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Article

Methodological framework for short-term electricity demand forecasting in desert regions using lstm and meteorological inputs

Marco metodológico para la predicción de la demanda eléctrica a corto plazo en regiones desérticas mediante lstm y variables meteorológicas

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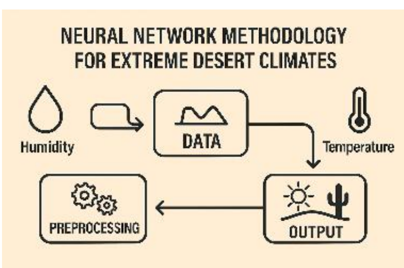
Abstract

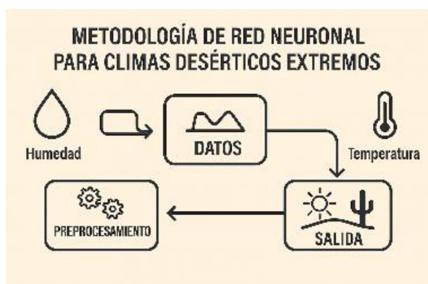
This study develops a model to predict electricity consumption peaks using artificial neural networks with continuous data recorded every 10 minutes. The research focuses on Ciudad Juárez, a desert region with high climatic variability, where temperature and humidity fluctuate substantially and unpredictably throughout the year. In such environments, temperatures can rise drastically during the day and drop sharply at night, creating unstable and irregular demand patterns. Sudden seasonal shifts and unexpected meteorological events further complicate electricity forecasting. Accurately predicting electricity demand in these conditions is essential for efficient energy management. Failure to forecast peaks may lead to shortages or excessive generation, with significant economic and environmental consequences. To address this, the model incorporates climatic variables such as time of day, day of the year, temperature, and relative humidity, which help capture the complex patterns of electricity use influenced by desert climate dynamics. Results show that including climatic factors substantially improves prediction accuracy, achieving 92% under validation. These findings demonstrate the potential of this approach to enhance energy planning in unstable climates, providing a reliable tool for sustainable resource management.



Neural Networks, Electricity Consumption, Desert Climates

Resumen

Este estudio desarrolla un modelo para predecir picos de consumo eléctrico utilizando redes neuronales artificiales con datos continuos registrados cada 10 minutos. La investigación se centra en Ciudad Juárez, una región desértica con alta variabilidad climática, donde la temperatura y la humedad fluctúan de manera sustancial e impredecible a lo largo del año. En estos entornos, las temperaturas pueden aumentar drásticamente durante el día y descender con fuerza por la noche, generando patrones de demandas inestables e irregulares. Los cambios estacionales repentinos y fenómenos meteorológicos inesperados complican aún más la predicción del consumo eléctrico. Predecir con precisión la demanda en estas condiciones resulta esencial para una gestión energética eficiente. No anticipar los picos puede ocasionar escasez o una generación excesiva, con consecuencias económicas y ambientales significativas. Para abordar este desafío, el modelo incorpora variables climáticas como la hora del día, el día del año, la temperatura y la humedad relativa, que permiten capturar los complejos patrones de uso eléctrico influenciados por la dinámica del clima desértico. Los resultados muestran que la inclusión de factores climáticos mejora sustancialmente la precisión de las predicciones, alcanzando un 92% bajo validación. Estos hallazgos demuestran el potencial de este enfoque para optimizar la planificación energética en climas inestables, proporcionando una herramienta confiable para la gestión sostenible de recursos.



Redes neuronales, Consumo eléctrico, Clima desértico

Area: Promotion of frontier research and basic science in all fields of knowledge

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Introduction

Accurate forecasting of electricity consumption is essential for the efficient management of energy resources, especially in regions where demand exhibits significant fluctuations due to rapidly changing climatic conditions and where supply shortages are exacerbated by accelerated urbanization. Desert areas, such as Ciudad Juarez Chihuahua, present a particular challenge in modeling energy demand because meteorological conditions can vary dramatically from year to year, even within the same season. A clear example of this variability is the contrast between the historic snowfall recorded on October 27, 2020, and the mild weather observed in October 2024 in the same location, as shown in Table 1.

