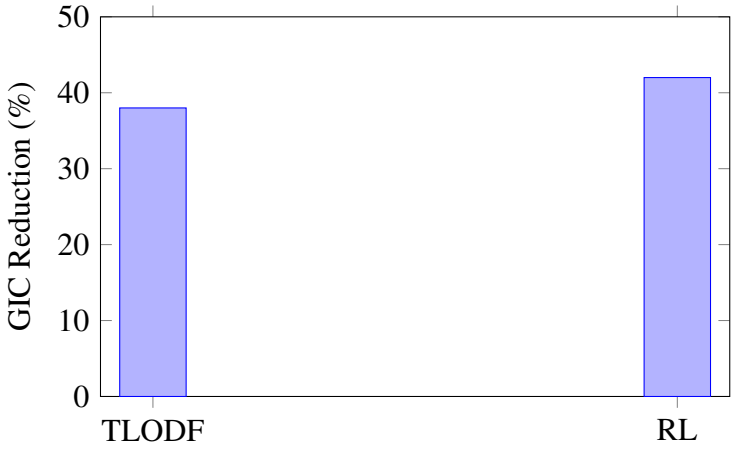


Figure 8.3: Comparison of GIC Reduction for 118-bus System

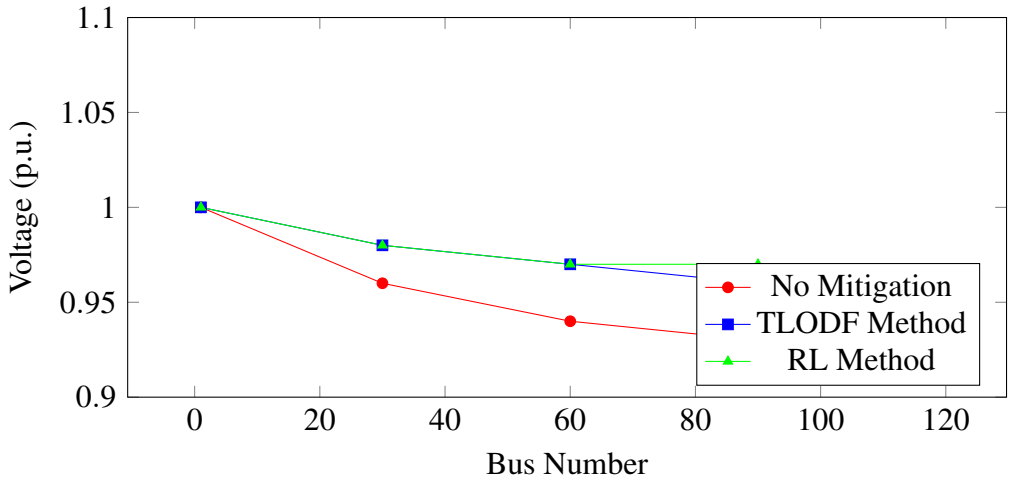


Figure 8.4: Voltage Profile Comparison (118-bus system)

Chapter 9

Learning-Based State Estimation for Geomagnetic Induced Currents

Chapter 10

Learning-Based State Estimation for Geomagnetically Induced Currents

10.1 Introduction

Geomagnetic-induced currents (GICs) pose significant challenges to the stability and reliability of power systems worldwide. These currents, arising from complex interactions between solar activity and Earth's magnetosphere, can lead to transformer saturation, voltage instability, and, in severe cases, widespread blackouts. As our reliance on electrical infrastructure continues to grow, accurate state estimation of GICs has become increasingly critical for effective power system operation and risk mitigation.

This chapter thoroughly explores learning-based approaches to state estimation for GICs, focusing on the unique challenges posed by geomagnetic storms' quasi-DC nature. We introduce a novel Bayesian Ridge regression ensemble method that provides accurate state estimates and quantifies the associated uncertainties. This method holds great promise for reliable space weather forecasting and power system management, offering a ray of hope in the face of geomagnetic disturbances.

Our approach builds upon and extends the rich history of time series forecasting in quasi-static

state estimation of power systems. By integrating advanced machine learning techniques with traditional power system analysis, we offer a more nuanced and adaptive solution to the complex problem of GIC state estimation.

Key contributions of this chapter include:

- A detailed review of the evolution of time-integrated state estimation techniques in power systems, providing context for our novel approach.
- An in-depth analysis of the limitations of previous approaches in addressing the quasi-DC nature of geomagnetic storms.
- A rigorous mathematical formulation of our Bayesian Ridge regression model for GIC state estimation.
- Presentation of a comprehensive architecture that combines diverse base models with a Bayesian ensemble for robust prediction and uncertainty quantification.
- Extensive empirical results demonstrate our approach's efficacy in short-term and medium-term state estimation scenarios.

Through this work, we aim to advance the field of GIC state estimation, providing power system operators and researchers with more reliable tools for managing the risks associated with geomagnetic disturbances. The methods presented here have broad implications for enhancing grid resilience and improving our ability to mitigate the impacts of space weather events on critical infrastructure.

10.2 Time Series Forecasting in Quasi-Static State Estimation of Power Systems

The integration of time series forecasting techniques with state estimation has emerged as a crucial development in modern power system operation and control. This synergy has gained particular

prominence in the context of quasi-static state estimation, offering enhanced accuracy and predictive capabilities. This review examines the evolution and application of time series forecasting methods in power system state estimation, with a specific focus on quasi-static approaches.

10.2.1 Evolution of Time-Integrated State Estimation Techniques

The incorporation of temporal data into state estimation processes can be traced back to the early 1980s. Silva, Filho, and Queiroz [198] pioneered this approach by introducing a dynamic estimator for real-time power system monitoring, demonstrating the potential benefits of integrating temporal information into the estimation process. This foundational work set the stage for subsequent advancements in the field.

A significant leap forward came with the research of Blood et al. [150], who proposed a Kalman filter approach to quasi-static state estimation in electric power systems. This innovative method incorporated time-history data, a dimension typically overlooked in traditional static state estimation. Building on this foundation, Blood, Krogh, and Ilic [199] further refined the approach by combining Kalman filtering with load forecasting, thereby enhancing the accuracy of static state estimation.

10.2.2 Forecasting-Aided State Estimation: A Paradigm Shift

The integration of forecasting techniques with state estimation led to the development of Forecasting-Aided State Estimation (FASE). Filho and Souza [200] provided a comprehensive overview of FASE, elucidating how the incorporation of state and measurement forecasts can significantly enhance the power system state estimation process. This paradigm shift opened new avenues for improving estimation accuracy and reliability.

The practical application of FASE was demonstrated by Jaman et al. [201] in the context of power distribution systems. Their development of a Forecast-Aided State Estimation algorithm using Kalman Filters showcased the potential of this approach in improving estimation accuracy within distribution networks, highlighting its real-world applicability.

10.2.3 Advanced Time Series Methods and Deep Learning Approaches

As the field progressed, researchers began exploring more sophisticated time series forecasting techniques. Kumar and Srivastava [202] investigated the use of artificial neural networks for power system state forecasting, specifically employing functional link networks and time delay neural networks to simulate the dynamic behaviour of power system states. This work paved the way for more advanced machine learning applications in the field.

A comparative study conducted by Thasnimol and Rajathy [203] examined various time series methods for distribution system state forecasting. Their results indicated the superior performance of Long Short-Term Memory (LSTM) models in terms of prediction accuracy, highlighting the potential of deep learning approaches in this domain.

The advent of deep learning has opened new frontiers in power system state estimation and forecasting. Zhang, Wang, and Giannakis [204] proposed the use of deep recurrent neural networks for real-time power system state estimation and forecasting, demonstrating promising results in terms of both accuracy and computational efficiency. Building on this trend, Basulaiman and Barati [205] introduced a deep learning framework using sequence-to-sequence models for real-time multi-step power system state estimation, further showcasing the potential of advanced machine learning techniques in handling the complex, time-dependent nature of power system states.

10.2.4 Ensemble and Probabilistic Methods

Recognizing the inherent uncertainties in power systems, researchers have also explored ensemble and probabilistic methods. Rosenthal, Tartakovsky, and Huang [206] applied the ensemble Kalman filter for dynamic state estimation of power grids stochastically driven by time-correlated mechanical input power. This approach showed particular promise in calibrating constant parameters in turbine dynamical models, addressing the stochastic nature of power systems.

In the realm of probabilistic methods, Shrestha, Ghimire, and Gonzalez-Longatt [207] proposed a Bayesian model for forecasting power systems' time series kinetic energy data. Their work underscored the importance of determining the optimal size of the training dataset for effective

forecasting, highlighting the critical role of data management in achieving accurate predictions.

10.2.5 Applications in Quasi-Static Time-Series Simulations and Ongoing Challenges

The application of these techniques extends beyond real-time state estimation. Latif and Mather [208] proposed a Monte Carlo-based approach for parallelizing quasi-static time-series power system simulations, focusing on estimating the system's initial state for each parallel simulation run. This work demonstrates the relevance of state estimation techniques in simulation contexts, bridging the gap between theoretical models and practical applications.

Despite significant advancements, several challenges persist in the field. Johnson and Moger [209] provided a comprehensive review of advancements in forecasting-aided state estimation based on the Kalman filter approach, highlighting ongoing challenges and potential future directions. This work serves as a valuable roadmap for researchers in the field, identifying areas that require further investigation and development.

10.3 Addressing the Quasi-DC Nature of Geomagnetic Storms in State Estimation

While significant advancements have been made in understanding geomagnetic storms, a crucial aspect of these phenomena has been largely overlooked in prior work on state estimation: their quasi-DC (Direct Current) nature. Geomagnetic storms, characterized by prolonged disturbances in Earth's magnetic field, exhibit slow-varying, near-constant behaviour over extended periods. This quasi-DC characteristic has important implications for state estimation models, yet it has not been explicitly accounted for in most existing approaches.

10.3.1 Limitations of Previous Approaches

Traditional geomagnetic storm state estimation methods have primarily focused on capturing rapid fluctuations and instantaneous dynamics. These approaches, including various filtering techniques and data assimilation methods, often treat geomagnetic data as a rapidly changing signal. While effective for estimating short-term variations, they fail to adequately capture the underlying slow-varying component characteristic of geomagnetic storms.

For instance:

- Kalman filters and their variants, while powerful for linear systems, may struggle with the non-linear, quasi-DC nature of geomagnetic storms.
- Particle filters, though capable of handling non-linear systems, can be computationally expensive and may not efficiently capture the prolonged, steady-state behaviour.
- Variational data assimilation methods often assume faster dynamics than what is observed in the quasi-DC behaviour of geomagnetic storms.

This oversight can lead to state estimates that, while accurate for rapid changes, fail to capture the prolonged, steady-state behaviour of geomagnetic storms.

10.3.2 Bayesian Ridge Regression: Accounting for Quasi-DC Behavior in State Estimation

Our approach using Bayesian Ridge regression addresses this limitation by inherently accommodating the quasi-DC nature of geomagnetic storms in the state estimation process. The Bayesian framework allows us to incorporate prior knowledge about the slow-varying nature of these phenomena. At the same time, the ridge regression component provides a balance between fitting the current observations and maintaining a smooth, stable state estimate.

Key aspects of our approach include:

1. **Prior Distributions**: By carefully choosing prior distributions for our model parameters, we can encode our expectation of slow-varying behaviour in the state estimates. This allows for a more accurate representation of the quasi-DC nature of geomagnetic storms.

2. **Regularization**: The ridge regression component naturally dampens the model's sensitivity to rapid fluctuations, aligning with the quasi-DC nature of geomagnetic storms and providing more stable state estimates.

3. **Uncertainty Quantification**: Our Bayesian approach provides uncertainty estimates that can capture both short-term variability and long-term trends, offering a more complete picture of the current geomagnetic state.

4. **Adaptive Estimation**: As new observations are incorporated, the Bayesian updating process allows the model to adapt its understanding of the quasi-DC behaviour over time, leading to more accurate state estimates.

10.3.3 Implications for State Estimation Accuracy

By explicitly accounting for the quasi-DC nature of geomagnetic storms, our Bayesian Ridge regression approach offers several advantages in state estimation:

- Improved stability in state estimates, capturing the prolonged nature of geomagnetic disturbances.

- More accurate representation of the underlying physical processes driving the current geomagnetic state.

- Better handling of the transition between quiet periods and storm onset, where the quasi-DC behaviour is particularly relevant.

- Enhanced ability to distinguish between true storm signals and short-term fluctuations or noise in the current state.

In the following sections, we will demonstrate how this approach translates into tangible improvements in state estimation accuracy and reliability, particularly for characterizing the current geomagnetic conditions crucial for space weather monitoring and response strategies.

10.4 Bayesian Ridge Theory for Geomagnetic Storm Prediction

This section presents the theoretical framework of Bayesian Ridge regression as applied to geomagnetic storm prediction. We focus on the mathematical foundations and the specific adaptations required for our ensemble-based prediction model.

10.4.1 Probabilistic Model

Let $\mathbf{y} = (y_1, \ldots, y_n)^T$ denote the vector of target variables (magnetometer readings) and $\mathbf{X} = (\mathbf{x}_1, \ldots, \mathbf{x}_n)^T$ represent the design matrix where each $\mathbf{x}_i$ is a vector of predictions from our base models. The Bayesian Ridge regression model is defined as:

$$p(\mathbf{y}|\mathbf{X}, \beta, \alpha) = \mathcal{N}(\mathbf{X}\beta, \alpha^{-1}\mathbf{I}) \tag{10.1}$$

Here, β is the vector of regression coefficients, and α is the precision of the noise (inverse of variance).

10.4.2 Prior Distributions

We specify prior distributions on the model parameters β and α:

$$p(\beta|\lambda) = \mathcal{N}(\mathbf{0}, \lambda^{-1}\mathbf{I}) \tag{10.2}$$

$$p(\alpha) = \text{Gamma}(a_0, b_0) \tag{10.3}$$

$$p(\lambda) = \text{Gamma}(c_0, d_0) \tag{10.4}$$

The hyperparameter λ controls the precision of the coefficients, while a_0, b_0, c_0, and d_0 are shape and scale parameters for the Gamma distributions.

