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Research Article

Machine Learning Approaches toward Automated Electricity Supply Balancing Mechanisms

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Abstract

The increasing complexity of modern electricity networks has created significant challenges in maintaining supply-demand equilibrium, ensuring grid reliability, and managing fluctuating energy resources. Traditional electricity balancing mechanisms rely heavily on predefined operational rules, centralized control strategies, and human intervention, which limits their adaptability in environments characterized by renewable energy integration, dynamic consumption patterns, and distributed generation. This research paper investigates machine learning approaches for developing automated electricity supply balancing mechanisms capable of improving prediction accuracy, operational flexibility, and real-time decision-making in smart grid environments. The study presents a conceptual and technical framework that integrates machine learning models, predictive analytics, optimization strategies, and intelligent energy management principles to address the limitations of conventional balancing approaches.

The research adopts an analytical methodology based on synthesis of existing theoretical foundations and technological concepts from the provided literature. Machine learning techniques, including regression-based learning, predictive modeling, and data-driven decision systems, are examined as mechanisms for forecasting demand variations, detecting operational patterns, and dynamically adjusting electricity distribution strategies. The study positions automated balancing systems as an intersection of artificial intelligence, energy management, and connected data architectures. Existing discussions on artificial intelligence-driven energy management highlight the potential of predictive analytics for improving smart grid efficiency and resilience (Philip, 2025).

The findings indicate that machine learning-enabled balancing mechanisms can enhance grid responsiveness by continuously learning from historical consumption data, environmental conditions, generation variability, and network behavior. However, challenges related to data quality, model transparency, computational requirements, and integration with existing infrastructure remain significant barriers. The analysis demonstrates that successful implementation requires not only advanced algorithms but also robust data management frameworks and adaptive control architectures.

This paper contributes a structured understanding of how machine learning can transform electricity balancing from reactive management toward proactive, automated, and intelligent operation. The proposed approach provides theoretical and practical insights for researchers, energy system designers, and policymakers seeking scalable solutions for future smart grid development.

Keywords: Machine Learning, Smart Grid, Electricity Supply Balancing, Artificial Intelligence, Predictive Analytics, Energy Management, Automated Control, Demand Forecasting

INTRODUCTION

1.1 Background

The Electricity supply balancing represents one of the fundamental operational requirements of modern power systems. Electrical grids must continuously maintain equilibrium between electricity generation and consumption because significant deviations can affect frequency stability, reliability, and overall system performance. Historically, balancing mechanisms have depended on centralized monitoring systems, predefined operational rules, and manual intervention by grid operators. Although these approaches have supported traditional electricity networks, increasing complexity in energy systems has exposed limitations in their ability to respond efficiently to rapid changes.

The emergence of smart grids has introduced a more interconnected and data-intensive electricity environment. Smart grids incorporate advanced monitoring technologies, communication networks, distributed energy resources, and intelligent control mechanisms. These developments generate large volumes of operational data that can be utilized to improve decision-making. However, converting these data streams into actionable balancing decisions requires computational approaches capable of identifying patterns, predicting future conditions, and adapting to changing circumstances.

Machine learning provides a promising framework for addressing these requirements because it enables systems to learn from historical and real-time data without relying exclusively on manually programmed rules. Unlike conventional approaches, machine learning models can identify complex relationships between electricity demand, generation patterns, weather influences, consumer behavior, and network conditions. This capability enables automated systems to anticipate imbalance situations and initiate corrective actions before disruptions occur.

The application of artificial intelligence and predictive analytics in energy management has become increasingly important due to the growing need for efficient and resilient electricity networks. Predictive approaches allow energy systems to optimize resource allocation, improve forecasting capabilities, and enhance operational decisions. Research on artificial intelligence-based smart grid management emphasizes that predictive analytics can support improved energy efficiency and dynamic control strategies (Philip, 2025).

1.2 Problem Statement

Traditional electricity balancing mechanisms face several limitations when applied to modern energy environments. Conventional systems generally depend on deterministic models that assume relatively predictable demand and generation patterns. However, contemporary electricity networks experience increased uncertainty due to renewable energy sources, changing consumption behaviors, electric vehicle adoption, and distributed generation.

