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Harnessing AI for smart demand forecasting in renewable-powered grids

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Abstract

The implementation of renewable energy systems creates power grid instability because solar and wind power generation operates intermittently thus requiring sophisticated demand forecasting systems for maintaining grid stability and efficiency. This research examines how artificial intelligence (AI) transforms smart demand forecasting for renewable-powered grids by solving essential problems related to intermittency management and real-time data processing and existing grid infrastructure integration. The analysis demonstrates how AI techniques including machine learning (random forests, gradient boosting) and deep learning (LSTMs, transformers) and hybrid physics-AI models outperform traditional statistical methods in terms of accuracy and adaptability. The research uses California ISO and European smart grids as case studies to show how AI-based forecasting improves demand management and decreases fossil fuel backup usage while supporting sustainability targets. The paper investigates system architecture needs while emphasizing the importance of IoT and edge computing and big data analytics. The research identifies major adoption challenges which include data quality issues and computational expenses before recommending future directions for scalable and resilient energy systems through federated learning and predictive maintenance.

Keywords: Artificial Intelligence (AI); Renewable Energy Integration; Smart Grid Optimization; Demand-Side Management; Machine Learning (ML) And Deep Learning (DL); Time-Series Forecasting; IOT and Edge Computing; Hybrid AI-Physical Models

1 Introduction

The topics of global warming, climate change, and environmental damage receive frequent discussion among researchers, academics, and business professionals. The leading cause of ecological damage and global warming problems stems from the release of greenhouse gases through the use of non-renewable energy sources, including coal, oil, and petroleum. Society now embraces Renewable Energy Sources (RESs) because they offer both economic benefits and significant help in lowering carbon emissions (Talaat, 2025). The energy sector has started to adopt RESs because of their growing popularity. The Figure. 1 presents various energy resources, including bioenergy, wind energy, hydropower, and Photovoltaic (PV) energy (Talaat, 2025). The worldwide energy infrastructure is experiencing a major transformation because solar and wind renewable energy sources will generate more than 40% of global electricity during 2030 according to the International Energy Agency (IEA, 2023). The transition toward renewable energy systems creates new operational challenges for grid operators because of decarbonization targets and decreasing technology expenses (Talaat, 2025). RES-dominated power grids experience built-in supply-demand mismatches because renewable energy sources have intermittent power generation patterns and depend on weather conditions and vary by geographic region (Onwusinkwue, 2024). Traditional forecasting methods based on historical load patterns and deterministic models fail to capture these nonlinear dynamics which risks grid instability, energy curtailment, or costly fossil-fuel backup reliance. The challenges require artificial intelligence (AI) to function as a fundamental solution (Onwusinkwue, 2024). AI uses machine learning (ML) and deep learning (DL) techniques including LSTMs, transformer models and reinforcement learning to perform granular adaptive demand forecasting that incorporates real-time

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weather data and consumer behavior shifts and distributed generation impacts. The combination of edge computing and IoT-enabled sensor networks enables AI to process high-frequency grid data which creates a closed loop between forecasting and automated demand response (Onwusinkwue, 2024).

