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Optimizing electricity trading decisions through weather-influenced demand and supply forecasting

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ABSTRACT

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The objective of this thesis was to improve the short-term electricity price forecasting to support trading decisions at BlueEnergy, a qualified supplier operating in Mexico's Wholesale Electricity Market. The work focused on understanding how weather conditions influence electricity demand, supply and price formation, and on developing a forecasting framework capable of capturing these interactions in a volatile and weather-sensitive market environment.

The Study was carried out using historical data from 2021 to 2023, consisting of hourly electricity prices, demand and generation levels, natural gas prices and meteorological variables. A case study was first conducted to analyse the relationship between temperature, demand and price behaviour across Mexican market zones. The data were pre-processed into daily averages and examined to identify seasonal patterns, weather-driven demand responses and the influence of calendar effects on price variability.

Building on these findings, a practical forecasting framework was developed using Long Short-Term Memory neural network. Its performance was evaluated against a linear regression baseline using a rolling test period. In addition, Conformal Prediction was applied to generate calibrated 90% prediction intervals, providing probabilistic measures of forecast uncertainty.

The results showed that the LSTM model improved forecast accuracy significantly compared to the linear baseline, reducing error metrics across most zones and capturing both short-term fluctuations and broader seasonal trends.

The study concluded that advanced forecasting tools can strengthen operational decision making for electricity trading in Mexico. The findings also highlighted areas for further development, including the integration of renewable generation data, transmission constraints and more advanced modelling architectures to refine local price forecasts.

Keywords: electricity price forecasting, LSTM, Conformal Prediction, weather-driven demand, Mexico, energy trading, machine learning

PREFACE

This thesis, titled “Optimizing Electricity Trading Decisions through Weather-Influenced Demand and Supply Forecasting” has been developed with the generous support and guidance of BlueEnergy, a pioneering company in Mexico’s energy trading market. I would like to extend my gratitude to BlueEnergy for their sponsorship and insights, which have substantially shaped the scope and practical applications of this study.

The forecasting models in this research were rigorously tested and evaluated, enabled by BlueEnergy’s provision of extensive historical data on electricity prices, supply, demand, and U.S. gas prices. This data allowed for a solid and trustworthy analysis of the relationship between weather patterns and market behaviours, thereby enhancing the thesis’s practical value.

Thank you BlueEnergy and everyone involved for their invaluable support and encouragement throughout this project.

CONTENTS

LIST OF SYMBOLS AND TERMS

MEM - Mexican Wholesale Electricity Market (Mercado Eléctrico Mayorista)
CENACE - National Energy System in Mexico (Centro Nacional de Control de Energía), state-owned utility
CFE – Federal electricity commission (Comisión Federal de Electricidad)
DAM - Day-Ahead Market, where hourly prices for the next day are cleared
RTM - Real-Time Market, balancing market for deviations from DAM forecasts
LMP - Locational Margin Price, node-level price reflecting energy cost, congestion and losses
Qualified Supplier - Market participants such as BlueEnergy that supplies energy to qualified users
Marginal-Cost Dispatch - Pricing mechanism where the cost of the last plant dispatched sets the market price
Physical-Order Dispatch - Dispatch based on plant type or ownership rather than marginal cost
Congestion - Transmission constraints that prevent low-cost power from flowing to high-demand regions
ARIMA/SARIMAX = Autoregressive Integrated Moving Average / Seasonal Autoregressive Integrated Moving Average with Exogenous Variables
LSTM - Long Short-Term Memory neural network
MXN – Mexico’s currency, Mexican peso
MAE (mean absolute error) - Average absolute difference between predicted and actual prices
RMSE (root mean squared error) - Square root of the mean squared difference between predicted and actual
sMAPE (symmetric mean absolute error) - Percentage-based error metric robust to near-zero values
CP (Conformal Prediction) – Framework for producing statistically valid prediction intervals

1 INTRODUCTION

1.1 Background

Mexico’s Wholesale Electricity Market (MEM) operates under a marginal cost dispatch, where hourly prices reflect the cost of the last unit dispatched to meet demand. In recent years, extreme temperatures, hydrological stress, and imported-gas price swings have increased short-term volatility (Balza et al., 2024, pp. 71, 95.)

These dynamics make weather a first-order driver of price formation, via demand (cooling/heating) and renewable output, while international gas benchmarks influence marginal generation costs. Methods that can learn nonlinear, time-dependent relationships and quantify uncertainty are therefore essential for reliable short-term price forecasting in the MEM (De la Torre et al., 2024, pp. 524-525.)

1.2 Research Motivation

This thesis is carried out in collaboration with BlueEnergy, a Qualified Supplier in the MEM that provides electricity supply contracts, financial coverage, and renewable energy solutions to large users. BlueEnergy operates a trading desk that manages wholesale market participation on behalf of clients, designs hedging strategies, and develops flexible pricing schemes. The company is therefore highly exposed to price volatility. Unexpected market fluctuations directly affect profitability, contract performance, and risk exposure.
For BlueEnergy, accurate price forecasts are not simply a technical exercise, but a practical necessity. Knowing whether prices are likely to rise or fall

relative to hedging positions can guide decision-making in real time. Interval forecasts can inform the degree of risk associated with given strategy. By developing models that integrate weather variables, demand patterns, and natural gas prices, this thesis aims to provide tools that can improve BlueEnergy’s ability to manage uncertainty and enhance the efficiency of its trading operations

1.3 Thesis outline

Chapter 2 summarizes market evolution and trading layers (DAM/RTM) and reviews price formation under marginal dispatch, with emphasis on volatility drivers and regulatory context. Chapter 3 outlines weather forecasting considerations for energy systems and their implications for Mexico. Chapter 4 presents the case study data and exploratory analysis. Chapter 5 develops the LSTM+CP forecasting framework, reports accuracy vs. the linear baseline and interprets intervals for trading. Chapter 6 concludes with key findings and target avenues for improvement.