Renewable energy integration introduces additional variability because sources such as solar and wind power depend on environmental conditions. Sudden fluctuations in generation require rapid balancing responses that conventional methods may not efficiently provide. Similarly, electricity demand has become more dynamic due to changing industrial, commercial, and residential consumption patterns.

Another significant challenge is the increasing volume of operational data generated by smart grid technologies. While this data provides valuable information, extracting meaningful insights requires advanced analytical methods. Without intelligent processing mechanisms, large datasets remain underutilized, limiting the potential improvements in grid management.

Machine learning-based balancing mechanisms address these challenges by enabling automated analysis, prediction, and optimization. However, the development of reliable machine learning systems requires careful consideration of model accuracy, computational efficiency, interpretability, and compatibility with existing energy infrastructure.

1.3 Research Relevance

The relevance of automated electricity supply balancing extends beyond technical optimization. Reliable electricity management directly influences economic stability, industrial productivity, and sustainable energy development. As electricity systems transition toward decentralized and renewable-oriented architectures, intelligent balancing mechanisms become increasingly necessary.

Artificial intelligence-based energy management approaches demonstrate how predictive models can transform conventional grid operation into adaptive systems capable of responding to complex conditions (Philip, 2025). Machine learning contributes to this transformation by enabling continuous improvement through experience-based learning.

The theoretical importance of this research lies in connecting machine learning methodologies with energy system management principles. While machine learning has demonstrated success in various prediction and optimization tasks, its application to electricity balancing requires integration with domain-specific operational constraints.

1.4 Research Objectives

This research aims to examine machine learning approaches for automated electricity supply balancing mechanisms. The specific objectives are:

1. To analyze the theoretical foundations of machine learning applications in electricity balancing systems.

2. To examine how predictive analytics and intelligent models support automated energy management.

3. To develop a conceptual framework for machine learning-enabled supply balancing mechanisms.

4. To evaluate practical benefits, limitations, and implementation challenges associated with automated balancing systems.

5. To identify future research directions for intelligent electricity network management.

1.5 Scope and Significance

This study focuses on machine learning approaches applied to electricity supply balancing within smart grid contexts. The research considers predictive modeling, automated decision-making, data-driven optimization, and intelligent energy management frameworks. It does not focus on hardware-level power system engineering but examines computational and analytical mechanisms supporting automated balancing.

The significance of this research is based on the need for adaptive electricity systems capable of managing increasing complexity. By exploring machine learning-driven balancing mechanisms, the study contributes to understanding how artificial intelligence can support reliable, efficient, and sustainable energy operations.

LITERATURE REVIEW

2.1 Theoretical Foundations of Data-Driven Energy Management

The development of machine learning-based electricity balancing mechanisms is supported by theories of data-driven decision-making, predictive modeling, and intelligent system adaptation. Machine learning systems operate by identifying patterns within historical datasets and applying learned relationships to future situations. This approach differs from traditional analytical methods because the system continuously improves its performance as additional data becomes available.

The concept of connected data and relationship-based analysis is relevant to modern energy systems where multiple operational elements interact. Robinson's discussion of graph databases highlights the importance of representing relationships among interconnected data points, providing theoretical support for analyzing complex networks (Robinson, 2016). Electricity systems similarly consist of interconnected generators, consumers, transmission components, and control systems where relationships influence operational outcomes.

Predictive modeling forms another essential foundation for automated balancing. Support vector regression and similar machine learning approaches demonstrate how mathematical models can estimate future values based on complex input relationships (Smola & Schölkopf, 2004). In electricity systems, such approaches can be applied to demand forecasting, renewable generation prediction, and imbalance detection.

2.2 Artificial Intelligence in Smart Grid Energy Management

Artificial intelligence has become an important component of smart grid development because of its ability to process large-scale operational information. AI-based energy management systems utilize predictive analytics to improve resource allocation, optimize consumption patterns, and enhance grid reliability.

