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Artificial Intelligence for the Optimization of Electrical Grids in Latin America

Inteligencia Artificial para la Optimización de Redes Eléctricas en Latinoamérica

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Abstract.- This article explores the transformation of electricity grids in Latin America through the integration of artificial intelligence (AI). With energy demand expected to triple by 2050, AI is crucial for optimizing efficiency, reliability, and the integration of renewable energy. Countries such as Brazil, Mexico, and Chile are leading this adoption, using AI to manage distribution, balance supply and demand, and improve grid reliability. The study highlights that linear regression models predict energy efficiency with high accuracy (R2 = 0.86), influenced by consumption, generation, and weather conditions. Optimization classification models achieve an accuracy close to 100%, while risk classification shows mixed results, with difficulties in minority classes, suggesting the need for data balancing. K-Means clustering identified three geographic segments of the grid with distinct operational and maintenance characteristics. ARIMA and LSTM models demonstrate a robust ability to predict energy demand and consumption, capturing complex temporal patterns. Linear optimization demonstrated effective balancing of energy distribution across diverse sources, and identified the potential for heuristic algorithms for future improvements. Despite challenges such as class imbalance in risk data, the need for more robust fault prediction models, and dynamic data integration, AI offers a promising path toward more efficient, resilient grids with greater customer satisfaction.

Keywords: *Artificial intelligence, machine learning, models, optimization, networks.*

Resumen.- El artículo explora la transformación de las redes eléctricas en América Latina mediante la integración de la inteligencia artificial (IA). Ante una demanda energética que se triplicará para 2050, la IA se vuelve crucial para optimizar la eficiencia, confiabilidad e integración de energías renovables. Países como Brasil, México y Chile lideran esta adopción, utilizando IA para gestionar la distribución, equilibrar la oferta y demanda, y mejorar la fiabilidad de la red.El estudio destaca que los modelos de regresión lineal predicen la eficiencia energética con alta precisión (R2 =0.86), influenciados por el consumo, generación y condiciones meteorológicas. Los modelos de clasificación de optimización alcanzan una precisión cercana al 100% , mientras que la clasificación de riesgo muestra resultados mixtos, con dificultades en clases minoritarias, sugiriendo la necesidad de balanceo de datos. El clustering K-Means identificó tres segmentos geográficos de la red con distintas características operativas y de mantenimiento. Los modelos ARIMA y LSTM demuestran una robusta capacidad para predecir la demanda y el consumo energético, capturando patrones temporales complejos. La optimización lineal demostró un balance efectivo en la distribución de energía entre diversas fuentes, y se identificó el potencial de algoritmos heurísticos para futuras mejoras.A pesar de los desafíos como el desequilibrio de clases en los datos de riesgo, la necesidad de modelos de predicción de fallas más robustos y la integración dinámica de datos, la IA ofrece un camino prometedor hacia redes más eficientes, resilientes y con mayor satisfacción del cliente.

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1. Introduction

The integration of artificial intelligence (AI) in smart electrical grids is transforming the energy landscape in Latin America, a region facing significant challenges and opportunities in its pursuit of sustainable energy solutions. With energy demand projected to triple by 2050, optimizing power grids through AI technologies has become crucial for improving efficiency, reliability, and the integration of renewable energy sources [1].

This development not only addresses the urgent need to modernize energy infrastructure but also reflects a broader commitment to environmental sustainability and economic growth [2].

Countries such as Brazil, Mexico, and Chile are at the forefront of this transformation, leveraging AI to optimize grid management, energy distribution, and the integration of intermittent renewable sources like solar and wind power [3]. For example, Brazil's national grid increasingly uses AI to manage variable power outputs, while Chile employs AI algorithms to balance supply and demand effectively, reducing outages and enhancing grid reliability.

However, AI integration also presents significant challenges, including regulatory barriers, data privacy concerns, and the need for robust cybersecurity measures [4].

The potential benefits of AI in smart grids are substantial—ranging from improved operational efficiency to predictive maintenance and economic optimization in the energy sector. As AI technologies mature, they enable data-driven decision-making that helps utilities manage resources and respond to fluctuations in energy supply and demand [5].

