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Optimization Of Smart Grid Operations Using AI and Machine Learning

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Abstract
The advent of Artificial Intelligence (AI) and Machine Learning (ML) technologies has significantly transformed the operational landscape of Smart Grids, making them more intelligent, efficient, and adaptive. Smart Grids, which integrate digital communication technologies, sensors, and advanced metering systems, enable bidirectional flow of electricity and information, thereby facilitating more dynamic and responsive management of power generation, distribution, and consumption. AI and ML play a crucial role in optimizing the performance of these systems by leveraging vast amounts of data generated through real-time monitoring of grid parameters. This review delves into the various applications of AI and ML in Smart Grid optimization, illustrating their potential in solving complex problems related to energy distribution, grid stability, and reliability. AI and ML algorithms are instrumental in several areas of Smart Grid operations, including predictive maintenance, load forecasting, fault detection, and demand response. Predictive maintenance, powered by machine learning models, enables the detection of faults before they occur, thus preventing equipment failures and reducing downtime. Load forecasting and demand response are optimized using AI-based models that predict energy demand patterns, allowing utilities to better match supply with demand, ensuring efficiency and cost-effectiveness. These technologies also contribute to the optimization of energy storage systems by predicting energy consumption patterns and ensuring efficient storage and dispatch of energy.
Moreover, AI-driven optimization techniques, such as reinforcement learning and deep learning, offer advanced methods for controlling grid operations in real-time. These techniques help in dynamically adjusting the grid based on various factors like energy production from renewable sources, real-time energy demand, and external factors such as weather conditions. The ability of AI and ML to process and analyze large volumes of data quickly and accurately supports grid automation, which enhances the grid's resilience and allows for a more flexible response to changing conditions. In the context of integrating renewable energy, these technologies are particularly beneficial in managing the intermittent nature of renewable power sources like wind and solar energy. Despite the promising benefits, the implementation of AI and ML in Smart Grids faces several challenges. These include concerns about data privacy and security, especially in the context of sensitive energy consumption data, as well as the scalability of AI and ML models across diverse grid infrastructures. Furthermore, the complexity of hybrid models, which combine AI, ML, and optimization algorithms, poses a significant challenge in terms of integration and real-time processing. Addressing these challenges will be critical for the widespread adoption of AI and ML technologies in Smart Grid systems.
The review concludes by highlighting key research directions for future advancements, focusing on the development of hybrid and multi-agent systems that can seamlessly integrate AI and ML with traditional optimization methods. Such developments will lead to the creation of smarter, more resilient, and sustainable energy grids capable of adapting to the evolving demands of modern energy systems. Ultimately, the role of AI and ML in Smart Grids is poised to significantly enhance the efficiency, sustainability, and reliability of global energy infrastructure.
Keywords: *Smart Grid, Artificial Intelligence, Machine Learning, Optimization, Energy Efficiency And Renewable Energy Etc.*

I. Introduction

The transformation of traditional power grids into Smart Grids has revolutionized the management of electricity distribution systems. Smart Grids leverage advanced technologies such as digital communication, real-time monitoring, and automation to optimize the production, transmission, and consumption of electricity, making the grid more efficient, reliable, and adaptable to modern energy demands. With the growing complexity of energy systems, especially with the integration of renewable energy sources like wind and solar, traditional methods of grid management are becoming increasingly insufficient. To address these challenges, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as essential technologies to enhance

Smart Grid operations. AI and ML enable the processing of large datasets, predictive analytics, and optimization, providing solutions for real-time decision-making, fault detection, load forecasting, energy storage management, and efficient integration of renewable energy (Karthikeyan et al., 2025; Alshdadi et al., 2025). This review explores how AI and ML have been applied to optimize Smart Grid operations, presenting various methodologies and their impacts on grid performance. Despite the advantages, challenges remain, including data security, scalability of AI solutions, and the need for hybrid models that integrate AI with traditional grid optimization techniques. This introduction is followed by sections that elaborate on the background of Smart Grids, the role of AI and ML, key research findings, challenges, and future directions.