Philip (2025) emphasizes the role of artificial intelligence and predictive analytics in smart grid energy management, particularly in improving forecasting accuracy and enabling adaptive operational strategies. Such approaches demonstrate that automated energy systems require integration between analytical models and practical control mechanisms.

However, AI implementation in electricity systems involves challenges related to reliability and transparency. Energy infrastructure requires highly dependable decision-making because incorrect predictions or control actions may affect grid stability. Therefore, machine learning models must achieve not only accuracy but also operational robustness.

Recent advances in intelligent cloud computing demonstrate that deep reinforcement learning can improve predictive decision-making in dynamic and data-intensive environments. Such adaptive learning frameworks continuously optimize model performance based on changing operational conditions, offering valuable insights for developing intelligent electricity supply balancing mechanisms in smart grid systems (Mirza et al., 2025).

METHODOLOGY

3.1 Research Design and Methodological Framework

This research adopts a conceptual analytical methodology to examine the application of machine learning approaches for automated electricity supply balancing mechanisms. The methodology is designed around the integration of artificial intelligence concepts, predictive analytics principles, and smart grid management strategies. Rather than conducting an experimental evaluation using a specific electricity network dataset, the study develops a theoretical framework based on synthesis and critical interpretation of the provided literature.

The methodological framework consists of four interconnected layers: data acquisition, intelligent prediction, decision optimization, and automated balancing execution. These layers represent the functional stages required for transforming conventional electricity management systems into adaptive machine learning-driven environments.

The first layer, data acquisition, focuses on collecting information from multiple electricity system components. Modern smart grids generate diverse datasets including historical electricity consumption records, generation patterns, network operating conditions, and user behavior information. The quality and diversity of these datasets directly influence the effectiveness of machine learning models.

The second layer involves intelligent prediction, where machine learning algorithms analyze collected information to identify patterns and forecast future electricity conditions. Predictive models estimate expected demand levels, renewable energy availability, and possible supply-demand deviations. This predictive capability enables electricity systems to transition from reactive balancing toward proactive management.

The third layer involves decision optimization. After predicting future system conditions, intelligent algorithms determine appropriate balancing actions. These actions may include adjusting generation levels, modifying storage utilization, redistributing electricity flows, or influencing demand-side management strategies.

The final layer represents automated execution, where optimized decisions are implemented through grid control mechanisms. The effectiveness of this layer depends on communication infrastructure, system reliability, and compatibility between machine learning models and existing electricity management technologies.

3.2 Conceptual Model of Machine Learning-Based Electricity Balancing

The proposed conceptual model considers electricity balancing as a continuous learning process. Unlike traditional balancing systems that operate according to fixed rules, machine learning-based systems continuously update their understanding of grid behavior.

The model consists of five major components:

3.2.1 Data Collection and Integration Layer

The foundation of automated balancing is reliable data collection. Electricity networks contain multiple sources of operational information, including smart meters, generation monitoring systems, weather-related inputs, and consumer activity patterns.

Data integration is essential because electricity imbalance rarely results from a single factor. For example, reduced solar generation may coincide with increased residential demand during evening hours. A machine learning system must evaluate multiple variables simultaneously to identify potential imbalance conditions.

Graph-based approaches provide conceptual support for representing complex relationships among interconnected system elements. Robinson (2016) explains that graph databases enable analysis of connected information structures, which is relevant for electricity networks where generators, consumers, and transmission components form complex relationships.

The data layer therefore requires mechanisms capable of handling large-scale, interconnected, and continuously changing information.

3.2.2 Data Preprocessing and Feature Engineering

Raw electricity data cannot be directly applied to machine learning models without preprocessing. Electricity datasets may contain missing values, inconsistent measurements, noise, and irregular patterns. Therefore, preprocessing is required to improve data quality.

Feature engineering represents a critical stage where meaningful variables are extracted from raw information. In electricity balancing applications, possible features include:

• Historical demand trends

• Seasonal consumption variations

• Generation availability patterns

• Time-based electricity usage behavior

• Network operational indicators

The selection of appropriate features significantly affects model performance. Excessive irrelevant variables may reduce efficiency, while insufficient variables may limit prediction accuracy.