Box 1

Table 1
Climatic Comparison: October 27, 2020, vs. October 27, 2024 – Ciudad Juarez

Variable	27-Oct-2020 (Historic Snowfall)	27-Oct-2024 (Mild Weather)
Minimum Temperature (°C)	-2.0 °C	11.5 °C
Maximum Temperature (°C)	5.0 °C	23.0 °C
Average Temperature (°C)	1.5 °C	17.5 °C
Average Relative Humidity (%)	80%	32%
Average Wind Speed	15 km/h	8 km/h
Accumulated Precipitation	3.5 mm (snow)	0 mm
Estimated Electricity Consumption	~20% above autumn average	~4% below autumn average
Impact on Power Grid	Overload, residential outages	Normal operation

Source: National Meteorological Service (SMN)

1.1 Problem Statement and Central Hypothesis

Electricity consumption in desert regions is strongly linked to thermal comfort needs, which drive the use of heating systems, refrigerators, evaporative coolers, and mini-split air conditioners. Climatic variables such as temperature and humidity directly influence household decisions, producing non-linear demand patterns during both summer heatwaves and winter cold spells.

In hot-dry climates such as Ciudad Juárez, evaporative coolers traditionally provide cost-effective cooling, achieving 60–85% effectiveness and saving up to ~75% of electricity compared to compression-based A/C units. However, their performance declines under humid conditions, prompting a switch to mini splits that sharply increase energy use (Haile *et al*., 2024; Alfraidi *et al*., 2024).

Cold spells, though less frequent, also increase electricity consumption through heating loads from resistive devices and heat pumps in mini splits. Research indicates that both heatwaves and cold events raise outage frequency and duration, highlighting resilience challenges (Liang *et al*., 2025).

Additionally, urban form modifies cooling needs: studies in desert cities demonstrate that vertical densification can reduce residential electricity demand by improving shading and decreasing exposed building surface (Lopez *et al*., 2024).

For Ciudad Juárez, this evidence justifies the integration of meteorological variables and comfort-related metrics such as Cooling Degree Days (CDD) and Cooling Degree Hours (CDH) into the forecasting model. Incorporating these indicators enhances the LSTM's capacity to capture the true drivers of energy consumption in desert regions.

Multiple studies have demonstrated that incorporating climatic variables such as temperature and humidity significantly improves the accuracy of electricity consumption prediction models. Based on the article of combined an Enhanced Inception V4 model with an Osprey optimizer to account for environmental factors (Chen, Fang *et al*., 2024).

This annex presents real and projected data that reinforce the necessity of predictive models based on neural networks for Ciudad Juárez, located in the Gran Consumo Regional (GCR) Norte region of the National Electric System.

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Box 2

Table 2

Simulation of increase of electricity consumption from 2019 to 2025

Year	Electricity Consumption (GWh)	Year-on-Year Growth (%)
2019	28,868	N/A
2020	29,291	1.47%
2021	30,378	3.71%
2022	31,850	4.85%
2023	34,200	7.38%
2024	36,483	6.68%
2025	40,000	9.64%

Source: PRODESEN 2025 and simulations for regional analysis

Patterns of hourly and annual electricity consumption growth are presented in the following tables. These patterns demonstrate irrational and non-linear increases that challenge conventional prediction methodologies.

Table 2 illustrates the evolution of temperature and humidity in Norte region between 2019 and 2025, highlighting a sustained growth trend over six years. This progression demonstrates that consumption patterns in Ciudad Juarez are strongly influenced by climatic variability, which does not always follow predictable seasonal cycles. The evidence confirms that models relying solely on historical consumption records and calendar dates are insufficient to accurately forecast demand. Incorporating climatic variables and adaptive prediction methods is essential to reflect the true dynamics governing electricity consumption in this region.

Box 3

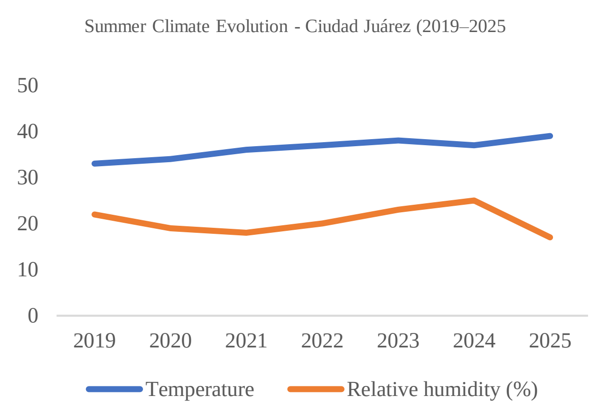

Figure 1

Summer Climate Evolution - Ciudad Juárez (2019–2025

Source: PRODESEN and simulations for projected behavior

The following comparison shows the changes in average temperature and relative humidity during the summers of 2019 to 2025. The evidence demonstrates a sustained increase and substantial variability in environmental conditions, further highlighting the importance of adaptive models such as neural networks to anticipate the impact of climate on electricity consumption.