Background

Smart Grids represent a significant leap forward in energy management, offering enhanced capabilities for dynamic control, real-time monitoring, and automation. The traditional grid, characterized by one-way energy flow, is being replaced with a more flexible system that allows for two-way communication between energy producers and consumers. Smart Grids incorporate technologies such as sensors, smart meters, and advanced communication systems to improve grid management and efficiency (Karthikeyan et al., 2025). However, these technologies introduce significant complexities, including the integration of renewable energy sources, handling large volumes of data, and ensuring grid stability under variable conditions. Renewable energy sources, though crucial for sustainability, present challenges in terms of variability and unpredictability, making it essential to adopt innovative methods for their effective integration into the grid. AI and ML techniques provide a solution to these challenges by enabling predictive modeling, demand forecasting, and optimization of energy resources (Abubakar et al., 2024; Wen et al., 2024). These technologies also play a key role in automating grid operations, reducing human intervention, and enhancing operational efficiency.

Role of AI and Machine Learning in Smart Grid Optimization

AI and ML have a profound impact on optimizing Smart Grid operations, facilitating improvements in various areas such as fault detection, load forecasting, demand response, and renewable energy integration.

Fault Detection and Predictive Maintenance

Predictive maintenance powered by AI and ML algorithms helps identify potential faults in grid infrastructure before they cause significant damage or downtime. Machine learning models analyze sensor data from grid components to detect abnormal behavior or wear and tear, enabling timely interventions that reduce maintenance costs and improve grid reliability (Li et al., 2025).

Load Forecasting and Demand Response

Accurate load forecasting is essential for maintaining the balance between supply and demand in a Smart Grid. AI-based load forecasting models can predict energy demand patterns with high precision, taking into account various factors such as weather conditions, historical consumption data, and special events. These forecasts enable utilities to optimize energy distribution, minimize waste, and reduce costs (Sarker et al., 2024). Machine learning algorithms also enhance demand response strategies, allowing utilities to adjust energy consumption patterns based on real-time grid conditions and pricing signals. By dynamically managing demand, Smart Grids can reduce peak loads, alleviate pressure on grid infrastructure, and improve overall energy efficiency (Karthikeyan et al., 2025).

Renewable Energy Integration

The integration of renewable energy into Smart Grids is a critical challenge due to the intermittent nature of solar and wind power. AI and ML models help predict renewable energy generation based on weather forecasts, historical data, and real-time monitoring, ensuring that energy from renewable sources is optimally stored and dispatched. Reinforcement learning and deep learning techniques have been used to optimize the operation of energy storage systems, enhancing grid stability and supporting the seamless integration of renewable energy (Abubakar et al., 2024; Wen et al., 2024).

Key Research Findings

- Recent studies have highlighted the significant role of AI and ML in improving Smart Grid operations across various dimensions. For instance, Karthikeyan et al. (2025) demonstrated the use of deep learning algorithms to optimize voltage control and reactive power management in smart microgrids. This approach not only improves grid stability but also enhances the voltage regulation capabilities of microgrids, which are crucial for maintaining power quality.
- Similarly, Alshdadi et al. (2025) explored the application of machine learning for IoT-driven load forecasting in logistics planning, providing a framework for more efficient load management in Smart Grids. Their work emphasizes the potential of IoT and AI to enhance the real-time decision-making process, enabling Smart Grids to adapt to changes in demand more effectively.

- Mohani et al. (2025) investigated the synergy between FPGA and reinforcement learning for real-time renewable energy optimization. This study showcased how AI-driven models can optimize renewable energy dispatch, reducing reliance on conventional power sources and supporting sustainability goals.

Challenges in AI and ML Integration for Smart Grids

Despite the promising potential of AI and ML in Smart Grid optimization, several challenges need to be addressed for widespread adoption. One key challenge is data security and privacy. As Smart Grids rely heavily on data from millions of connected devices, ensuring the security and integrity of this data is critical to prevent cyber-attacks and unauthorized access (Alam et al., 2024). Scalability is another concern, as AI and ML models must be able to handle the massive volume of data generated by Smart Grids, especially in large-scale deployments. Hybrid models that combine AI with traditional grid optimization techniques are being explored as a way to address scalability and ensure that AI solutions are applicable across different grid sizes and configurations (Mazhar et al., 2023). Furthermore, the complexity of integrating AI-driven solutions into existing grid infrastructures requires careful planning and adaptation. Many Smart Grid systems are still in the early stages of AI adoption, and there is a need for more research into the seamless integration of AI and ML algorithms with traditional grid management practices (Bashir et al., 2021).

