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ENHANCING ELECTRICITY DEMAND PREDICTION IN MEXICO: A COMPARATIVE ANALYSIS OF FORECASTING MODELS USING CONFORMAL PREDICTION

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ABSTRACT

Objectives: This study aims to identify a reliable prediction model for Mexico's wholesale electricity market to prevent supply-demand imbalances by analyzing three machine learning models with conformal prediction techniques.

Theoretical Framework: Electricity demand forecasting traditionally uses SARIMAX models or artificial neural networks (ANN)/deep learning (DL). However, SARIMAX models are sensitive to data perturbations, while ANN/DL models face interpretability and computational challenges. Decision tree-based models (LGBM and CatBoost) have emerged as alternatives, offering potential advantages for time series prediction.

Method: The study analyzed electricity demand data from CENACE (2018-2022), using four years for training and one for validation. Model performance was evaluated using MAPE, MAE, MSE, RMSE, and R^2 metrics, along with Conformal Prediction metrics for uncertainty quantification.

Results and Discussion: CatBoost demonstrated superior performance (MAPE: 1.85%, R^2: 0.9) compared to LGBM and SARIMAX models. SARIMAX showed significant limitations in prediction accuracy, particularly during seasonal variations. LGBM achieved intermediate performance with acceptable accuracy (R^2: 0.89).

Research Implications: The LGBM and CatBoost models achieved MAPE values within the literature's benchmark range (0.4-3%) while requiring fewer computational resources than complex DL models, making them practical alternatives for electricity demand forecasting.

Originality/Value: This research pioneers the application of three prediction models with conformal prediction techniques in the Mexican electricity market context, offering probabilistic guarantees for prediction validity instead of traditional point predictions.

Keywords: Electricity Demand, Wholesale Electricity Markets, Time Series Forecast, Conformal Prediction.

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MELHORANDO A PREVISÃO DA DEMANDA DE ELETRICIDADE NO MÉXICO: UMA ANÁLISE COMPARATIVA DE MODELOS DE PREVISÃO USANDO PREVISÃO CONFORME

RESUMO

Objetivos: Este estudo tem como objetivo identificar um modelo de previsão confiável para o mercado atacadista de eletricidade do México para evitar desequilíbrios entre oferta e demanda, analisando três modelos de aprendizado de máquina com técnicas de previsão conformes.

Estrutura teórica: A previsão da demanda de eletricidade tradicionalmente usa modelos SARIMAX ou redes neurais artificiais (ANN)/aprendizagem profunda (DL). No entanto, os modelos SARIMAX são sensíveis a perturbações nos dados, enquanto os modelos ANN/DL enfrentam desafios de interpretação e computacionais. Os modelos baseados em árvores de decisão (LGBM e CatBoost) surgiram como alternativas, oferecendo possíveis vantagens para a previsão de séries temporais.

Método: O estudo analisou dados de demanda de eletricidade do CENACE (2018-2022), usando quatro anos para treinamento e um para validação. O desempenho do modelo foi avaliado usando as métricas MAPE, MAE, MSE, RMSE e R^2, juntamente com as métricas de previsão conforme para quantificação da incerteza.

Resultados e discussão: O CatBoost demonstrou desempenho superior (MAPE: 1,85%, R^2: 0,9) em comparação com os modelos LGBM e SARIMAX. O SARIMAX mostrou limitações significativas na precisão da previsão, especialmente durante variações sazonais. O LGBM obteve desempenho intermediário com precisão aceitável (R^2: 0,89).

Implicações para a pesquisa: Os modelos LGBM e CatBoost alcançaram valores de MAPE dentro da faixa de referência da literatura (0,4-3%) e, ao mesmo tempo, exigiram menos recursos computacionais do que os modelos DL complexos, tornando-os alternativas práticas para a previsão da demanda de eletricidade.

Originalidade/valor: Esta pesquisa é pioneira na aplicação de três modelos de previsão com técnicas de previsão conformes no contexto do mercado de eletricidade mexicano, oferecendo garantias probabilísticas para a validade da previsão em vez das previsões pontuais tradicionais.

Palavras-chave: Procura de Eletricidade, Mercados Grossistas de Eletricidade, Previsão de Séries Temporais, Previsão Conformacional.