1.4 Use of AI in this Thesis

In this thesis, artificial intelligence (AI) tools were used in accordance with the SAMK guidelines. I used ChatGPT primarily to assist with planning the structure of the thesis, clarifying theoretical concepts and receiving general guidance when encountering methodological or writing-related questions. AI was also used to improve wording and refine the organization of text I had already written. Whenever rewording was done, I verified all facts using original academic and professional sources. All analyses, interpretations, modelling decisions, data processing steps and conclusions presented in this thesis are entirely my own. Citations and articles used in this thesis were all independently acquired and researched.

2 ELECTRICITY TRADING IN MEXICO

Mexico's electricity market has gone through major transformations in the past decade, shifting from a state-owned monopoly to a partially competitive market, and then gradually back toward stronger state control. Understanding this evolution, and how electricity is traded through its different timeframes, is essential to explain how prices are formed and the operating environment for trading today.

2.1 Electricity Market History and Structure

For much of the 20th century, the Federal Electricity Commission (Comisión Federal de Electricidad, CFE) controlled every part of the electricity system: generation, transmission, distribution, and retail supply. This meant that one state-owned company produced electricity, moved it through high-voltage transmission lines (called the grid, the network that carries electricity from power plants to homes and industries), and sold it directly to customers. Such model is known as a vertically integrated state monopoly.

The 2013 constitutional energy reform and the 2014 Electricity Industry Law (Ley de la Industria Eléctrica, LIE) aimed to modernize this structure. The reform opened the sector to private investment, allowing companies to build generation facilities and sell electricity through a new Wholesale Electricity Market (WEM). CFE retained ownership of the transmission and distribution networks, but private participants could now compete in the power generation and commercialization (Miranda et al., 2022, p. 2-3). These auctions helped integrate large amounts of wind and solar power and attracted substantial private investment.

In 2018, however, a new administration began revising these liberalization measures. Further auctions were cancelled, new permitting restrictions were placed on private renewable projects, and CFE regained preferential access to the grid. In 2021, reforms to the LIE granted priority dispatch to CFE's power plants regardless of their cost or environmental impact, effectively undermining the merit-order principle that governs efficient market operation. (Miranda et

al., 2022, p. 2-3.) A constitutional amendment proposed in 2022 sought to return full control of generation to CFE was rejected by Congress, but the direction of policy increased uncertainty.
Despite these political shifts, the Mexican WEM still operates as a hybrid system, coordinated by CENACE (Centro Nacional de Control de Energía), which acts as the independent system operator responsible for balancing supply and demand and setting market prices. Most short-term transactions occur in the Day-Ahead Market (DAM) and Real-Time Market (RTM). In the DAM, participants submit hourly bids for the following day; CENACE clears the market and sets locational marginal prices (LMP) at each node. In the RTM, deviations from forecasts are balanced in real time, with prices more volatile than in the DAM. “In both bidding schemes, the electricity price is calculated using algorithms where forecasted demand is satisfied by considering the supply biddings from market participants” (De la Torre et al., 2024, p. 525) either at the nodal (LMP) or zonal level depending on regulation. Beyond short-term trading, Mexico uses long-term, mid-term, ancillary-services markets and a Clean Energy Certificate (CEL) scheme to incentivize clean generation. (De la Torre et al., 2024, p. 525.)(Balza et al., 2024, pp.13-16, 28-29.)

Although the regulatory framework still formally supports competitive trading, ongoing legal disputes and frequent policy changes have introduced uncertainty. Many private investors have suspended new projects, while CFE remains dominant in both generation and basic supply. As a result, Mexico’s electricity market today operates as a hybrid structure - part competition, part monopoly - where the efficiency of dispatch and price formation depends as much on political and regulatory decisions as on economic forces.

2.2 Market Fundamentals: Supply, Demand and Price Behaviour

Understanding the behaviour of electricity prices in Mexico requires a close look at how supply and demand interact in real time. Electricity is not like most commodities; it cannot be stored in large quantities at an affordable cost, meaning that generation and consumption must always remain balanced. As

Locela (2009, p. 4) describes, “electricity has to be produced practically at the same time that it is consumed”, which makes it a “commodity whose supply and demand have to be balanced at all times”.

On the supply side, Mexico’s generation mix is made up of combination of renewable and thermal technologies. Wind and solar have grown considerably since the 2013 energy reform, while combined-cycle natural gas plants remain the main source of generation. According to Masiriz & Stronelli (2024, p. 5), these gas-based plants produced nearly 59 percent of total electricity in 2023, showing that the country’s electricity prices are still heavily linked to natural gas costs. Because most of this gas is imported from the United States, any fluctuation in U.S. gas prices – such as those caused by extreme weather – directly affects Mexican electricity prices. Demand follows daily and seasonal patterns shaped by temperature and humidity; heatwaves and cold spells intensify these cycles and influence U.S. gas demand and prices.

Transmission capacity further shapes how supply meets demand. When certain parts of the grid become congested, electricity can’t flow freely from cheaper regions to others where demand is high. As a result, local generators with higher cost must step in, increasing prices. Locela (2009, p. 7) notes that such congestion “generates a loss of economic efficiency” because it “favours the less efficient generator in giving it market power”. This makes electricity markets not only a matter of cost but also of location and grid conditions.

Overall, electricity prices in Mexico reflect three interacting elements: variable renewable generation, the cost of natural gas, and the limits of the transmission network. These relationships mean that price forecasting in the Mexican market must account for both physical and economic drivers, not just historic trend.