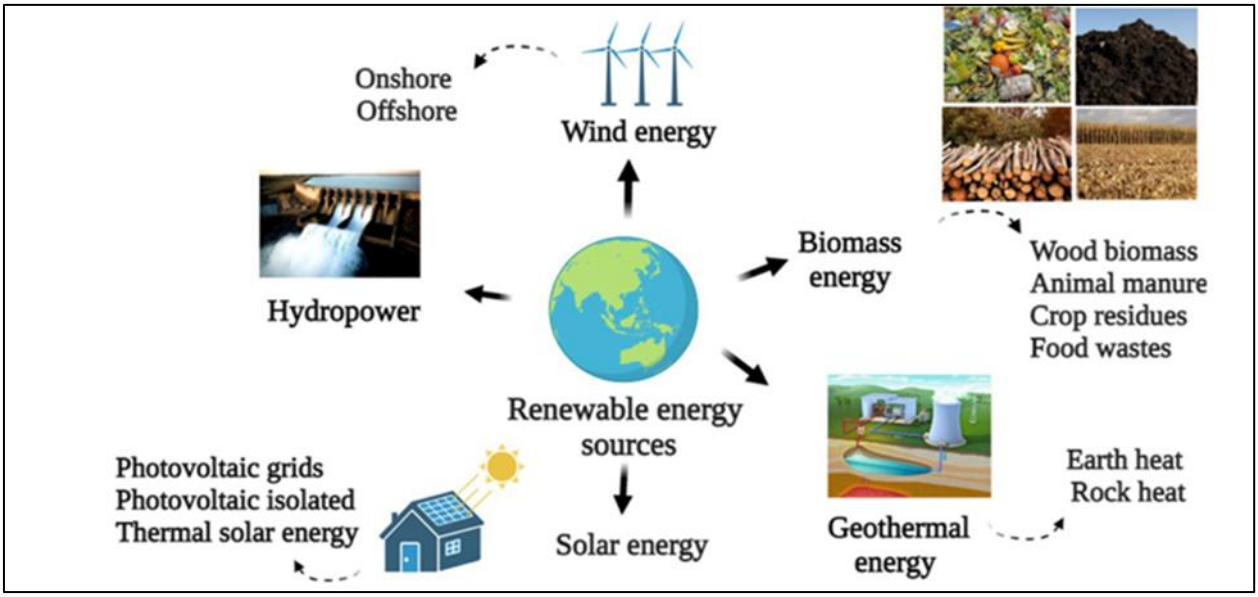

Figure 1 Various Types of Renewable Energy (Talaat, 2025)

The research evaluates the complete application of AI systems for smart demand forecasting in power grids that rely on renewable energy sources. The paper begins by explaining basic demand forecasting principles and the difficulties that arise from integrating renewable energy sources. The paper examines current AI methods through their implementation in California ISO and European smart grid systems. The paper discusses how AI forecasting can help reduce emissions and achieve ESG goals. We then discuss the sustainability implications of AI-driven forecasting, highlighting its potential to reduce emissions and aligning with ESG goals. Finally, we identify emerging trends—such as federated learning and predictive maintenance—and outline policy recommendations to accelerate adoption. This work aims to equip researchers, grid operators, and policymakers with actionable knowledge to harness AI for a more resilient and sustainable energy future by bridging technical innovation with operational and strategic insights.

2 Background and Literature Review

The integration of renewable energy sources (RES), such as solar and wind power, into power systems requires modernization through innovative grid technologies. Smart grids provide the ability to transmit power in both directions while enabling real-time monitoring and sophisticated control systems to manage the unpredictable output of RES (Ohalete, 2023). The intermittent nature of these sources, which causes solar power to disappear at night and wind power to vary by location, presents significant difficulties for grid operators to achieve supply-demand equilibrium (Ohalete, 2023).

Traditional demand forecasting methods, which include time-series approaches such as Auto Regressive Integrated Moving Average (ARIMA) and exponential smoothing, have performed well for conventional power systems with predictable load patterns (Ohalete, 2023). These methods depend heavily on historical consumption data and assume stationary relationships between variables. These methods fail to detect the complex, non-linear relationships that arise from renewable generation variability, distributed energy resources, and changing consumption behaviors. Recent developments in artificial intelligence have transformed the way demand forecasting is conducted (Murgod, 2025). Random forests and support vector machines are machine-learning techniques that are superior in handling high-dimensional data from smart meters and weather sensors. Deep learning approaches, particularly Long Short-Term Memory (LSTM) networks and transformer models are very successful in capturing temporal dependencies in energy time-series data (Murgod, 2025). Hybrid models that combine physical grid knowledge with data-driven AI techniques are emerging as particularly promising for maintaining interpretability while improving accuracy (Ohalete, 2023). Recent advancements in AI technology have enhanced the accuracy and efficiency of energy system operations across various domains. The deep learning architecture of Long Short-Term Memory (LSTM) networks has improved short-term forecasting. The results show that LSTM models can reduce hour-ahead load prediction errors by 25–40%

compared to conventional statistical approaches. The authors demonstrate that CNNs are well-suited for handling spatial weather data in the field of renewable energy prediction, resulting in more accurate forecasts of solar energy output (Yousef, 2023). The authors emphasize the significance of AI-based forecasting in enhancing the coordination between distributed energy resources and central grid operations. The optimization process ensures efficient load balancing, minimizes curtailment, and improves overall grid reliability (Murgod, 2025).

