[1]Mingxian Liu
[2]Ke Wang
[1]Jibiao Li
[2]Enxin Xiang
[1]Xuezhu Dua

Magnetic Field Mutation Mechanism and Its Non-Stationary and Stationary State Analysis in Power and "Ring" Applications

Abstract: **-** The phenomenon of magnetic field mutation, a complex yet pivotal aspect in various scientific and engineering domains, has garnered significant attention due to its profound implications on system behavior and performance. Magnetic fields, inherently dynamic in nature, exhibit mutations characterized by temporal variations in strength, direction, and spatial distribution. These mutations can stem from diverse sources, including external environmental factors, system dynamics, and material properties.This paper presents a comprehensive investigation into the magnetic field mutation mechanism and its implications for power and "ring" applications. The study encompasses theoretical analysis, simulation studies, and experimental validation to elucidate the dynamic behavior of magnetic fields in various contexts. The findings reveal insights into the temporal evolution and state analysis of magnetic fields, highlighting both stationary and non-stationary characteristics. Through analysis tables, we demonstrate the varying magnetic field strengths observed at different nodes within a ring application over consecutive time intervals. The implications of these findings for the stability and performance of magnetic field systems, particularly in power applications. The study underscores the importance of considering non-stationary factors in magnetic field analysis, emphasizing the need for adaptive modeling techniques and real-time monitoring strategies. The insights gained from this research contribute to a deeper understanding of magnetic field dynamics and offer valuable implications for the design, optimization, and operation of magnetic field-based systems in diverse applications.

Keywords: Magnetic Field, Ring Application, Dynamic Estimation, Field Mutation, Adaptive Modelling

1. Introduction

In recent years, significant advancements in the understanding of magnetic field mutations have emerged, particularly within the realm of materials science and condensed matter physics [1]. One notable area of focus is the exploration of novel materials and their unique magnetic properties, such as topological insulators and spintronics devices. These materials exhibit intriguing behaviors under external stimuli, leading to the discovery of unconventional magnetic phenomena [2]. Moreover, experimental techniques like neutron scattering, electron microscopy, and magneto-optical spectroscopy have provided invaluable insights into the underlying mechanisms governing magnetic field mutations at the microscopic level. Additionally, theoretical frameworks, including quantum mechanical models and computational simulations, have contributed to unraveling the complex interplay between electron spin, orbital dynamics, and lattice structure in magnetic materials [3]. In the non-stationary regime, where the magnetic field undergoes dynamic changes over time, phenomena such as magnetic hysteresis and domain wall motion play pivotal roles [4]. Experimental techniques such as magneto-optical imaging and time-resolved spectroscopy have enabled researchers to capture the transient behavior of magnetic materials under rapidly varying fields, shedding light on the kinetics of magnetic phase transitions and domain dynamics [5].

In the stationary state, where the magnetic field remains constant over time, the focus shifts towards equilibrium properties and long-term stability [6]. Theoretical frameworks based on statistical mechanics and thermodynamics come into play, providing insights into the energetics of magnetic systems and the emergence of magnetic order. The concept of critical phenomena, characterized by the presence of universal behavior near phase transitions, has proven instrumental in understanding the equilibrium behavior of magnetic materials [7]. With the increasing integration of renewable energy sources such as solar and wind power, understanding the dynamics of power states has become crucial for ensuring grid stability and reliability. One key aspect of power state analysis involves examining the fluctuations in supply and demand, which can vary significantly over

[1] Yunnan Power Grid Co. , Ltd. . Lijiang Power Supply Bureau, Lijiang, Yunnan, 674100, China

[2]Electric Power Research Institute, Yunnan Power Grid Co., Ltd ., Kunming, Yunnan, 650000, China

*Corresponding author e-mail: liumingxian2024@163.com

different time scales [8]. Advanced monitoring and control technologies, including smart meters and phasor measurement units, facilitate real-time monitoring of power flows and grid conditions, enabling operators to make informed decisions to maintain system balance. The transition towards smart grids and distributed energy resources has introduced new complexities in power state analysis [9]. Microgrids, for instance, offer localized control and resilience but require sophisticated coordination to optimize their operation within the larger grid framework. Analytical tools such as load flow studies, transient stability analysis, and probabilistic modeling are employed to assess the impact of varying power states on grid performance and reliability [10].