2.3 Challenges in The Mexican Market as a Qualified Service Supplier

Qualified service suppliers (QSS) such as BlueEnergy operate within Mexico's wholesale electricity market by purchasing power from generators and selling it to qualified users, mainly large industrial and commercial consumers. In theory, the market reform was designed to open competition in generation and supply while keeping transmission and distribution under the control of the state-owned Comision Federal de Electricidad (CFE). In practice, however, private suppliers face significant operational and regulatory challenges.

The first challenge is market volatility. Because electricity prices in Mexico are closely tied to the price of natural gas and the variability of renewable energy, suppliers must constantly manage the risk of sudden price increases. According to Balza et al. (2024, p. 24), short-term electricity prices in Latin America and the Caribbean are affected by fuel price volatility, hydrological variability and network constraints, all of which are also key characteristics of the Mexican system. Despite Mexico having a significant number of natural reserves, due to the demand increase and the declining of gas production, they still rely on natural gas imports from the USA.

The second challenge is regulatory uncertainty. Since 2018, reforms have strengthened CFE's role in planning and dispatch. In 2021, the LIE reform granted preferred grid access and "priority dispatch of all CFE generators, independently of considerations for costs or emissions" (Miranda et al., 2022, pp. 2-3). This undermines competitive dispatch and complicates long-term planning.

A third challenge comes from transmission congestion and limited interconnection capacity, which restrict access to cheaper electricity from other regions. When congestion occurs, qualified supplies must obtain power locally at higher prices or rely on expensive balancing energy in the real-rime market.

Lastly, financial exposure in the Day-Ahead and Real-Time Markets makes risk management critical. Suppliers like BlueEnergy often use bilaterial contracts or hedging instruments to stabilize costs, but these tools are still limited in the Mexican context. Balza et. al (2024, p. 15), notes that most electricity in the region is traded through long-term contracts rather than flexible short-term markets, which “limits liquidity and makes it difficult to hedge against short-term price movements”.

Together, these factors mean QSS must actively manage risk in an environment where policy changes can shift the market framework quickly, while end-users demand cost stability and clean energy.

2.4 Marginal Dispatch and Price Formation in the Mexican Electricity Market

Electricity dispatch in Mexico follows the marginal cost principle, where the system operator (CENACE) selects which power plants will generate electricity based on their variable cost. This is known as economic or merit-order dispatch. Cheaper plants are used first, and more expensive ones are only called upon when demand increases. The last plant needed to meet demand sets the marginal price, which becomes the price paid to all generators for that period. Renewable sources such as solar and wind have no fuel cost, so their marginal cost is effectively zero. They are therefore dispatched first when available. Once renewable capacity is exhausted, more expensive plants such as coal, diesel or fuel oil are called. The last unit needed to meet demand sets the marginal price for the interval. Gutiérrez-Meave et al. (2021, p. 7) provide a detailed explanation of this mechanism, describing that under normal conditions, an ISO chooses generators according to their marginal costs, “starting with the lowest cost plant and finishing with the highest cost generator that finally meets demand. Then, it determines the equilibrium price according to the last dispatched bid”. Which nodal pricing details appear in Section 2.1, it is this marginal unit that determines prices observed in DAM and RTM.

3 WEATHER FORECASTING AND ENERGY SYSTEMS

Weather forecasting plays a central role in modern electricity systems, particularly in countries like Mexico where renewable energy and electricity demand are strongly influenced by climate conditions. Weather affects both how much energy is produced and how much is consumed, which in turn drives market prices and operational decisions. In this chapter, I first provide an overview of weather forecasting – how it's done and what it's limits are – then examine how weather affects both energy supply and demand and finally discuss how seasonal and extreme events complicate the energy system.

3.1 Overview of weather forecasting

Weather forecasting is the scientific estimation of atmospheric conditions for future time periods, using a combination of physics-based models, statistical methods and as of in recent years machine learning approaches. The core of most forecasting systems lies in numerical weather prediction models (NWP), which simulate the atmosphere's dynamics by solving equations for temperature, pressure, humidity and wind at different altitudes and locations. These models provide forecasts that are refined through data understanding, which combines observations from satellites, radars and ground stations. However, their precision depends on the availability and quality of data, therefore these models essentially contain error and biases, especially when downscaling to the spatial and temporal resolution needed for energy systems.

For energy applications, forecasts need to be adapted to shorter timeframes and smaller geographical scales than those typically produced for general meteorological purposes. This is because electricity systems depend on hourly and even minute-by-minute information to match supply and demand. According to Amin & Mourshed., global weather models must be downscaled and bias-corrected to capture the local conditions that influence renewable generation, such as solar radiation or wind speed. In Mexico, this adaptation is particularly important given the country's geographical diversity: strong solar potential in the north, steady wind resources in the south and significant regional variation in temperature and humidity (Amin & Mourshed, 2023, pp. 1, 6-7, 14-15.)

To address these challenges, recent developments have introduced hybrid forecasting techniques that combine physical models with machine learning. These approaches use historical weather data alongside real-time sensor measurements to improve short-term predictions. For instance, proposing a two-step machine learning approach that enhances the predictive accuracy of ensemble weather forecasts for energy systems. ML models such as Long Short-Term Memory (LSTM) networks are now widely used to capture complex time dependencies in weather variables, allowing for better short-term forecasting of solar or wind output (Amin & Mourshed, 2023, pp. 9-10.)

3.2 Weather Impact on Demand, Supply and Seasonal Events

Weather is one of the strongest forces shaping Mexico's electricity system. It affects both how much energy people use and how much can be produced, influencing prices every day.