MEJORAR LA PREDICCIÓN DE LA DEMANDA DE ELECTRICIDAD EN MÉXICO: UN ANÁLISIS COMPARATIVO DE MODELOS DE PRONÓSTICO UTILIZANDO PREDICCIÓN CONFORME

RESUMEN

Objetivos: El objetivo de este estudio es identificar un modelo de predicción confiable para el mercado mayorista de electricidad de México para prevenir desequilibrios entre oferta y demanda, mediante el análisis de tres modelos de aprendizaje automático con técnicas de predicción conformadas.

Marco teórico: La previsión de la demanda de electricidad utiliza tradicionalmente modelos SARIMAX o redes neuronales artificiales (ANN)/aprendizaje profundo (DL). Sin embargo, los modelos SARIMAX son sensibles a perturbaciones de datos, mientras que los modelos ANN/DL enfrentan desafíos de interpretación y computación. Los modelos basados en el árbol de decisiones (LGBM y CatBoost) han surgido como alternativas, ofreciendo potenciales ventajas para la predicción de series temporales.

Método: El estudio analizó los datos de demanda de electricidad del CENACE (2018-2022), utilizando cuatro años para capacitación y uno para validación. El rendimiento del modelo se evaluó utilizando las métricas MAPE, MAE, MSE, RMSE y R^2, junto con las métricas de predicción conformal para la cuantificación de la incertidumbre.

Resultados y Discusión: CatBoost demostró un rendimiento superior (MAPE: 1,85%, R^2: 0,9) en comparación con los modelos LGBM y SARIMAX. SARIMAX mostró limitaciones significativas en la precisión de la predicción, particularmente durante las variaciones estacionales. LGBM logró un rendimiento intermedio con una precisión aceptable (R^2: 0,89).

Implicaciones de la investigación: Los modelos LGBM y CatBoost lograron valores de MAPE dentro del rango de referencia de la literatura (0,4-3%) al tiempo que requerían menos recursos computacionales que los modelos DL complejos, lo que los convirtió en alternativas prácticas para la predicción de la demanda de electricidad.

Originalidad/Valor: Esta investigación es pionera en la aplicación de tres modelos de predicción con técnicas de predicción conformadas en el contexto del mercado eléctrico mexicano, ofreciendo garantías probabilísticas de validez de predicción en lugar de predicciones puntuales tradicionales.

Palabras clave: Demanda De Electricidad, Mercados Mayoristas De Electricidad, Previsión De Series Temporales, Predicción Conformal.

1 INTRODUCTION

The accurate prediction of electricity demand (EDF) holds significant importance within wholesale electricity markets due to the inherent inability to store generated electrical energy, thereby necessitating consumption in real-time. Such precision becomes essential to avert any excess or deficit in supply, which could lead to severe system failures. Thus, the development of a meticulous forecast model holds paramount significance for various stakeholders within the market. This influence extends directly to the operational, financial, and regulatory aspects of the overarching energy ecosystem. For instance, electricity producers and suppliers stand to gain by aligning their production capabilities with precisely projected demand, thereby circumventing wasteful overproduction or underproduction scenarios and subsequently minimizing resource consumption and costs. In a similar manner, accurate demand forecasts empower distributors and grid operators to anticipate fluctuations in load, thereby orchestrating network operations adeptly. By averting grid congestions, equipment malfunctions, and the specter of power outages, these entities effectively mitigate operational risks.