Nevertheless, successful deployment of AI solutions requires addressing ethical considerations and systemic barriers to ensure that the shift to AI-powered energy systems is equitable and sustainable for all stakeholders [6].

Ongoing efforts to harness AI for smart grid optimization in Latin America underscore the region's commitment to a sustainable energy future [7]. By fostering innovation, improving energy management, and addressing existing challenges, Latin American countries are not only preparing to meet rising energy demands but also positioning themselves as leaders in the global transition to renewable energy sources and intelligent energy systems.

Power grids have undergone a significant transformation from centralized systems to today's advanced "smart grids," driven largely by technological advances and the need for efficiency and sustainability [8]. Originally designed for simple energy delivery, traditional grids faced limitations in reliability and scalability.

This shift has led to the emergence of decentralized networks, where AI plays a central role in enhancing operational efficiency, security, and resilience through real-time data analytics and automated systems [9].

Edge computing—conceptualized in the late 1990s and gaining prominence in the mid-2010s—has been critical in minimizing latency and bandwidth usage by processing data closer to its source [10].

This technological approach is especially relevant given the rise of the Internet of Things (IoT) and the growing demand for real-time data processing in modern energy systems.

In Latin America and the Caribbean, the energy sector is undergoing a significant transformation, focusing on integrating renewable and conventional energy sources [11]. With energy demand expected to triple by 2050, accelerating renewable adoption while maintaining economic growth is critical.

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Brazil exemplifies this transition, with renewables now accounting for over 50% of its national consumption—highlighting sustainable practices in the region. However, challenges like inadequate transmission infrastructure persist, leading to energy bottlenecks and pricing issues in several nodal electricity markets [12].

To address these challenges, smart grids characterized by intelligent automation and predictive energy management are being adopted to enhance grid stability and optimize power distribution, ensuring the network meets modern demands without compromising reliability [13].

AI and machine learning technologies are foundational to this evolution, enabling enhanced monitoring, predictive maintenance, and efficient integration of renewables, ultimately yielding a more adaptable and efficient power grid [14].

Continued efforts to deploy these technologies reflect a commitment to a sustainable energy future in Latin America, balancing the region's diverse energy mix and advancing technological innovation [15].

Government Policies Supporting AI Integration

Successful integration of AI in smart grids requires strong government policies that foster innovation while mitigating potential challenges. These policies must align with the rapidly evolving energy technology landscape and the growing demand for sustainable practices in the energy sector [16]. A comprehensive regulatory framework is essential for establishing standards that promote AI interoperability, security, and ethical use in energy systems.

Regulatory Enhancements

Governments are encouraged to update existing regulatory frameworks to better accommodate AI applications in smart grids. This includes revising policies to ensure AI systems can effectively communicate with legacy infrastructure [17].

Dedicated task forces can streamline policy implementation and coordination among diverse regulatory agencies, such as energy ministries and regulatory commissions. Moreover, regulatory approvals for AI-driven services should be expedited to foster timely innovation in digital energy markets [18].

Promoción de asociaciones público-privadas

Public–private partnerships (PPPs) are essential for fostering innovation in the energy sector. By collaborating with private entities, governments can leverage AI technology expertise while ensuring compliance with legal standards. Policies should incentivize R&D in AI-driven energy solutions, creating an ecosystem conducive to integrating renewables into the grid.

These collaborations are vital for tackling the complexities of large-scale AI deployments in energy infrastructure, particularly around data privacy and cybersecurity [19].

Cybersecurity and Ethical Standards

As AI usage expands in the energy sector, implementing robust cybersecurity standards becomes imperative to protect critical infrastructure. Governments should adopt international guidelines and mandate regular vulnerability assessments for energy companies [20].

Additionally, ethical challenges associated with AI—such as bias and transparency in decision-making—must be addressed within governance frameworks that ensure fairness and accountability [21].

Support for Sustainable Development Goals

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AI integration in smart grids is closely tied to achieving Sustainable Development Goals (SDGs), particularly climate action and responsible consumption. Policies promoting AI for optimizing energy usage and minimizing waste can significantly reduce carbon emissions and support climate mitigation efforts [22].