On the demand side, temperature and humidity are the main drivers. When heatwaves occur, air-conditioners use increases sharply, especially in northern and coastal states. During cooler periods or cold fronts, heating and industrial fuel use rise, particularly in the central highlands. These patterns create daily and seasonal cycles that system operators and supply must constantly balance. Reports from CENACE show that the hottest months of May to September consistently bring the highest electricity consumption in the country.

On the supply side, weather determines how much renewable energy is available. Solar generation depends on sunlight and cloud cover and is strongest in Mexico's dry northern regions. Wind generation concentrated in the Isthmus of Tehuantepec, where steady winds make it one of Latin America's most productive wind areas. Hydropower relied on rainfall and reservoir levels, which vary across seasons and regions. When renewable output falls, because of cloudy skies, weak winds or drought, CENACE relies more on gas-fired plants, increasing costs and emissions. This relationship was evident during 2023 and early 2024, when a long heatwave and low rainfall pushed demand to record levels and reduced hydro generation, contributing to sharp price increases in the MEM (Masiriz & Stornelli, 2024, pp. 3-4, 8-9.)(Balza et al., p. 81.)

Seasonal patterns generally follow Mexico's climate cycle. The dry season (November-April) brings clear skies that favour solar generation, while the rainy season (May-October) increases hydropower, but can reduce solar output due to cloud cover. However, large-scale climate phenomena such as the El Niño-Southern Oscillation (ENSO) can disrupt these expected patterns. ENSO describes a natural climate cycle that alternates between El Niño (warmer Pacific waters) and La Niña (cooler Pacific waters). These events influence global weather through what scientists call teleconnections – changes in atmospheric circulation that affect temperature and rainfall far from the Pacific Ocean (Mendéz & Magaña, 2009, pp. 1177-1178.)
In Mexico, El Niño often brings hotter and drier conditions, while La Niña usually brings cooler and wetter weather. Yet these effects are not always predictable. Research shows that ENSO's influence varies by region and season: some areas may become drier during El Niño, others wetter, and the same event can have opposite effects from one year to the next. This variability makes it difficult for energy planners, who analyse energy needs, to rely on past patterns alone. Even though El Niño and La Niña occur roughly every few years, their local impacts are uncertain, and forecasts made months in advance can lose accuracy, particularly in spring when climate models are less reliable (Mendéz & Magaña, 2009, pp. 1182-1185, 1185-1187.)

For the electricity sector, this uncertainty matters because it directly impacts both supply and demand forecasts. An unexpected dry El Niño year can lower hydro generation and increase air-conditioning use, while an unusually wet La Niña can raise hydro output, but reduce solar generation. These surprises can distort short-term forecasts of demand, renewable production, and even fuel prices. As a result, traders and system operators must prepare for a range of possible scenarios rather than assuming that each ENSO phase will behave the same way as in the past.

In practical terms, this means that weather forecasting for Mexico's energy market should combine seasonal climate information with probabilistic approaches that express uncertainty as a rage of outcomes instead of a single prediction. Recognizing these unpredictable weather patterns can help improve decision-making in an increasingly climate-sensitive market like this one.

4 CASE STUDY: HISTORICAL DATA ANALYSIS IN MEXICO

4.1 Data Collection and Preprocessing

For this case study, I collected and prepared a comprehensive dataset covering the period from January 2021 to March 2023, aimed to describe how operational, economic and meteorological variables interact to shape electricity demand and price formation. The analysis also identifies the relationships that will later serve as inputs to the forecasting framework developed in Chapter 5.

The core of the dataset consists of hourly electricity prices by city and hourly electricity demand, both obtained directly from CENACE's public database. These two variables represent the operational dynamics of the Mexican grid and serve as the main indicators for the analysis. To account for external economic factors that influence electricity generation costs, I added the daily natural gas price from the Houston Ship Channel API provided by Natural Gas Intelligence (NGI) and converted it to Mexican Pesos with the currency exchange corresponding to that day. The exchange rate for USD-MXN was extracted from the National Bank of Mexico's API.

Meteorological variables – mean temperature, wind speed, relative humidity, rainfall and sunshine duration – were gathered from open-mateo.com and BlueEnergy's internal servers. These weather parameters were included because they directly affect both electricity consumption and renewable generation.

All datasets were converted to a consistent datetime format and resampled to daily averages. Weather gaps were interpolated with the mean of adjacent hours, while electricity-market variables retained zero values to preserve authentic operational signals such as low-demand periods or maintenance outages. I also added empirical variables like weekdays as well as if a day is a holiday or preholiday, to capture systematic behavioural effects.

For visualization and exploratory analysis, the variables were kept in their physical units. All cleaning and plotting were performed in Python using Pandas, NumPy, Matplotlib and Seaborn.

4.2 Exploratory Analysis and Insights

Seasonal Patterns and Market Overview

The evolution of daily average electricity prices and total generation is shown in (Figure 1). Both Variables exhibit pronounced seasonality, with demand and generation peaks during the summer months, coinciding with elevated prices. Short-term price spikes correspond to sudden declines in generation, which can occur due to plant outages, fuel-supply constraints, weather-related reductions in renewable output or just congestions.