The implementation of AI solutions on the scale continues to face ongoing difficulties despite recent progress. The research community actively studies three main issues, which include data quality requirements com, reputational costs, and model interpretability (Murgod, 2025). The following section introduces the essential principles of these forecasting methods before analyzing specific AI methods and their practical applications (Onwusinkwue, 2024).

3 Demand forecasting fundamentals

The management of power grids depends on electricity demand forecasting because it helps utilities predict consumption patterns to maintain system reliability. The forecasting process divides into three time-based categories which include short-term and medium-term and long-term predictions (Boroojeni, 2017). The operational decisions for unit commitment and demand response receive support from short-term forecasting which predicts consumption patterns from minutes to days in advance. The time frame of medium-term forecasting enables organizations to schedule maintenance and plan reserves (Boroojeni, 2017). The long-term forecasting period of years enables organizations to determine infrastructure investment needs and capacity expansion requirements. Statistical accuracy metrics evaluate the performance of demand forecasting models (Senthil Kumar, 2024). The evaluation of forecasting models uses three main metrics: Mean Absolute Error (MAE) calculates average absolute differences between predictions and actual values and Root Mean Square Error (RMSE) penalizes large errors and Mean Absolute Percentage Error (MAPE) measures errors as percentage values (Senthil Kumar, 2024). The performance of classification models is evaluated through accuracy scores and R-squared (R^2) values (Senthil Kumar, 2024). The choice of metric depends on the specific use case and the level of error tolerance. Accurate forecasting is essential in systems with high renewable energy penetration. Inaccurate forecasts can cause inefficient dispatches, increased costs, and risks of blackouts. Poor demand forecasts may require expensive standby generation or result in market penalties (Boroojeni, 2017). Inaccuracies in forecasting can lead to increased reliance on fossil fuels for unexpected demand. As renewable integration grows, precise demand forecasting becomes vital for grid stability and sustainability (Boroojeni, 2017).

3.1. AI Techniques for Demand Forecasting

Operations management relies on advanced artificial intelligence (AI) techniques, including machine learning (ML) and deep learning (DL), to perform demand forecasting as a fundamental operational requirement. The two methods offer distinct advantages for specific applications, enhancing both accuracy and effectiveness in supply chain management and energy management systems (Nandha Gopal, 2025).

3.2. Deman Forecasting on the Basis of Machine Learning

The application of machine learning models in demand forecasting has been widespread because they excel at processing complex and nonlinear data relationships. The field primarily employs linear regression, along with random forest and ensemble methods, as its main techniques (Islam, 2024). Research on electricity demand forecasting demonstrates that ML models that use deep learning and big data analytics perform better than conventional forecasting approaches. Machine learning models demonstrate an exceptional ability to adapt to various situations, making them particularly useful for markets with rapidly changing demand patterns (Islam, 2024) (Nandha Gopal, 2025).

3.3. Deep Learning Techniques

The analysis of sequential and time-dependent data benefits significantly from Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and transformers, as these models demonstrate exceptional power. These models achieve outstanding results in pattern recognition, producing highly accurate predictions (Birim, 2022). The models enable supply chain operations to perform sequence forecasting and identify intricate patterns that basic ML models would miss. The application of LSTM networks in financial and logistics forecasting for U.S. supply chains has delivered substantial improvements in predictive accuracy (Islam, 2024).

3.4. Hybrid Models

The combination of AI techniques with traditional physical or grid-based models yields hybrid systems that enhance forecasting accuracy by leveraging multiple methodologies (Aderibigbe, 2023). Research into solar energy forecasting models indicates that integrating deep learning with ensemble and hybrid models yields more reliable forecasts. The implementation of similar methods in energy demand forecasting has shown better prediction results through the analysis of multiple influencing factors and diverse data sources (Aderibigbe, 2023).