Machine learning systems must therefore balance computational complexity with predictive capability. Effective feature selection allows models to identify important relationships while maintaining operational efficiency.

3.3 Machine Learning Algorithms for Electricity Balancing

Different machine learning approaches provide different capabilities for automated balancing systems. The selection of algorithms depends on operational requirements, available data, and desired outcomes.

3.3.1 Regression-Based Prediction Models

Regression models are among the most commonly applied machine learning techniques for forecasting continuous values. In electricity systems, regression-based models can predict future electricity demand, generation levels, or imbalance magnitude.

Support vector regression provides a theoretical foundation for nonlinear prediction problems. Smola and Schölkopf (2004) explain that support vector regression can effectively model complex relationships by transforming input information into higher-dimensional representations.

For electricity balancing, regression models can estimate expected supply-demand differences:

Predicted imbalance = Forecasted demand − Forecasted generation

When the predicted imbalance exceeds predefined thresholds, automated control mechanisms can initiate corrective responses.

The advantage of regression approaches lies in their ability to provide quantitative predictions. However, their effectiveness depends heavily on training data quality and appropriate model configuration.

3.3.2 Classification-Based Decision Models

Classification algorithms categorize electricity system conditions into predefined states. For example, a system may classify conditions as:

• Balanced operation

• Potential shortage

• Excess generation

• Critical imbalance

Such classification enables rapid decision-making because the system does not need to calculate every possible response from the beginning.

Classification models are particularly useful for anomaly detection. If electricity behavior significantly differs from learned patterns, the system can identify unusual conditions and recommend corrective actions.

However, classification accuracy depends on the quality of historical examples. Rare events, such as extreme demand spikes or unexpected generation failures, may be difficult for models to learn effectively.

3.3.3 Neural Network-Based Learning Approaches

Neural networks are suitable for complex electricity systems because they can capture nonlinear relationships among multiple variables. Electricity consumption and generation patterns often depend on interconnected factors that cannot be represented through simple mathematical relationships.

Neural networks can process large datasets and identify hidden operational patterns. They are particularly useful when electricity systems include renewable energy sources, distributed generation, and dynamic consumer behavior.

The limitation of neural network approaches is reduced interpretability. Energy operators may require explanations for automated decisions, especially in critical infrastructure environments. Therefore, balancing systems must consider both predictive performance and transparency.

3.4 Predictive Analytics Framework for Automated Balancing

Predictive analytics forms the central operational mechanism of machine learning-based electricity balancing. The framework operates through continuous forecasting and adjustment cycles.

Initially, historical and real-time data are collected and processed. Machine learning models then generate predictions regarding future electricity conditions. These predictions are evaluated against operational requirements.

For example, if a system predicts that electricity demand will exceed available generation within the next hour, automated balancing mechanisms may increase stored energy utilization or adjust generation schedules.

Artificial intelligence-driven predictive analytics has demonstrated potential for improving energy management efficiency by enabling more adaptive decision processes (Philip, 2025). However, prediction alone does not guarantee improved grid performance. The predicted information must be effectively integrated into operational control systems.

Furthermore, intelligent cloud-based frameworks employing deep reinforcement learning have demonstrated the capability to optimize predictive decision-making under dynamic operational conditions. These adaptive approaches continuously learn from evolving datasets and can support more responsive, scalable, and intelligent electricity balancing strategies within modern smart grid infrastructures (Mirza et al., 2025).

RESULTS

The analysis of machine learning approaches toward automated electricity supply balancing demonstrates that intelligent models can significantly improve the adaptability and efficiency of electricity management systems. The findings indicate that the primary contribution of machine learning lies in its ability to transform large-scale operational data into predictive insights and automated responses.

The first major finding is that predictive capability represents the foundation of effective balancing mechanisms. Machine learning models can identify relationships among electricity demand, generation variability, and operational conditions. This enables grid systems to anticipate imbalance situations rather than responding after instability occurs.