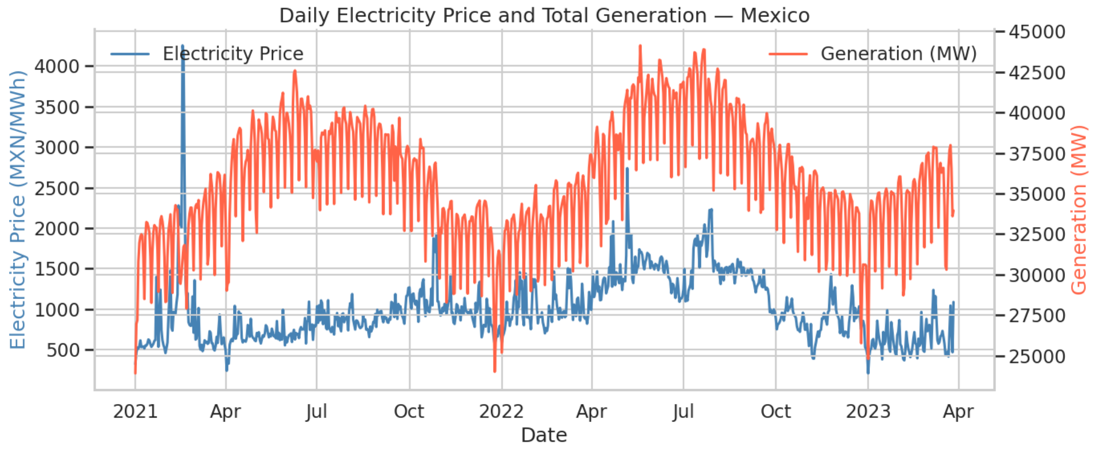

Figure 1. Relationship between total generation and electricity price

Monthly variability further reflects this pattern. As illustrated in Figure 2, price dispersion widens noticeably between May and August, when high temperatures increase cooling loads. Inversely, the winter months show narrower distributions, indicating greater market stability during cooler periods.

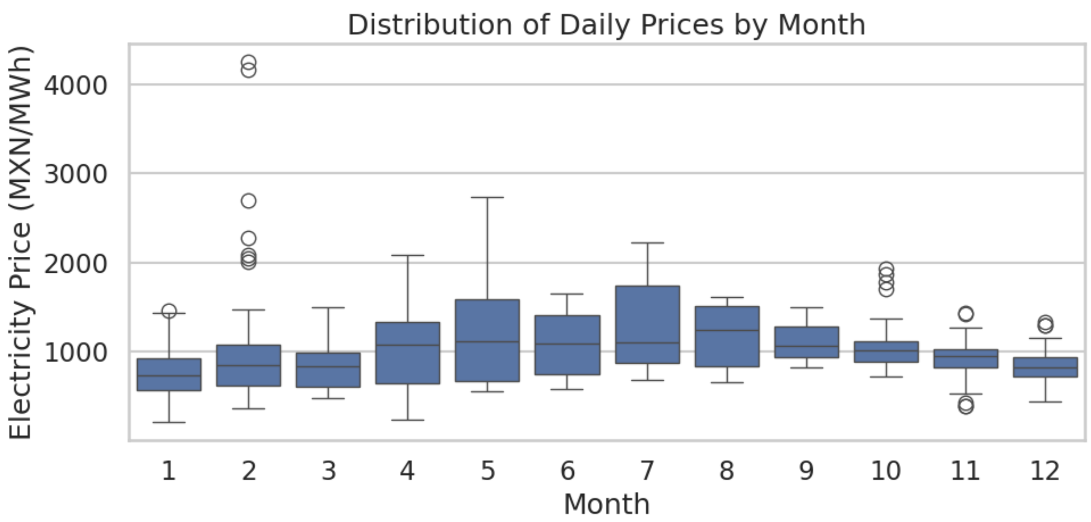

Figure 2. Distribution of daily electricity prices by month

Weather Influence on Demand and Generation

Temperature plays a dominant role in determining electricity consumption. Figure 3 shows the relationship between mean temperature and electricity demand. Demand increases almost linearly above approximately 15°C, as air-conditioning and refrigeration requirements intensify. This pattern highlights the strong dependence of Mexico's load profile on ambient temperature and supports its inclusion as a key explanatory variable for price forecasting.

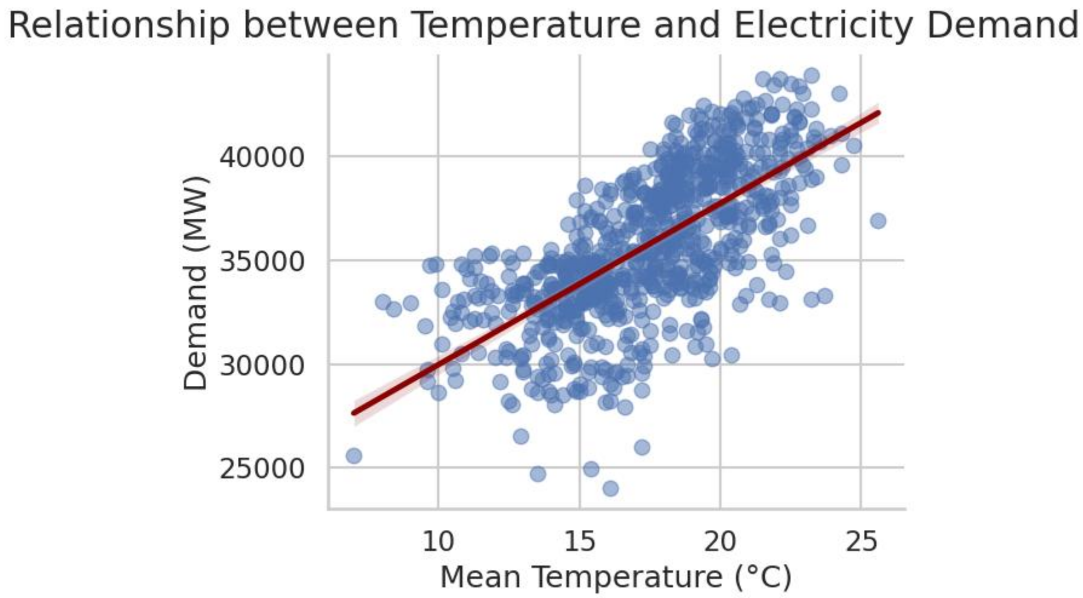

Figure 3. Relationship between mean temperature and electricity demand

The influence of solar irradiance is evident in Figure 4, which plots sunshine duration against total generation. Longer sunshine hours correlate with higher generation, confirming the growing contribution of solar energy in Mexico's power mix. The slight flattening at the upper end suggests the presence of generation-capacity limits that cap additional solar output even during extended sunny periods.