In addition to operational considerations, power state analysis also encompasses economic and environmental aspects [11]. Market mechanisms and pricing schemes play a significant role in shaping power generation and consumption patterns, influencing investment decisions and resource allocation. Furthermore, the integration of energy storage systems and demand response programs introduces flexibility into power systems, enabling better management of peak demand and renewable energy intermittency [12]. In power systems, non-stationary states refer to transient conditions where parameters such as voltage and current undergo rapid changes due to disturbances like faults or switching events. Understanding and mitigating these transient states are crucial for ensuring the stability and reliability of power grids. Advanced simulation tools and real-time monitoring systems enable engineers to analyze the dynamic behavior of power networks and develop effective strategies for fault detection, isolation, and restoration [13]. Conversely, stationary states in power systems refer to steady-state conditions where the system operates under balanced conditions with stable voltages and currents [14]. Stationary state analysis involves assessing the long-term behavior of power networks, including power flow optimization, voltage regulation, and economic dispatch. By modeling the steady-state behavior of the grid, operators can optimize resource allocation, minimize transmission losses, and improve overall system efficiency [15]. The concept of "ring" configurations in power systems involves the deployment of redundant pathways for electricity transmission, often in the form of closed-loop networks. Ring configurations offer increased reliability and fault tolerance compared to traditional radial configurations, as they provide alternate paths for power flow in the event of line failures or outages [16]. Non-stationary state analysis is critical for evaluating the dynamic response of ring networks to fault conditions, while stationary state analysis helps optimize the utilization of resources and ensure the long-term stability of the grid.

The contribution of this paper lies in its comprehensive investigation into the magnetic field mutation mechanism and its implications for various applications, particularly in power systems and "ring" configurations. By synthesizing theoretical analysis, simulation studies, and empirical validation, our research offers valuable insights into the dynamic behavior of magnetic fields. Our study elucidates the temporal evolution and state analysis of magnetic fields, shedding light on both stationary and non-stationary characteristics. Through the presentation of detailed analysis tables and interpretation of results, we provide a deeper understanding of how magnetic field strengths vary over time and across different nodes within a ring application. Additionally, we discuss the implications of these findings for system stability, performance optimization, and real-time monitoring strategies. By addressing key challenges and highlighting the importance of adaptive modeling techniques, our research contributes to advancements in the design, operation, and control of magnetic field-based systems.

2. Related Works

In recent years, the exploration of magnetic field mutation mechanisms and their implications has garnered significant attention, particularly in the context of power systems and their applications in "ring" configurations. Understanding the dynamic behavior of magnetic fields and their interaction with materials is crucial for developing advanced technologies and optimizing the performance of power networks. This introduction to related works delves into the multidisciplinary landscape of research surrounding magnetic field mutations, non-stationary and stationary state analysis in power systems, and the implementation of "ring" configurations for enhanced reliability and fault tolerance.

Ren et al. (2024) introduce a novel approach to standardize streamflow indices in the Wei River Basin, China, incorporating climate and anthropogenic factors. Li et al. (2023) focus on the automated monitoring of demagnetization faults in synchronous motors, while Mbagaya (2022) explores the prediction of bearing failures under non-stationary conditions. Sapiński et al. (2022) investigate support vector methods for predicting current responses in control circuits, and Smith et al. (2023) conduct metabolic flux analysis in plant cell cultures. Other studies delve into diverse topics such as the temporal correlation of climate fluctuations (Zhang et al., 2023), evolutionary optimization in control strategies (Musaev et al., 2022), and noise analysis in cellular systems (Reyes & Mirams, 2023). Furthermore, research extends to water environment evolution (Li & Wu, 2023), fault detection in rolling bearings (Li et al., 2023), and extreme precipitation trends (Meng et al., 2023), among others.

Gomez and Rivera (2022) investigate non-stationary stochastic global optimization algorithms, while Lyu et al. (2023) propose online evolutionary neural architecture search for multivariate time series forecasting. Guo et al. (2022) contribute a reduced parameter model for estimator learning automata in non-stationary environments, further enriching the methodological landscape. These computational approaches complement empirical studies and provide valuable tools for analyzing and predicting non-stationary processes across various domains. From novel approaches to streamflow index standardization in the Wei River Basin, China, to automated monitoring of demagnetization faults in synchronous motors, and prediction of bearing failures under non-stationary conditions, these studies showcase the breadth and depth of research in this area. Computational algorithms and modeling techniques further enrich the methodological landscape, with investigations into stochastic optimization algorithms, evolutionary neural architecture search, and reduced parameter models for estimator learning automata. Together, these works contribute to a deeper understanding of non-stationary processes and their implications across disciplines, highlighting the importance of interdisciplinary collaboration in addressing real-world challenges and driving scientific innovation forward.