Box 4

Table 3

Climatic Comparison – Ciudad Juárez Summers 2019–2025

Year	Average Summer Temperature (°C)	Average Relative Humidity (%)
2019	33.2	22
2020	34.1	19
2021	35.7	18
2022	36.5	20
2023	37.8	23
2024	36.9	25
2025	39.0	17

Source: Developed with data from CONAGUA, historical local records, and recent trend simulations

This study presents the development and implementation of a predictive model to anticipate short-term electricity consumption peaks using Artificial Neural Networks (ANNs), specifically a Long Short-Term Memory (LSTM) network. The model is trained using continuous time-series data recorded at 10-minute intervals, allowing the system to learn from fine-grained fluctuations in electrical demand. The main objective is to build a reliable tool for short-term load forecasting (STLF), which is critical for optimizing grid stability, energy distribution, and operational planning in smart grid systems (Hong & Fan, 2016).

Compared to traditional time series forecasting techniques, LSTM networks offer significant advantages over other Recurrent Neural Network (RNN) architectures. Conventional RNNs often suffer from the vanishing gradient problem when dealing with long sequences, limiting their effectiveness in capturing long-range dependencies. In contrast, LSTMs are specifically designed to retain relevant information over extended periods through the use of input, forget, and output gates (Hochreiter & Schmidhuber, 1997).

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This capability makes them particularly suitable for modeling the complex temporal dynamics of energy consumption, which can be influenced by nonlinear and delayed climatic patterns such as temperature, humidity, and solar radiation (Marino *et al*., 2016). As a result, LSTMs demonstrate greater robustness, training stability, and generalization performance in real-world scenarios with high variability and noise.

Methodology

Problem Definition

The central problem addressed in this study is the high unpredictability of electricity consumption in desert regions, where extreme climatic fluctuations disrupt conventional demand patterns. In cities such as Ciudad Juárez, rapid changes in temperature, relative humidity, wind speed, and precipitation drive abrupt shifts in household cooling and heating needs. These dynamics produce nonlinear and highly volatile consumption profiles that traditional statistical and time-series forecasting models—primarily dependent on historical load records and seasonal trends—struggle to capture accurately.

Traditional models tend to assume stationarity and smooth seasonality, which makes them poorly suited for environments where energy demand is shaped by sudden heatwaves, cold spells, and monsoonal humidity surges. As a result, forecasts often underestimate peak loads during extreme events and overestimate demand during mild conditions, undermining both grid reliability and resource planning.

To address this gap, this study hypothesizes that explicitly integrating climatic variables—with emphasis on temperature and humidity, complemented by wind speed and precipitation—into a Long Short-Term Memory (LSTM) neural network can significantly enhance predictive accuracy. Unlike traditional models, LSTM architectures are capable of learning long-range temporal dependencies and nonlinear interactions, making them well suited to capture the complex interplay between thermal comfort needs and electricity consumption in desert climates.

General Objective

The objective of this study is to develop and validate a predictive model capable of accurately forecasting short-term electricity consumption in desert regions with high climatic variability. The model produces 10-minute interval predictions with a forecasting horizon of up to 4 hours, providing sufficient resolution to support both real-time grid operation and demand-side management strategies.

The modeling framework is based on artificial neural networks (ANNs), with emphasis on a Long Short-Term Memory (LSTM) architecture, chosen for its ability to capture nonlinear relationships and long-term temporal dependencies in electricity consumption data. The model incorporates as input variables:

– **Hour of the day** (temporal dynamics of daily load patterns)
– **Ambient temperature** (thermal comfort needs driving cooling/heating loads)
– **Relative humidity** (modulator of cooling technology efficiency and household energy choices)

By integrating these temporal and climatic variables, the model aims to represent the complex interaction between human comfort requirements and electricity demand. Ultimately, this approach contributes to improving forecasting accuracy in arid and semi-arid regions, enhancing the resilience and efficiency of electricity grid management.