By aligning AI initiatives with sustainability goals, governments can create more resilient and efficient energy systems that benefit both consumers and the environment [23].

AI Technologies

The application of AI technologies in smart grids is transforming energy systems in Latin America [24], where there is a growing need for effective energy management solutions. This section outlines the key AI techniques used to optimize smart grid operations, highlighting their roles in improving energy efficiency and supporting renewable integration.

Machine Learning in Smart Grids

Machine learning (ML) has emerged as a cornerstone in smart grid optimization, offering robust methodologies to analyze large datasets and automate decision-making. ML techniques such as supervised learning—including linear regression and support vector machines—are commonly applied to load forecasting and demand response management [25].

These models enable utilities to anticipate energy consumption patterns, which is critical for balancing supply and demand in real time. Furthermore, ML facilitates energy efficiency by optimizing HVAC systems in smart buildings and scheduling industrial processes to minimize waste [26].

Real-world ML implementations in energy distribution and storage have shown significant improvements in operational efficiency and customer experience [27].

Data Analytics and Predictive Analytics

Integrating AI in smart grids requires sophisticated data analytics capabilities. AI algorithms can process large volumes of data from diverse energy sources, allowing utilities to apply predictive analytics to foresee operational scenarios. By utilizing descriptive, diagnostic, predictive, and prescriptive analytics, grid operators can improve decision-making and proactively address potential issues [28].

However, data quality challenges persist, as many models are trained on synthetic datasets due to limited access to real-world operational data. Efforts to enhance data collection and develop high-quality multimodal datasets are critical to improving AI accuracy in energy systems [29].

Renewable Energy System Optimization

AI technologies play a pivotal role in optimizing renewable energy systems (RES), which are vital for the transition to sustainable energy solutions. ML techniques are applied to various RES applications—including solar, wind, and waste-to-energy systems—to forecast performance and improve operational parameters. For example, ML models have enhanced the efficiency of municipal waste-to-energy systems, demonstrating AI's versatility in addressing environmental challenges while optimizing energy production [30].

AI Applications in Smart Grids

AI technologies play a pivotal role in improving the efficiency, reliability, and sustainability of smart grids in a variety of applications. These applications address critical challenges associated with energy management and the integration of renewable energy sources. [31].

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Energy Distribution Optimization

AI-driven smart grids optimize energy distribution to reduce losses and prevent outages. Utilizing smart meters and demand-response systems, AI analyzes consumption patterns to balance load in real time, ensuring efficient energy flow across the network [32]. This is particularly vital as more consumers adopt distributed energy resources like rooftop solar panels and battery systems [33].

Enhanced Outage Management

AI improves outage management through sophisticated sensor networks that provide real-time data, enabling utilities to predict and respond to disruptions more effectively. For instance, AI can differentiate between individual, street, and zonal outages, giving operators clear alerts that facilitate faster restoration and improved reliability [34].

Advanced Load Forecasting

Accurate load forecasting is essential for effective grid management, especially with variability introduced by renewables. AI enables utilities to use predictive models combined with Advanced Metering Infrastructure (AMI) data to generate more reliable load forecasts, crucial for managing supply-demand fluctuations and addressing the "duck curve" phenomenon [35]. This level of precision is critical for managing fluctuations in demand and supply, which are often represented by the "duck curve" phenomenon.

Renewable Energy Integration

As wind and solar sources become more prevalent, AI helps integrate renewables seamlessly into the grid. AI optimizes generation and storage to manage the intermittent nature of these sources, enabling effective load shifting and balancing supply and demand [36].

The incorporation of AI-supported energy storage further enhances grid resilience by storing excess energy during peak production [37].

Cybersecurity and Resilience

AI also plays a vital role in improving smart grid cybersecurity. With the increasing digitalization of energy systems, AI-powered solutions can identify and respond to potential cyber threats, ensuring the integrity and security of grid operations. [38]. Robust security measures, encrypted communication channels, and advanced defense mechanisms are essential to protecting the network from vulnerabilities.