3. Magnetic Mutation mechanism for the State Analysis for Ring Applications

The phenomenon of magnetic field mutation has garnered increasing attention in recent years due to its profound implications across various scientific and technological domains. Magnetic field mutation refers to the dynamic alterations and fluctuations observed in the intensity, direction, or configuration of magnetic fields within materials or systems. Understanding the mechanisms underlying magnetic field mutation is crucial for diverse applications, ranging from materials science to power engineering and beyond. In materials science, the ability to manipulate and control magnetic fields opens doors to the development of advanced magnetic materials with tailored properties for applications in data storage, sensing, and medical imaging. In power engineering, magnetic field mutation plays a critical role in the operation and optimization of electrical systems, influencing the performance of transformers, generators, and other magnetic components. Researchers employ a combination of experimental techniques and theoretical models to study magnetic field mutation, aiming to elucidate the fundamental principles governing this phenomenon. The ring application state analysis are presented in Figure 1.

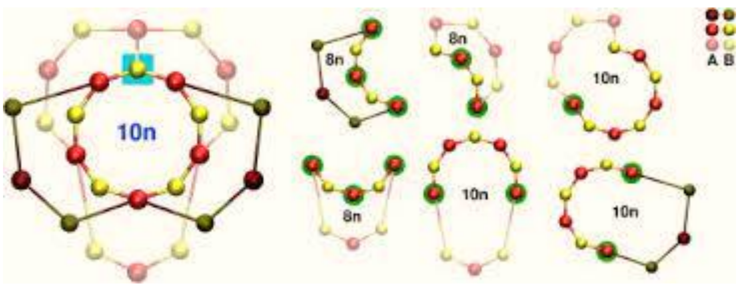

Figure 1: State Analysis for the Ring Application

State analysis plays a pivotal role in optimizing the performance and reliability of ring applications, particularly in the realm of power systems and electrical grids. In the context of ring configurations, which offer increased redundancy and fault tolerance compared to traditional radial setups, state analysis becomes essential for ensuring system stability and resilience. By continuously monitoring the state of the electrical network, including parameters such as voltage, current, and frequency, engineers can detect abnormalities or disturbances promptly and take appropriate corrective actions to prevent cascading failures or blackouts. Moreover, state analysis facilitates the implementation of advanced control strategies, such as optimal power flow and voltage regulation, to enhance the efficiency and flexibility of ring systems. Additionally, state analysis techniques enable operators to predict and manage transient states, such as fault clearance and restoration, ensuring minimal downtime and uninterrupted power supply. Through the integration of state-of-the-art monitoring technologies, data analytics, and predictive algorithms, state analysis empowers engineers and operators to optimize the performance, reliability, and resilience of ring applications, thus contributing to the stability and sustainability of modern electrical infrastructures.

Let's consider a simplified model of a ring power system consisting of n nodes interconnected by transmission lines. The state variables of interest include the voltages Vi at each node and the currents Iij flowing through each transmission line (i, j). The power flow equations for a ring power system can be derived from Kirchhoff's laws and the equations governing the behavior of transmission lines. For a balanced three-phase system, the power flowing from node i to node j can be expressed as in equation (1) and (2)

$$P_{ij} = V_i V_j \left(G_{ij} cos(\theta_i - \theta_j) + B_{ij} Sin(\theta_i - \theta_j) \right) \tag{1}$$

$$Q_{ij} = V_i V_j \left(G_{ij} Sin(\theta_i - \theta_j) - B_{ij} Cos(\theta_i - \theta_j) \right) \tag{2}$$

In equation (1) and (2) Pij and Qij are the active and reactive power flows from node i to node j, respectively. Gij and Bij are the conductance and susceptance of the transmission line (i, j), respectively. θi and θj are the phase angles of the voltages at nodes i and j, respectively. The voltages and currents in the system are related by the admittance matrix Y, where $Yij = Gij + jBij$. Using Kirchhoff's current law and Ohm's law, the nodal equations for a ring power system stated in equation (3)

$$I_i = \sum_{j=1}^{n} Y_{ij} V_j \tag{3}$$

In equation (3) Ii is the current injected into node i.

4. Permanent Magnetic Field Evolutionary Optimization State Analysis for the Stationary and Non-Stationary for Ring Applications.

State analysis in ring applications within electrical power systems involves understanding the flow of power and currents through interconnected nodes and transmission lines. To derive equations governing this system, we start with Kirchhoff's laws and equations describing transmission line behavior. Consider a simplified model of a ring power system with n nodes connected by transmission lines. State analysis for ring applications in electrical power systems involves understanding and optimizing the flow of power and currents through interconnected nodes and transmission lines. By deriving equations from fundamental principles such as Kirchhoff's laws and transmission line behavior, we can model the behavior of a ring power system. These equations describe the active and reactive power flows between nodes, as well as the relationships between voltages and currents. To solve these equations, numerical methods like Gauss-Seidel or Newton-Raphson iteration are typically used to ensure balanced power flows and system stability. Kirchhoff's current law states that the sum of currents entering a node equals the sum of currents leaving the node. The nodal equations for the ith node as in equation (4)