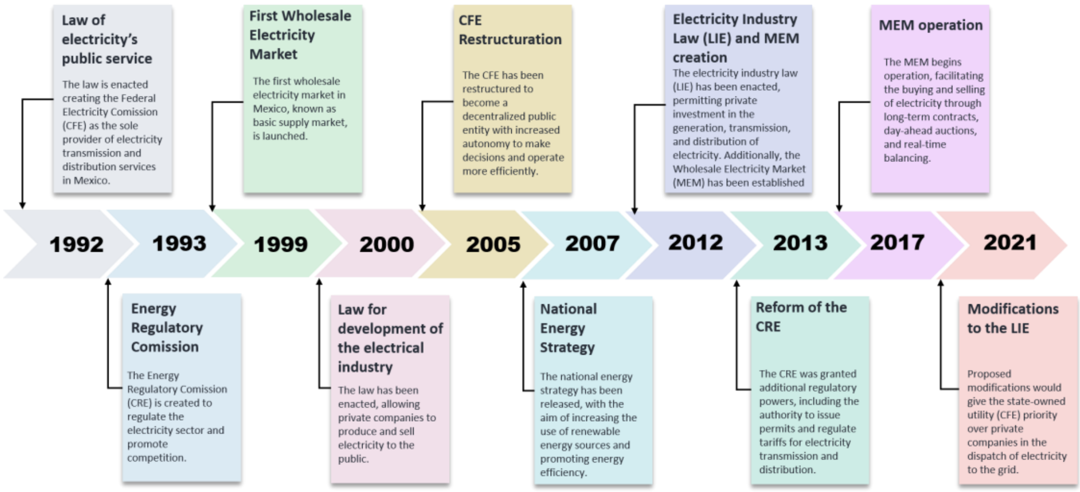
However, predicting electricity demand presents challenges due to the distinct timeseries behavior across different markets, further influenced by the intricate variations in demand patterns stemming from the electricity generation mix within each market. In the realm of EDF, prevailing literature has conventionally employed two categories of models (Dai et al., 2021). The first category employs traditional statistical techniques, with Seasonal Autoregressive Integrated Moving Average with Exogenous variables (SARIMAX) being a prominent example. Notably, SARIMAX's susceptibility to random data disturbances significantly constrains its implementation. The second category encompasses contemporary models founded on artificial neural networks (ANN), machine learning (ML), and/or deep learning (DL). Nevertheless, the interpretability and computational overhead associated with ANN and DL models pose challenges. Furthermore, it is pertinent to observe that both categories of EDF models have predominantly focused on predictions centered on discrete points. This emphasis on point predictions carries inherent limitations, as it offers singular deterministic values that frequently neglect the dynamic nature of energy consumption patterns. Such oversight can culminate in unforeseen supply-demand imbalances, potentially leading to grid congestion, voltage oscillations, and even blackouts. Also, a model based on point predictions lacks the capacity to incorporate uncertainties influencing revenue generation and cost management along with suboptimal resource allocation, inefficient power generation scheduling, and missed avenues for profit optimization. Hence, it is imperative to account for uncertainties in electricity demand to promote a reliable forecast model.

In recent years, the Conformal Prediction (CP) (Shafer & Vovk, 2007) has garnered significant attention within energy forecast models. Notably, this method has not been harnessed for electricity demand forecast, thereby presenting a novel avenue. CP facilitates the derivation of prediction intervals, thereby encompassing both the best and worst scenarios for electrical demand.

Concerning worldwide electrical markets, there are four major types (Mielczarski, 2018) namely: the monopoly scheme, the scheme of intermediary companies for the buying and selling of electricity, the wholesale market scheme, and finally, the scheme of both a wholesale and retail electricity market. In the case of Mexico, as seen in Figure 1, the wholesale electricity market has transitioned from a monopolistic scheme, in which only the public entity known as the Federal Electricity Commission (CFE) had exclusivity over the generation, transmission, and distribution of electricity, towards a wholesale market scheme. Currently, in addition to the CFE, there are several independent electricity producers who can offer the electricity produced to the grid, and the “Centro Nacional de Control de Energía” (CENACE) an independent regulatory entity responsible for managing the wholesale electricity market (Diario Oficial de la Federación, 2005).

Figure 1

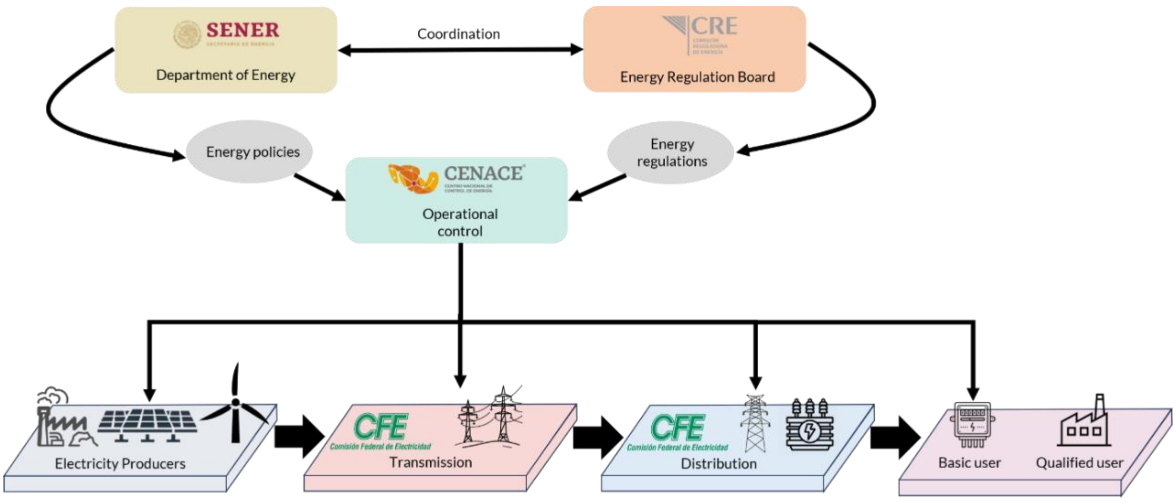
Timeline of the major changes in wholesale electrical market in Mexico since 1992 to date. Independent electricity producer status is fairly recent (2017).