Experimental Data Acquisition

To validate the forecasting model under realistic operating conditions, an initial experimental dataset was collected from a typical residential household. The measurement setup consisted of two main components:

1. Electricity consumption monitoring

A Shelly EM smart meter was installed on the household's electrical system to provide high-resolution measurements of energy usage. The device was configured to record electricity consumption at minute-level intervals, allowing the capture of both short-term fluctuations (e.g., appliance switching events) and longer-term patterns (e.g., cooling and heating cycles).

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2. Indoor environmental monitoring

To account for the effect of thermal comfort variables on electricity demand, a Groove temperature and humidity sensor was placed inside the residence. This sensor continuously measured ambient temperature (°C) and relative humidity (%), ensuring that variations in indoor environmental conditions could be correlated with household energy consumption.

By combining these two datasets, it was possible to establish a direct relationship between user comfort requirements (driven by temperature and humidity) and the corresponding electricity consumption behavior. This integrated dataset provides a reliable foundation for validating the proposed model, since it reflects the actual interaction between environmental stressors, comfort needs, and residential energy demand.

Data Integration

A custom data aggregation program was developed to synchronize, preprocess, and compile all sensor readings into a unified dataset. This program automatically merged consumption data from the Shelly EM with environmental records from the Groove sensor, creating a clean and chronologically ordered datasheet. This unified dataset was then prepared for model training and validation.

Model Architecture and Rationale for LSTM

The model architecture was implemented in Python using the TensorFlow and Keras libraries. The design consists of:

– **Input Layer:** Accepts the three normalized variables (hour, temperature, humidity).

– **Two stacked LSTM layers:** These layers were specifically chosen because LSTM networks excel at learning long-term dependencies in time series data, which is critical when past temperature and humidity exert delayed effects on consumption.

– **Dense output layer:** Produces continuous consumption predictions.

– **Dropout layers:** Applied to reduce overfitting.

The rationale for selecting the LSTM architecture over other neural network types lies in its proven capability to retain historical information over extended sequences, making it especially suitable for modeling recurrent consumption patterns influenced by climatic cycles. Unlike simpler Recurrent Neural Networks (RNN), LSTM avoids vanishing gradients and maintains performance even when dependencies span several hours.

Data Preparation

All recorded data were normalized to zero mean and unit variance, ensuring stable gradient descent and comparable feature scales. The dataset was split chronologically into:

– 70% training
– 15% validation
– 15% testing

This chronological partition prevents data leakage and simulates the operational scenario of predicting unseen future consumption.

Training and Optimization

The model was trained using the Mean Squared Error (MSE) as the loss function and the Adam optimizer with adaptive learning rates. To improve generalization, early stopping and learning rate decay were applied based on validation loss.

Evaluation Metrics

Performance was assessed through the coefficient of determination (R^2), calculated as:

$$R^2 = 1 - [\Sigma(y_i - \hat{y}_i)^2] / [\Sigma(y_i - \bar{y})^2]$$

where:
y_i: Actual consumption
$\hat{y}_i$: Predicted consumption
$\bar{y}$: Mean consumption

This metric quantifies the variance explained by the model, supporting robust comparison with alternative architectures.

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Comparative Analysis of Neural Network Architectures

Box 5

Table 4
Comparative Analysis of Neural Network Architectures

Neural Network Type	Main Advantages	Main Disadvantages	Ideal For
MLP (Multilayer Perceptron)	Fast training; suitable for tabular data; simple to deploy.	Cannot model sequential dependencies; sensitive to scaling.	Point predictions with static variables (e.g., time, weather).
RNN	Captures temporal dependencies; handles sequential inputs.	Degrades over long sequences; harder to optimize.	Continuous time series forecasting.
LSTM	Retains long-term memory; robust to sequence length.	Higher computational cost; requires more data.	Predicting consumption with strong historical dependence.
GRU	Simpler than LSTM; faster convergence.	Lower accuracy on complex datasets.	Low-resource applications.
CNN	Detects local patterns; effective with spatially structured inputs.	Not inherently sequential; requires reshaping input data.	Multivariate datasets with spatial dimensions.
Transformer	Models' long-range dependencies; highly scalable.	High computational demands; prone to overfitting with few samples.	Large-scale meteorological or extended regional consumption datasets.