The second finding is that automated balancing requires integration between prediction and control. Forecasting alone cannot solve electricity management challenges unless predictions are connected with decision mechanisms capable of implementing corrective actions. Therefore, successful systems require combined architectures involving data processing, machine learning models, optimization techniques, and automated execution.

The third finding concerns the importance of data quality. Machine learning performance depends strongly on accurate and representative datasets. Incomplete or biased operational information may reduce reliability and produce incorrect balancing decisions.

The fourth finding indicates that artificial intelligence-based energy management provides opportunities for improving smart grid efficiency. Predictive analytics approaches support dynamic resource allocation and adaptive operation, particularly in environments where electricity conditions change rapidly (Philip, 2025).

However, the findings also reveal several limitations. Machine learning models may experience difficulties when encountering unexpected events that are not represented in training data. Additionally, highly complex models may create challenges related to interpretation and operational trust.

Overall, the research findings suggest that machine learning-based balancing mechanisms provide a pathway toward more intelligent electricity systems. Their effectiveness depends not only on algorithmic advancement but also on reliable infrastructure, appropriate data management, and integration with practical energy management strategies.

DISCUSSION

The findings of this research demonstrate that machine learning approaches provide a significant opportunity for improving electricity supply balancing mechanisms through predictive intelligence, adaptive decision-making, and automated control. The transition from traditional balancing methods toward data-driven systems represents a fundamental change in electricity management philosophy. Instead of relying primarily on predefined operational responses, intelligent balancing mechanisms use historical and real-time information to anticipate system behavior and recommend appropriate actions.

A major implication of machine learning-based balancing is the improvement of operational responsiveness. Conventional electricity systems generally respond to imbalance after it occurs, whereas predictive models enable proactive intervention. By forecasting demand fluctuations and generation availability, machine learning systems can support earlier adjustments in generation scheduling, storage utilization, and demand management. This capability is increasingly important in modern smart grids where renewable energy sources introduce greater uncertainty. Artificial intelligence-based predictive analytics approaches similarly emphasize the importance of forecasting and adaptive strategies for efficient energy management (Philip, 2025).

The theoretical contribution of this research lies in connecting machine learning concepts with electricity system management. Previous approaches often consider machine learning as a forecasting tool; however, automated balancing requires a broader perspective where prediction, optimization, and control operate as integrated components. The combination of these elements creates an intelligent feedback system capable of continuously improving operational decisions.

The analysis also highlights important trade-offs. Higher model complexity may improve prediction accuracy but reduce interpretability. In critical infrastructure environments, electricity operators require confidence that automated decisions are reliable and explainable. A highly accurate but opaque model may create operational challenges because decision-makers may be unable to understand why a particular action was recommended.

Another important consideration is data dependency. Machine learning systems require extensive and representative datasets to achieve reliable performance. Electricity networks, however, continuously evolve due to technological changes, changing consumer behaviors, and new energy resources. Models trained on historical conditions may perform poorly when exposed to unfamiliar situations. Therefore, continuous learning mechanisms and periodic model evaluation are necessary.

The discussion also reveals that automation should not be viewed as complete replacement of human expertise. Electricity systems involve safety requirements, regulatory constraints, and complex operational decisions. Human supervision remains valuable for validating automated recommendations and managing unusual circumstances. A balanced approach combining artificial intelligence capabilities with expert oversight may provide greater reliability.

The relationship between connected data structures and intelligent energy systems further supports the importance of effective information management. Robinson (2016) highlights the value of connected data approaches for understanding complex relationships, which is relevant for electricity networks containing numerous interconnected components. Efficient data organization allows machine learning models to identify relationships that may remain hidden within traditional analytical methods.

Despite these advantages, several limitations remain. Implementation costs, cybersecurity concerns, computational requirements, and infrastructure compatibility can restrict widespread adoption. Furthermore, different electricity networks have unique operational characteristics, meaning machine learning solutions may require customization rather than universal application.

Overall, the discussion indicates that machine learning-based electricity balancing mechanisms represent an important development direction for future smart grids. Their success depends on achieving a balance between technological capability, operational reliability, transparency, and practical integration.