The Wholesale Electricity Market in Mexico (MEM) consists of four modalities: the short-term (spot) energy market, the power balance market, the clean energy certificates market, and the auction for financial transmission rights. Furthermore, the spot market is divided into two modalities referred to as the day-ahead market (MDA) and the real-time market (MTR). The structure of the MEM is shown in Figure 2.

Figure 2

Actual structure of Mexico's wholesale electricity market (MEM).

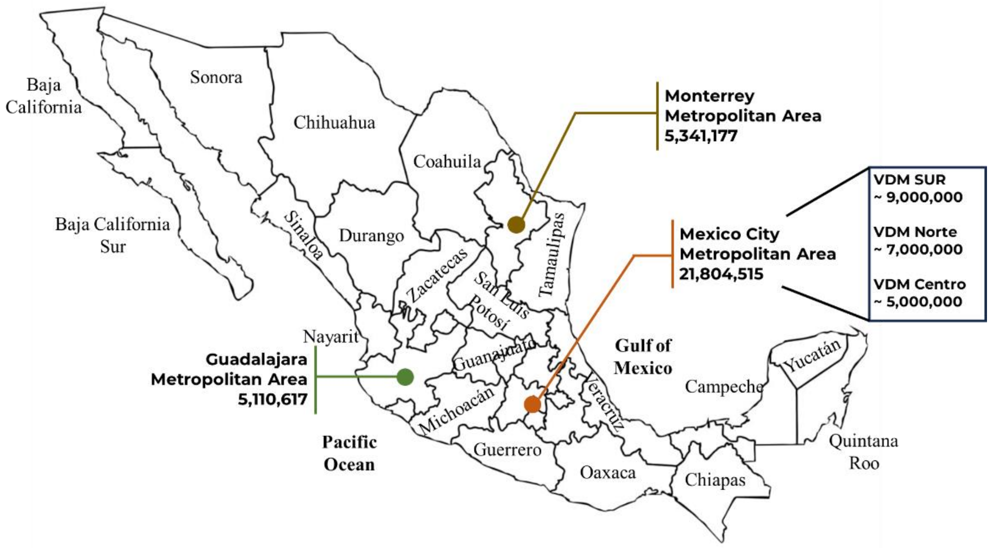


The flowchart in Figure 2 highlights the importance of having an accurate demand forecast for both participants of the MEM and the regulatory entity CENACE. The CENACE divides the national electrical system into two main zones: the BC Peninsular System and the

Interconnected National System (SIN), with the latter being the larger of the two. In turn, each of these zones is divided in interconnection nodes (PNodes) giving a total of 2,570 nodes. On the other hand, the SIN is divided in 108 load zones (a load zone being defined as a specific region in which electricity consumers are grouped to facilitate energy demand management and analysis). Among the 108 load zones, the most populated accordingly to Mexico’s National Institute of Statistics and Geography (INEGI, n.d.) are: Mexico City Metropolitan Area (21,804,515 inhabitants), Monterrey Metropolitan Area (5,341,177 inhabitants) and Guadalajara Metropolitan Area (5,110,617 inhabitants) as depicted in Figure 3. However, the CENACE subdivides the Mexico City Metropolitan Area into three load zones namely VDM Norte (about 7,000,000 inhabitants), VDM Centro (about 5,000,000 inhabitants) and VDM Sur (about 9,000,000 inhabitants).

Figure 3

Population distribution of the 3 biggest metropolitan areas in Mexico (INEGI, n.d.).



