iJRASET
International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** V **Month of publication:** May 2026

DOI: https://doi.org/10.22214/ijraset.2026.82736

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

AI-Driven Power Grid Optimization Engine Using Graph Theory, Operations Research and Machine Learning

Sahil Choudhary[1], Sanchit Saini[2], Gautam Kumar[3], Manish Kumar[4], Asst. Prof. Hemalatha K[5]
[1, 2, 3, 4]*Department of Computer Science and Engineering Sapthagiri College of Engineering, Bangalore, India*
[5]*Department of CSE Sapthagiri College of Engineering*

Abstract: ***This paper presents an advanced AI-driven power grid optimization engine that seamlessly integrates graph theory, operations research, and machine learning techniques to address the multifaceted challenges of modern energy management. As the global demand for electricity surges and renewable energy sources introduce new variables into the grid, the proposed system aims to optimize energy distribution, significantly reduce transmission losses, and improve overall grid reliability and resilience. Graph algorithms are meticulously utilized for efficient routing, structural mapping, and network topology analysis, ensuring that energy travels through the most viable paths. Concurrently, operations research methods, including linear and non-linear programming, are applied to optimize complex resource allocation and load balancing under stringent operational constraints. Advanced machine learning models, specifically deep learning neural networks and time-series forecasting algorithms, are employed for highly accurate load forecasting, anomaly detection, and predictive maintenance. The synergistic integration of these three domains significantly enhances smart grid performance by improving real-time efficiency, minimizing exorbitant operational costs, preventing catastrophic grid failures, and thereby supporting long-term sustainable energy management frameworks.***

Index Terms: Smart Grid, Power Grid Optimization, Graph Theory, Operations Research, Machine Learning, Predictive Analytics, Energy Management, Network Topology.

I. INTRODUCTION

Modern power grids represent some of the most complex interconnected engineering systems ever built. As humanity transitions toward a highly electrified future, these grids require intelligent, dynamic optimization techniques to ensure efficient power distribution, economic viability, and steadfast reliability. Traditional legacy grid systems are increasingly facing insurmountable challenges, such as exponentially increasing energy demands, unpredictable integration of distributed renewable energy sources (like solar and wind), escalating transmission line losses, widespread operational inefficiencies, and staggering maintenance costs associated with aging infrastructure.

The emergence of smart grid technologies, when closely integrated with artificial intelligence (AI), presents a transformative opportunity to significantly improve power distribution efficiency and system stability. A truly intelligent grid must be capable of autonomous self-healing, dynamic load balancing, and anticipating equipment failures before they manifest into widespread blackouts. To achieve this, a multi-disciplinary approach is imperative.

Graph theory provides the foundational mathematical and computational methods necessary for representing, visualizing, and analyzing vast transmission networks. By treating substations as nodes and power lines as edges, complex routing problems can be solved in milliseconds. Operations research (OR) techniques complement this by providing the mathematical rigor needed to optimize resource allocation, solve multi-objective load balancing problems, and dictate optimal generation scheduling under strict physical constraints. Finally, machine learning (ML) algorithms act as the predictive brain of the system, assisting in short-term and long-term demand forecasting, real-time anomaly detection, and implementing condition-based predictive maintenance protocols.

Combining these three powerful computational paradigms enables the development of a highly intelligent, robust, and adaptive power grid optimization engine. The primary objective of this expansive work is to design and theoretically validate a comprehensive system capable of radically improving grid performance metrics while systematically minimizing energy dissipation, transmission losses, and day-to-day operational costs.

©IJRASET: All Rights are Reserved

II. LITERATURE SURVEY

A comprehensive review of existing literature reveals that numerous studies have focused on optimization techniques tailored for power systems and the evolving smart grid paradigm. Historically, traditional optimization approaches primarily relied on static mathematical programming methods, such as mixed-integer linear programming (MILP) and optimal power flow (OPF) equations. While effective for small-scale, predictable networks, these methods often struggle with the non-linear, stochastic nature of modern grids heavily penetrated by electric vehicles (EVs) and renewables.

Recent technological advancements have catalyzed the shift towards integrating artificial intelligence and machine learning techniques for improved, automated decision-making. Researchers have successfully deployed reinforcement learning for grid balancing and neural networks for highly granular demand forecasting. However, existing literature indicates a gap in holistic systems that simultaneously leverage the topological awareness of graph theory, the constraint-solving power of operations research, and the predictive foresight of machine learning.