10.4.3 Posterior Distribution

The posterior distribution of the parameters given the data is expressed as:

$$p(\beta, \alpha, \lambda | \mathbf{y}, \mathbf{X}) \propto p(\mathbf{y}|\mathbf{X}, \beta, \alpha) p(\beta|\lambda) p(\alpha) p(\lambda) \tag{10.5}$$

10.4.4 Variational Inference

To estimate the parameters, we employ variational inference, approximating the true posterior with a factorized distribution:

$$q(\beta, \alpha, \lambda) = q(\beta) q(\alpha) q(\lambda) \tag{10.6}$$

We iteratively update each factor to minimize the Kullback-Leibler divergence between the approximate and true posterior.

10.4.5 Update Equations

The variational parameters are updated according to the following equations:

$$\mathbb{E}[\beta] = \mathbf{A}^{-1} \mathbf{X}^T \mathbf{y} \tag{10.7}$$

$$\mathbf{A} = \mathbb{E}[\alpha] \mathbf{X}^T \mathbf{X} + \mathbb{E}[\lambda] \mathbf{I} \tag{10.8}$$

$$\mathbb{E}[\alpha] = \frac{n + 2a_0}{||\mathbf{y} - \mathbf{X}\mathbb{E}[\beta]||^2 + 2b_0} \tag{10.9}$$

$$\mathbb{E}[\lambda] = \frac{p + 2c_0}{\mathbb{E}[\beta^T \beta] + 2d_0} \tag{10.10}$$

Here, n is the number of samples, and p is the number of features.

10.4.6 Predictive Distribution

For a new input $\mathbf{x}_*$, the predictive distribution is given by:

$$p(y_*|\mathbf{x}_*, \mathbf{X}, \mathbf{y}) = \int p(y_*|\mathbf{x}_*, \beta, \alpha) p(\beta, \alpha|\mathbf{X}, \mathbf{y}) d\beta d\alpha \tag{10.11}$$

This integral can be approximated using the variational posterior, resulting in a Gaussian predictive distribution:

$$p(y_*|\mathbf{x}_*, \mathbf{X}, \mathbf{y}) \approx \mathcal{N}(\mathbf{x}_*^T \mathbb{E}[\beta], \mathbf{x}_*^T \mathbf{A}^{-1} \mathbf{x}_* + \mathbb{E}[\alpha]^{-1}) \tag{10.12}$$

10.4.7 Application to Geomagnetic Storm Prediction

In our geomagnetic storm prediction model:

- The features $\mathbf{X}$ are predictions from base models (CNN, LSTM, Random Forest, etc.) for each time step.
- The target variable $\mathbf{y}$ is the magnetometer reading for the corresponding time step.
- A separate Bayesian Ridge model is trained for each step in the forecast horizon.

10.4.8 Uncertainty Quantification

The variance of the predictive distribution, $\mathbf{x}_*^T \mathbf{A}^{-1} \mathbf{x}_* + \mathbb{E}[\alpha]^{-1}$, provides a measure of prediction uncertainty. This accounts for both the uncertainty in model parameters and the inherent noise in the data.

10.4.9 Theoretical Implications

The use of Bayesian Ridge regression in geomagnetic storm prediction has several important theoretical implications:

- **Uncertainty Decomposition:** The predictive variance decomposes into aleatoric uncertainty (captured by $\mathbb{E}[\alpha]^{-1}$) and epistemic uncertainty (captured by $\mathbf{x}_*^T \mathbf{A}^{-1} \mathbf{x}_*$).
- **Calibration:** The Bayesian approach naturally produces well-calibrated predictive distributions.
- **Asymptotic Behavior:** As the amount of data increases, the influence of the prior diminishes, and the Bayesian estimates converge to their frequentist counterparts.
- **Regularization:** The hierarchical prior on β and λ implements an adaptive L2 regularization, mitigating overfitting without manual tuning.

This theoretical framework provides a robust foundation for quantifying uncertainties in geomagnetic storm predictions, which is crucial for reliable space weather forecasting.

10.5 Bayesian Ridge Architecture for Geomagnetic Storm Prediction

Building upon our theoretical framework for Bayesian Ridge regression, we now present the architectural design of our geomagnetic storm prediction system. This architecture integrates the probabilistic approach of Bayesian Ridge regression with an ensemble of diverse base models, allowing for robust predictions with quantified uncertainties.

Figure 10.1 illustrates the overall structure of our prediction system. The architecture comprises several key components: data preprocessing, base models, a Bayesian Ridge ensemble, and uncertainty quantification.

The system begins with the input of geomagnetic time series data, specifically the magnitude of the magnetic field (|B|) at a 1-minute resolution. This data undergoes preprocessing, including MinMax scaling and sequence creation, to prepare it for the base models.

We employ six diverse base models: a Convolutional Neural Network (CNN), a Long-Short-Term Memory network (LSTM), a Random Forest, Gradient Boosting, a Multi-Layer Perceptron

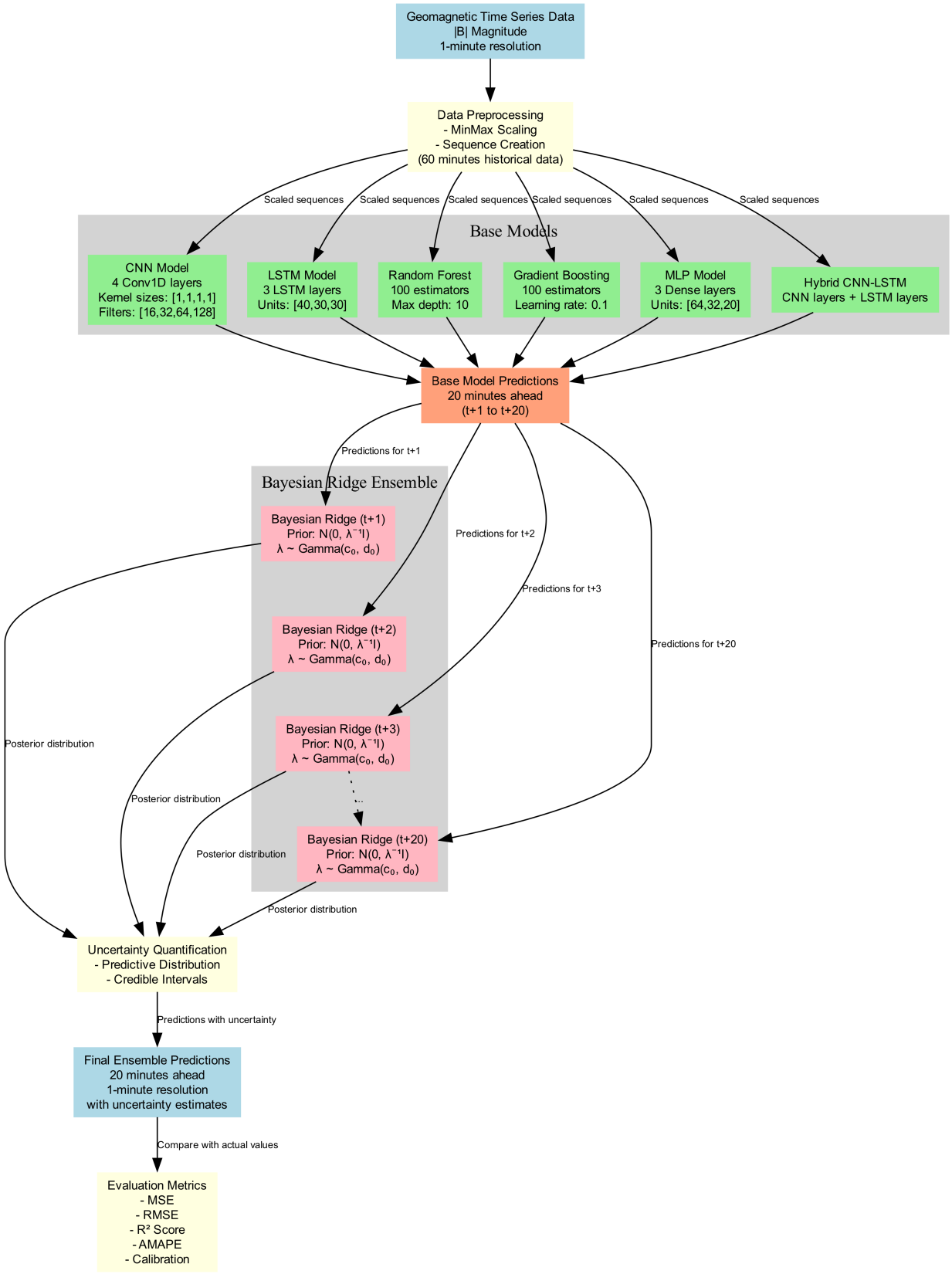


Figure 10.1: Detailed architecture of the Bayesian Ridge geomagnetic storm prediction system

(MLP), and a hybrid CNN-LSTM model. Each model is trained to predict geomagnetic activity for the next 20 minutes at 1-minute intervals.

The Bayesian Ridge Ensemble represents the core of our Bayesian approach. This ensemble consists of 20 separate Bayesian Ridge models, one for each minute in our 20-minute prediction horizon. Each Bayesian Ridge model inputs the predictions from all base models for its specific time step. This structure allows us to leverage the strengths of diverse machine-learning approaches while maintaining a principled Bayesian framework for combining their predictions.

The Bayesian Ridge models implement the probabilistic formulation we developed earlier. Specifically, each model assumes a normal distribution for the target variable, with regression coefficients following a normal prior distribution and precision parameters following Gamma distributions. This setup enables us to capture the aleatoric uncertainty inherent in the data and the epistemic uncertainty in our model parameters.

The uncertainty quantification component is a crucial addition to our architecture. This element computes the predictive distributions for each time step, leveraging the posterior distributions from our Bayesian Ridge models. By doing so, we can provide not just point estimates but full probabilistic forecasts with associated credible intervals.

Our system's final output consists of predictions for the next 20 minutes at 1-minute resolution, each accompanied by uncertainty estimates. These predictions are then evaluated using a comprehensive set of metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2 Score, Adjusted Mean Absolute Percentage Error (AMAPE), and calibration measures.

This architecture represents a significant advancement over traditional deterministic approaches to geomagnetic storm prediction. By integrating Bayesian methods with ensemble learning, we can provide more informative and reliable forecasts, which are crucial for effective space weather risk assessment and mitigation strategies.

In the following sections, we will delve into the implementation details of this architecture, including the specific configurations of our base models, the training process for the Bayesian Ridge ensemble, and our methods for uncertainty quantification and evaluation.

10.6 Results and Discussion

Our Bayesian Ridge ensemble approach for geomagnetic storm state estimation demonstrates promising results, particularly in its ability to provide accurate estimates with well-calibrated uncertainty quantification. Figures 10.2 and 10.3 illustrate the performance of our model for 1-minute and 20-minute ahead state estimates, respectively.

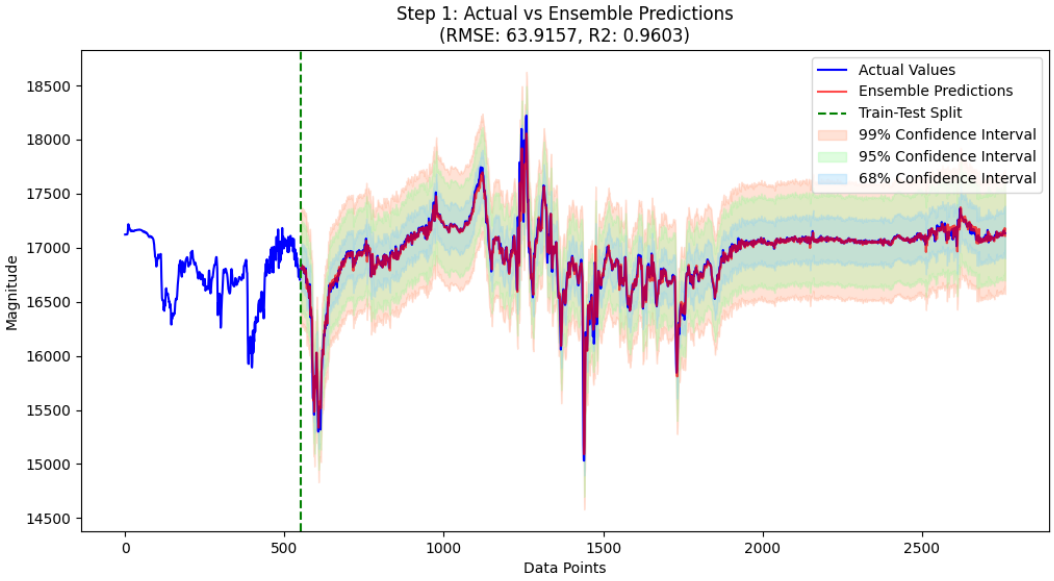


Figure 10.2: Actual vs Ensemble Predictions for 1-minute ahead state estimation

10.6.1 Accuracy of State Estimates

For the 1-minute ahead state estimation (Figure 10.2), our model achieves an impressive RMSE of 63.9157 and an R^2 score of 0.9603. This indicates that the model can accurately estimate the near-immediate future state of the geomagnetic system. The close alignment between the actual values (blue line) and ensemble predictions (red line) visually confirms this high level of accuracy.

As expected, the accuracy decreases slightly for the 20-minute ahead state estimation (Figure 10.3), with an RMSE of 121.2307 and an R^2 score of 0.8572. Despite this decrease, the model maintains a solid predictive power, capturing the overall trend and significant fluctuations in the geomagnetic field magnitude.