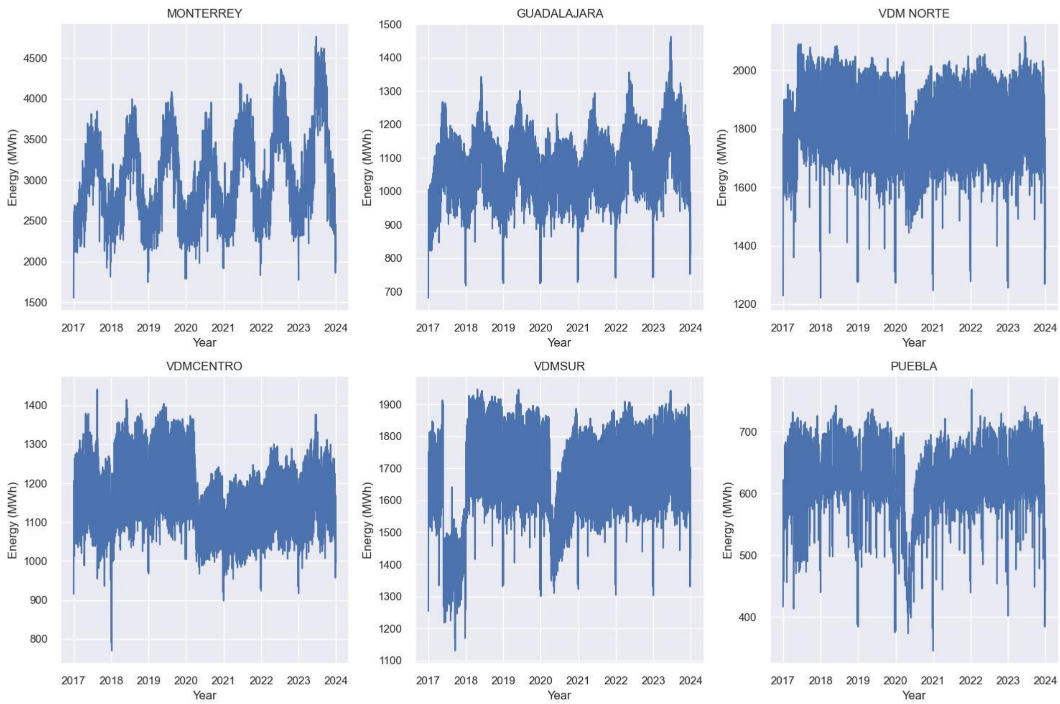
In this work we study for the first time the use of three different forecast models to predict electricity demand in the mexican market reinforced by the incorporation of conformal prediction framework to generate prediction intervals instead point predictions thus offering probabilistic guarantees on the validity of the forecast. The novelty of our research lies in the comprehensive adaptation and application of these models to the unique dynamics of the Mexican electricity market, a context that has not been extensively explored in existing literature. This paper undertakes an assessment of various demand prediction models within the mexican electricity market, utilizing data sourced from the publicly available database of CENACE.

2 MATERIALS AND METHODS

Electricity demand data for the MEM were sourced from the public database of CENACE (CENACE, 2018). These raw data were subsequently resampled to transition from an hourly to a daily time interval. A comprehensive analysis of electricity demand over the previous 7 years was then conducted to identify the top five electricity-consuming load zones. As depicted in figure 4, the regions exhibiting the highest averages of electricity consumption are Monterrey, VDM Norte, VDM Sur, VDM Centro, Guadalajara, and Puebla. This distribution contrasts markedly with the population reported for these regions. Consequently, the elevated electricity consumption in Monterrey can be attributed to its substantial industrial activity due to the USA border proximity. Due to these considerations, Monterrey was selected for the three forecast models evaluation.

Figure 4

Electricity demand for the six most populated areas in Mexico



To select the exogenous variables for use in the models, we conducted an exploratory data analysis employing SHAP (SHapley Additive exPlanations) package for Python

(Lundberg et al., 2020) for the tree-based models (LGBM and Catboost) whereas for the SARIMAX model we used four different analysis included in scikit-learn Python package namely: the Feature Importance (Coefficient Analysis), Cross-correlation Analysis, AIC Difference Analysis and Residual Sensitivity were performed.

The results of the SHAP analysis on LGBM and Catboost models are presented in figures 5 and 6.

Figure 5

Shapley values for LGBM model.