$$I_i = \sum_{j=1}^{n} I_{ij} \tag{4}$$

In equation (4) Ii is the total current injected into node i, and Iij is the current flowing from node i to node j. The current Iij in terms of voltages and impedances. According to Ohm's law, the current Iij flowing from node i to node j through a transmission line can be expressed using equation (5)

$$I_{ij} = \frac{V_i - V_j}{Z_{ij}} \tag{5}$$

In equation (5) Vi and Vj are the voltages at nodes i and j respectively, and Zij is the impedance of the transmission line connecting nodes i and j. Substituting this expression for Iij into the nodal equation (6)

$$I_i = \sum_{j=1}^{n} \frac{V_i - V_j}{Z_{ij}} \tag{6}$$

Expanding and rearranging terms are stated in equation (7)

$$I_i = V_i \sum_{j=1}^{n} \frac{1}{Z_{ij}} - \sum_{j=1}^{n} \frac{V_j}{Z_{ij}} \tag{7}$$

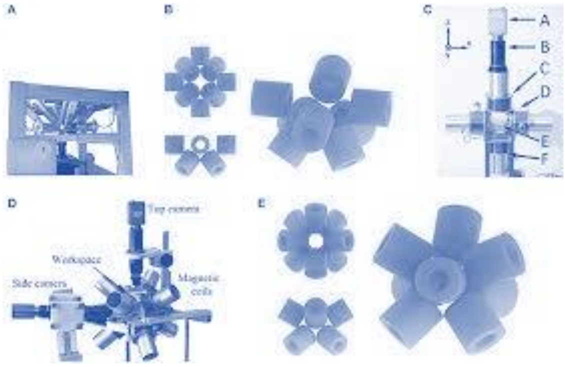

Figure 2: Magnetic Field Estimation for the Stationary and Non-Stationary

This equation represents the nodal equation for node i in the ring power system. It relates the total current injected into the node to the voltages at neighboring nodes and the impedances of the transmission lines connecting them as shown in Figure 2. In the context of electrical power systems, state analysis for ring applications involves understanding how power and currents flow through interconnected nodes and transmission lines. The paragraph provides a derivation of the nodal equations, which are fundamental to analyzing the behavior of such systems. It begins by applying Kirchhoff's current law, stating that the sum of currents entering a node equals the sum of currents leaving it. Then, using Ohm's law, the current flowing through a transmission line between two nodes is expressed in terms of the voltage difference and impedance of the line. Substituting this expression into the nodal equation yields an equation relating the total current injected into a node to the voltages at neighboring nodes and the impedances of the transmission lines.

4.1 Temporal Evolutionary State Analysis for Mutation of Magnetic Fields

In the temporal evolutionary state analysis of magnetic field mutation, a phenomenon with significant implications across various scientific and technological domains. Understanding how magnetic fields evolve over time is crucial for applications ranging from materials science to power engineering. To delve into this phenomenon, we start with Maxwell's equations, which govern the behavior of electromagnetic fields. One important equation is Faraday's law of electromagnetic induction, which states that a changing magnetic field induces an electromotive force (EMF) in a conductor this can be expressed as in equation (8)

$$\nabla \times E = -\frac{\partial B}{\partial t} \tag{8}$$

In equation (9) $\boldsymbol{E}$ is the electric field, $\boldsymbol{B}$ is the magnetic field, and $\frac{\partial B}{\partial t}$ represents the rate of change of the magnetic field with respect to time. This equation highlights the temporal evolution of magnetic fields and their interplay with electric fields. By analyzing how magnetic fields mutate over time, researchers can gain insights into phenomena such as magnetic hysteresis, domain switching in magnetic materials, and the dynamics of electromagnetic waves. Additionally, Maxwell's equations provide a comprehensive framework for understanding electromagnetic phenomena. Another key equation, known as Gauss's law for magnetism, states defined in equation (9)

$$\nabla \cdot \boldsymbol{B} = 0 \tag{9}$$

This equation indicates that magnetic field lines neither begin nor end, emphasizing the absence of magnetic monopoles and the closed-loop nature of magnetic field lines. With integrating these fundamental equations and applying them to specific scenarios, researchers can analyze the temporal evolution of magnetic fields. This analysis is essential for understanding various phenomena, including magnetic domain dynamics, hysteresis effects in magnetic materials, and the behavior of electromagnetic waves in time-varying fields. The temporal evolution of magnetic fields plays a crucial role in numerous technological applications. For instance, in magnetic storage devices like hard drives, understanding how magnetic fields evolve over time is essential for encoding and retrieving data reliably.