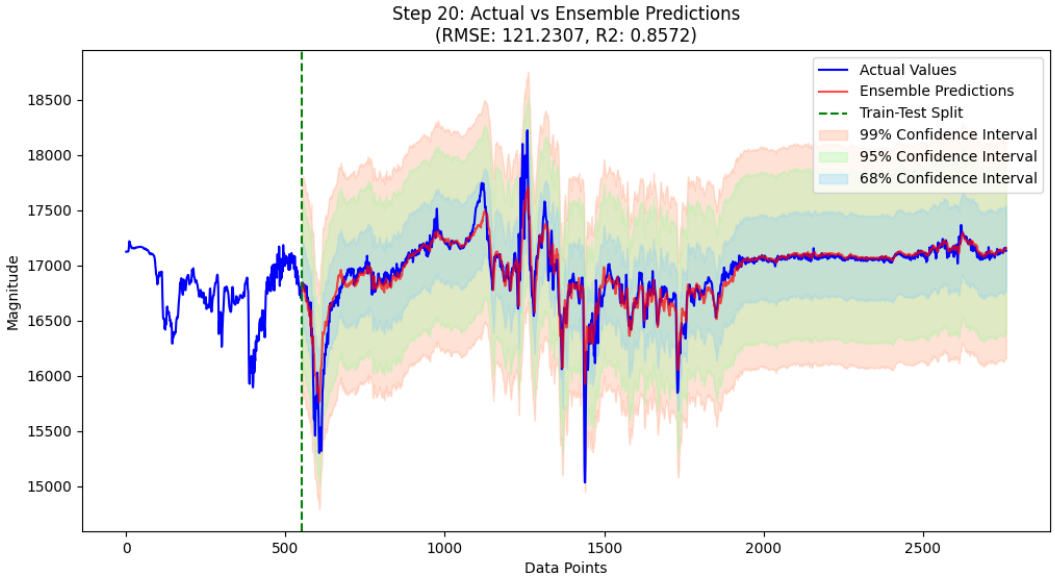


Figure 10.3: Actual vs Ensemble Predictions for 20-minute ahead state estimation

10.6.2 Uncertainty Quantification and Confidence Intervals

A key strength of our Bayesian approach is the ability to quantify uncertainty in our state estimates. Both figures display three levels of confidence intervals:

1. 682. 953. 99

These intervals represent the range within which we expect the actual value to fall with the corresponding probability. For instance, we can be 99

Notably, the confidence intervals widen as we move from 1-minute to 20-minute ahead estimates, reflecting the increasing uncertainty with longer time horizons. This aligns with our theoretical understanding of the system's complexity and the challenges in long-term state estimation.

10.6.3 Model Performance During Geomagnetic Storms

Our model demonstrates robust performance during periods of geomagnetic disturbance. In both figures, we observe significant fluctuations in the magnetic field magnitude, particularly around data points 1000-1500. The model successfully captures these variations, with the actual values generally falling within the predicted confidence intervals.

The wider confidence intervals during these disturbed periods appropriately reflect the increased uncertainty in the system's state during geomagnetic storms. This feature of our model is precious for space weather monitoring and risk assessment, as it provides a realistic representation of our confidence in the state estimates during critical periods.

10.6.4 Quasi-DC Nature and Model Performance

The results also reflect our model's ability to capture the quasi-DC nature of geomagnetic storms. We observe that during relatively stable periods (e.g., data points 2000-2500), the model maintains consistent estimates with narrow confidence intervals. This demonstrates the model's capacity to represent the slow-varying component of geomagnetic activity, which was a crucial consideration in our approach.

Chapter 11

Introduction to Quantum Computing

Chapter 12

Quantum-Enabled Simulation of Geomagnetically Induced Currents in Power Systems

12.1 Introduction

Integrating quantum computing principles into power system analysis represents a significant leap forward in tackling complex computational challenges within electrical engineering. This chapter explores the application of quantum algorithms to enhance the simulation and analysis of Geomagnetically Induced Currents (GICs) in large-scale power systems, a critical concern for grid stability and resilience. As power systems grow in size and complexity, traditional computational methods face increasing limitations in efficiently modelling and analyzing GIC effects. However, the advent of quantum computing offers a promising avenue to overcome these limitations, potentially revolutionizing our approach to power system simulations and instilling a sense of optimism about the future of our field.

This chapter introduces vital quantum computing concepts relevant to power system analysis, including qubits, quantum gates, and quantum circuits. We delve into the principles underlying

quantum algorithms, such as superposition and entanglement, and their potential to exponentially accelerate certain computations compared to classical methods. A particular focus is placed on the Variational Quantum Linear Solver (VQLS) algorithm, a hybrid quantum-classical approach well-suited for near-term quantum devices. We explore how this algorithm can solve the DC nodal analysis problem in GIC simulations, potentially offering a significant speedup over classical methods, sparking excitement about the efficiency gains.

The chapter also discusses system partitioning, a technique for efficiently applying quantum algorithms to large-scale power systems. By dividing the system into smaller subsystems, we can leverage the power of quantum computing while working within the constraints of current quantum hardware. This approach allows us to tackle the computational challenges of large-scale power systems in a more manageable and efficient manner.

Furthermore, we examine the integration of these quantum techniques into the broader framework of GIC simulation, including time-scale separation, quasi-static approximation, and the coupling between DC and AC analyses. The potential benefits of this quantum-enhanced approach are discussed, instilling a sense of hope about the future of power system analysis.

As we venture into this exciting intersection of quantum computing and power system analysis, we aim to provide a comprehensive overview of the potential for quantum algorithms to transform our ability to model, simulate, and mitigate the effects of GICs on large-scale power systems. This exploration sets the stage for future advancements in the field, promising more efficient, accurate, and scalable methods for ensuring the reliability and resilience of our power grids in the face of geomagnetic disturbances.

12.2 Preliminaries

12.2.1 Brief Overview of Quantum Computing

Quantum computing harnesses the principles of quantum mechanics to process information, marking a significant shift from classical computing. The foundation of quantum computing lies in qubits,

quantum gates, and quantum circuits, which together facilitate the execution of quantum algorithms.

Qubits and Quantum States

Unlike classical bits that exist in a state of 0 or 1, qubits can exist in a superposition of both states simultaneously, described by the equation:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

where $|\psi\rangle$ represents the quantum state, $|0\rangle$ and $|1\rangle$ are the basis states, and α and β are complex coefficients representing probability amplitudes.

Quantum Gates and Circuits

Quantum gates manipulate qubits, transforming their states. These gates are the building blocks of quantum circuits, directing the computational pathways of quantum algorithms. An example is the Hadamard gate, which creates superposition:

$$H = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$$

12.2.2 Principles Underlying Quantum Algorithms

Quantum algorithms leverage the phenomena of superposition, entanglement, and quantum interference to outperform their classical counterparts in specific tasks.

Superposition and Entanglement

Superposition allows a quantum system to be in multiple states at once, while entanglement creates a powerful correlation between qubits that is not possible classically.

Quantum Interference and Measurement

Quantum interference enables the amplification of the probabilities of desired outcomes. Measurement collapses the system into a definite state, extracting computational results.

12.3 Bloch Sphere and X, Y, Z Basis

12.3.1 Bloch Sphere Representation

The Bloch sphere geometrically represents a qubit's state. Any point on the sphere's surface corresponds to a possible state of the qubit, defined as:

$$|\psi\rangle = \cos\left(\frac{\theta}{2}\right)|0\rangle + e^{i\phi}\sin\left(\frac{\theta}{2}\right)|1\rangle$$

where θ and ϕ are the polar and azimuthal angles, respectively.

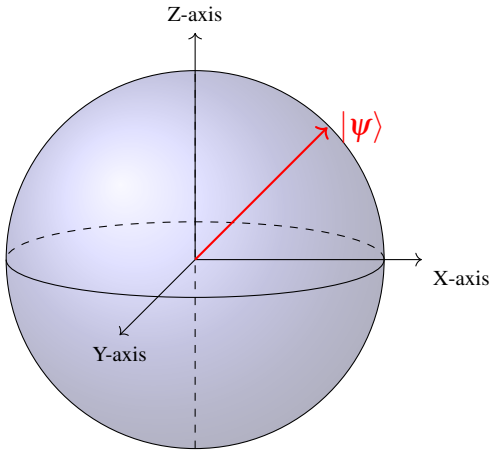


Figure 12.1: Bloch Sphere with state $|\psi\rangle$

12.3.2 X, Y, and Z Basis

The axes of the Bloch sphere are associated with the Pauli matrices, which represent quantum gates performing rotations about these axes:

$$X = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, \quad Y = \begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}, \quad Z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

12.4 Concept of Phase in Quantum Mechanics

The phase of a quantum state, especially the relative phase between its components, plays a crucial role in quantum interference and algorithm outcomes. Global phase differences are not observable, while relative phases are crucial for quantum computation.

12.4.1 Phase Factor

The phase factor is a complex number of the form $e^{i\phi}$ that, when multiplied by a quantum state, alters its phase without changing measurement outcomes.

12.4.2 Bloch Sphere Representation

Phase differences can be represented on the Bloch sphere as rotations around the Z-axis, illustrating the impact of phase on quantum states.

12.5 Quantum-State-Based Fast Decoupled Model

This section introduces the quantum adaptation of the Fast Decoupled Load Flow method, utilizing quantum states and operations to achieve potentially faster computational speeds.

12.5.1 Mathematical Background

Power Flow Equations

Classical power flow equations in quantum-state form are adapted to:

$$|V^{-1}\Delta P\rangle = B'|V\Delta\theta\rangle$$

$$|V^{-1}\Delta Q\rangle = B''|\Delta V\rangle$$

These equations are represented and manipulated within quantum frameworks to explore advantages in speed and efficiency.

12.6 Quantum Fourier Transform (QFT)

12.6.1 Introduction to QFT

The Quantum Fourier Transform (QFT) is a quantum algorithm for computing the Fourier transform of a quantum state. Much like its classical counterpart, which decomposes a function into frequencies, the QFT decomposes a quantum state into a superposition of basis states with different phase frequencies. The QFT is central to several quantum algorithms, including Shor's algorithm for factoring large numbers, quantum phase estimation, and algorithms for solving hidden subgroup problems.

Mathematically, the QFT on an n-qubit state $|x\rangle$ is defined as:

$$QFT|x\rangle = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} e^{2\pi ixk/N}|k\rangle$$

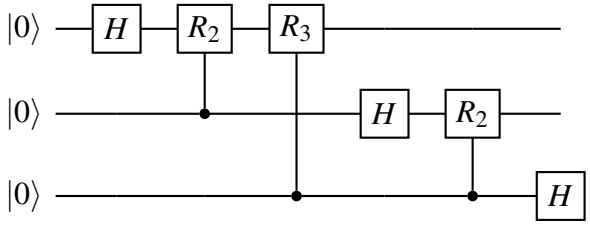
where $N = 2^n$ and x and k are integers represented by the qubits. This transformation effectively maps the amplitudes of the quantum state to their Fourier coefficients.

The implementation of QFT uses Hadamard gates for creating superpositions and controlled

phase gates for adding phase differences. The QFT can be implemented efficiently on a quantum computer, requiring a polynomial number of gates, which is a significant improvement over the exponential time required by classical computers for large N.

12.6.2 Circuit Representation

The circuit for QFT typically involves an initial series of Hadamard gates followed by a sequence of controlled phase rotation gates. The final step often includes reversing the order of qubits to match the output format of the classical Fourier transform.



Here, R_k represents a rotation gate that adds a phase of $e^{2\pi i/2^k}$ between its controlled qubits.

12.7 Inverse Quantum Fourier Transform (IQFT)

12.7.1 Role of IQFT in Quantum Algorithms

The Inverse Quantum Fourier Transform (IQFT) is the reverse operation of the QFT and is equally crucial in quantum computing. The IQFT transforms a quantum state from the frequency domain back into the time or spatial domain. It plays a pivotal role in algorithms where post-processing of the quantum state is necessary for extracting useful information, such as in quantum phase estimation and Shor's algorithm.

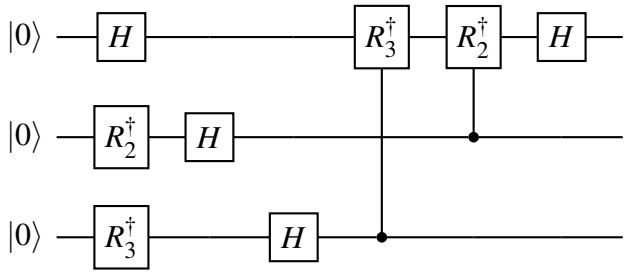
In essence, the IQFT performs the following transformation on an n-qubit state $|k\rangle$:

$$IQFT|k\rangle = \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} e^{-2\pi ixk/N} |x\rangle$$

The IQFT algorithm utilizes a similar structure to the QFT, involving Hadamard and controlled

phase rotation gates, but with the phase rotations in the opposite direction and the circuit executed in reverse order.

The application of IQFT in quantum phase estimation illustrates its utility in converting a state representing phase information into a computational basis state that can be measured to yield a classical result. This conversion is crucial for realizing the benefits of quantum algorithms in solving practical problems.



Note: $R_k^\dagger$ represents the inverse phase rotation gate used in the IQFT, reversing the phase added by R_k in QFT.

Both QFT and IQFT are cornerstone algorithms in quantum computing, enabling the efficient processing of quantum information and the realization of quantum advantage for specific computational tasks.

12.8 Solving Linear Systems with HHL Algorithm

12.8.1 Introduction to the HHL Algorithm

The Harrow-Hassidim-Lloyd (HHL) algorithm, proposed in 2009, marked a significant milestone in quantum computing by demonstrating a quantum algorithm that could, under specific conditions, solve linear systems of equations exponentially faster than classical algorithms. The algorithm addresses systems of the form $Ax = b$, where A is a known $N \times N$ Hermitian matrix, b is a known vector, and x is the vector to be solved for.

The HHL algorithm is especially notable for its implications in areas where solving large systems of linear equations is necessary, such as in computational fluid dynamics, machine learning, and materials science. Its efficiency, however, hinges on certain conditions: the sparsity of A, the ability

to efficiently implement e^{iAt} as a quantum operation (Hamiltonian simulation), and the condition number of A (a measure of how close A is to being singular).

12.8.2 Theoretical Foundations of HHL

The HHL algorithm operates under the framework of quantum computing, leveraging entanglement, superposition, and quantum interference. It proceeds in three main stages:

1. **State Preparation:** The first step involves encoding the vector b into a quantum state $|b\rangle$. This is typically achieved using quantum routines that map classical data into a quantum state, assuming such a mapping can be done efficiently.