The application of AI forecasting models is becoming increasingly significant in microgrid systems. A microgrid functions as a self-contained power network that operates independently or in conjunction with the primary power grid by combining distributed energy resources (DERs), including solar PV systems, wind turbines, and battery storage facilities as shown in Figure 2 (Talaat, 2025). AI technologies within microgrid systems predict local energy requirements, renewable power output, and storage patterns to optimize scheduling operations and real-time control functions (Islam, 2024). A standard microgrid system consists of smart meters, local weather sensors, edge-based computing nodes, and a central energy management system (EMS) that implements AI models to predict load and dispatch resources accordingly (Birim, 2022). The implementation of AI-based forecasting systems in microgrids enhances their operational independence, ability, and financial efficiency, particularly when serving remote locations or experiencing grid failures. Multiple case studies have demonstrated the relative performance of AI models in various operational settings. The study evaluated LSTM, Boost, and ARIMA models across various utility datasets and found that LSTM performed best in terms of RMSE and MAPE under volatile demand conditions (Talaat, 2025).

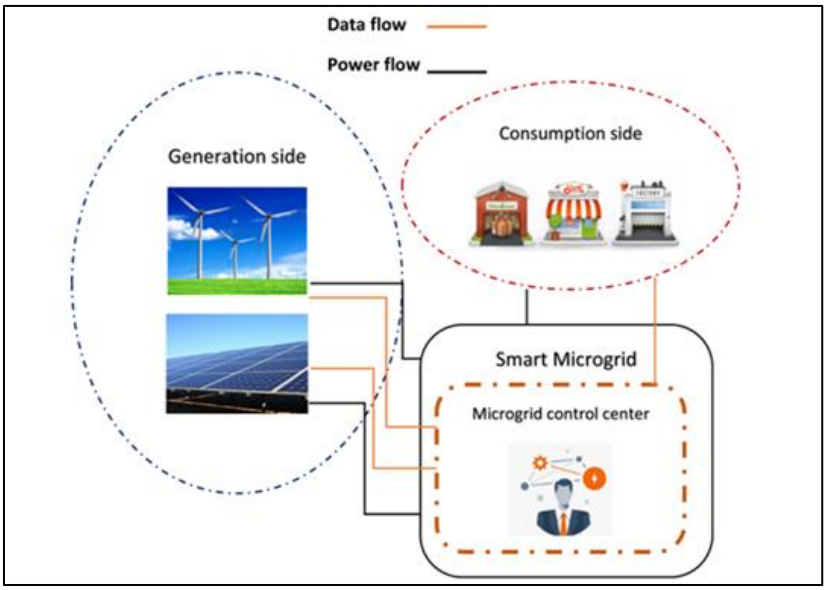

Figure 2 Microgrid Architecture (Talaat, 2025)

In contrast, Boost performed best in datasets with structured and periodic patterns. These results underscore the importance of selecting models that align with system characteristics and operational objectives (Talaat, 2025).

3.5. Renewable Energy Integration Challenges

The implementation of solar and wind renewable energy sources into existing power grids faces multiple obstacles because their power output varies unpredictably. Artificial intelligence (AI) provides effective solutions to these challenges which improve operational efficiency and economic viability and reliability of renewable energy systems.

3.5.1 Intermittency and Variability

The power output of solar and wind energy systems depends on weather patterns and daily time cycles which causes their intermittent nature. Power grid stability faces challenges because of the variable output patterns that result from weather conditions and time-dependent changes (Liang, 2017).

3.5.2 Grid Management During Low-Output Periods

The proper management of power grids during periods of low power output such as nighttime or cloudy days is essential for maintaining power supply stability. The management of power grids requires both energy storage systems and advanced grid management techniques. AI technologies help manage these systems through predictive energy production pattern analysis and resource optimization to maintain continuous supply during periods of low renewable generation (Hamdan et al., 2024; Liang, 2017).

3.5.3 Implementing AI Technology for Predicting Renewable Power Generation and Consumer Demand

The challenges are addressed through AI technology which improves both renewable energy generation prediction and demand management. Machine learning algorithms process extensive datasets about weather patterns and consumption trends to enhance the accuracy of these predictions (Adewumi et al., 2024). AI enables grid operators to optimize their operations through accurate predictions of energy demand and renewable generation which helps them better manage diverse energy sources (Onwusinkwue et al., 2024).