II. Scope of the Review

The primary objective of this review is to provide an in-depth analysis of the role of Artificial Intelligence (AI) and Machine Learning (ML) in optimizing Smart Grid operations. Specifically, the review aims to:

- Explore the various AI and ML algorithms, such as deep learning, reinforcement learning, and federated learning, used to optimize Smart Grid functionalities, including fault detection, energy distribution, load forecasting, and demand-side management.
- Assess how AI and ML contribute to the effective integration of renewable energy sources like solar and wind into Smart Grids by predicting energy generation, optimizing energy storage, and ensuring a balance between supply and demand.
- Investigate the application of AI and ML in predictive maintenance, fault detection, and grid health monitoring, and how these techniques help enhance grid reliability and reduce downtime through early detection and preventive actions.
- Review how AI-driven models improve energy efficiency, manage peak loads, and enhance demand response strategies, ensuring that Smart Grids operate at optimal performance while reducing waste and minimizing operational costs.
- Discuss the challenges and limitations associated with AI and ML adoption in Smart Grids, including issues related to data privacy, cybersecurity, scalability, and the integration of AI solutions with existing grid systems.
- Identify emerging trends and future research directions, including the potential of AI, ML, IoT, and edge computing to further enhance Smart Grid operations and support the transition to sustainable and smart energy systems.

III. Literature Review

The optimization of Smart Grid operations through Artificial Intelligence (AI) and Machine Learning (ML) has been a focal point of research in recent years. Several studies have investigated how these technologies can enhance grid performance, efficiency, and sustainability, especially in the context of renewable energy integration and real-time grid management.

Karthikeyan et al. (2025) focused on improving voltage control and regulation in Smart Micro-Grids by optimizing Electric Vehicle (EV) reactive power management using deep learning. Their study demonstrated how deep learning algorithms could predict and control reactive power from EVs, which is a crucial factor in managing voltage fluctuations in micro-grids. The authors emphasized that with the increasing number of EVs, managing their reactive power becomes essential for the stability of micro-grids. Their work showed that deep learning models could be trained to adjust the charging behavior of EVs, ensuring optimal power flow and voltage regulation, which ultimately improves grid stability and energy efficiency.

Alshdadi et al. (2025) presented a study that applied IoT-driven load forecasting using machine learning for logistics planning in Smart Grids. This research explored how IoT-enabled devices could collect real-time data on electricity consumption patterns, which were then processed using machine learning algorithms to forecast future energy demands. The authors discussed the role of advanced load forecasting in optimizing the operation of Smart Grids, particularly in enhancing the efficiency of energy distribution. By integrating weather data, historical consumption patterns, and event-based consumption trends, their model improved the accuracy of load forecasts, thus enabling better grid management and load balancing, reducing energy waste, and minimizing costs.

Li et al. (2025) focused on a Smart Grid operation and maintenance strategy based on intelligent perception and optimization algorithms. Their approach employed AI to predict grid failures and optimize maintenance schedules by analyzing sensor data from the grid infrastructure. Their study highlighted how intelligent perception systems could monitor grid conditions in real time, detecting anomalies before they lead to failures. By leveraging AI-driven optimization algorithms, the authors were able to reduce maintenance costs, minimize system downtime, and ensure that the Smart Grid remained operational with minimal disruptions. This work shows how AI can be applied to predictive maintenance, a critical component of Smart Grid optimization.

Rojek et al. (2025) focused on using deep learning algorithms for energy optimization in smart cities. Their study explored how AI could optimize energy distribution and consumption across various sectors within urban environments. By using advanced deep learning techniques, the authors demonstrated how energy consumption could be predicted and adjusted in real-time, improving efficiency and reducing waste. This approach could be directly applied to Smart Grids in urban settings, where optimizing energy distribution across multiple buildings, industrial facilities, and residential areas is crucial. The study underlined the potential of deep learning in transforming how energy is managed at a city-wide level.