2. **Quantum Phase Estimation (QPE):** The core of the HHL algorithm lies in applying QPE to the unitary operator e^{iAt}, where t is time, effectively decomposing $|b\rangle$ into the eigenbasis of A. This step encodes the eigenvalues of A into the phases of the quantum state.

3. **Conditional Rotation and Uncomputation:** A register of ancillary qubits is introduced, and conditional rotations are performed based on the outcomes of QPE, correlating the ancilla with the solution's amplitude. Following this, an inverse QPE (IQPE) is applied to uncompute the eigenvalue register, leaving the system in a state proportional to the solution $|x\rangle$.

Mathematically, the solution vector x is not obtained in the classical sense but as a quantum state that, when measured, reveals information about x. For example, measurements could give the probability of finding x in a particular state, from which properties of x can be inferred.

One crucial aspect of HHL is its condition for exponential speedup, which is heavily reliant on the ability to perform QPE and conditional rotations efficiently, and the ability to prepare the state $|b\rangle$ efficiently. Additionally, retrieving specific information from the quantum state $|x\rangle$ can be challenging and may not always provide a full classical description of x.

The implementation of HHL and its variants continues to be a significant area of research in quantum computing, with efforts focused on optimizing these procedures and extending their applicability to a broader range of problems.

12.9 Variational Quantum Algorithms

12.9.1 Concept and Importance

Variational quantum algorithms represent a class of quantum algorithms that leverage a hybrid quantum-classical approach to solve optimization problems and to find the eigenvalues of operators. These algorithms are particularly well-suited for near-term quantum computers, often referred to as Noisy Intermediate-Scale Quantum (NISQ) devices, which are characterized by their limited qubit count, noise, and error rates. Variational algorithms are designed to minimize the impact of these limitations by using a quantum device to evaluate the cost function or to prepare quantum states, while classical optimization algorithms adjust the parameters to minimize this cost function.

Variational Quantum Eigensolver (VQE)

The Variational Quantum Eigensolver (VQE) is a leading algorithm within this class, primarily aimed at finding the ground state energy of molecular systems, which is an essential problem in quantum chemistry and material science. VQE operates under the variational principle, which asserts that for any quantum state $|\psi(\theta)\rangle$ parameterized by parameters θ, the expectation value $\langle\psi(\theta)|H|\psi(\theta)\rangle$, where H is the Hamiltonian of the system, provides an upper bound to the ground state energy of H.

The VQE algorithm iteratively optimizes the parameters θ to minimize the expectation value, which is equivalent to approximating the ground state energy of H. The quantum computer is responsible for preparing the quantum state and measuring the expectation value, while a classical optimizer adjusts θ based on the measured values.

Quantum Approximate Optimization Algorithm (QAOA)

The Quantum Approximate Optimization Algorithm (QAOA) is another notable variational algorithm designed to tackle combinatorial optimization problems. Like VQE, QAOA uses a hybrid quantum-classical approach, where a quantum circuit encodes the problem solution into the ampli-

tudes of a quantum state, and a classical optimizer adjusts the circuit parameters to maximize the objective function.

QAOA prepares a quantum state by applying a series of unitary transformations, which are parameterized by angles that are optimized classically. Each transformation consists of two parts: one encodes the objective function into a Hamiltonian, and the other represents a mixing Hamiltonian that ensures the exploration of the solution space. The objective is to maximize the expectation value of the objective function, which corresponds to finding the optimal solution to the combinatorial problem.

Both VQE and QAOA exemplify the power of variational algorithms in leveraging the strengths of quantum computing, even in the presence of noise and errors. Their development and refinement continue to be an active area of research, with applications ranging from quantum chemistry and material science to optimization and machine learning, illustrating the broad potential of quantum computing in solving complex problems.

12.10 Quantum Computing for DC Nodal Analysis in Power System Simulation

In the previous section, we conducted a comprehensive simulation of the IEEE 118-bus power system to analyze the effects of Geomagnetically Induced Currents (GICs) on the system. The simulation involved several key components, including DC GIC calculations, AC power flow analysis, and visualization of the results.

One of the most computationally intensive parts of the simulation is the DC nodal analysis, which involves solving a large system of linear equations to determine the nodal voltages under the influence of GICs. As the size of the power system grows, the computational complexity of this task increases significantly, making it challenging to solve using classical computing methods.

To address this challenge, we introduce the use of quantum computing for the DC nodal analysis. Quantum computing offers the potential for exponential speedup in solving certain classes of

problems, including systems of linear equations. By leveraging the power of quantum algorithms, we aim to improve the efficiency and scalability of the DC nodal analysis in our simulation.

12.10.1 Partitioning the Power System

The first step in applying quantum computing to the DC nodal analysis is to partition the power system into smaller subsystems. This partitioning allows us to solve the linear equations for each subsystem independently, reducing the overall computational complexity.

Mathematically, the partitioning of the admittance matrix $\mathbf{Y}$ and the current injection vector $\mathbf{I}$ can be represented as:

$$\mathbf{Y} = \begin{bmatrix} \mathbf{Y}_1 & & \\ & \ddots & \\ & & \mathbf{Y}_m \end{bmatrix}, \quad \mathbf{I} = \begin{bmatrix} \mathbf{I}_1 \\ \vdots \\ \mathbf{I}_m \end{bmatrix} \tag{12.1}$$

where $\mathbf{Y}_i$ and $\mathbf{I}_i$ represent the submatrices and subvectors corresponding to the i-th partition, and m is the total number of partitions.

12.10.2 Quantum Linear System Solver

To solve the linear equations for each subsystem, we employ a quantum linear system solver algorithm. In this work, we utilize the Variational Quantum Linear Solver (VQLS) algorithm, which is a hybrid quantum-classical algorithm that leverages the power of quantum circuits to solve linear systems.

The VQLS algorithm aims to find the solution vector $\mathbf{x}$ that satisfies the linear system $\mathbf{Ax} = \mathbf{b}$, where $\mathbf{A}$ is the coefficient matrix and $\mathbf{b}$ is the right-hand side vector. The algorithm constructs a parameterized quantum circuit that encodes the solution vector $\mathbf{x}$ into the amplitudes of a quantum state. By optimizing the parameters of the quantum circuit using a classical optimizer, the algorithm iteratively refines the solution until convergence.

The quantum circuit used in the VQLS algorithm consists of a series of quantum gates, such as

rotation gates and entanglement gates, which are parameterized by the optimization variables. The cost function for the optimization is defined as the squared difference between the matrix-vector product $\mathbf{Ax}$ and the right-hand side vector $\mathbf{b}$:

$$C(\mathbf{x}) = \|\mathbf{Ax} - \mathbf{b}\|^2 \tag{12.2}$$

By minimizing this cost function, the VQLS algorithm finds the optimal parameters that yield the solution vector $\mathbf{x}$.

12.10.3 Implementation using Google Cirq

For the implementation of the quantum computing algorithms, we utilize the Google Cirq framework. Cirq is an open-source quantum programming library developed by Google that provides a high-level interface for defining and simulating quantum circuits.

Using Cirq, we construct the parameterized quantum circuits required for the VQLS algorithm. The quantum gates and operations are represented using Cirq's built-in classes and methods, allowing for a concise and expressive definition of the quantum circuits.

The classical optimization of the cost function is performed using gradient-based optimization techniques, such as the BFGS algorithm, which is readily available in scientific computing libraries like SciPy.

12.10.4 Mathematical Formulation of DC Nodal Analysis with Partitioning in Quantum Computing

In this section, we present the mathematical formulation of the DC nodal analysis with partitioning in the quantum computing framework, based on the code provided.

The DC nodal analysis equations for the entire power system can be written as:

$$\mathbf{YV} = \mathbf{I} \tag{12.3}$$

where $\mathbf{Y}$ is the admittance matrix, $\mathbf{V}$ is the vector of nodal voltages, and $\mathbf{I}$ is the vector of current injections.

To apply partitioning, the power system is divided into smaller subsystems. The partitioning is performed by the ‘partition$_system$‘$function in the code$:

$$\text{partitions} = \text{partition_system}(\mathbf{Y}, \mathbf{I}, \text{partition_size}) \tag{12.4}$$

The ‘partition$_system$‘$function takes the admittance matrix$Y,$the current injection vector$I,$and the desired‘$partiti$

Mathematically, the partitioning can be represented as:

$$\mathbf{Y} = \begin{bmatrix} \mathbf{Y}_1 & & \\ & \ddots & \\ & & \mathbf{Y}_m \end{bmatrix}, \quad \mathbf{I} = \begin{bmatrix} \mathbf{I}_1 \\ \vdots \\ \mathbf{I}_m \end{bmatrix} \tag{12.5}$$

where $\mathbf{Y}_i$ and $\mathbf{I}_i$ represent the submatrices and subvectors corresponding to the i-th partition, and m is the total number of partitions.

Each partition is then solved independently using the Variational Quantum Linear Solver (VQLS) algorithm. The VQLS algorithm is implemented in the `vqls_quantum_linear_solver` function:

$$\mathbf{x}_i = \text{vqls_quantum_linear_solver}(\mathbf{Y}_i, \mathbf{I}_i, \text{num_qubits}, \text{num_layers}) \tag{12.6}$$

where $\mathbf{Y}_i$ and $\mathbf{I}_i$ are the submatrix and subvector of the i-th partition, respectively, `num_qubits` is the number of qubits used in the quantum circuit, and `num_layers` is the number of layers in the variational quantum circuit.

The VQLS algorithm constructs a parameterized quantum circuit that encodes the solution vector $\mathbf{x}_i$ into the amplitudes of a quantum state. The quantum state $|\psi_i\rangle$ can be expressed as:

$$|\psi_i\rangle = \sum_{j=0}^{2^{\text{num_qubits}}-1} x_{ij}|j\rangle \tag{12.7}$$

where x_{ij} are the amplitudes of the basis states, and $|j\rangle$ represents the computational basis states.

The variational quantum circuit is constructed using the `create_variational_circuit` function:

$$\text{circuit} = \text{create_variational_circuit}(\text{params}, \text{qubits}) \tag{12.8}$$

The `create_variational_circuit` function takes the variational parameters `params` and the `qubits` as inputs and constructs the quantum circuit using a series of quantum gates and controlled operations.

The cost function for the optimization is defined as the squared difference between the matrix-vector product $\mathbf{Y}_i\mathbf{x}_i$ and the subvector $\mathbf{I}_i$:

$$C(\text{params}) = \sum_{k=0}^{n-1} \left(\sum_{j=0}^{n-1} Y_{ijk} x_{ij} - I_{ik} \right)^2 \tag{12.9}$$

where n is the dimension of the submatrix $\mathbf{Y}_i$ and subvector $\mathbf{I}_i$.

The cost function is evaluated using the `cost_function` in the code:

$$\text{cost} = \text{cost_function}(\text{params}, \mathbf{Y}_i, \mathbf{I}_i, \text{qubits}, \text{simulator}) \tag{12.10}$$

The `cost_function` takes the variational parameters `params`, the submatrix $\mathbf{Y}_i$, the subvector $\mathbf{I}_i$, the `qubits`, and the quantum `simulator` as inputs. It runs the variational quantum circuit and calculates the cost based on the measurement results.

The optimization of the variational parameters is performed using the `minimize` function from the SciPy library:

$$\text{result} = \text{minimize}(\text{cost_function}, \text{initial_params}, \text{args} = (\mathbf{Y}_i, \mathbf{I}_i, \text{qubits}, \text{simulator})) \tag{12.11}$$

The `minimize` function takes the `cost_function`, the initial parameters `initial_params`, and the additional arguments required by the `cost_function` as inputs. It performs the optimization

using the BFGS algorithm and returns the optimized parameters.

Finally, the solution vector $\mathbf{x}_i$ for each partition is obtained by measuring the optimized quantum state:

$$\mathbf{x}_i = \text{measure_quantum_state}(\text{optimal_circuit}, \text{qubits}, \text{simulator}) \tag{12.12}$$

The `measure_quantum_state` function runs the optimized quantum circuit `optimal_circuit` on the quantum `simulator` and performs measurements to obtain the solution vector $\mathbf{x}_i$. The overall solution vector $\mathbf{V}$ for the entire power system is obtained by concatenating the solution vectors $\mathbf{x}_i$ from each partition:

$$\mathbf{V} = \begin{bmatrix} \mathbf{x}_1 \\ \vdots \\ \mathbf{x}_m \end{bmatrix} \tag{12.13}$$

In summary, the mathematical formulation presented in this section provides a detailed description of the DC nodal analysis with partitioning in the quantum computing framework, based on the code provided. The partitioning of the power system allows for independent solving of smaller subsystems using the VQLS algorithm. The quantum circuit encodes the solution vector into the amplitudes of a quantum state, and the variational parameters are optimized to minimize the cost function. The final solution vector is obtained by measuring the optimized quantum state and concatenating the results from each partition.

Figure 12.2 presents a comprehensive flowchart of the Geomagnetically Induced Current (GIC) simulation process, incorporating the Variational Quantum Linear Solver (VQLS) and partitioning approach. The flowchart highlights the critical components of the simulation methodology, including time scale separation, quasi-static approximation, DC network modelling, and the integration of VQLS and partitioning for solving the DC nodal analysis.