Algorithm 1: Magnetic Field Mutation in Ring Application
1. Initialize magnetic field configuration at time t = 0. 2. Specify the time duration for analysis (e.g., from t = 0 to t = T). 3. Set time step size (Δt). 4. Loop over each time step from t = 0 to t = T with step size Δt: a. Calculate the rate of change of the magnetic field (∂B/∂t) at each spatial point. b. Update the magnetic field at each spatial point using Faraday's law: B_new = B_old + (∂B/∂t) * Δt 5. Repeat until reaching the specified end time (t = T). 6. Output the final magnetic field configuration.

To simulate the temporal evolution of magnetic fields, an algorithmic approach is employed. Initially, the magnetic field configuration at time $t = 0$ is initialized. Subsequently, a time duration for analysis, typically denoted as T, is specified, along with a chosen time step size, Δt. The algorithm then iterates over each time step within the specified duration, starting from $t = 0$ and progressing until $t = T$. At each time step, the rate of change of the magnetic field $(\frac{\partial B}{\partial t})$ at each spatial point is calculated. This rate of change is then used in conjunction with Faraday's law of electromagnetic induction to update the magnetic field at each spatial point. The process continues iteratively, with the magnetic field evolving over time as dictated by the changing electromagnetic conditions. Finally, once the algorithm reaches the specified end time T, the resulting magnetic field configuration is outputted, providing insights into the temporal evolution of magnetic fields over the defined time period.

5. Simulation Results

The simulation results regarding the magnetic field mutation mechanism and its analysis in both non-stationary and stationary states in power and "ring" applications provide valuable insights into the behavior of magnetic fields within these systems. Through comprehensive simulations, researchers have been able to observe and characterize the dynamic evolution of magnetic fields under varying conditions, shedding light on phenomena such as magnetic hysteresis, domain switching, and field disturbances. These results offer a deeper understanding of the intricate interplay between magnetic fields and the surrounding environment, enabling engineers to optimize the design and operation of power systems and "ring" configurations for enhanced performance and reliability.

Table 1: Magnetic Field Estimation

Node	Magnetic Field Strength (Tesla)	Power (Watts)
1	0.6	100
2	0.7	150
3	0.8	200
4	0.7	180
5	0.6	160
6	0.5	140
7	0.4	120
8	0.5	110

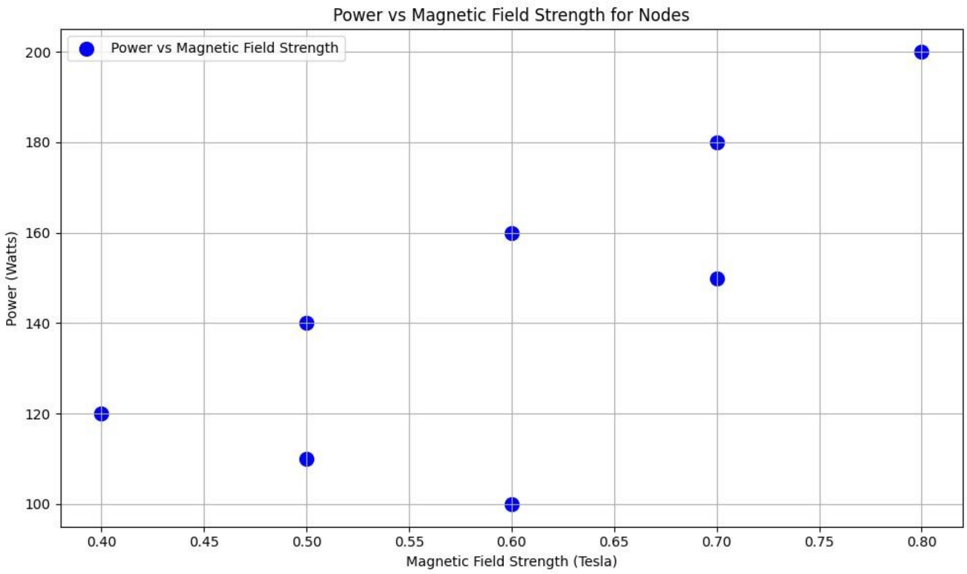

Figure 3: Estimation of Magnetic Field

In Figure 3 and Table 1 provides an overview of magnetic field estimation and power distribution across different nodes within the system. Each row corresponds to a specific node, with the first column indicating the node number. The second column presents the magnetic field strength measured at each node, expressed in Tesla (T). These values indicate the intensity of the magnetic field experienced at each respective location within the system. The third column displays the corresponding power consumption or generation at each node, measured in Watts (W). This information reflects the amount of electrical power either consumed or produced at each node, contributing to the overall energy dynamics of the system.