CONCLUSION

The increasing complexity of electricity networks requires advanced approaches capable of maintaining supply-demand balance under dynamic and uncertain conditions. This research examined machine learning approaches toward automated electricity supply balancing mechanisms by analyzing their theoretical foundations, technical components, operational benefits, and implementation challenges.

The study demonstrates that machine learning can enhance electricity balancing by enabling predictive analysis, pattern recognition, and automated decision-making. Unlike conventional approaches that depend mainly on predefined rules, machine learning-based systems can learn from historical and real-time information, allowing them to adapt to changing electricity conditions. This capability is particularly valuable in smart grid environments where renewable energy integration and changing consumption patterns increase operational uncertainty.

The proposed framework highlights that effective automated balancing requires integration of multiple components, including data acquisition, preprocessing, predictive modeling, optimization, and control execution. Machine learning algorithms such as regression models, classification approaches, and neural networks provide different capabilities for forecasting demand, detecting imbalance conditions, and supporting operational decisions.

The research also emphasizes that artificial intelligence and predictive analytics have significant potential for improving energy management efficiency. Intelligent approaches can support more flexible and resilient electricity systems by enabling proactive responses rather than reactive corrections (Philip, 2025). However, technological advancement alone is insufficient. Successful implementation requires reliable data management, secure communication infrastructure, transparent models, and compatibility with existing grid systems.

The study contributes to the understanding of machine learning as more than a prediction technology. It presents machine learning as an integrated intelligence layer capable of supporting continuous monitoring, forecasting, and automated balancing within future electricity networks.

Future research should focus on developing explainable machine learning models, improving real-time decision capabilities, and testing intelligent balancing frameworks using diverse electricity system environments. Additional investigation is also required into hybrid approaches that combine machine learning with traditional energy management methods to achieve greater reliability and operational acceptance.

In conclusion, automated electricity supply balancing mechanisms based on machine learning represent a significant pathway toward intelligent, adaptive, and sustainable power systems. As electricity networks continue to evolve, the integration of artificial intelligence-driven balancing strategies will become increasingly important for maintaining reliability and efficiency.

REFERENCES

1. M. Cummins, N. S. Rajan, C. Hodge, and R. Gouripeddi, “Patterns and Perceptions of Asynchronous Video Discussion in a Graduate Health Sciences Course,” J. Nurs. Educ., vol. 55, no. 12, pp. 706–710, Nov. 2016.

2. Dr. Nana Yaw Addo, & Ms. Efua Osei. (2025). A Unified Multi-Source Gene Expression Data Integration Framework Based on Advanced Clustering Techniques for Robust Biological Pattern Discovery . Applied Data Science Research, 6(04), 22-26. https://adsrjournal.online/publication/index.php/adsr/article/view/156

3. Dr. Andi Prasetyo, & Dr. Siti Rahmawati. (2025). A Scalable Bootstrap-Driven Feature Selection Framework for Generalized Linear Models in High-Dimensional Massive Data Analytics. Applied Data Science Research, 6(03), 10-13. https://adsrjournal.online/publication/index.php/adsr/article/view/148

4. Dr. Andika Prasetyo, & Siti Rahmawati, M.Sc. (2025). A Comprehensive Framework for Advancing Spatial Statistical Methods in Large-Scale Data Competition Environments. Applied Data Science Research, 6(01), 13-16. https://adsrjournal.online/publication/index.php/adsr/article/view/136

5. R. H. James, Visions for Australian Tertiary Education. 2017.

6. Dr. Nguyen Minh Quan, & Dr. Tran Thi Mai. (2025). Entropy-Based Information Measure Analysis for Ranked Set Sampling under the Farlie–Gumbel–Morgenstern Copula Framework. Applied Data Science Research, 6(06), 11-15. https://adsrjournal.online/publication/index.php/adsr/article/view/168

7. Mr. Kofi Asare, & Ms. Abena Owusu. (2025). A Stochastic Modeling Framework for Cinematic Editing Dynamics Using Self-Exciting Point Processes. Applied Data Science Research, 6(04), 16-21. https://adsrjournal.online/publication/index.php/adsr/article/view/155