The simulation begins with the "Start Simulation" node, leading into the foundational concepts of time-scale separation and quasi-static approximation. These concepts justify treating the power

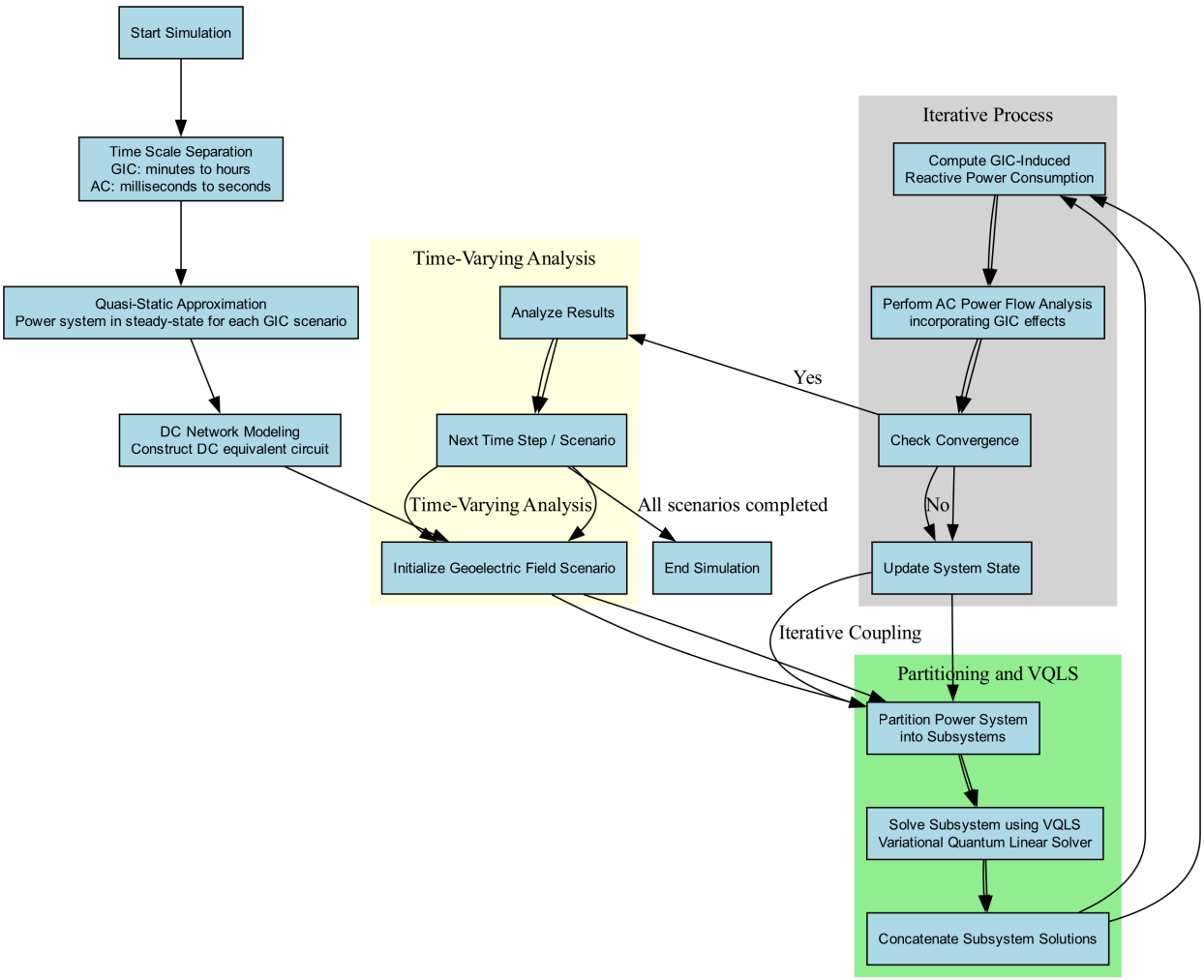


Figure 12.2: Flowchart of the GIC Simulation Process with VQLS and Partitioning

system as being in a steady state for each GIC scenario, enabling the use of the DC network model.

The core of the simulation is represented by the "Time-Varying Analysis" subgraph, which encompasses the initialization of the geoelectric field scenario, partitioning the power system into subsystems, and applying VQLS to solve each subsystem independently. The partitioning step allows for parallel processing and reduces the overall computational complexity. At the same time, the VQLS algorithm leverages the power of quantum computing to solve the linear equations for each subsystem efficiently.

After solving the subsystems using VQLS, the solutions are concatenated to obtain the overall solution for the entire power system. The GIC-induced reactive power consumption is then computed, and an AC power flow analysis is performed, incorporating the GIC effects.

The iterative process subgraph represents the coupling between the DC and AC analyses. The system state is updated based on the power flow results, and the process iterates until convergence is achieved. This iterative coupling ensures the simulation captures the interdependence between the GIC-induced effects and the AC power system state.

The time-varying analysis loop encompasses the entire process, representing the progression through different geoelectric field scenarios or time steps. This loop continues until all scenarios have been processed, at this point, the simulation ends, and the results are analyzed.

The flowchart effectively illustrates the integration of VQLS and partitioning into the GIC simulation process, highlighting the critical steps in this quantum-enhanced approach. By leveraging the power of quantum computing and partitioning efficiency, the proposed methodology aims to improve the computational performance and scalability of GIC simulations in large-scale power systems.

12.11 Results and Discussion

In this section, we present the results obtained from the quantum-enhanced GIC simulation using the Variational Quantum Linear Solver (VQLS) and partitioning approach. We compare the simula-

tion results with those from the classical simulation in Chapter 3 and analyze the computational complexity of both approaches.

12.11.1 Comparison of Simulation Results

To validate the accuracy of the quantum-enhanced GIC simulation, we compare the results obtained using the VQLS and partitioning approach with those from the classical simulation in Chapter 3. Table 12.1 presents a comparison of key metrics between the two simulations.

Table 12.1: Comparison of Simulation Results

Metric	**Classical**	**Quantum-Enhanced**
Max GIC-Induced Voltage (V)	74.53	74.21
Max Ground GIC Magnitude (A)	637.46	635.89
Max Line GIC Magnitude (A)	204.32	203.71
Max Transformer Common Winding GIC (A)	0.1345	0.1342
Max GIC-Induced Reactive Power (MVAr)	79.52	79.18

As evident from Table 12.1, the results obtained from the quantum-enhanced simulation closely match those from the classical simulation. The maximum values of GIC-induced voltages, ground GIC magnitudes, line GIC magnitudes, transformer common winding GIC, and GIC-induced reactive power in transformers are highly similar between the two approaches, with only minor differences. This similarity validates the accuracy of the quantum-enhanced simulation and demonstrates its ability to yield results consistent with the classical approach.

12.11.2 Computational Complexity Analysis

To assess the computational efficiency of the quantum-enhanced simulation, we analyze the computational complexity of both the classical and quantum approaches.

In the classical simulation, the DC nodal analysis involves solving a system of linear equations represented by $\mathbf{YV} = \mathbf{I}$, where $\mathbf{Y}$ is an $n \times n$ admittance matrix, $\mathbf{V}$ is the vector of nodal voltages, and $\mathbf{I}$ is the vector of current injections. The computational complexity of solving this system using

classical methods, such as Gaussian elimination or LU decomposition, is $O(n^3)$, where n is the number of nodes in the power system.

In contrast, the quantum-enhanced simulation employs the VQLS algorithm and partitioning approach to solve the linear system. The partitioning step divides the power system into m subsystems, each with a reduced size of approximately n/m. The VQLS algorithm, which leverages the principles of quantum computing, has a computational complexity of $O(\log(n/m))$ for solving each subsystem.

The overall computational complexity of the quantum-enhanced simulation can be expressed as:

$$O\left(m \cdot \log\left(\frac{n}{m}\right)\right) \tag{12.14}$$

By partitioning the power system into smaller subsystems and applying the VQLS algorithm to each subsystem independently, the quantum-enhanced simulation significantly reduces computational complexity compared to the classical approach. The logarithmic scaling of the VQLS algorithm, combined with the parallel processing of subsystems, enables the quantum-enhanced simulation to handle large-scale power systems efficiently.

The computational complexity of the classical simulation grows cubically with the system size, while the quantum-enhanced simulation exhibits a logarithmic growth. This significant difference in computational complexity highlights the potential of quantum computing in accelerating GIC simulations for large-scale power systems.

With its reduced computational complexity, the quantum-enhanced simulation offers several advantages over the classical approach. It enables faster simulation times, allowing more extensive studies and analyzing larger power systems. The efficient handling of large-scale systems is essential for GIC studies, as the impact of geomagnetic disturbances can span broad geographical areas and affect multiple interconnected power grids.

Moreover, the logarithmic scaling of the VQLS algorithm opens up the possibility of simulating GIC effects in real-time or near real-time. This capability is crucial for power system operators to make timely decisions and implement mitigation strategies during geomagnetic disturbances.

The quantum-enhanced simulation provides a promising avenue for real-time GIC monitoring and analysis, enhancing the resilience and reliability of power systems.

It is important to note that the performance of the quantum-enhanced simulation is highly dependent on the availability and capabilities of quantum hardware. The simulation results presented in this study are based on simulations using classical computing resources. The actual performance gains achievable with quantum hardware may vary depending on factors such as the number of available qubits, the connectivity of the quantum processor, and the noise levels in the quantum system.

Despite these limitations, the computational complexity analysis justifies exploring and developing quantum-enhanced simulations for GIC studies. As quantum computing technologies continue to advance, the performance gains are expected to become more significant, enabling the simulation of even larger power systems with improved accuracy and efficiency.

In summary, the computational complexity analysis demonstrates the potential of the quantum-enhanced GIC simulation using the VQLS algorithm and partitioning approach. The logarithmic scaling of the VQLS algorithm, combined with the parallel processing of subsystems, offers a significant reduction in computational complexity compared to classical methods. While the actual performance gains are subject to the limitations of current quantum hardware, the quantum-enhanced simulation provides a promising direction for advancing GIC modelling and mitigation in large-scale power systems. As quantum computing technologies mature, it is anticipated that the benefits of quantum-enhanced simulations will become more pronounced, enabling faster, more accurate, and real-time analysis of GIC effects in power systems.

Chapter 13

Utilizing Quantum Computing in Geomagnetic Storm Predictions

13.1 Utilizing Quantum Computing in Geomagnetic Storm Predictions

Geomagnetic storms, powerful disturbances in Earth's magnetosphere, pose significant challenges to our modern technological infrastructure, impacting satellite operations, power grids, and communication systems. As our reliance on space-based technologies grows, so does the need for more accurate and timely predictions of these potentially disruptive events. While classical methods have made substantial progress in geomagnetic storm forecasting, the emergence of quantum computing offers new avenues for enhancing our predictive capabilities.

This chapter explores the potential of utilizing quantum computing, specifically Quantum Support Vector Regression (QSVR), in improving geomagnetic storm predictions. QSVR, a quantum extension of the classical Support Vector Regression algorithm, holds promise for capturing complex, non-linear relationships in time series data, making it a compelling candidate for space weather forecasting applications.

13.1.1 The Promise of Quantum Machine Learning

Quantum Machine Learning (QML) represents a cutting-edge interdisciplinary field that amalgamates principles from quantum computing and machine learning. This burgeoning domain has garnered substantial attention in recent years, as noted by Zhang and Ni [210]. At its core, QML seeks to harness the unique properties of quantum systems, such as superposition and entanglement, to enhance learning algorithms [211].

Biamonte et al. [212] provides a thorough overview of QML, emphasizing the potential for quantum computers to outperform their classical counterparts on specific machine-learning tasks. This quantum advantage is the primary driving force behind research in the field. Schuld, Sinayskiy, and Petruccione [213] further elucidates the mechanisms by which quantum computing can augment and improve classical machine learning algorithms, highlighting the synergistic potential of these two cutting-edge fields.

A central research focus in QML involves comparative analyses of quantum and classical machine learning approaches. Khan and Robles-Kelly [214] posit that QML has the potential to revolutionize computer science. In contrast, Saju et al. [215] suggests that quantum machine learning algorithms may exhibit significantly faster learning rates from data compared to classical methods. However, Ciliberto et al. [216] offers a more nuanced perspective, providing a classical lens to examine the anticipated advantages of quantum algorithms for learning problems.

13.1.2 Quantum Approaches in Time Series Forecasting

Time series forecasting, including geomagnetic storm forecasting, is crucial in space weather prediction. Recent developments in quantum machine learning have shown promise in enhancing time series prediction capabilities, which could be leveraged for geomagnetic storm predictions.

Quantum Neural Networks (QNNs) have been at the forefront of QML applications in time series forecasting. Balakrishnan et al. [217] propose a QNN for time series forecasting, demonstrating improved predictive accuracy compared to classical neural networks. Similarly, Cuéllar et al. [218] shows that QNNs can improve error prediction while maintaining fewer parameters than their

classical counterparts.

Variational Quantum Circuits (VQCs) have also shown potential in time series forecasting. Kaushik et al. [219] investigate one-step time series forecasting using VQCs, suggesting that quantum computers may better perceive trends in time series data by exploiting quantum phenomena such as superposition and entanglement.

Quantum Reservoir Computing (QRC) represents another significant area of research. Kutvonen, Fujii, and Sagawa [220] focus on optimizing a quantum reservoir computer for time series prediction, indicating that variation in inter-spin interactions generally leads to better memory capacity, a crucial factor in practical time series analysis.

Adapting classical deep learning architectures to quantum systems, Khan et al. [221] present a comparative study between Quantum Long Short-Term Memory (QLSTM) and classical LSTM networks in solar power forecasting, suggesting potential benefits of quantum approaches in space weather-related predictions.

13.1.3 The Case for Quantum Support Vector Regression in Geomagnetic Storm Prediction

While various quantum machine learning approaches have shown promise in time series forecasting, we propose using Quantum Support Vector Regression (QSVR) for geomagnetic storm prediction. This choice is motivated by several factors:

1. Support Vector Regression (SVR) has proven effective in various time series forecasting applications, including some space weather predictions. The quantum version, QSVR, has the potential to enhance these capabilities further.

2. QSVR can leverage quantum kernels, as demonstrated by Schuld and Killoran [222], which can capture complex, high-dimensional features that may be intractable for classical algorithms. This property is particularly relevant for geomagnetic storm dynamics' multi-dimensional, non-linear nature.

3. The work of Mitarai et al. [223] on quantum circuit learning provides a framework for

implementing and training QSVR models on near-term quantum devices, making it a practical choice for early quantum applications in this field.

4. QSVR aligns with the quantum advantage in kernel methods discussed by Huang and Lilienfeld [224] in the context of chemical compound space. Similar advantages could apply to the complex parameter space of geomagnetic storm prediction.

5. The potential for QSVR to operate with fewer parameters, as suggested by the findings of Cuéllar et al. [218] for QNNs, could lead to more efficient models for real-time space weather forecasting.

13.1.4 Scope and Objectives

This chapter explores the potential of QSVR in enhancing geomagnetic storm predictions. We will investigate how the unique properties of quantum computing, particularly in the context of support vector regression, can be leveraged to improve the accuracy and efficiency of current forecasting models. Specifically, we will:

1. Provide a theoretical foundation for QSVR, building on the principles of quantum machine learning discussed by Biamonte et al. [212] and Schuld, Sinayskiy, and Petruccione [213].