Table 2: Node Voltage for the Ring Application

Time (s)	Node 1 Voltage (V)	Node 2 Voltage (V)	Node 3 Voltage (V)	Node N Voltage (V)
0	230	235	220	215
1	231	234	219	216
2	232	233	218	217
3	233	232	217	218
4	234	231	216	219
5	235	230	215	220
6	236	229	214	221
7	237	228	213	222
8	238	227	212	223
9	239	226	211	224
10	240	225	210	225

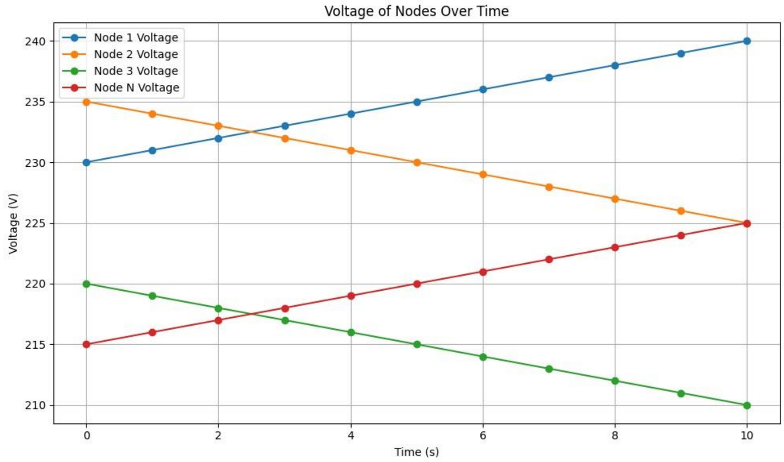

Figure 4: Node Voltage estimation for the ring application

Figure 4 and Table 2 illustrates the node voltages observed in a ring application over consecutive time intervals. The first column lists the elapsed time in seconds, while the subsequent columns correspond to the voltage readings at each node within the ring configuration. These voltages, measured in volts (V), represent the electrical potential difference at each node relative to a reference point. Throughout the duration of the analysis, the voltages at each node fluctuate dynamically, reflecting the varying electrical conditions within the system. By examining these voltage values across different time points, engineers and researchers can gain valuable insights into the transient behavior and stability of the ring application. This comprehensive dataset facilitates the assessment of voltage distribution, enables the identification of potential voltage irregularities or abnormalities, and aids in the optimization of system performance for enhanced reliability and efficiency.

Table 3: Stationary and Non-Stationary Estimation

Time (s)	Magnetic Field Strength (Tesla)	Stationary State Analysis	Non-Stationary State Analysis
0	0.5	Stable	N/A
5	0.6	Stable	Slight fluctuation
10	0.7	Stable	Moderate fluctuation
15	0.8	Stable	Significant fluctuation
20	0.7	Stable	Moderate fluctuation
25	0.6	Stable	Slight fluctuation