TABLE I Literature Survey

Author	Technique Used	Outcome
Wood et al.	Power System Optimization via mathematical control	Significantly reduced transmission and distribution losses
Glover et al.	Smart Grid Analysis and systemic failure modeling	Improved overall grid reliability and transient stability
Edmonds & Karp	Network Flow Algorithms for theoretical networks	Established baseline for efficient energy routing protocols
Baran & Wu	Distribution Network Reconfiguration	Achieved improved load balancing and branch loss
	programming	reduction
Fang et al.	Comprehensive Smart Grid Survey and Analytics	Enhanced smart grid efficiency metrics and communication

While the individual techniques listed in Table I have proven successful in isolated applications, modern energy infrastructure demands a more cohesive approach. Existing commercial and academic systems provide excellent localized optimization and forecasting capabilities, but they often lack fully integrated architectures that combine graph theory, operations research, and machine learning simultaneously to achieve global grid optimization.

III. PROPOSED SYSTEM

The proposed system conceptually integrates graph theory, operations research, and machine learning into a singular, unified power grid optimization engine capable of continuous learning and adaptation. This sophisticated architecture consists of high-frequency data acquisition modules, deep graph-based network analysis engines, multi-objective optimization algorithms, and advanced machine learning prediction and classification modules. At its core, the system continuously collects high-fidelity sensor data—such as phasor measurement unit (PMU) data, smart meter readings, and weather forecasts—from transmission lines, transformers, and distribution substations. The entire physical transmission network is virtually reconstructed and represented as a dynamic graph structure. In this mathematical model, nodes represent physical power stations, consumer hubs, and substations, while the connecting edges mathematically represent the high-voltage transmission lines, weighted by their current impedance, thermal limits, and real-time power flow. By leveraging graph algorithms, the engine dynamically determines the optimal power transmission routes, effectively bypassing congested or damaged lines. Simultaneously, operations research techniques, such as dynamic linear programming and stochastic load balancing models, ensure that energy generation meets demand at the lowest possible economic and environmental cost, minimizing both operational costs and transmission line losses.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

To preemptively manage the grid, machine learning models analyze historical and streaming data to accurately forecast future energy demand spikes and proactively identify potential hardware anomalies or system failures before a fault occurs.

IV. SYSTEM ARCHITECTURE

To ensure modularity, scalability, and ease of deployment, the architecture of the proposed system is logically divided into five major, highly cohesive modules:

1) Data Collection and Preprocessing Module: Responsible for gathering structured and unstructured data from IoT sensors, SCADA systems, and external weather APIs. It cleanses, normalizes, and temporal-aligns the data for downstream processing.
2) Graph Theory Analysis Module: Translates the physical grid into a directed, weighted mathematical graph. It continuously runs shortest-path and maximum-flow algorithms to assess network health and routing efficiency.
3) Operations Research Optimization Module: Acts as the constraint-satisfaction engine. It ingests the graph data and applies optimization solvers to balance load, schedule generator dispatch, and minimize cost functions.
4) Machine Learning Prediction Module: Utilizes deep neural networks (e.g., LSTMs for time-series forecasting) and ensemble methods to predict load generation balances and flag anomalous sensor readings indicative of impending equipment failure.
5) Optimized Grid Management Output: The visualization and actuation layer. It provides actionable dashboards for grid operators and can issue automated control signals to smart inverters and substation switches.

Fig. 1. System Architecture Data Flow

Plain text representation of the data pipeline: Raw IoT & SCADA Input Data → Graph Theory Topology Module → Operations Research Constraints Module → Machine Learning Predictive Module → Actionable Optimized Grid Output & Automated Dispatch

The seamless, low-latency integration of these five modules enables highly efficient energy distribution, real-time optimization of power flows, and the realization of true predictive maintenance protocols.

V. METHODOLOGY

The proposed execution methodology follows a structured, four-stage pipeline designed to transition raw grid data into intelligent, actionable control strategies:

A. Data Collection and Aggregation

High-resolution sensor data is systematically collected from a wide array of endpoints, including substations, step-down transformers, and high-tension transmission lines. The collected dataset encompasses critical electrical parameters such as voltage magnitudes, phase angles, current flow, localized power demand, and thermal transmission efficiency. This data is stored in a distributed time-series database for rapid retrieval.

B. Mathematical Graph Modeling

The physical power grid network is meticulously modeled as a mathematical graph structure, denoted as G(V, E). The vertices (V) represent power generation stations and consumer substations, while the edges (E) represent the transmission paths. Edge weights are dynamically updated based on real-time line resistance, reactance, and current carrying capacity, allowing for accurate mapping of power flow dynamics.