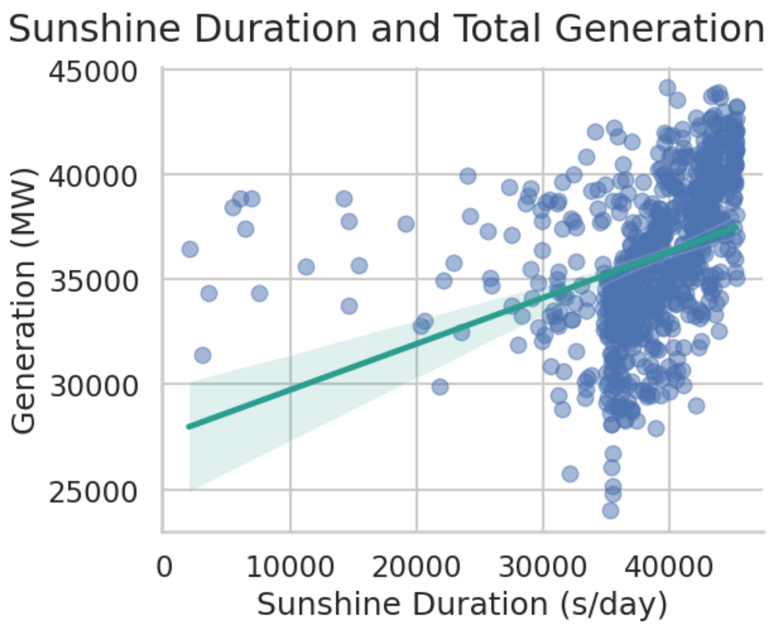

Figure 4. Sunshine duration and total generation

Market Fundamentals and Price Formation

The connection between system generation and price is shown in (Figure 5). Higher generation levels coincide with higher average prices, consistent with a marginal-cost dispatch system where increased demand activates costlier thermal units. Occasional deviations from this trend – where prices spike despite moderate generation – indicate localized constraints or short-term volatility in fuel costs.

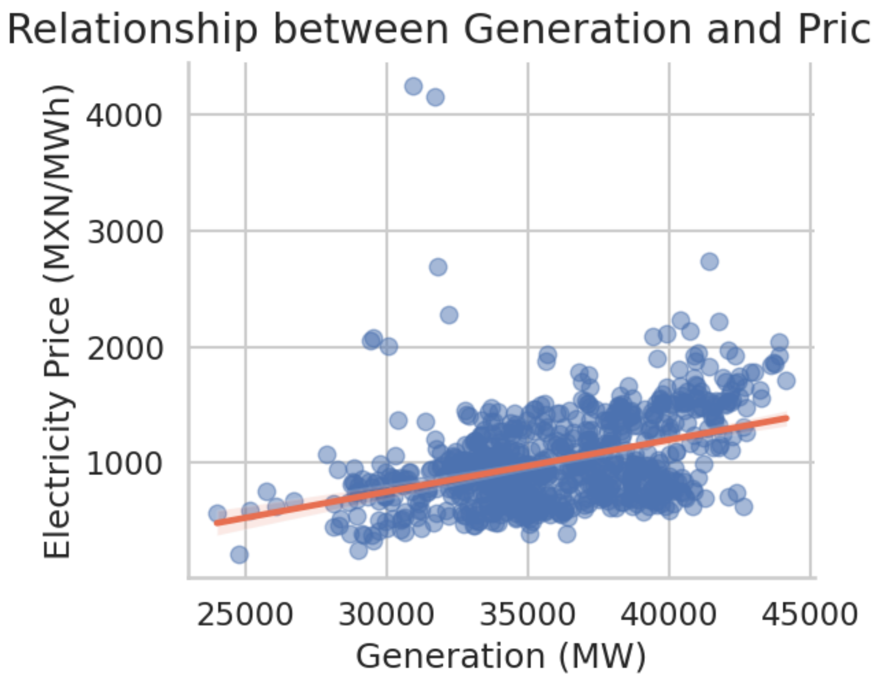

Figure 5. Relationship between total generation and electricity price

Inter-Variable Relationship

To provide a consolidated view, Figure 6 presents the correlation matrix among all main variables. Electricity price correlation moderately with both demand (r ≈ 0,40) and temperature (r ≈ 0,30), while demand and generation show a strong correlation (r ≈ 0,67). The negative correlation between gas price and generation (r ≈ -0,28) reflects the asynchronous timing of gas trading nature of market fundamentals, fuel inputs and weather conditions in Mexico's short-term electricity dynamics.