Electric Vehicle Integration

The growing adoption of electric vehicles (EVs) presents both challenges and opportunities for smart grids. AI facilitates dynamic EV charging management by coordinating charging and discharging schedules to reduce peak load stress and enhance energy efficiency [39].

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Considering the positive experiences of artificial intelligence in energy management, the objective of this research is to demonstrate its importance for the optimization of electrical grids in Latin America and lead to sustainable management of natural resources.

2. Materials and Methods

2.1 Statistical Models

Multiple Linear Regression

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A multiple linear regression model was implemented to predict the energy efficiency of the electrical grid. The predictor variables included: energy consumption (kWh), energy generation (kWh), weather conditions (temperature, humidity, wind speed, solar radiation), and equipment characteristics (age, maintenance score, transformer status, cable condition).

Logistic Regression
Se aplicó regresión logística para dos propósitos: clasificación de riesgo de falla en la red y clasificación de potencial de optimización

ARIMA (Autoregressive Integrated Moving Average) An ARIMA model was implemented to forecast energy demand and energy generation. The model identified significant temporal patterns in the data, with statistically significant coefficients for the AR terms (Lags 1–5).

Recurrent Neural Networks (RNN) with LSTM
Se desarrolló un modelo LSTM para predecir el An LSTM model was developed to predict energy consumption using temporal data sequences. The model showed strong performance with an RMSE of 51.5277 kWh, demonstrating its ability to capture complex consumption patterns.

Clustering with K-Means

K-Means was applied to group substations and distribution points based on their performance and geographic characteristics. The results showed three distinct clusters with significant characteristics: Cluster 0: Average latitude (-17.43), response time 13.83 minutes. Cluster 1: Positive latitude (4.90), response time 13.60 minutes. Cluster 2: Negative latitude (-20.67), response time 14.23 minutes.

Optimization

Two optimization approaches were implemented: Linear programming: To optimize the energy distribution between different sources (solar, wind, thermal) and Heuristic optimization: The concepts of Genetic Algorithms and Particle Swarm Optimization were discussed as potential approaches for complex optimization problems.

2.2 Data Used

The simulated dataset contained detailed information about the operation of a smart power grid in Latin America, generated for a 5-year period (2020–2025) with hourly frequency. The dataset consists of 5,000 records and 20 variables.

Main Variables

Consumption and Generation Variables: energy_consumption_kWh`: Energy consumption in kilowatt-hours, energy_generation_kWh`: Total energy generation in kilowatt-hours, energy_demand_kWh`: Energy demand in kilowatt-hours, energy_efficiency`: Energy efficiency of the system and `energy_losses_percent`: Percentage of energy losses.

Weather Variables: emperature_C`: Ambient temperature in degrees Celsius, humidity_percent`: Relative humidity percentage, `wind_speed_mps`: Wind speed in meters per second and `solar_radiation_Wm2`: Solar radiation in watts per square meter.

System Status Variables: equipment_age_years`: Equipment age in years, maintenance_score`: Maintenance score (0-1), `transformer_status`: Transformer status (0: Normal, 1: Warning, 2: Fault) and `cable_condition`: Cable condition (0: Good, 1: Worn).

Geographic Variables: `latitude`: Geographic latitude, longitude`: Geographic longitude and altitude_m`: Altitude in meters.

Operation Variables: `response_time_minutes`: Incident response time in minutes, operational_cost_USD`: Operational cost in

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dollars and customer_satisfaction`: Customer satisfaction index (0-1).

Dataset Features

Temporal Distribution: Period: 5 years (2020-2025), frequency: Hourly with a total of 5000 records.

Patterns and Variations: Daily patterns: Higher consumption during peak hours (evening/night), Seasonal patterns: Variations in consumption and generation according to the season, Geographic variations: Different climatic and topographic conditions and Operational variations: Different maintenance status and age of equipment.

Data Quality

Consistency: No null values, physically plausible values, and consistency between related variables.