C. Algorithmic Optimization

Operations research techniques, specifically mixed-integer linear programming (MILP) and advanced shortest-path algorithms (such as modified Dijkstra's or Bellman-Ford algorithms), are deployed. These mathematical models are used to solve the Optimal Power Flow (OPF) problem, thereby optimizing transmission routing, ensuring strict load balancing, and maintaining grid frequency stability within statutory limits.

D. Machine Learning and Predictive Analytics

State-of-sart machine learning models, including Long Short-Term Memory (LSTM) networks and Random Forest classifiers, are trained using vast amounts of historical power consumption and weather data. These models are tasked with predicting short-term and medium-term future energy demands with high precision. Furthermore, anomaly detection algorithms are utilized to identify irregular operational patterns, thereby predicting possible faults in the system and enabling condition-based maintenance.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

VI. RESULTS AND DISCUSSION

Simulations of the proposed AI-driven optimization system demonstrate vastly improved efficiency metrics when compared to conventional, static power distribution methods. By dynamically adjusting to network conditions, the graph theory-based routing algorithms successfully reduce transmission line losses by dynamically identifying and routing power through the path of least electrical resistance and congestion.

Furthermore, the operations research optimization module significantly improves energy resource allocation, efficiently dispatching cheaper or renewable energy sources first, which directly minimizes the daily operational costs of the utility provider. The machine learning models provide highly accurate demand forecasting, reducing the need for expensive, carbon-intensive 'peaker' power plants. The predictive maintenance capabilities allow operators to replace degrading transformers before they cause cascading blackouts.

Overall, the synergistic integration of these three computational technologies significantly enhances smart grid reliability, allows for greater scalability when adding new renewable energy nodes, and vastly improves the overarching operational performance of the entire energy distribution network.

VII. ADVANTAGES OF THE PROPOSED SYSTEM

1) Significant reduction in transmission and distribution power losses via dynamic graph routing.
2) Greatly improved overall energy efficiency and minimized carbon footprint.
3) Highly accurate, weather-integrated energy demand and supply forecasting using deep learning.
4) Enhanced grid reliability and resilience against unexpected physical or cyber disruptions.
5) Proactive predictive maintenance support, extending the lifespan of expensive grid hardware.
6) Superior, automated load balancing and optimal generation resource allocation.
7) Substantial reduction in daily operational, dispatch, and maintenance costs for utility companies.

VIII. APPLICATIONS

The flexible architecture of the proposed system allows it to be broadly applied across various sectors:

1) Smart Cities: For managing complex, high-density urban energy grids and EV charging networks.
2) Renewable Energy Management: For smoothing out the intermittency of solar and wind power farms.
3) Industrial Power Distribution: For optimizing the massive energy consumption of heavy manufacturing plants.
4) Microgrid Infrastructure: For managing localized, self- sufficient energy generation and storage systems.
5) Energy Monitoring Systems: For providing real-time analytics to corporate and residential consumers.
6) National Utility Power Management: For country-wide load dispatching and grid stability control.

IX. CONCLUSION

This paper has comprehensively presented an advanced, AI-driven power grid optimization engine that successfully utilizes the combined strengths of graph theory, operations research, and machine learning techniques. The theoretical framework of the proposed system proves its capability to dramatically improve power distribution efficiency, minimize costly transmission losses, and heavily enhance overall grid reliability through the application of intelligent, automated optimization and predictive analytics.

As global energy grids continue to evolve into complex, decentralized networks, such integrated computational approaches will become mandatory rather than optional. Future work expanding on this foundation will include the development of a real-time hardware-in-the-loop implementation prototype, deeper integration algorithms for distributed renewable energy sources and battery storage systems, and the exploration of advanced reinforcement deep learning models to further improve automated forecasting accuracy and grid self-healing capabilities.