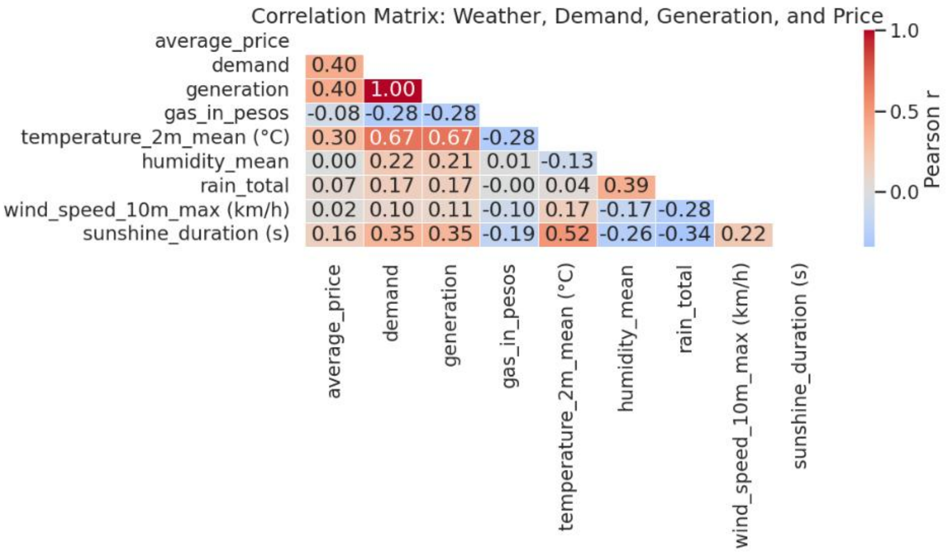

Figure 6. Correlation matrix of weather, demand, generation and price variables

Calendar Effects

Electricity prices also respond to calendar patterns, as shown in (Figure 7). Prices are systematically higher on weekdays than on weekends or holidays, mirroring industrial and commercial load cycles. Pre-holiday days exhibit slightly higher averages, suggesting that market participants adjust trading positions and generation scheduling ahead of expected demand reductions. Such behavioural regularities are critical for improving model accuracy in day-ahead forecasting.

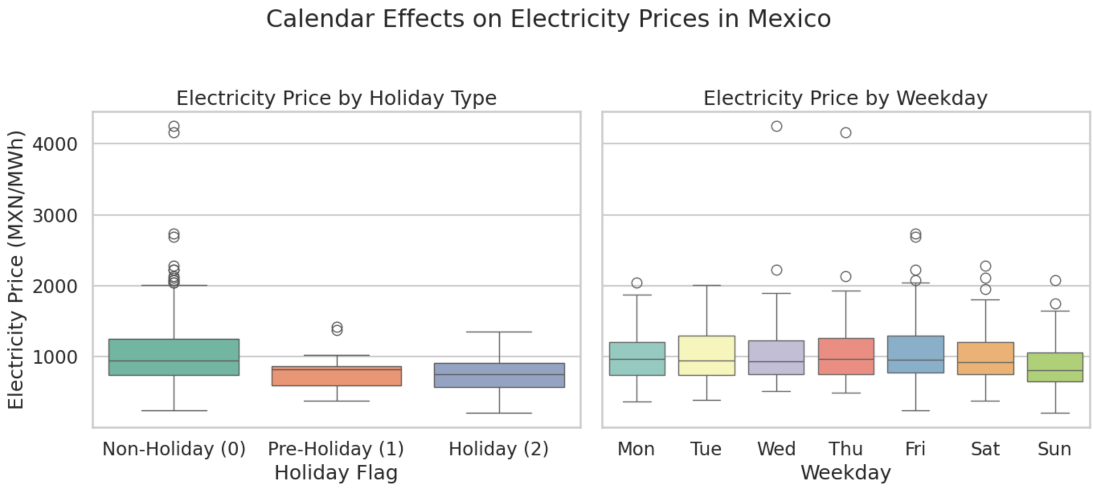

Figure 7. Average electricity prices by weekday and holiday category

These insights confirm that electricity price dynamics are highly responsive to both weather and calendar factors, validating the need for forecasting models that can capture nonlinear dependencies across these variables. Chapter 5 builds these findings by implementing LSTM-based probabilistic forecasting framework to quantify and predict these interactions for more efficient electricity-trading decisions.

5 PRACTICAL STUDY: FORECASTING FRAMEWORK AND PROBABILISTIC ANALYSIS

5.1 Forecasting Framework and Model Design

This chapter depicts the forecasting stage, which applies a deep-learning approach to model non-linear dependencies between our selected variables and to predict short-term electricity prices in Mexico. The selected architecture is a Long Short-Term Memory (LSTM) neural network, which belongs to the family of recurrent networks specifically designed to capture correlations of data points closer in time and long-range dependencies in sequential data. Traditional linear or autoregressive models perform adequately under stationary conditions, but struggle with the nonlinear dynamics that are typical of wholesale electricity markets, where sudden price jumps occur. The LSTM structure, consisting of memory cells that selectively retain or forget information, allows the model to learn these temporal patterns effectively.

Each of the 101 market zones was modelled individually to account for local variety in demand and weather. The feature set included daily demand, total generation, natural-gas prices in MXN, weekday and holiday indicators and meteorological variables (mean, maximum and minimum temperatures, humidity, wind speed and sunshine duration). All explanatory variables were normalized using Min-Max scaling, while the target variable (average daily electricity prices) was scaled and later inversely transformed back to pesos. The final architecture contained two LSTM layers (64 and 32 neurons) followed by a dense output layer, trained with a dropout rate = 0,2 and early stopping regularization to prevent overfitting. The loss function was mean absolute error (MAE) and the optimizer Adam. Forecast horizons of one day ahead and seven days ahead were produced using a rolling-window approach covering the period October 2022 – March 2023 for validation.

5.2 Model Evaluation and Baseline Comparison

To verify the added value of nonlinear modelling, a Linear Regression baseline was implemented under the same train-test split and feature configuration. The comparison shows a consistent improvement in accuracy across almost all zones. Table 1 summarizes representative results.