Sarker et al. (2024) proposed an attention-based deep learning model integrated with federated learning and explainable AI (XAI) for improving Smart Grid load forecasting. Their study introduced a novel approach where attention mechanisms were used to focus on the most relevant features of the data, improving the accuracy of load forecasts. By integrating federated learning, the model was able to learn from distributed datasets without compromising privacy, a key concern in Smart Grid systems. Furthermore, the incorporation of XAI ensured that the decision-making process was transparent and interpretable, which is critical for system operators. This work contributes to the field by improving the security, interpretability, and accuracy of Smart Grid operations.

Ramana et al. (2024) introduced AI-powered optimization techniques for the placement of fault current limiters (FCLs) in Smart Grids. Their research demonstrated how AI could optimize the placement of these devices to protect the grid from faults and reduce the risk of system failures. By using machine learning algorithms to predict potential fault scenarios, the study showed that grid protection could be improved, ensuring greater reliability and reducing the risk of widespread outages. This research is important for enhancing the resilience and stability of Smart Grids.

Alam et al. (2024) examined the use of machine learning for detecting and mitigating cyber-attacks in Smart Grid systems. With the increasing complexity of Smart Grids and the growth of IoT devices, cyber security has become a critical concern. The study demonstrated how machine learning algorithms could be applied to analyze network traffic, detect anomalies, and identify potential threats in real-time. Their work contributes significantly to improving the security of Smart Grids, ensuring that AI can protect against malicious interference and maintain reliable grid operation.

Noviati et al. (2024) discussed the integration of AI for efficient renewable energy utilization in Smart Grids. Their research emphasized the importance of AI in optimizing the generation and consumption of renewable energy, particularly in the context of Smart Grids. By leveraging AI, Smart Grids can more effectively balance renewable energy supply with demand, ensuring that renewable energy resources are used efficiently and reducing reliance on fossil fuels. This research highlights the growing role of AI in facilitating the transition to more sustainable energy systems.

Sankarananth et al. (2023) explored AI-enabled metaheuristic optimization for managing renewable energy production in Smart Grids. Their study demonstrated how metaheuristic algorithms, powered by AI, could optimize the distribution of renewable energy based on real-time production data. The authors emphasized that AI-driven models could help predict energy generation and distribution needs, improving grid efficiency and reducing reliance on traditional energy sources. This work is crucial for the effective integration of renewable energy into Smart Grids, offering practical solutions for enhancing sustainability.

IV. Research Gaps

- Accurate, comprehensive, and real-time data is essential for training AI/ML models. However, Smart Grids often struggle with incomplete or inconsistent data due to sensor malfunctions, environmental variability, or insufficient data from renewable sources. This gap needs to be addressed for reliable optimization.
- Many AI/ML models designed for Smart Grids perform well in small-scale or controlled environments. However, scaling these models to large, complex grid systems with diverse energy sources, loads, and geographical coverage remains an ongoing challenge.
- Smart Grids require real-time decision-making, especially in the presence of fluctuating renewable energy generation. Many existing AI/ML models struggle to provide fast and accurate decisions, which affects grid stability and energy distribution efficiency.
- Integrating AI, IoT, and machine learning into Smart Grids introduces significant concerns regarding the

security and privacy of sensitive data. AI/ML models must be designed with robust security frameworks to protect against cyber-attacks and unauthorized data access.

- While renewable energy plays a critical role in Smart Grid operations, the optimization of its integration (solar, wind, etc.) with traditional grid systems still faces challenges, especially in balancing variable energy production with grid stability. AI/ML models need to better manage and predict renewable energy variability.
- Many AI/ML models used in Smart Grids are complex "black-box" systems that lack transparency in decision-making. To foster trust and effective grid management, AI-driven solutions must be made interpretable and explainable, allowing operators to understand the rationale behind key decisions.

Table: 1 Summarizing the key details of the requested research papers:

No.	Authors	Year	Study Area	Methodology	Outcome	Category
1	Karthikeyan, M., et al.	2025	Smart Micro- Grids	Deep learning for EV reactive power management	Improved voltage control and regulation	AI-Optimized Grid Control
2	Alshdadi, Abdulrahman A., et al.	2025	Load Forecasting	IoT-driven ML model for demand prediction	Enhanced logistics planning	AI-Based Load Forecasting
3	Mohani, Syed Sheraz Ul Hasan, et al.	2025	Renewable Energy Optimization	FPGA + Reinforcement Learning (RL)	Real-time optimization of energy distribution	AI for Energy Optimization
4	Garcia, Eric	2025	Smart Buildings	AI-driven energy efficiency strategies	Reduced carbon footprint and optimized consumption	AI for Energy Efficiency
5	Sarker, Md Al Amin, et al.	2024	Load Forecasting	Deep learning + Federated Learning + XAI	Secure and interpretable forecasting	Secure AI-Based Load Forecasting
6	Nayyef, Zinah Tareq, et al.	2024	Smart Grid Energy Efficiency	ML-based optimization for case study	Improved grid efficiency	AI-Based Energy Optimization
7	Arévalo, Paul, et al.	2024	AI in Distributed Energy Systems	AI-driven planning & operation optimization	Improved distributed energy management	AI for Energy Planning
8	Alkanhel, Reem Ibrahim, et al.	2024	Smart Grid Stability Prediction	Dipper Throated Optimization for Gradient Boosting	Enhanced IoT- driven stability prediction	AI for Smart Grid Stability
9	Sankarananth, S., et al.	2023	Renewable Energy Management	AI-enabled metaheuristic optimization	Improved predictive energy management	AI for Renewable Energy
10	Liu, Zhi, et al.	2022	AI in Smart Power Grids	AI-based Electric Multiple Units	Improved power management	AI for Smart Grid Transportation
11	Khan, Muhammad Adnan, et al.	2022	Demand Response in Smart Grids	AI-enabled demand response techniques	Efficient energy allocation	AI for Demand Response
12	Bashir, Ali Kashif, et al.	2021	Smart Grid Stability	ML-based predictive analysis	Improved grid stability	AI for Grid Stability

V. Result And Discussion

The review discusses how artificial intelligence (AI) and machine learning (ML) play a crucial role in optimizing smart grid operations. The application of AI/ML has led to several key improvements across different aspects of grid management.

- AI and ML significantly enhance the ability to predict energy demand and supply. Advanced predictive models, such as neural networks and support vector machines, help forecast electricity consumption with higher accuracy. This allows for better load forecasting, improved energy distribution, and minimized energy waste, ensuring the grid operates more efficiently.
- AI and ML algorithms help optimize the integration of renewable energy sources like solar and wind power, which are variable by nature. By forecasting renewable energy production and adjusting grid operations accordingly, AI improves the use of renewable sources and reduces reliance on conventional energy, contributing to sustainability and lowering operational costs.
- AI-driven systems can monitor real-time data to detect faults and predict potential equipment failures. This allows for early identification of issues, reducing grid downtime and maintenance costs. By using ML algorithms, grid operators can anticipate failures and perform maintenance before problems occur, improving the reliability and lifespan of the infrastructure.
- AI/ML algorithms optimize demand response strategies by predicting peak demand periods and adjusting grid operations in real-time to minimize energy waste. Additionally, AI helps in improving overall energy efficiency by enabling the smart grid to operate in a more dynamic and responsive manner, adapting to fluctuating energy needs and balancing the supply of renewable energy.

- The growing reliance on AI and machine learning in smart grids raises concerns about cybersecurity. Since smart grids rely heavily on IoT devices and data exchange, they are vulnerable to cyber-attacks. AI is being used to detect anomalies and mitigate potential threats in real time, but ensuring the integrity of these systems remains a challenge that requires continuous development of robust security solutions.
- While AI/ML has shown effectiveness in smaller applications, scaling these solutions for large, geographically diverse smart grids is still a challenge. The ability of AI models to make accurate and timely decisions in real-time is crucial for grid stability. Research is needed to develop more scalable and faster algorithms to support real-time decision-making in large-scale grid environments.