3.5.4 Optimizing Renewable Energy Systems

The implementation of AI technology enables better performance optimization and integration of renewable energy systems through predictive maintenance and energy optimization. The system achieves its goals by reducing equipment downtime while extending infrastructure lifespans and maximizing energy production (Onwusinkwue et al., 2024). The predictive maintenance system powered by AI detects equipment faults in advance which leads to better system reliability and reduced operational expenses (Koba et al., 2024).

3.6. System Architecture and Data Requirements

The architecture and data requirements of smart grids play a crucial role in achieving efficient operation and integration. The following summary is based on the available literature.

3.6.1 Data Requirement Types

- Weather Data: Weather data serves as an essential component for predicting energy consumption and supply management particularly in power grids that depend heavily on renewable energy sources including solar and wind power. Weather conditions directly affect the energy output of these sources (PRIMEDIA et al., 2018).
- Historical Usage Data: The analysis of historical energy consumption data enables the prediction of future energy requirements which helps the grid to operate efficiently by balancing supply and demand (Viswanath et al., 2016).
- Grid Signals: These include real-time operational data from various parts of the grid, such as voltage levels, frequency, and load data, crucial for maintaining grid stability and efficiency (Alsatian et al., 2022).

3.6.2 Real-time vs. batch data processing

- Real-time Processing: This is crucial for processes such as demand response, supply adjustments, and real-time pricing. This is where the role of IoT comes in, providing real-time data transmission and processing capabilities (Borgaonkar et al., 2021).
- Batch Processing: The analysis of big data volumes across time enables pattern detection for strategic planning and grid enhancement through batch processing. This method proves effective for processing historical data to guide future operational decisions and infrastructure spending according to Mehmood et al. (2021).

3.6.3 Role of IoT and Sensors

- Data Collection and Transmission: The Internet of Things (IoT) devices especially sensors are essential for data collection and transmission in the grid environment. Real-time monitoring of various parameters across extensive geographical areas is possible through these devices with high efficiency (Li et al., 2011).
- Integration and Interoperability: The Internet of Things enables the unification of different systems and technologies within the smart grid through its ability to establish smooth communication and operational connections. The backbone of the smart grid connects smart meters and grid devices and control systems to enhance both flexibility and reliability (Tighten and Yang, 2020).
- Security and Reliability: The smart grid IoT systems implement strong security protocols to defend against cyber threats. The development of security protocols and architectures focuses on maintaining safe and reliable grid operations while addressing unauthorized access and data integrity concerns (Zhong et al., 2021).

- Enhanced Efficiency: The implementation of edge computing and IoT technology enables smart grids to process data more efficiently which is essential for high-speed operations (Mehmood et al., 2021).
- The operation and adaptability of smart grids improve through the combination of real-time data processing and IoT integration and efficient management of various data types.

3.7. Implementation Case Studies

The implementation of artificial intelligence (AI) in smart grids provides innovative solutions to handle the rising complexity and unpredictability of power systems. The implementation of AI in smart grids includes power supply optimization and system stability assessment and demand-side management which are essential for developing efficient sustainable energy systems (Jiao, 2020; Guo et al., 2023).

3.7.1 Successful AI Applications in Real-World Grids

The optimization of renewable energy systems (RES) and smart grids benefits from AI applications through load forecasting and fault detection and power quality management. The reliability and operation of renewable energy systems and smart grids has been improved through the implementation of expert systems and fuzzy logic and artificial neural networks according to Bose (2017). The applications have shown substantial enhancements in grid stability and efficiency and integration capacity (McHargue et al., 2024).

3.7.2 Lessons Learned from Demand Prediction Projects

The accurate prediction of demand serves as an essential requirement for maintaining stable grid operations. The Long Short-Term Memory (LSTM) networks serve as advanced models which use historical data to predict future energy demand according to Barath et al. (2024). The predictive capabilities of demand forecasting models in decentralized power grids receive improvement through machine learning techniques including Boost and other neural network architectures according to Ibra et al. (2022). These methods enable improved management of renewable energy source variability which supports efficient demand-side management programs (Arumugam et al., 2023)

3.7.3 Barriers to Implementation

AI implementation in smart grids faces multiple obstacles which prevent its widespread adoption despite its advantages. The adoption of AI technology faces two main barriers: high costs and the requirement of reliable data for model training and infrastructure readiness (Ommateum and Niu, 2021). The power industry faces two major challenges because of insufficient specialized algorithms and unexplained model behavior (Jiao, 2020). The implementation of AI-driven solutions requires advanced data analytics and processing abilities which not all grid systems possess (McHargue et al., 2024).