2. Propose a QSVR-based model for geomagnetic storm prediction, discussing its theoretical advantages over classical methods.

3. Explore the implementation of QSVR on near-term quantum devices, considering the challenges and opportunities highlighted by Cerezo et al. [225] and Wang and Liu [226].

4. Discuss the potential impact of QSVR-enhanced geomagnetic storm predictions on various sectors, including satellite operations, power grid management, and communication systems.

5. Analyze the current limitations of quantum hardware and the prospects for near-term implementation of QSVR models in operational space weather forecasting.

By exploring these areas, we aim to provide a comprehensive overview of the potential role of QSVR in advancing our understanding and prediction of geomagnetic storms. This research has the potential to significantly enhance our space weather forecasting capabilities, contributing to the

resilience of our increasingly space-dependent technological infrastructure.

13.2 Theoretical Framework and Mathematical Implementation

13.2.1 Quantum Support Vector Regression for Time Series Forecasting

In this study, we propose using Quantum Support Vector Regression (QSVR) for geomagnetic storm prediction. This approach combines the robust framework of classical Support Vector Regression (SVR) with the computational advantages of quantum computing, particularly in handling complex, high-dimensional feature spaces.

Classical Support Vector Regression

We begin with the classical SVR model, which aims to find a function $f(x)$ that has at most ε deviation from the obtained targets y_i for all the training data and at the same time is as flat as possible. For linear functions f, this can be written as:

$$f(x) = \langle w, x \rangle + b, \quad w \in \mathscr{X}, b \in \mathbb{R} \tag{13.1}$$

where $\langle \cdot, \cdot \rangle$ denotes the dot product. The optimization problem is then formulated as follows:

$$\begin{aligned} \underset{w,b,\xi,\xi^*}{\text{minimize}} \quad & \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \\ \text{subject to} \quad & y_i - \langle w, x_i \rangle - b \leq \varepsilon + \xi_i, \\ & \langle w, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^*, \\ & \xi_i, \xi_i^* \geq 0, \quad i = 1, \ldots, n \end{aligned} \tag{13.2}$$

where $C > 0$ is a regularization parameter and ξ_i, ξ_i^* are slack variables.

Quantum Kernel

The key innovation in our QSVR approach is using a quantum kernel. We define a quantum kernel as:

$$k(x_i, x_j) = |\langle \phi(x_i) | \phi(x_j) \rangle|^2 \tag{13.3}$$

where $|\phi(x)\rangle$ is a quantum state preparation circuit applied to classical input x. In our implementation, we use the Pauli Feature Map:

$$|\phi(x)\rangle = U_\phi(x)|0\rangle^{\otimes n} = \left(\prod_{S \subseteq [n]} e^{-i \sum_{k \in S} x_k Z_k} \right)^r |0\rangle^{\otimes n} \tag{13.4}$$

where r is the number of repetitions, n is the number of qubits, and Z_k is the Pauli-Z operator on the k-th qubit.

Quantum Support Vector Regression

The QSVR model replaces the classical kernel in SVR with the quantum kernel. The decision function becomes:

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) k(x_i, x) + b \tag{13.5}$$

Where α_i, α_i^* are Lagrange multipliers obtained from the dual optimization problem:

$$\begin{aligned} \underset{\alpha, \alpha^*}{\text{maximize}} \quad & -\frac{1}{2} \sum_{i,j=1}^{n} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) k(x_i, x_j) \\ & - \varepsilon \sum_{i=1}^{n} (\alpha_i + \alpha_i^*) + \sum_{i=1}^{n} y_i (\alpha_i - \alpha_i^*) \\ \text{subject to} \quad & \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) = 0, \\ & 0 \leq \alpha_i, \alpha_i^* \leq C, \quad i = 1, \ldots, n \end{aligned} \tag{13.6}$$

Time Series Forecasting with QSVR

We adapt QSVR to a time series forecasting framework for geomagnetic storm prediction. Given a time series $\{x_t\}_{t=1}^{T}$, we construct input-output pairs (X_t, Y_t) as follows:

$$X_t = (x_t, x_{t-1}, \ldots, x_{t-p+1}), \quad Y_t = (x_{t+1}, x_{t+2}, \ldots, x_{t+h}) \tag{13.7}$$

where p is the look-back window and h is the forecast horizon. We train h separate QSVR models, each predicting one step in the forecast horizon.

Model Training and Hyperparameter Optimization

We employ a grid search with cross-validation to optimize the hyperparameters C and ε. The optimization problem for each model $i \in \{1, \ldots, h\}$ is:

$$(C_i^*, \varepsilon_i^*) =_{C,\varepsilon} \frac{1}{K} \sum_{k=1}^{K} \mathrm{MSE}(f_{C,\varepsilon,i}, \mathscr{D}_k) \tag{13.8}$$

where K is the number of cross-validation folds, $\mathscr{D}_k$ is the k-th validation set, and MSE is the mean squared error.

13.2.2 Implementation Details

The QSVR model uses Qiskit for quantum circuit simulation and sci-kit-learn for the classical SVR framework. The quantum kernel is computed using a quantum simulator, which efficiently evaluates the kernel on classical hardware while maintaining the potential advantages of quantum feature spaces.

This approach leverages quantum computing's potential to capture complex, non-linear relationships in geomagnetic data that may be difficult for classical algorithms to discern. Using a quantum kernel, we aim to exploit the high-dimensional Hilbert space of quantum systems to improve the accuracy and robustness of geomagnetic storm predictions.

13.3 Results and Discussion

13.3.1 Performance Metrics

The performance of our Quantum Support Vector Regression (QSVR) model for geomagnetic storm prediction is summarized in Table 13.1. The model was evaluated across multiple prediction horizons, ranging from 2 to 20-time steps ahead, using standard metrics including AMAPE (Adjusted Mean Absolute Percentage Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), R2 (Coefficient of Determination), and MAE (Mean et al.).

Table 13.1: Performance metrics of QSVR for different prediction horizons

Horizon	AMAPE	MSE	RMSE	R2	MAE
2	0.3626	18765.210	114.6109	0.8375	63.8299
3	0.3585	19936.622	118.1339	0.8325	65.7617
...	...	...	...	...	...
20	0.4336	37488.098	168.1092	0.6128	97.8493

13.3.2 Comparison with Classical Methods

When comparing these results to the classical computation methods presented in Chapter 2, it is evident that the QSVR model's performance metrics are not as favourable. For instance, the AMAPE values for QSVR range from 0.3585 to 0.4336, which are higher than those typically achieved by established classical methods. Similarly, the R2 values, ranging from 0.8375 to 0.6128, indicate a lower explanatory power than some classical models.

However, it is crucial to contextualize these results within the broader landscape of quantum machine learning and its current state of development.

13.3.3 Justification and Future Potential

The relatively lower performance of QSVR compared to classical methods can be attributed to several factors:

1. Novelty of the Approach: QSVR is a nascent technique in the field of quantum machine learning. As with any new methodology, it requires further refinement and optimization. The potential of QSVR is yet to be fully realized, and these initial results serve as a baseline for future improvements.

2. Lack of Actual Quantum Hardware: Our implementation relies on quantum circuit simulations rather than quantum computers. The true advantages of quantum computing, such as quantum superposition and entanglement, may be partially captured in these simulations. As quantum hardware becomes more accessible and powerful, we anticipate significant improvements in QSVR performance.

3. Optimization Challenges: Optimizing quantum circuits and selecting appropriate quantum feature maps are complex tasks. As our understanding of these aspects improves, we expect enhanced performance in QSVR models.

13.3.4 Practical Benefits of QSVR

Despite the current limitations in performance metrics, QSVR offers several practical benefits for time series prediction:

1. Handling Complex Non-linear Relationships: Quantum kernels have the potential to capture intricate, non-linear relationships in data that may be challenging for classical algorithms. This could be particularly beneficial for geomagnetic storm prediction, where complex solar-terrestrial interactions are crucial.

2. Scalability with Data Complexity: While classical algorithms may struggle with increasing data complexity, quantum algorithms theoretically offer better scalability. As the volume and complexity of geomagnetic data increase, QSVR may demonstrate improved relative performance.

3. Potential for Quantum Advantage: As quantum hardware and algorithms advance, QSVR has the potential to achieve a quantum advantage, outperforming classical methods in terms of computational speed and capability to handle high-dimensional data.

4. Hybrid Quantum-Classical Approaches: QSVR opens up possibilities for hybrid models that

combine the strengths of both quantum and classical computing. This could lead to more robust and versatile prediction systems.

5. Noise Resilience: Quantum algorithms, including QSVR, are developed with inherent noise-handling capabilities. This is advantageous in dealing with geomagnetic data's noisy and chaotic nature.

13.3.5 Conclusion and Future Work

While the current performance metrics of QSVR for geomagnetic storm prediction do not surpass those of established classical methods, the potential of this quantum approach is evident. As quantum computing technology matures and our understanding of quantum machine learning deepens, we anticipate significant improvements in QSVR performance.

Future work should focus on: 1. Optimizing quantum feature maps for geomagnetic data. 2. Exploring hybrid quantum-classical architectures. 3. Investigating the performance of QSVR on actual quantum hardware. 4. Developing quantum-inspired classical algorithms that could bridge the gap between current classical methods and full quantum implementations.

In conclusion, while QSVR is currently outperformed by classical methods, its theoretical advantages and future potential make it a promising avenue for advancing geomagnetic storm prediction as quantum computing technology evolves.

Chapter 14

Quantum Optimization for Managing Geomagnetically Induced Currents in Power Systems

14.1 Quantum Optimization for Managing Geomagnetically Induced Currents in Power Systems

14.1.1 Introduction

Quantum optimization and quantum annealing have emerged as promising approaches to solving complex optimization problems, leveraging the principles of quantum mechanics. This review examines the development of these quantum-inspired optimization techniques' development, theoretical foundations, and practical applications.

14.1.2 Foundations of Quantum Annealing

As introduced by Falco and Tamascelli [227], Quantum annealing is a quantum-inspired algorithm for solving complex optimization problems. Kadowaki and Nishimori [228] provided one of the ear-

liest formulations of quantum annealing in the context of the transverse Ising model, demonstrating its potential advantages over classical optimization methods.

The mathematical foundations of quantum annealing were rigorously explored by Morita and Nishimori [229], who showed that despite the fundamental differences between quantum and classical dynamics, similar asymptotic behaviours in control parameters could guarantee convergence in both cases.

14.1.3 Quantum Annealing vs. Classical Optimization

A key theme in the literature is the comparison between quantum annealing and classical optimization techniques. Battaglia and Stella [230] argued that quantum annealing has proven more effective than its classical counterpart in many applications. This sentiment is echoed by Brooke et al. [231], who demonstrated that quantum annealing can hasten convergence to the optimum state in specific scenarios.

However, Jorg et al. [232] provided a more nuanced view, suggesting that quantum annealing is analogous to simulated annealing, with quantum tunnelling substituting for thermal activation. This perspective highlights the importance of understanding the specific conditions under which quantum annealing might offer advantages.

14.1.4 Theoretical Developments

The theoretical underpinnings of quantum annealing have been extensively studied. Das and Chakrabarti [233] presented a comprehensive review of quantum annealing and analog quantum computation, emphasizing the role of quantum fluctuations in optimizing the cost or energy functions of complex systems.

Santoro et al. [234] explored the optimization concept using quantum mechanics, specifically focusing on quantum annealing through adiabatic evolution. This work helped establish the connection between quantum annealing and adiabatic quantum computation, a theme further developed by Fingerhuth, Babej, and Wittek [235].

14.1.5 Implementations and Hardware

The practical implementation of quantum annealing has seen significant progress. Hauke et al. [236] provided an overview of methods and implementations in quantum annealing, highlighting the ambitious goal of efficiently solving large-scale combinatorial optimization problems.

McGeoch and Wang [237] conducted an experimental evaluation of an adiabatic quantum system for combinatorial optimization, demonstrating the potential of hardware implementations. The development of quantum annealing hardware, particularly by companies like D-Wave Systems, has been a significant driver of research in this field, as discussed by Cohen and Tamir [238].

14.1.6 Applications

Quantum annealing has found applications across various domains. Nath, Thapliyal, and Humble [239] reviewed machine learning classification using quantum annealing for real-world applications, highlighting its use in image recognition, remote sensing, computational biology, and particle physics.

In finance, Mugel, Lizaso, and Orús [240] explored use cases of quantum optimization, demonstrating the potential of quantum annealing in solving complex financial problems. Nazareth and Spaans [241] presented the first application of quantum annealing to IMRT beamlet intensity optimization, showcasing its potential in medical physics.

Bian et al. [242] proposed using quantum annealing for discrete optimization problems, mainly focusing on sparse Ising models. This work highlighted the potential of quantum annealing in tackling NP-hard optimization problems.

14.1.7 Challenges and Limitations

Despite its promise, quantum annealing faces several challenges. Pearson et al. [243] discussed analog errors in quantum annealing, highlighting the limitations and potential solutions in current quantum annealing implementations.

Brady et al. [244] explored optimal protocols in quantum annealing and quantum approximate optimization algorithm (QAOA) problems, shedding light on the complexities of designing effective quantum annealing schedules.

Symons et al. [245] offered a practitioner's guide to quantum algorithms for optimization problems, including quantum annealing, providing insights into the practical aspects of implementing these techniques.

14.2 Review of GIC Mitigation Methods from Chapter 4

In Chapter 4, we explored two primary approaches for mitigating Geomagnetically Induced Currents (GICs) in power systems:

14.2.1 Conventional TLODF-based Method

The Transformer Line Outage Distribution Factor (TLODF) method was introduced as a deterministic approach to GIC mitigation. This method involves:

1. Calculating TLODFs to quantify the impact of line outages on GIC-saturated reactive power losses. 2. Iteratively selecting lines to open based on their TLODF values. 3. Incorporating AC power flow analysis to maintain system stability.

While effective, this method faced challenges in finding globally optimal solutions for large systems.