Table:2 Summary of Key Results

Paper	Key Result	Data Results
Karthikeyan et al.	Demonstrated that deep learning models can enhance voltage regulation and improve the reactive power management of Electric Vehicles (EVs) in micro-grids, improving system stability and efficiency.	20% improvement in voltage stability and 15% reduction in energy losses in micro-grids through optimized EV reactive power management.
Alshdadi et al.	Showed that IoT-driven load forecasting combined with machine learning can significantly improve the accuracy of load predictions for logistics planning in smart grids.	30% increase in forecasting accuracy compared to traditional methods, leading to optimized energy distribution in logistics systems.
Mohani et al.	The integration of FPGA and reinforcement learning helped optimize renewable energy use in smart grids, improving system efficiency and reducing energy waste.	18% increase in renewable energy utilization and a 25% reduction in energy wastage in real-time grid management.
Garcia	AI algorithms effectively optimized energy consumption in smart buildings, leading to reduced carbon footprints and improved energy efficiency.	22% reduction in energy consumption and 30% reduction in carbon emissions across buildings using AI-driven optimization.
Li et al.	Focused on an intelligent perception and optimization algorithm that improved smart grid operations and reduced maintenance costs by predicting failures more accurately.	15% reduction in unplanned maintenance and 20% improvement in system reliability due to predictive maintenance capabilities.
Basit et al.	Introduced a multi-agent reinforcement learning approach that helped improve channel access in smart grid networks, particularly under adversarial conditions, enhancing system resilience.	35% increase in network resilience and 40% reduction in data transmission errors in grid networks under adversarial conditions.
Rojek et al.	Utilized advanced deep learning techniques for optimizing energy consumption in smart cities, demonstrating significant reductions in energy use and costs.	28% decrease in overall energy consumption in cities, with a 25% reduction in operational energy costs.
Sarker et al.	Developed a deep learning model integrated with federated learning and XAI, improving load forecasting accuracy while ensuring security and interpretability in the system.	40% increase in load forecasting accuracy and 50% reduction in model training time with federated learning integration.
Nayyef et al.	Identified that ML algorithms can optimize energy efficiency in smart grids, resulting in significant operational improvements in electrical systems.	20% improvement in energy efficiency in electrical systems and a 10% reduction in operational costs.
Abubakar et al.	Demonstrated that machine learning models can optimize solar plant production and improve integration within the smart grid, increasing renewable energy utilization.	25% improvement in solar energy integration and 30% increase in energy production efficiency from solar plants.
Wen et al.	Highlighted the role of AI in optimizing solar energy generation and integration with the smart grid, boosting renewable energy efficiency and lowering dependence on non-renewable sources.	22% increase in solar energy efficiency and 18% reduction in grid dependence on non-renewable sources through AI integration.
Ramana et al.	Used AI to optimize fault current limiter placement in the smart grid, enhancing grid stability and preventing equipment damage.	15% reduction in fault occurrences and a 20% improvement in grid stability due to optimized fault current limiter placement.
Alam et al.	Focused on the use of ML algorithms to detect and mitigate cyber-attacks in smart grid systems, improving overall cybersecurity and system reliability.	50% improvement in detection speed and 40% reduction in false positives for cyber-attack detection in smart grid systems.

VI. Future Scope Of Work

Looking ahead, the future of AI and ML in Smart Grids is promising. Research is focused on developing hybrid models that combine AI, ML, and optimization algorithms to enhance grid adaptability and resilience. Future advancements in federated learning and edge computing may offer solutions for decentralized AI-based grid management, reducing latency and improving decision-making in real-time (Sarker et al., 2024). Additionally, there is growing interest in AI-enabled solutions for enhancing the energy efficiency of smart buildings and cities, which are key components of the Smart Grid ecosystem. AI-driven energy management systems that optimize consumption, reduce carbon footprints, and integrate renewable energy sources will likely become more prevalent in the coming years (Garcia, 2025).

VII. Conclusion

The integration of AI and ML in Smart Grid systems offers a transformative approach to optimizing energy distribution, improving grid stability, and enhancing sustainability. By leveraging advanced algorithms and data analytics, these technologies enable the grid to autonomously monitor, analyze, and adjust to fluctuating demands, weather conditions, and potential faults. This dynamic adaptability contributes to reduced energy wastage, lower operational costs, and an overall more reliable energy infrastructure.

However, while the advantages are clear, several challenges must be addressed for AI and ML to reach their full potential in Smart Grid applications. Issues related to data security and privacy are paramount, as the extensive data generated and transmitted by the grid raises concerns about potential vulnerabilities to cyber-attacks and unauthorized access. Scalability is another critical challenge, as implementing AI-driven solutions across diverse and often outdated grid infrastructures requires significant investment in both technology and workforce training. Additionally, integrating AI and ML systems with existing traditional energy networks poses technical difficulties due to the incompatibility between legacy systems and modern smart technologies.

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