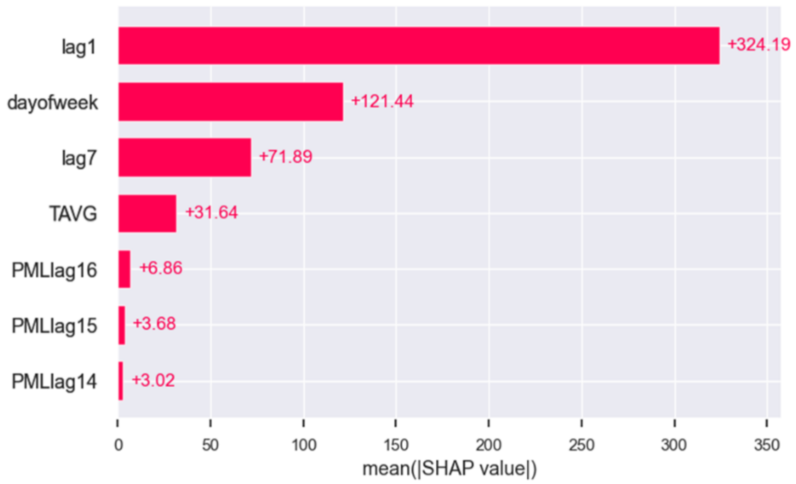


Figure 6

Shapley values for Catboost model

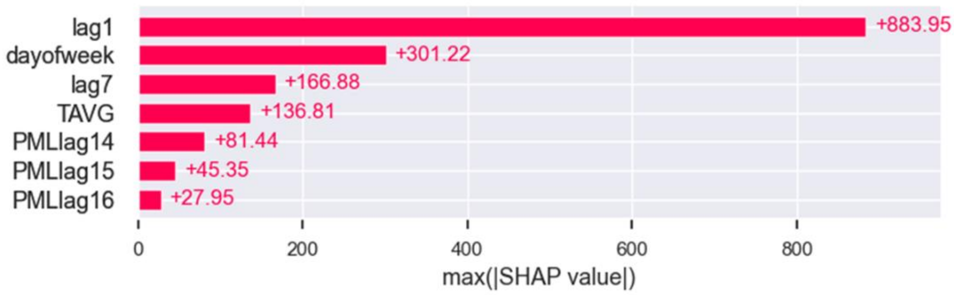


Figure 5 reveals that for both models (LGBM and Catboost) the three most influential variables are Lag1 (values from the previous day), Dayoftheweek (day of the week), and Lag7 (values from the previous 7 days). However, in the case of Catboost model, all the variables contribute to increasing the prediction, whereas in the LGBM model, the variables tend to reduce it.

Finally, for the SARIMAX model four different analysis were performed in order to determine the importance of each exogenous variables and the results are shown in table 1.

Table 1

Exogenous variables importance determination for SARIMAX model.

Variable	Feature Importance	Cross Correlation	Variable importance AIC	Residual sensitivity
dayofweek	-0.13	1.60	438.55	0.08
Lag1	0.00	9.47	153.53	0.06
Lag7	0.00	8.86	-76.69	0.06
PMLlag14	0.00	2.56	-1.87	0.04
PMLlag15	0.00	2.54	-1.98	0.04
PMLlag16	0.00	2.52	-1.55	0.07
TAVG	0.00	0.82	-1.89	0.01

Based on the four different analytical methods applied to the SARIMAX model, we can conclude that the day of the week is consistently the most influential exogenous variable, showing significant importance across all tests with the strongest direct effect (-0.13) and the largest impact on model fit (AIC difference of 438.55). The first lag (lag1) emerges as the second most crucial variable, while lag7 suggests a complex relationship with the model's performance. The analysis also reveals that the model heavily relies on weekly patterns and recent historical values.

Even if TAVG (average temperature) obtained from NOAA (U.S. National Oceanic and Atmospheric Administration, 2024) and electricity locational marginal price (LMP) pre-processed in (De La Torre et al., 2024) demonstrate limited impact on the output of all the three models, we decided to include them as additional exogenous variables in order to improve their accuracy.

Once the site and exogenous variables were selected, the next step was to conduct the electricity demand forecast using each of the three proposed models. Only for the SARIMAX model, data normalization was performed to enhance its performance. Subsequently, for all three models, the data were divided into a training set (spanning 4 years) and a test set (spanning 1 year). Next, hyperparameters for each model were adjusted using the training data and the exogenous variables were incorporated as additional features in all models. For the case of LGBM and CatBoost models, 1-day and 7-day lags were added as features as this additional information could potentially improve forecasting accuracy.

Finally, the models were validated using the test data, prediction intervals were calculated using the conformal prediction framework, and error metrics were computed to compare the results.