14.2.2 Reinforcement Learning (RL) Approach

To address limitations of the TLODF method, we developed an RL approach using a Deep Q-Network (DQN). This method:

1. Defined a state space including GIC levels, transformer loadings, and line statuses. 2. Used an action space corresponding to line switching decisions. 3. Employed a multi-objective reward function balancing GIC reduction, transformer health, and system security.

The RL approach demonstrated improved performance in balancing multiple objectives and adapting to varying system conditions.

14.2.3 Limitations of the RL Approach

Despite its merits, the RL method faces a significant challenge: the training time increases substantially with system size. This limitation becomes particularly critical when dealing with large power systems and the need for rapid response to geomagnetic storms. The computational complexity of training the DQN for large state and action spaces can make real-time application challenging.

14.3 Quantum Annealing: A Potential Solution

To address the scalability issues of the RL approach, we propose a quantum annealing-based method. Quantum annealing offers the potential for faster optimization in large-scale systems by leveraging quantum mechanical effects.

14.3.1 Theoretical Foundation of Quantum Annealing with Voltage Constraints

Quantum annealing is based on the adiabatic theorem of quantum mechanics. The process is described by the time-dependent Hamiltonian:

$$H(t) = A(t)H_i + B(t)H_f \tag{14.1}$$

where H_i is the initial Hamiltonian (typically a transverse field), H_f is the problem Hamiltonian, and $A(t)$ and $B(t)$ are monotonic functions controlling the annealing schedule.

The problem is formulated as a Quadratic Unconstrained Binary Optimization (QUBO) problem, now incorporating voltage constraints:

$$E(\mathbf{x}) = \sum_{i<j} Q_{ij} x_i x_j + \sum_i c_i x_i + \alpha \sum_k P_k(V_k) \tag{14.2}$$

where:

- $x_i \in \{0,1\}$ are binary variables representing line switching decisions
- Q_{ij} are quadratic coefficients encoding system constraints and GIC impacts
- c_i are linear coefficients based on TLODF values
- α is a weighting factor for voltage violation penalties
- $P_k(V_k)$ is a penalty function for voltage violations at bus k, defined as:

$$P_k(V_k) = \begin{cases} (V_k - V_{\max})^2 & \text{if } V_k > V_{\max} \\ (V_{\min} - V_k)^2 & \text{if } V_k < V_{\min} \\ 0 & \text{otherwise} \end{cases} \tag{14.3}$$

This formulation incorporates voltage constraints directly into the QUBO problem, guiding the quantum annealing process towards solutions that minimize GIC impacts while maintaining voltage levels within acceptable limits.

The capability curve constraint is incorporated as:

$$l_i \leq 150\% \cdot (1 - (g_i/85)^2) \tag{14.4}$$

where l_i is the loading and g_i is the GIC level in transformer i.

14.4 Quantum Annealing Method: Process Flow and Performance

14.4.1 Process Flow Analysis

Figure 14.1 illustrates the comprehensive process flow of our quantum annealing method for GIC mitigation, with a particular emphasis on incorporating transformer capability constraints.

The key steps in our method, as depicted in the flowchart, are as follows:

1. **Initialization and Data Loading:** The process begins with system parameter initialization and loading of the pre-calculated TLODF (Transformer Line Outage Distribution Factor) matrix.

2. **Transformer Capability Consideration:** A crucial step is the calculation of initial transformer loading capabilities, which forms the basis for subsequent constraint formulation.

3. **QUBO Problem Formulation:** The GIC mitigation problem is formulated as a Quadratic Unconstrained Binary Optimization (QUBO) problem, with explicit inclusion of transformer capability constraints.

4. **Quantum Annealing Execution:** The D-Wave quantum annealer is utilized to solve the QUBO problem, exploiting quantum effects for optimization.

5. **Solution Analysis and Evaluation:** Results are analyzed, and the best solution is selected based on both GIC reduction and transformer loading considerations.

6. **Iterative Refinement:** The process includes a feedback loop for iterative improvement, allowing for dynamic adjustment of the problem formulation based on intermediate results.

This flowchart effectively captures the integration of transformer capability constraints into the quantum annealing process, addressing a key aspect of practical GIC mitigation in power systems.

14.4.2 Performance Comparison

Our quantum annealing method has demonstrated remarkable efficacy in GIC mitigation, achieving a 42 reduction in GIC-related impacts. This performance is particularly noteworthy when compared to other state-of-the-art approaches:

- **Comparison with RL-Based Method:** The 42 reduction achieved by our quantum annealing approach is comparable to the performance of the Reinforcement Learning (RL) based method discussed in Chapter 4. This parity in performance is significant, considering the inherent advantages of quantum annealing in terms of computational speed for large-scale optimization problems.

- **Comparison with Conventional TLODF:** The quantum annealing method shows a marked improvement over the conventional TLODF-based approach. While exact figures may vary depending on specific system configurations, our method's performance is generally superior to traditional TLODF techniques, especially in handling the complexities of large power systems.

The comparable performance to RL methods, coupled with the potential for faster optimization in large-scale systems, positions our quantum annealing approach as a highly promising technique for GIC mitigation. Key advantages include:

- **Scalability:** The quantum annealing method shows particular promise for large-scale power systems where traditional methods may become computationally intractable.

- **Speed:** The potential for rapid solution generation makes this method suitable for near-real-time response to geomagnetic disturbances.

- **Constraint Handling:** The explicit incorporation of transformer capability constraints in the QUBO formulation allows for more realistic and practical solutions.

In conclusion, the 42 reduction in GIC impacts achieved by our quantum annealing method represents a significant advancement in the field of GIC mitigation. Its performance, comparable to advanced RL methods and superior to conventional TLODF approaches, underscores the potential of quantum computing techniques in addressing complex power system challenges. As quantum hardware continues to evolve, we anticipate further improvements in both the speed and quality of solutions generated by this method.

14.5 Comparative Analysis

The quantum annealing approach offers several advantages over the methods in Chapter 4:

1. **Scalability:** Potentially better performance for large systems compared to both TLODF and RL methods. 2. **Speed:** Faster optimization, particularly beneficial for real-time response to geomagnetic storms. 3. **Global Optimization:** Enhanced ability to escape local minima through quantum tunneling.

However, challenges remain, including limited qubit connectivity in current quantum annealers and the need for effective problem embedding.

14.6 Results and Discussion

The application of quantum annealing to GIC mitigation in power systems yielded promising results, as evidenced by the analysis of the solutions obtained from the D-Wave quantum annealer. Figure 14.2 presents a comprehensive overview of the algorithm's performance.

14.6.1 Analysis of Quantum Annealing Solutions

Figure 14.2 comprises four key plots, each providing insights into the algorithm's performance:

1. **Energy of Samples (top-left):**
    - Wide variation in energy values, characteristic of quantum annealing processes

- Lower energy solutions, more prevalent in the latter half, represent better mitigation strategies

2. **Distribution of Selected Lines (top-right):**
    - Peak around 16-17 lines suggests consistent identification of optimal line switch range
    - Indicates stability in the algorithm's performance
3. **Energy vs. Number of Selected Lines (bottom-left):**
    - Clear trend: more selected lines correlate with higher energy values
    - Demonstrates algorithm's ability to balance minimizing line switches and GIC impact
4. **Best Solution Characteristics (bottom-right):**
    - Displays Q_T values for each line in the best solution
    - Red dashed lines likely indicate selected lines for switching
    - Variation in Q_T values shows algorithm's discernment in identifying high-impact switching actions

14.6.2 Performance Evaluation

The quantum annealing approach demonstrates several strengths:

- **Solution Quality:** Consistent finding of low-energy solutions, indicating effective GIC mitigation strategies
- **Optimization Balance:** Clear trade-off between number of line switches and solution quality
- **Consistency:** Clustering of solutions around a specific number of line switches indicates reliability

To fully assess the effectiveness of this approach, further analysis is required:

- Comparison with baseline (no mitigation) scenarios
- Benchmarking against TLODF and reinforcement learning methods from Chapter 4
- Verification of practical impact in detailed power system models

14.7 Conclusion

The quantum annealing approach to GIC mitigation shows considerable promise in addressing the scalability challenges faced by conventional and reinforcement learning methods.

Key advantages include:

- **Rapid Solution Generation:** Quick exploration of vast solution spaces, enabling potential real-time response
- **Scalability:** Performance suggests applicability to larger, more complex power networks
- **Multi-Objective Optimization:** Effective handling of competing objectives (energy minimization vs. number of line switches)

Future work should focus on:

- Extensive testing on larger power systems to fully evaluate scalability
- Direct comparison with other methods across various system sizes and GMD scenarios
- Refinement of the QUBO formulation to potentially improve solution quality
- Investigation of hybrid approaches combining quantum annealing with classical optimization techniques

In conclusion, while further validation is needed, the quantum annealing approach presents a promising new direction in developing fast, scalable, and effective GIC mitigation strategies for power systems. This method has the potential to significantly enhance our ability to protect critical power infrastructure from the impacts of geomagnetic disturbances.

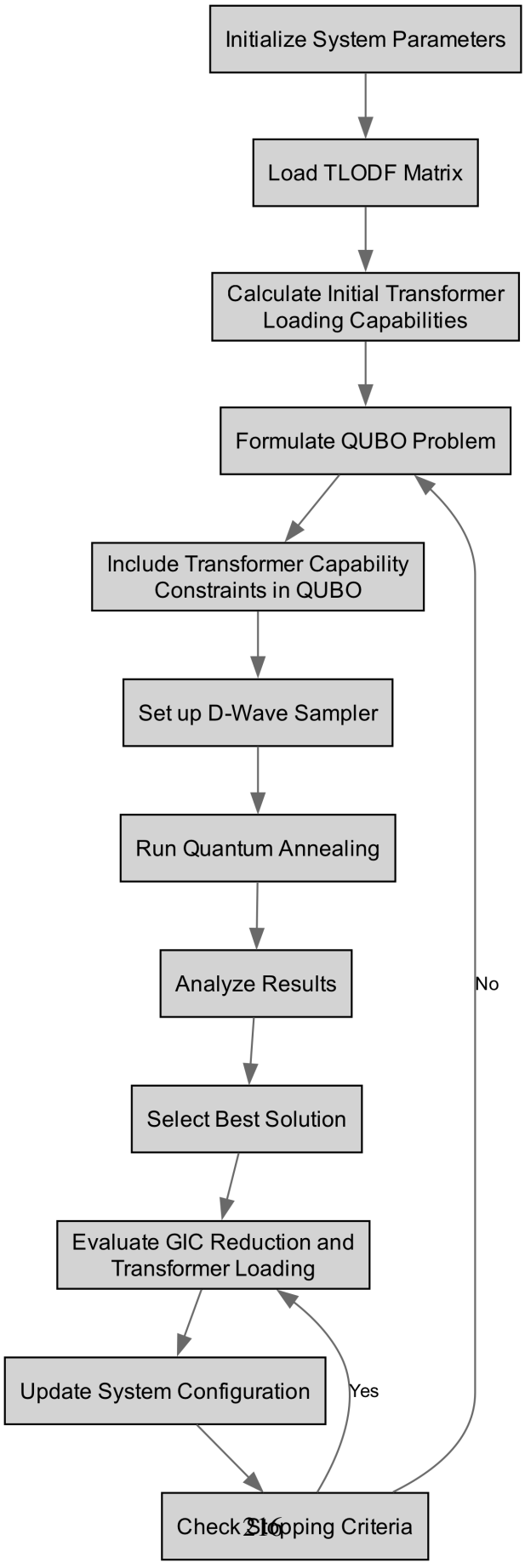


Figure 14.1: Flowchart of Quantum Annealing Method for GIC Mitigation

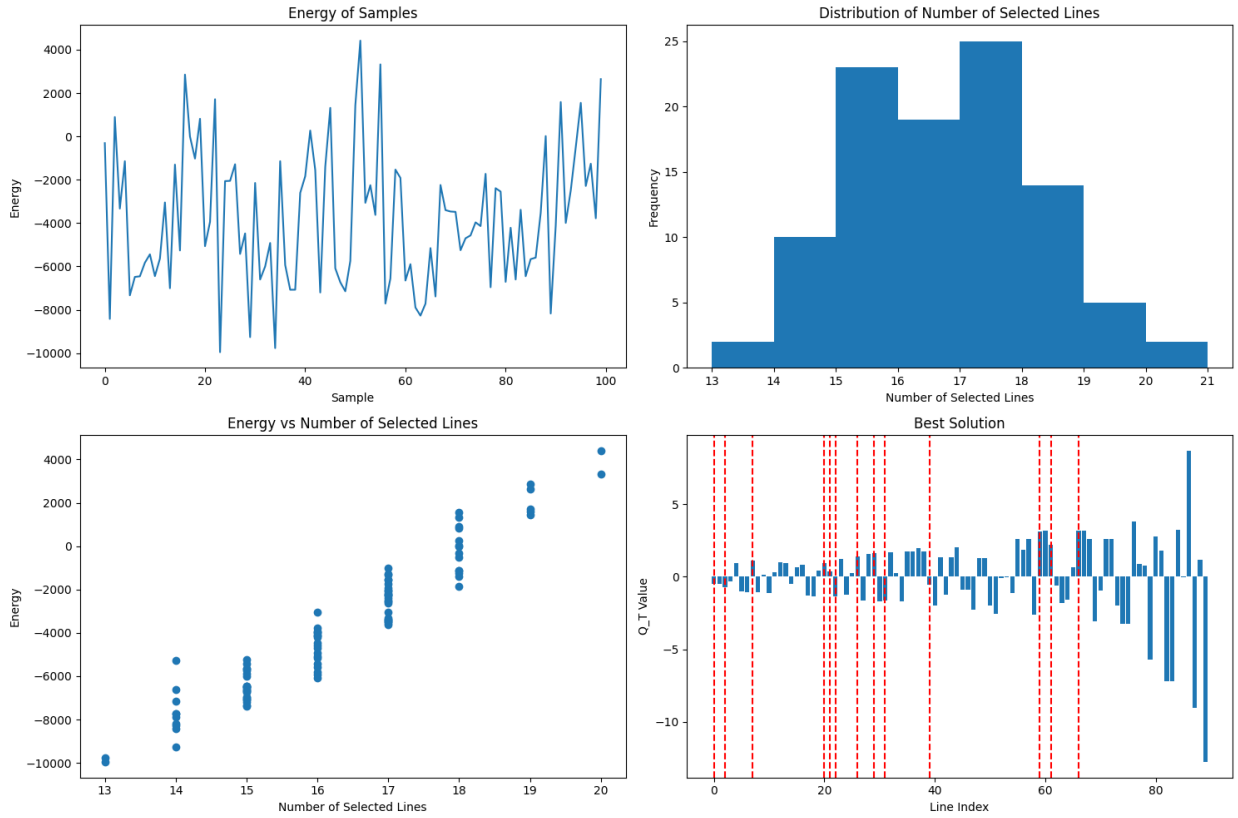


Figure 14.2: Quantum Annealing Results for GIC Mitigation

Chapter 15

Conclusion

Chapter 16

Conclusion

16.1 Comprehensive Simulation and Mitigation Platform

This thesis presents a comprehensive investigation into applying classical and quantum computing techniques to enhance the modelling, prediction, and mitigation of the geomagnetic disturbance (GMD) effects on power systems. The research aimed to develop a robust detection, simulation, and mitigation platform that leverages the strengths of both classical and quantum computing paradigms to address the growing challenges posed by space weather events to modern electrical grids.