8. Mr. Zahir Khan, & Ms. Laila Mohammadi. (2025). A Robust Statistical Framework for Quantifying the Relationship Between Body Mass Index and Body Fat Percentage Using Incomplete Longitudinal Proportion Data: Evidence from the Fels Cohort Study. Applied Data Science Research, 6(03), 5-9. https://adsrjournal.online/publication/index.php/adsr/article/view/147

9. Dr. Antoine Moreau, & Dr. Sophie Bernard. (2025). A Comprehensive Editorial Framework on Emerging Trends and Methodological Innovations in Network Data Science. Applied Data Science Research, 6(01), 9-12. https://adsrjournal.online/publication/index.php/adsr/article/view/135

10. J. Kuzilek, M. Hlosta, and Z. Zdrahal, “Open University Learning Analytics dataset,” Sci. Data, vol. 4, p. 170171, Nov. 2017.

11. Philip, P. G. (2025). Strategies for Energy Management in Smart Grids Using Artificial Intelligence and Predictive Analytics. The American Journal of Engineering and Technology, 7(02), 97–112. Retrieved from https://theamericanjournals.com/index.php/tajet/article/view/ai-predictive-analytics-energy-management-smart-grids

12. Dr. Rachmat Hidayat, & Ms. Nabila Putr. (2025). Advanced Computational Framework for t-Copula and Related Dependence Structures: Efficient Modeling, Optimization Techniques, and High-Dimensional Statistical Inference . Applied Data Science Research, 6(05), 7-11. https://adsrjournal.online/publication/index.php/adsr/article/view/158

13. I. Robinson, Graph Databases: New Opportunities for Connected Data. S.l. : Shroff Publishers Distributors Pvt Ltd, 2016.

14. M. H. Mirza, A. Budaraju, S. S. Sravanthi Valiveti, W. Sarma, H. Kaur and V. Malik, "Intelligent Cloud Framework for Dynamic Portfolio Risk Prediction Using Deep Reinforcement Learning," 2025 IEEE International Conference on Computing (ICOCO), Kuching, Malaysia, 2025, pp. 54-59, doi: 10.1109/ICOCO67189.2025.11334118.

15. Prof. Mehdi Hosseini, & Dr. Niloofar Karimi. (2025). Advanced Influence Diagnostics and Sensitivity Analysis Framework for Constrained General Linear Models with Parameter Restrictions . Applied Data Science Research, 6(05), 12-15. https://adsrjournal.online/publication/index.php/adsr/article/view/159

16. Mr. Zahir Khan, & Ms. Laila Mohammadi. (2025). A Spatiotemporal Transmission Modeling Framework for Assessing Business Reopening Risks in New York, New Jersey, and Connecticut Under Pre-Symptomatic and Asymptomatic COVID-19 Spread Dynamics. Applied Data Science Research, 6(04), 11-15. https://adsrjournal.online/publication/index.php/adsr/article/view/154

17. Dr. Lucas Petit, & Dr. Élise Martin. (2025). A Probabilistic Framework for Community Detection in Social Networks Using Mixed-Membership Clustering Models. Applied Data Science Research, 6(02), 19-22. https://adsrjournal.online/publication/index.php/adsr/article/view/145

18. A. J. Smola and B. Schölkopf, A tutorial on support vector regression, Stat. Comput., vol. 14, no. 3, pp. 199–222, Aug. 2004.

19. Mr. Budi Santoso, & Ms. Dewi Lestari. (2025). Layer-Adaptive Neural Ordinary Differential Equation Framework with Hierarchical Parameterization for Continuous-Time Dynamical System Modeling . Applied Data Science Research, 6(06), 16-20. https://adsrjournal.online/publication/index.php/adsr/article/view/169

20. Dr. Ahmad Rahimi, & Dr. Fatima Noori. (2025). A Pre-Symptomatic and Asymptomatic Transmission Modeling Framework for Assessing COVID-19 Business Reopening Risks in the New York–New Jersey–Connecticut Region. Applied Data Science Research, 6(02), 14-18. https://adsrjournal.online/publication/index.php/adsr/article/view/144