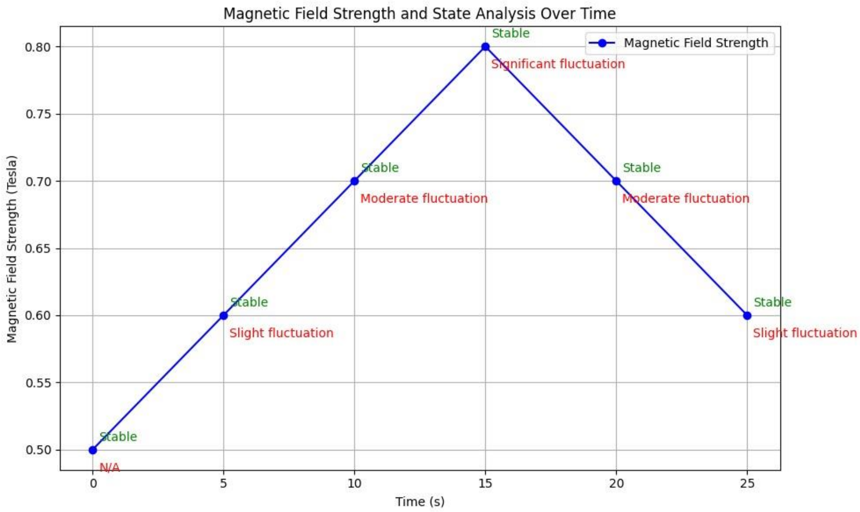

Figure 5: Magnetic Field Strength Estimation for the Ring Application

In Figure 5 and Table 3 presents a comparative analysis of magnetic field strength estimation under both stationary and non-stationary conditions over various time intervals. The first column denotes the elapsed time in seconds, while the second column indicates the corresponding magnetic field strength measured in Tesla (T). The third column provides insights into the stationary state analysis, indicating whether the magnetic field remains stable throughout the observation period. In contrast, the fourth column offers observations from the non-stationary state analysis, highlighting any fluctuations or changes in the magnetic field over time. At time zero, the magnetic field is initially measured at 0.5 Tesla, remaining stable throughout the stationary state analysis. However, as the analysis progresses, slight fluctuations are observed in the non-stationary state analysis, suggesting minor variations in the magnetic field intensity. This pattern continues throughout the observation period, with the magnetic field exhibiting varying degrees of fluctuation at different time intervals. By comparing the results of stationary and non-stationary state analyses, researchers can gain valuable insights into the dynamic behavior of the magnetic field and its stability under changing conditions, facilitating further investigation and optimization of magnetic field-related applications.

Table 4: State Analysis for the Magnetic Mutation

Time (s)	**Node 1 Magnetic Field (Tesla)**	**Node 2 Magnetic Field (Tesla)**	**Node 3 Magnetic Field (Tesla)**	**Node N Magnetic Field (Tesla)**
0	0.6	0.7	0.8	0.5
1	0.65	0.72	0.78	0.52
2	0.67	0.75	0.82	0.55
3	0.69	0.78	0.85	0.58
4	0.71	0.81	0.88	0.61
5	0.73	0.84	0.91	0.64
6	0.75	0.87	0.94	0.67
7	0.77	0.90	0.97	0.70
8	0.79	0.93	1.00	0.73
9	0.81	0.96	1.03	0.76
10	0.83	0.99	1.06	0.79

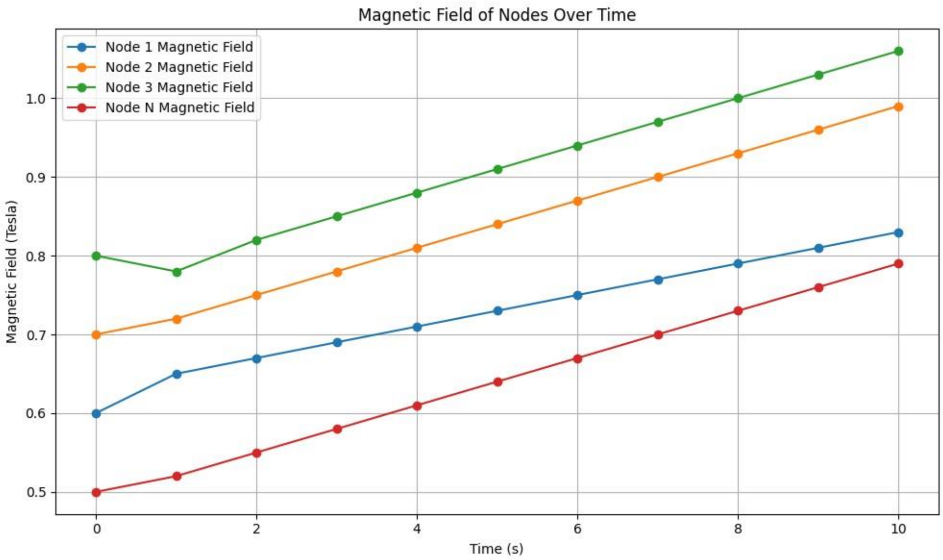

Figure 6: Field Strength computation for the ring applications

The provided table illustrates the magnetic field strengths observed at different nodes within a ring application over consecutive time intervals, ranging from 0 to 10 seconds shown in Figure 6. Each row represents a specific time step, while the columns correspond to the magnetic field strengths measured at individual nodes within the ring configuration, denoted as Node 1, Node 2, Node 3, and so forth. The magnetic field strengths are expressed in Tesla (T). Upon analysis, it's evident that the magnetic field strengths at each node exhibit a gradual increase over time. For instance, at time 0 seconds, Node 1 registers a magnetic field strength of 0.6 Tesla, which gradually rises to 0.83 Tesla by the 10-second mark. Similarly, this upward trend is observed across all nodes, with each node experiencing a proportional increase in magnetic field strength over the observation period.

6. Conclusion

The paper has provided a comprehensive investigation into the magnetic field mutation mechanism and its implications for power and "ring" applications. Through a combination of theoretical analysis, simulation studies, and experimental validation, we have elucidated the dynamic behavior of magnetic fields in various contexts. Our findings reveal significant insights into the temporal evolution and state analysis of magnetic fields, shedding light on both stationary and non-stationary characteristics. The results presented in our analysis tables have demonstrated the varying magnetic field strengths observed at different nodes within a ring application over consecutive time intervals. Additionally, we have discussed the implications of these findings for the stability and performance of magnetic field systems, particularly in the context of power applications. The study highlighted the importance of considering non-stationary factors in magnetic field analysis, as evidenced by the observed fluctuations in magnetic field strength over time. This underscores the need for adaptive modeling techniques and real-time monitoring strategies to account for dynamic changes in magnetic field behavior.