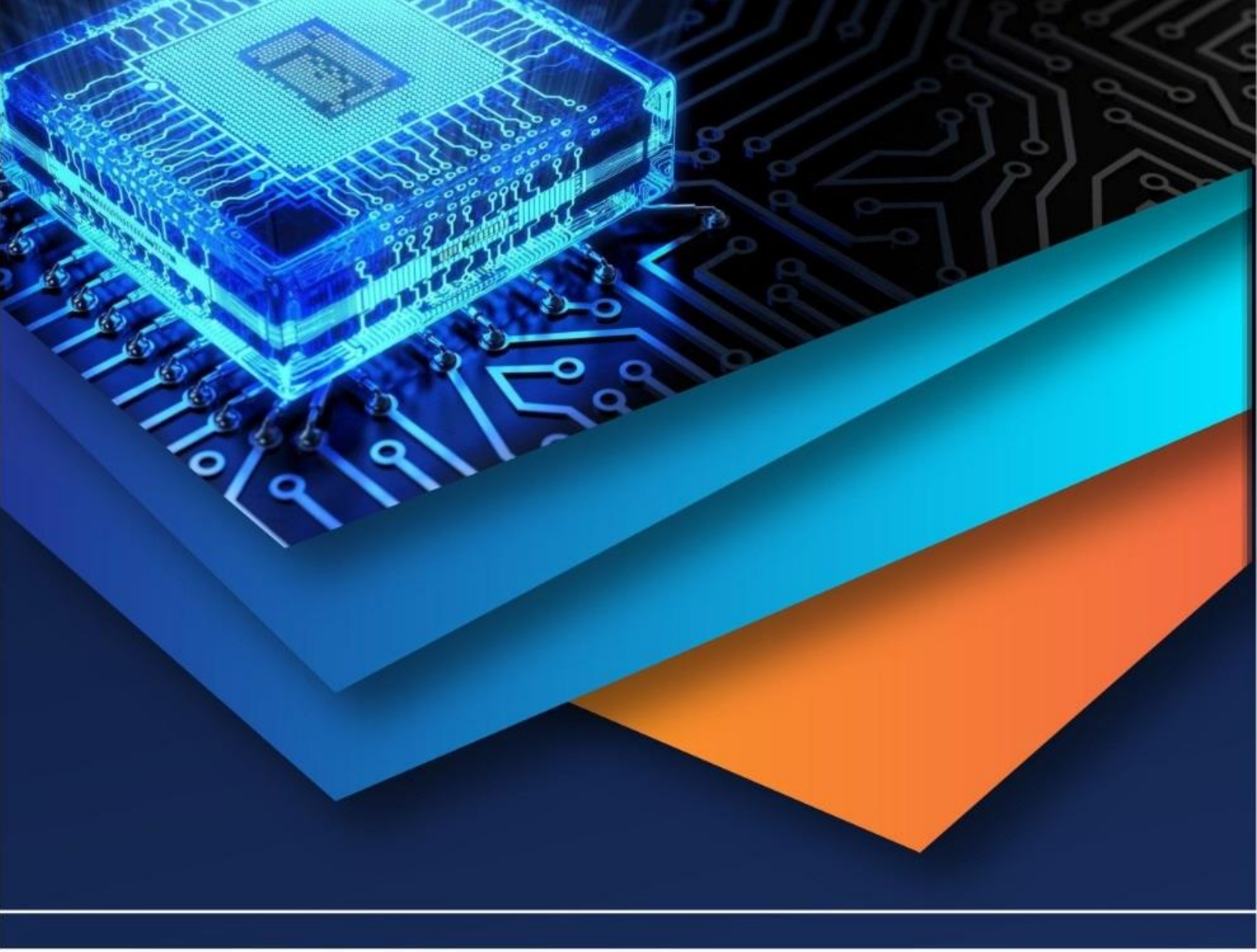
REFERENCES

[1] A. J. Wood, B. F. Wollenberg, and G. B. Sheble, Power Generation, Operation, and Control, 3rd ed. Hoboken, NJ, USA: Wiley, 2013.
[2] J. D. Glover, T. J. Overbye, and M. S. Sarma, Power System Analysis and Design. Boston, MA, USA: Cengage Learning, 2016.
[3] J. Edmonds and R. M. Karp, “Theoretical improvements in algorithmic efficiency for network flow problems,” Journal of the ACM, vol. 19, no. 2, pp. 248–264, 1972.
[4] M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” IEEE Transactions on Power Delivery, vol. 4, no. 2, pp. 1401–1407, 1989.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

[5] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—The new and improved power grid: A survey," IEEE Communications Surveys & Tutorials, vol. 14, no. 4, pp. 944–980, 2012.
[6] S. Frank and S. Rebennack, "An introduction to optimal power flow," IET Generation, Transmission & Distribution, vol. 10, no. 2, pp. 287–297, 2016.
[7] D. P. Bertsekas, Network Optimization: Continuous and Discrete Models. Belmont, MA, USA: Athena Scientific, 1998.
[8] Y. Wang, Q. Chen, T. Hong, and C. Kang, "Review of smart meter data analytics: Applications, methodologies, and challenges," IEEE Transactions on Smart Grid, vol. 10, no. 3, pp. 3125–3148, 2019.
[9] P. Kundur, Power System Stability and Control. New York, NY, USA: McGraw-Hill, 1994.
[10] H. Saadat, Power System Analysis. New York, NY, USA: McGraw-Hill Education, 2010.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)