Zone	MAE (LR)	MAE (LSTM)	RMSE (LR)	RMSE (LSTM)	sMAPE (LR)	sMAPE (LSTM)
Acapulco	386	193	450	247	39,7%	23,2%
Aguas-calientes	374	147	438	200	41,9	19,8%
Ap-atzingán	396	170	464	217	41,1%	21,0%
Camargo	414	158	471	203	57,5%	29,0%
Cancún	632	436	763	664	50,9%	37,9%

Table 1. Comparison of the first 5 zones error differences

On average, the LSTM reduced MAE by ≈ 200 MXN/MWh and sMAPE by ≈ 20 percentage points relative to the linear model. The best-performing zones are Monclova, Huasteca, Sabinas, Victoria and Uruapan, which achieved MAE bellow 150 MXN/MWh and sMAPE near 19%. The weakest performance occurred in Obregón, Navojoa and Guasave, regions characterized by strong renewable penetration and frequent network congestion. These disparities confirm that local volatility and renewable irregularity remain difficult to model purely from aggregated variables.

5.3 Forecasting Results and Interpretation

Overall, the LSTM captured daily and weekly fluctuations well, especially during stable demand periods. Most residual errors correspond to sudden spikes caused by short-term generation outages or fuel-price jumps. Forecast accuracy declined slightly toward the seven-day horizon, as expected, but the model still preserved trend directionality. The results demonstrate that deep learning can outperform conventional linear baselines when the system exhibits nonlinear, weather-driven patterns. Nevertheless, over-fitting risk increases rapidly if additional layers or neurons are introduced, and the current architecture offers a balanced compromise between accuracy and generalization.

5.4 Probabilistic Forecasting with Conformal Prediction

While point forecasts are useful for estimating expected prices, traders require information about forecast uncertainty to evaluate risk. To achieve this, a Conformal Prediction (CP) method was applied to the LSTM outputs to generate 90% prediction intervals (PIs) for each zone and day.

The conformal framework operates by splitting the training set into a core training subset and calibration subset. After training the LSTM, residuals from the calibration period are ranked, and the (1-α) quantile of their absolute values defines a symmetric error bound q. Each forecast is the expanded to the interval

$$[\widehat{y_t} - q, \widehat{y_t} + q\ ]$$

Which statistically contains the true price with probability ≈ 90%. The empirical coverage calculated for most zones was close to this target, confirming valid uncertainty estimation.

From a practical perspective, the width of the PI reflects market volatility and model confidence. Industrial regions such as Monterrey or Saltillo showed narrow bands (< ± 40 MXN/MWh), indicating predictable behaviour, while coastal and Yucatán nodes displayed much wider intervals (> ± 100 MXN/MWh), signalling high exposure to renewable and weather volatility.

5.5 Discussion and Practical Implications

The combined LSTM + Conformal Prediction framework provides BlueEnergy with both precise and probabilistically meaningful forecasts.

- The LSTM outperforms classical linear regression, which was previously used by them for this type of task, by capturing nonlinear and temporal relationships among demand, weather and gas-price drivers.
- The prediction intervals offer a quantitative measure of forecast confidence, enabling traders to measure the likelihood that real market prices will deviate from expectations.

For contract pricing, a narrow PI implies high confidence, supporting fixed price offers; a wide PI indicates uncertainty, suggesting flexible or indexed pricing strategies. This directly enhances BlueEnergy’s risk-management capability.
The approach also supports hedging by highlighting nodes where forecast volatility is structural – information that can guide financial coverage or geographic diversification.

6 CONCLUSION

The Mexican wholesale electricity market operates under a marginal-cost dispatch system, where prices are determined by the intersection of generation costs and real-time demand. Since the market liberalization reforms, increased participation of renewable energy has brought higher volatility making short-term price forecasting essential for market participants such as BlueEnergy. Weather conditions play a decisive role in this structure: temperature, humidity and wind patterns directly affect both consumption and renewable generation, while international gas prices influence marginal generation costs. This interdependence creates a dynamic market that requires advanced analytical tools capable of capturing nonlinear interactions between physical and economic variables.
The practical component of this thesis addressed this challenge by developing a Long Short-Term Memory (LSTM) forecasting model complemented by Conformal Prediction (CP) intervals. The approach extended the case study of Mexico’s electricity market into a predictive application, combining historical demand, generation, gas and weather data to produce day-ahead and week-

ahead price forecasts for all market zones. Compared to the linear regression method previously used BlueEnergy, the LSTM reduced forecasting errors by roughly 40-50% in MAE and improved overall robustness across regions. The integration of 90% prediction intervals further enhanced clarity by providing a quantitative measure of uncertainty for each forecast, thereby translating the model outputs into a practical risk-assessment tool.

These results demonstrate that advanced data-driven forecasting can complement traditional market analysis, offering BlueEnergy greater confidence in contract pricing and trading decisions while maintaining transparency in forecasting uncertainty.

6.1 Room for Improvement and Future Work

Although the forecasting framework achieved strong results, there remains scope for refinement. Future development should focus on improving data quality and granularity, particularly by incorporating zone-specific renewable generation, transmission constraints, and short-term weather forecasts to better capture local volatility. Methodologically, exploring more advanced network structures such as hybrid LSTM-attention models or graph-based approaches could enhance the model's ability to learn both temporal and spatial dependencies between zones. From an operational perspective, establishing an automated retraining process and connecting the model directly to BlueEnergy's trading platform would allow real-time updates and integration into daily decision-making. Finally, extending the model to support scenario-based simulations could help quantify financial risks associated with price uncertainty, strengthening its value as a decision-support tool for market operations.

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