Results

Box 6

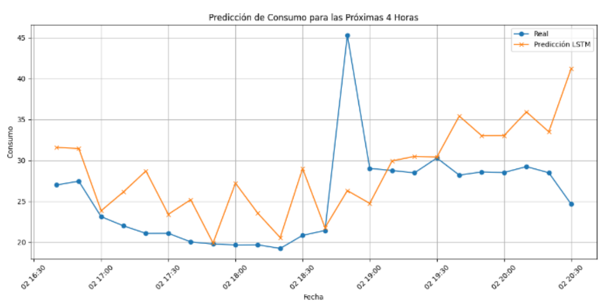

Figure 2
Comparison between the actual electricity consumption values and the predictions generated and real values

The graph presented shows the comparison between the actual electricity consumption values and the predictions generated by the LSTM model for a 4-hour forecast horizon. As more historical data has been incorporated into the model training, a progressive improvement in predictive capability has been observed. At this stage of the research, the training dataset has been fed with a total of 17,280 records, corresponding to 10-minute intervals over a 4-month period.

In the graph, the actual electricity consumption values are represented in blue, while the predicted values generated by the LSTM model are shown in orange. This visual differentiation helps to assess the alignment and divergence between the real and forecasted series.

The model has achieved an average error margin (to be completed with the average from the error table), representing a confidence level of approximately [verify how the confidence level is expressed in %], depending on the metric evaluated. The trend shows that as the volume of input data increases, the model improves its fit, reducing deviation from actual values and demonstrating greater stability in the face of unexpected consumption spikes.

This behavior is consistent with the adaptive nature of the LSTM model, which benefits from sequential learning to identify nonlinear temporal patterns. Although notable deviations are still observed in the face of abrupt events—as evidenced by the spike located in the center of the series—the model increasingly responds more accurately to the general behavior of the system, showing a positive convergence trend.

Conclusions and recommendations

The LSTM model has proven to be a promising architecture for electricity consumption forecasting in desert environments, characterized by high thermal variability and extreme climatic conditions that significantly impact the stability of energy demand. Although the current results have not yet reached a sufficiently low error threshold to guarantee full operational reliability, this limitation is mainly attributed to the insufficiency of training data.

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It is anticipated that by increasing the amount and diversity of input data, the model will converge toward an optimal point at which the error margin will stabilize within acceptable ranges, thereby eliminating the need for parallel comparative analyses and enabling the direct generation of highly accurate predictions.

Additionally, to mitigate the effects of prediction errors during sudden consumption spikes, it is recommended to incorporate value-weighting mechanisms in the model's loss function. This would allow the model to assign greater importance to peak deviations, enhancing its ability to stabilize forecasts under high-variance conditions.

This research not only establishes a solid methodological foundation for future developments in energy forecasting but also opens the way for critical applications in contexts of energy vulnerability. In desert areas where electrical systems face resource scarcity, limited infrastructure, and frequent overloads, accurate prediction of voltage peaks can be used to:

- Optimize the dispatch of energy from renewable sources and temporary storage systems (such as batteries or flywheels), improving the efficiency of the electrical system.
- Prevent service interruptions by implementing real-time preventive measures upon detecting an imminent increase in demand.
- Support flexible demand strategies by activating demand response programs or load regulation in non-priority sectors.
- Improve electrical infrastructure planning, enabling smart grid expansion based on historical data and robust forecasts.
- Facilitate the integration of microgrids or distributed generation, better coordinating the interaction between local generators and the main grid.

Overall, this approach represents a step forward toward more resilient, adaptive, and intelligent electrical systems capable of proactively responding to the specific energy challenges of arid regions, where the balance between supply and demand becomes critically delicate.

Conflict of Interest Statement

The authors declare no conflict of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Author Contributions Statement

Cabrera, Misael: I contributed with the conceptualization, methodology, and original draft writing. I also prepared figures and the initial version of the manuscript.

Martínez, Ulises: I contributed with data curation, software implementation, and validation. I also optimized neural networks and ensured reproducibility.

Woocay, Arturo: I contributed with supervision, methodological review, and editing. I ensured scientific rigor and improved the clarity of the manuscript.

Valles, Delia: I contributed with project administration, funding acquisition, and industrial engineering guidance. I aligned the neural network methodology with energy management strategies and practical applications.

Availability of Data and Materials

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Abbreviations

CNN	Convolutional Neural Network
Gcr	
GRU	Gated Recurrent Unit
GWh	Giga Watts per hour
LSTM	Long Short-Term Memory
MLP	Multilayer Perceptron
PRODECEN	Programa de Desarrollo del Sistema Eléctrico Nacional
RNN	Recurrent Neural Network

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