Value ranges: temperature: 18°C - 35°C, humidity: 60% - 95%, wind speed: 0 - 15 m/s, solar radiation: 0 - 350 W/m², equipment age: 1 - 30 years, maintenance score: 0 – 1, energy efficiency: 0 – 1, and customer satisfaction: 0 – 1.

Relationships between Variables: energy efficiency was influenced by consumption and generation, summer response time related to equipment age and maintenance, customer satisfaction depended on losses, response time and system status, and energy generation considered renewable (solar and wind) and non-renewable (thermal) sources.

Methodological Considerations

The data were generated based on patterns observed in Latin American power grids, including typical consumption patterns, regional climate variations, grid operating characteristics, and relevant geographic factors.

This data provided a realistic representation of smart grid performance in Latin America, enabling the analysis and optimization of various aspects of the system.

3. Results

Energy Efficiency Analysis

Linear Regression Model

The linear regression model for predicting energy efficiency showed highly significant results, with RMSE: 0.0347 y R^2: 0.86.

These values indicate that the model explains 86% of the variability in energy efficiency and has a relatively low prediction error. The most influential variables include energy consumption and generation, weather conditions, and equipment status and maintenance.

Classification Analysis

Risk Classification

The classification models used to identify risks in the grid showed mixed results. The Random Forest model achieved an accuracy of 85.87%, while the Gradient Boosting model reached an accuracy of 85.13% (Figure 1).

Fig 1. Risk classification using applied models.

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The models correctly identified most of the low-risk cases (class 0) but struggled with the minority classes (class 2). This suggests the need to: improve dataset balance, implement techniques for handling imbalanced classes, and consider additional metrics such as the F1-score to better evaluate performance on minority classes.

Optimization Potential Classification

The models used to identify optimization opportunities demonstrated excellent performance. The Random Forest model achieved an accuracy of 99.87%, while the Gradient Boosting model reached 100%, as shown in Figure 2.

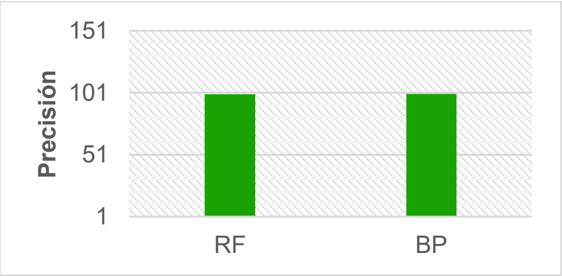

Fig 2. Optimization Potential Classification of the Models Used.

These results indicate that the system can accurately identify areas requiring optimization, which is crucial for preventive network management.

Clustering Analysis

Network Segmentation

The K-Means clustering analysis identified three main clusters with distinct characteristics (Figure 3).

Fig 3. Cluster Response Time.

Cluster 1 (Latitude -17.43): Response time: 13.83 minutes, geographic location: South-Central, with excellent response and maintenance.

Cluster 2 (Latitude 4.90): Response time: 13.60 minutes, geographic location: North, excellent response and maintenance.

Cluster 3 (Latitude -20.67): Response time: 14.23 minutes, geographic location: South, longer response time, potential for improvement.

Time Series Analysis

Demand Forecasting

The ARIMA model identified significant temporal patterns: significant AR coefficients for lags 1-5. It also demonstrated good predictive power demand and identified seasonality and temporal trends.

LSTM Model

The LSTM model for consumption prediction showed: RMSE: 51.5277 kWh, the ability to capture complex consumption patterns, and effective utilization of temporal sequences.

Optimization Analysis

Energy Distribution

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Linear optimization for energy distribution showed optimal generation: 110.86 kWh, effective balance between sources (solar, wind, thermal), and compliance with energy demand.

Heuristic Optimization Potential: Opportunities for implementing genetic algorithms for expansion planning and particle swarm optimization for dynamic adjustments were identified.

The system's strengths were robust prediction due to high levels of accuracy in predicting efficiency and demand; effective classification: excellent identification of optimization opportunities; and clear segmentation: well-defined geographic clusters with distinctive characteristics and adequate balance in energy distribution.