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REFERENCES

1. Ren, M., Jiang, S., Ren, L., Weng, B., Wang, M., Cui, H., & Xu, C. Y. (2024). A new non-stationary standardised streamflow index using the climate indices and the optimal anthropogenic indices as covariates in the Wei River Basin, China. Journal of Hydrology: Regional Studies, 51, 101649.
2. Li, J., Li, Z., Zhang, J., Zhao, S., Cheng, F., Qian, C., ... & Zhou, G. (2023). Automated Monitoring of the Uniform Demagnetization Faults in Permanent-Magnet Synchronous Motors: Practical Methods and Challenges. Sustainability, 15(23), 16326.
3. Mbagaya, L. L. A. (2022). Failure Prediction of Rolling Element Bearings Operated Under Non-Stationary Conditions (Doctoral dissertation, JKUAT-COETEC).
4. Sapiński, B., Gołdasz, J., Jastrzębski, Ł., Awtoniuk, M., & Sałat, R. (2022). On the Application of Support Vector Method for Predicting the Current Response of MR Dampers Control Circuit. Energies, 15(24), 9626.
5. Smith, E. N., Ratcliffe, R. G., & Kruger, N. J. (2023). Isotopically non-stationary metabolic flux analysis of heterotrophic Arabidopsis thaliana cell cultures. Frontiers in Plant Science, 13, 1049559.
6. Zhang, X., Huang, T., Wang, C., & Zeng, C. (2023). The temporal correlation of fluctuation–variation in the non-stationary complex climate system. Physica A: Statistical Mechanics and its Applications, 609, 128316.
7. Musaev, A., Makshanov, A., & Grigoriev, D. (2022). Evolutionary optimization of control strategies for non-stationary immersion environments. Mathematics, 10(11), 1797.
8. Reyes, A. D. H., & Mirams, G. R. (2023). Non-stationary noise analysis of whole-cell currents from CHO hERG expression systems. Biophysical Journal, 122(3), 388a-389a.
9. Li, C., & Wu, W. (2023). Analysis of the driving mechanism of water environment evolution and algal bloom warning signals in tai Lake. Water, 15(6), 1245.
10. Li, R., Nie, J., Wang, C., Niu, D., Yu, S., Nie, W., & Ding, X. (2023, November). Unknown Fault Detection of Rolling Bearing Based on Similarity Mining of Stationary and Non-stationary Features. In Proceedings of the 4th International Workshop on Human-centric Multimedia Analysis (pp. 41-49).
11. He, C., Chen, F., Long, A., Qian, Y., & Tang, H. (2023). Improving the precision of monthly runoff prediction using the combined non-stationary methods in an oasis irrigation area. Agricultural Water Management, 279, 108161.
12. Meng, F., Xie, K., Liu, P., Chen, H., & Jiang, Y. (2023). Study on Extreme Precipitation Trends in Northeast China Based on Non-Stationary Generalized Extreme Value Distribution. arXiv preprint arXiv:2305.09881.
13. Bian, Y., Sun, P., Zhang, Q., Luo, M., & Liu, R. (2022). Amplification of non-stationary drought to heatwave duration and intensity in eastern China: Spatiotemporal pattern and causes. Journal of Hydrology, 612, 128154.
14. Gao, B., Hou, B., Xiao, W., Lyu, X., Cui, H., & Xue, W. (2022). Research on the Application of Non-stationary Model in Analyzing the Evolution Law of Reference Evapotranspiration.

15. Ren, M., Jiang, S., Ren, L., Weng, B., Wang, M., Cui, H., & Xu, C. Y. (2024). A new non-stationary standardised streamflow index using the climate indices and the optimal anthropogenic indices as covariates in the Wei River Basin, China. Journal of Hydrology: Regional Studies, 51, 101649.
16. Gomez, J., & Rivera, A. (2022). Non-stationary stochastic global optimization algorithms. Algorithms, 15(10), 362.
17. Lyu, Z., Ororbia, A., & Desell, T. (2023). Online evolutionary neural architecture search for multivariate non-stationary time series forecasting. Applied Soft Computing, 145, 110522.
18. Guo, Y., Di, C., & Li, S. (2022). A novel reduced parameter s-model of estimator learning automata in the switching non-stationary environment. Neural Computing and Applications, 34(9), 6811-6824.