The research demonstrates the importance of strategic sector collaboration to address these challenges while showing the need to develop infrastructure and build AI deployment capacity in the energy sector for better grid performance and sustainability.

4 Future Trends

The distributed machine learning paradigm known as Federated Learning (FL) has gained popularity because it trains models across multiple devices without sharing raw data while maintaining data privacy. The method shows great promises for healthcare (Moon and Lee, 2023) and manufacturing (Rosero et al., 2024) applications as well as numerous other industries. FL presents several challenges which include high communication expenses and privacy risks and difficulties with data management (Supriya and Gadepalli, 2023). Research directions for the future concentrate on resolving these obstacles through the combination of soft computing approaches and nature-inspired solutions and the creation of systems that mirror deep learning frameworks including Porch and TensorFlow to simplify FL implementation (Li et al., 2023). The protection of privacy in FL systems requires immediate attention because it affects applications that handle sensitive information (Yin et al., 2021). The field of predictive maintenance (PDM) experiences a transformation through AI technology which improves equipment management across all industries. AI-driven analytics together with real-time data monitoring enables equipment failure predictions which leads to reduced downtime and optimized maintenance protocols (Arinze et al., 2024). The implementation of Pd.M. strategies enables oil and gas industries along with other sectors to shift from reactive to proactive maintenance practices which results in better asset integrity and operational efficiency (Oxalate et al., 2023). The combination of AI technologies with digital twins and the metaverse and Industrial Internet of Things (IIOT) presents promising research directions for developing adaptive and autonomous maintenance systems (Car et al., 2024).

The integration of energy storage optimization with demand response systems plays a crucial role in improving grid efficiency while allowing the use of renewable energy sources. The development of lithium-ion batteries and supercapacitors and compressed air energy storage systems has led to high power density and fast response capabilities which are vital for power grid stability (Ahmadi and Mohammed, 2024). Hybrid energy storage systems provide flexible and resilient operation which makes them appropriate for various applications including microgrids and transport systems (Farhadi and Mohammed, 2016). The integration of model predictive control with thermal energy storage systems enables efficient management of energy loads and integration of intermittent renewable resources (Cole et al., 2012). The implementation of energy storage technologies faces ongoing challenges because of their expensive installation costs and the requirement for standardized performance metrics (Sparacino et al., 2012). Future research needs to develop cost-efficient standardized solutions to achieve the complete potential of energy storage technologies for grid efficiency and renewable energy integration (LaLiga et al., 2024). The following information about future trends and research directions can be derived from the available literature although I am unable to produce a complete essay.

5 Conclusion

The development of artificial intelligence (AI) has brought about a transformative solution to address the ongoing challenge of intermittent renewable energy sources in modern energy systems. The global energy transition requires grid operators to handle increasing complexity when maintaining reliable and efficient sustainable energy supply during nighttime or low-output periods. The research shows that AI forecasting techniques including machine learning models (Boost and random forest) and deep learning models (LSTM and transformers) enhance the precision of demand and renewable generation predictions. The research demonstrates that intelligent models require high-quality multidimensional datasets which include weather conditions and historical load profiles to dynamically forecast and adapt to grid needs. Utilities achieve better dispatch strategies and improved renewable integration and reduced fossil-fuel peaking plant usage through real-time data acquisition and edge computing and AI-based analytics. The operational benefits include improved grid resilience, reduced curtailment of renewables, and greater economic efficiency, particularly during high-risk periods such as nighttime demand peaks.

The complete realization of AI in energy systems depends on proper policy support and regulatory backing and industry assistance. The successful implementation of AI in energy systems requires standardized data protocols and incentives for digital infrastructure investments and transparent and fair AI application practices. The regulatory systems need to adapt their structures to support decentralized control systems and data sharing between stakeholders and ethical automated system deployment in critical infrastructure. The integration of AI into grid operations requires policymakers to work with technology developers and utility operators for developing scalable energy solutions that promote equity and climate alignment.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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