Despite the positive results, areas for improvement are needed, such as improving the detection of minor risks, implementing more robust models for fault prediction, developing more advanced models for real-time adjustments, and incorporating more external data sources. Therefore, it is recommended to implement the optimization classification system for preventive maintenance, develop specific strategies for each geographic cluster, improve monitoring of areas with the longest response times, maintain continuous updates of predictive models, improve efficiency, reduce energy losses, optimize preventive maintenance, and improve resource allocation.

Likewise, resilience improvements are required through early risk identification, improved incident response, optimization of resources in critical areas, improved customer satisfaction, reduced response times, improved demand management, and service optimization.

4. Discussion

The research results reveal a promising outlook for the integration of artificial intelligence (AI) into energy network management, highlighting its potential to significantly improve efficiency, resilience, and customer satisfaction. These findings align with the growing literature underscoring the transformative role of AI in energy systems [41].

In the energy efficiency analysis, the linear regression model demonstrated a robust ability to predict efficiency, explaining 86% of its variability with a low prediction error (RMSE: 0.0347). Variables such as energy consumption and generation, weather conditions, and equipment status were identified as the most influential. This is consistent with the vision of AI-driven smart grids, which can optimize energy management in various sectors, including manufacturing [42].

Risk classification models exhibited an accuracy of 85.87% for Random Forest and 85.13% for Gradient Boosting. While these models were effective in identifying majority class risks (low risk, class 0), they showed limitations with minority classes (class 2). This difficulty highlights the need to address class imbalance in datasets and consider additional metrics such as the F1 score for a more comprehensive performance assessment, a recurring challenge in the application of machine learning to energy systems [43].

On the other hand, the classification models for optimization potential demonstrated exceptional performance, achieving accuracies of 99.87% (Random Forest) and 100% (Gradient Boosting). These results are crucial for preventive network management, allowing for the identification of areas requiring optimization with high reliability [44], [45].

K-Means clustering analysis revealed a clear segmentation of the network into three distinct geographic groups: a central-southern cluster (latitude −17.43) with a response time of 13.83 minutes and good response and maintenance; a northern cluster (latitude 4.90) with a response time of 13.60 minutes and excellent response and maintenance; and a southern cluster (latitude −20.67) with the longest response time of 14.23 minutes and potential for improvement. This segmentation is essential for the development of preventive maintenance and optimization strategies tailored to the specific characteristics of each region [46].

Regarding time series analysis, the ARIMA model demonstrated a good ability to predict energy demand, identifying significant seasonal patterns and time trends. The LSTM model, meanwhile, demonstrated a superior ability to capture complex consumption patterns, with an RMSE of 51.5277 kWh, reinforcing its usefulness for energy consumption prediction [47].

Finally, the linear optimization analysis for power distribution indicated an optimal generation of 110.86 kWh, achieving an effective balance between various sources (solar, wind, thermal) and meeting energy demand. Opportunities were also identified for the implementation of heuristic algorithms such as genetic algorithms and particle swarm optimization for expansion planning and dynamic adjustments, respectively. This is consistent with current trends exploring AI for power grid optimization. [48].

5. Conclusions

The results obtained clearly demonstrate the great potential of artificial intelligence (AI) to revolutionize energy grid management, enabling more efficient, resilient, and customer-oriented operations. The accuracy and robustness of the predictive models for energy efficiency and demand, along with the excellent classification capabilities for identifying optimization opportunities, are undeniable strengths of the system. Furthermore, the geographic segmentation of the grid through K-Means clustering analysis provides a solid foundation for differentiated management strategies.

While there is a clear need to improve the detection of minor risks and to develop more advanced models for fault prediction and real-time dynamic optimization, these challenges do not overshadow the significant achievements. The identified optimization opportunities, the ability to effectively balance energy sources, and the improved response times are indicative of a system capable of positively transforming grid operations.

Ultimately, the implementation of this AI-based system represents a fundamental step toward creating truly adaptive and proactive smart grids, capable of efficiently anticipating and responding to the complexities of the current and future energy landscape. Investment in the identified areas for improvement, along with the adoption of implementation recommendations, will be crucial to maximizing the impact of this innovative technology on efficiency, resilience, and customer satisfaction.

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