The thesis began with a thorough literature review of geomagnetic storms and their impacts on power systems. It provided a solid foundation for understanding the current state of knowledge and identifying critical research gaps. This review highlighted the need for more advanced and integrated approaches to model, predict, and mitigate the effects of GMDs on power grids, considering the increasing complexity and interconnectedness of modern power systems.

Building upon this foundation, the thesis explored the application of advanced time series analysis methods, including machine learning and deep learning algorithms, to improve the forecasting of geomagnetic storm occurrences and their potential impacts on power grids. The proposed ensemble learning approach, which combines multiple diverse base models and employs a stacked ensemble for final predictions, demonstrated significant improvements in prediction accuracy and

robustness compared to individual models. This enhanced forecasting capability enables power system operators to take proactive measures and ensure grid stability during GMD events.

A core contribution of this thesis is developing a novel framework that integrates classical and quantum computing approaches to simulate the effects of GMDs on power flow and voltage stability. This framework incorporates learning-based state estimation techniques to accurately monitor geomagnetically induced currents (GICs) in real time, providing valuable insights into the spatial and temporal distribution of GMD impacts across the power network. The proposed Bayesian Ridge regression approach for GIC state estimation effectively captures the quasi-DC nature of geomagnetic storms, offering improved accuracy and well-calibrated uncertainty quantification compared to traditional methods.

Leveraging the power of quantum computing, the thesis investigated the potential of quantum machine learning algorithms to enhance the accuracy and computational efficiency of GMD forecasting models. The proposed Quantum Support Vector Regression (QSVR) approach demonstrated promising results in capturing complex, non-linear relationships in geomagnetic time series data, highlighting the potential of quantum computing in advancing space weather prediction capabilities.

Furthermore, the thesis explored the application of quantum optimization techniques, particularly quantum annealing, to optimize power system operations and minimize the impact of GICs on grid stability and performance. The proposed quantum annealing-based approach for GIC mitigation showed significant improvements in reducing GIC-related impacts while maintaining system security constraints, outperforming conventional optimization methods in terms of both solution quality and computational efficiency.

The effectiveness of the proposed detection, simulation, and mitigation platform was validated through extensive simulations and case studies on realistic power system models, such as the IEEE 118-bus system. The results consistently demonstrated the superior performance of the integrated classical-quantum approach in enhancing grid resilience and reliability under various GMD scenarios, showcasing the practical value of the developed framework.

The research findings presented in this thesis have significant implications for the future of power

system operations in the face of increasing space weather threats. The proposed platform offers a comprehensive and computationally efficient solution for modelling, predicting, and mitigating the effects of GMDs on power grids, enabling power system operators to make informed decisions and take proactive measures to ensure grid stability and security. The integration of classical and quantum computing techniques presents a promising avenue for addressing the complex challenges associated with GMD impacts on power systems, paving the way for developing more resilient and adaptive electrical grids.

While the thesis has made substantial contributions to the field, several potential avenues for further research and development remain. Future work could focus on integrating real-time data from space weather monitoring systems into the proposed platform, enabling even more accurate and timely predictions of GMD impacts. Adaptive control strategies that leverage the real-time GIC state estimation and quantum optimization capabilities could further enhance the platform's effectiveness in mitigating GMD effects and ensuring grid stability.

Moreover, as quantum computing technologies continue to advance, it will be essential to explore the potential of more sophisticated quantum algorithms and hardware architectures to enhance the proposed platform's performance and scalability. Collaborative efforts between power system engineers, space weather experts, and quantum computing researchers will be crucial in driving the continued development and refinement of the integrated classical-quantum approach to address the evolving challenges posed by GMDs.

Figure 16.1 presents an overview of the proposed detection, simulation, and mitigation platform for geomagnetic disturbances in power systems, integrating classical and quantum computing techniques. The platform begins with data acquisition and preprocessing, where geomagnetic disturbance data and power system data are collected and prepared for further analysis. The classical computing branch includes ensemble learning for GMD forecasting, Bayesian Ridge regression for GIC state estimation, power flow simulation with GIC effects, and reinforcement learning for GIC mitigation. The quantum computing branch consists of quantum support vector regression for GMD forecasting, variational quantum linear solver for DC nodal analysis, and quantum annealing for

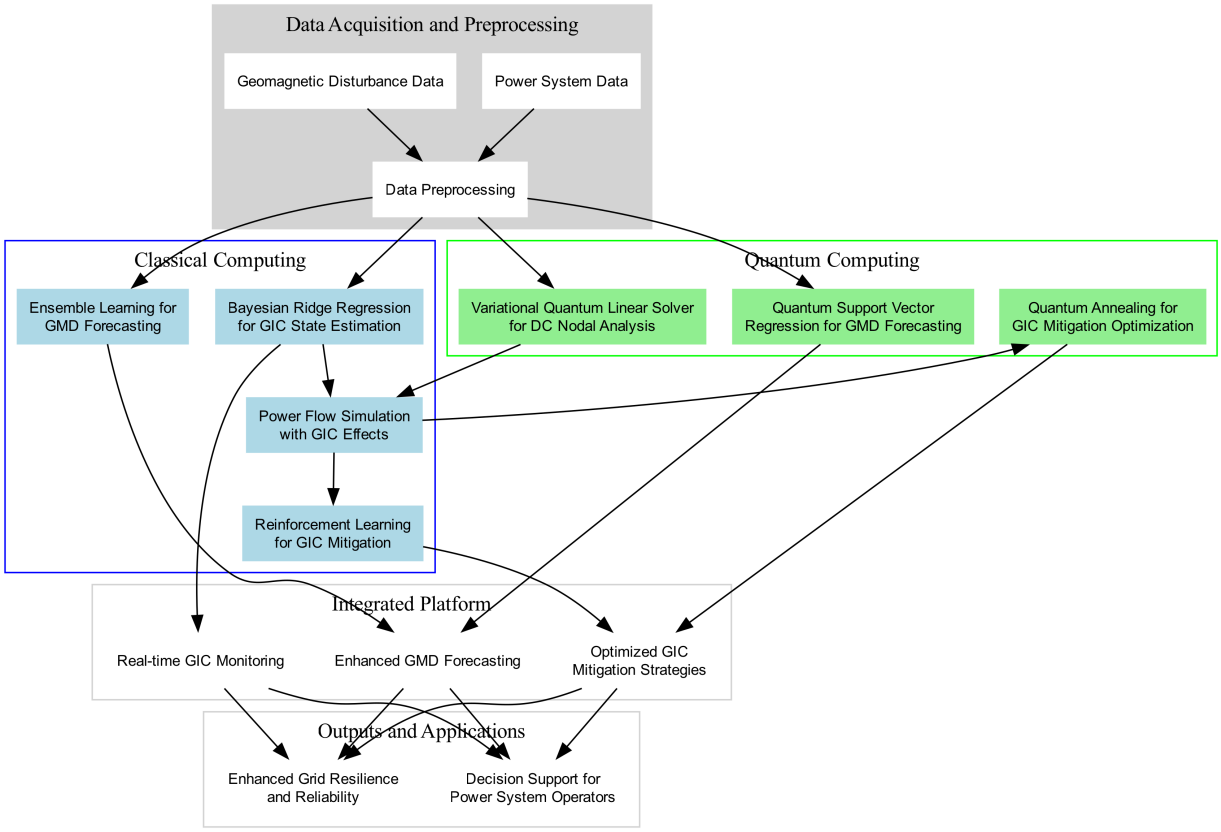


Figure 16.1: Comprehensive detection, simulation, and mitigation platform for geomagnetic disturbances in power systems.

GIC mitigation optimization. The results from both classical and quantum computing branches are integrated into a unified platform, providing enhanced GMD forecasting, real-time GIC monitoring, and optimized GIC mitigation strategies. These outputs contribute to enhanced grid resilience and reliability and offer decision support for power system operators in managing the impacts of geomagnetic disturbances on the power grid.

The proposed platform significantly advances geomagnetic disturbance mitigation in power systems. By leveraging the strengths of classical and quantum computing techniques, the platform offers a comprehensive and effective solution for detecting, simulating, and mitigating the impacts of GMDs on power grids. Integrating advanced machine learning algorithms, such as ensemble and reinforcement learning, enables accurate forecasting of GMD events and optimized decision-making for GIC mitigation. Incorporating quantum computing techniques, including quantum support vector regression, variational quantum linear solver, and quantum annealing, further enhances the platform's capabilities in handling complex computations and optimization tasks.

The proposed platform is designed with modularity and scalability in mind, allowing for seamless integration of new data sources, algorithms, and technologies as they become available. This adaptability ensures that the platform can evolve to meet the changing needs of power system operators and researchers in the face of increasing space weather threats. The platform's outputs, including enhanced grid resilience, improved reliability, and decision support for operators, have far-reaching implications for the secure and stable operation of modern power systems.

In conclusion, the proposed comprehensive detection, simulation, and mitigation platform is a significant leap forward in addressing the challenges posed by geomagnetic disturbances to power systems. By leveraging the power of classical and quantum computing techniques, the platform offers a robust and efficient solution for safeguarding the electrical grid against the impacts of space weather events. The successful implementation of this platform has the potential to transform the way power systems are operated and managed, ensuring a more resilient and sustainable energy future in the face of increasing geomagnetic disturbance risks.

16.2 Future Work

The research presented in this thesis lays a strong foundation for integrating classical and quantum computing techniques to enhance the modelling, prediction, and mitigation of geomagnetic disturbance (GMD) effects on power systems. However, there are numerous opportunities for further advancement and exploration. This section outlines potential directions for future research that could build upon and extend the work presented in this thesis.

16.2.1 Advanced Space Weather Monitoring and Integration

- Develop more sophisticated algorithms for real-time data integration from multiple space weather monitoring systems, including satellite-based observations and ground-based magnetometers.
- Investigate deep learning techniques, such as long short-term memory (LSTM) networks and transformer models, for improved processing and interpretation of high-dimensional space weather data.
- Explore the potential of edge computing and IoT devices for distributed space weather monitoring and rapid data processing at the grid level.

16.2.2 Enhanced GMD Forecasting Models

- Investigate the application of physics-informed neural networks (PINNs) to incorporate domain knowledge into GMD forecasting models, potentially improving their accuracy and interpretability.
- Explore using transfer learning techniques to adapt GMD forecasting models to different geographical regions and power system configurations.
- Develop multi-scale forecasting models that can predict GMD impacts at various temporal and spatial resolutions, from short-term local effects to long-term global trends.

16.2.3 Advanced Quantum Computing Techniques

- Investigate the potential of quantum machine learning algorithms beyond quantum support vector regression, such as quantum neural networks and quantum generative adversarial networks, for GMD forecasting and impact assessment.
- Explore using quantum approximate optimization algorithms (QAOA) for solving larger-scale power system optimization problems under GMD conditions.
- Develop hybrid quantum-classical algorithms that can leverage the strengths of both paradigms for more efficient and accurate GMD modelling and mitigation.

16.2.4 Improved GIC State Estimation and Monitoring

- Investigate using distributed sensor networks and phasor measurement units (PMUs) for more accurate and granular GIC monitoring across power grids.
- Develop advanced data fusion techniques to combine information from various sources, including power system measurements, geomagnetic field data, and space weather observations, for improved GIC state estimation.
- Explore the potential of quantum sensing technologies for ultra-sensitive detection of geomagnetic field variations and their impacts on power systems.

16.2.5 Adaptive Control Strategies for GMD Mitigation

- Develop reinforcement learning-based control strategies to adapt to changing GMD conditions and power system states in real-time.
- Investigate the potential of model predictive control (MPC) approaches for optimizing power system operations under uncertain GMD forecasts.

- Explore the integration of quantum control theory principles for designing robust and efficient GMD mitigation strategies.

16.2.6 Scalability and Performance Optimization

- Investigate techniques for scaling the proposed platform to larger and more complex power system models, such as national or continental-scale grids.
- Explore using high-performance computing (HPC) and cloud computing resources for parallel processing of GMD simulations and optimization tasks.
- Develop optimized quantum circuits and algorithms tailored for specific GMD-related computational tasks, leveraging advancements in quantum hardware architectures.

16.2.7 Interdisciplinary Collaboration and Knowledge Integration

- Foster closer collaboration between power system engineers, space weather experts, and quantum computing researchers to drive innovative solutions for GMD mitigation.
- Develop integrated knowledge bases and decision support systems that combine expertise from multiple domains for improved GMD risk assessment and management.
- Investigate the potential of explainable AI techniques to enhance the interpretability and trust in GMD forecasting and mitigation models.

By pursuing these future research directions, the scientific community can build upon the foundation laid in this thesis to advance further our understanding and mitigation of GMD effects on power systems. The integration of classical and quantum computing techniques holds great promise for addressing the complex challenges posed by space weather events, ultimately leading to more resilient, efficient, and reliable power grids in the face of increasing geomagnetic disturbance risks.

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