2.1 SARIMAX MODEL

Alongside ANN-based models, ARIMA-based models are among the most used in the literature for making predictions of electricity demand at the wholesale market level (Amini et al., 2016), (Arora & Taylor, 2018) and (De Felice et al., 2013). The SARIMAX model is a form of regression analysis that measures the influence of one or several independent variables on a dependent variable, taking into account seasonal components.

In our study, we constructed the SARIMAX model assuming that the underlying electricity demand data followed a stationary process, meaning that the statistical properties of the data did not change over time. We also assumed that the seasonal patterns in the data were consistent across the entire time series and that the residuals of the model were normally distributed and exhibited no autocorrelation. The goal of the model is to predict future values of electricity demand by examining the differences between the series values rather than the actual values. The model's adjustment parameters were calculated using the autoarima library for Python using initial values derived from an analysis of the Autocorrelation Function (ACF) and Partial Auto-correlation Function (PACF) of dataset These calculated parameters are described in Table 2.

Table 2

Tunning parameters for SARIMAX model.

Parameter	Description	Value
p	Trend autoregression order	3
d	Trend difference order	1
q	Trend moving average order	1
P	Seasonal autoregressive order	1
D	Seasonal difference order	0
Q	Seasonal moving average order	1
M	Number of time steps for a single seasonal period	7

2.2 LGBM MODEL

Decision tree-based models have been relatively underutilized in predicting electricity demand and have primarily focused on end-user level schemes (Tso & Yau, 2007) and (Wei et al., 2018). LGBM is a gradient boost decision tree (GBDT)-based model published in 2017 by (Ke et al., 2017) where a GBT model is improved using Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). The adjustment parameters for this model are very diverse and are described in detail in reference (Microsoft Corporation, 2023). In this work we selected the parameters listed in table 3 to be adjusted by using the OPTUNA library in Python.

Table 3

Hyperparameters tunning for LGBM model.

Parameter	Value
objective	regression
metric	mse
linear_tree	False
n_estimators	404
learning_rate	0.101
max_depth	1
num_leaves	2795
max_bin	129
min_child_samples	177
random_state	101

2.3 CATBOOST MODEL

The third model was first published in 2018, (Dorogush et al., 2018) and is also a GBDT-based model as LGBM. CatBoost employs a gradient boosting algorithm, which is appropriate for time series data. As for the LGBM model, the CatBoost model has numerous hyperparameters to be adjusted, (Gulin, 2024), therefore we selected the hyperparameters shown in table 4 to be adjusted by OPTUNA library.

Table 4

Hyperparameters tunning for Catboost model.

Parameter	Value
learning_rate	0.13
depth	1
subsample	0.142
colsample_bylevel	0.46
min_data_in_leaf	7
random_state	101

2.4 STATISTICAL METRICS

For model evaluation in the literature, the Mean Absolute Percentage Error (MAPE) along with the Root Mean Square Error (RMSE) are mainly used. Additionally, the Mean Absolute Error (MAE) and the Coefficient of Determination (R2) are also reported. Each error metric is defined by the following expressions:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (2)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{|y_i|} \qquad (3)$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \qquad (4)$$

Where:

$y_i = Actual\ values$

$\hat{y}_i = Predicted\ values$

$\bar{y}_i = Average\ values$

2.5 PREDICTION INTERVALS METRICS

For prediction intervals evaluation the Coverage, Validity, Sharpness and Interval Score metrics were used. The equations defining each of these metrics are shown below:

$$\text{Coverage} = \sum_{i=1}^{n} c_i/n \ , c_i \begin{cases} 1, t_i \in [Low_i, Upp_i] \\ 0, t_i \notin [Low_i, Upp_i] \end{cases} \qquad (5)$$

$$\text{Validity} = c_i \begin{cases} 1, t_i \in [Low_i, Upp_i] \\ 0, t_i \notin [Low_i, Upp_i] \end{cases} \qquad (6)$$

$$\text{Sharpness} = \frac{1}{n}\sum_{i=1}^{n} Upp_i - Low_i \qquad (7)$$

$$\text{Interval Score} = \frac{1}{n}\sum_{i=1}^{n}[\alpha \cdot 1(c_i < Low_i) + (1-\alpha) \cdot 1 \cdot (c_i > Upp_i)] \qquad (8)$$

Where:

c_i = Actual values

Low_i = Lower bound

Upp_i = Upper bound

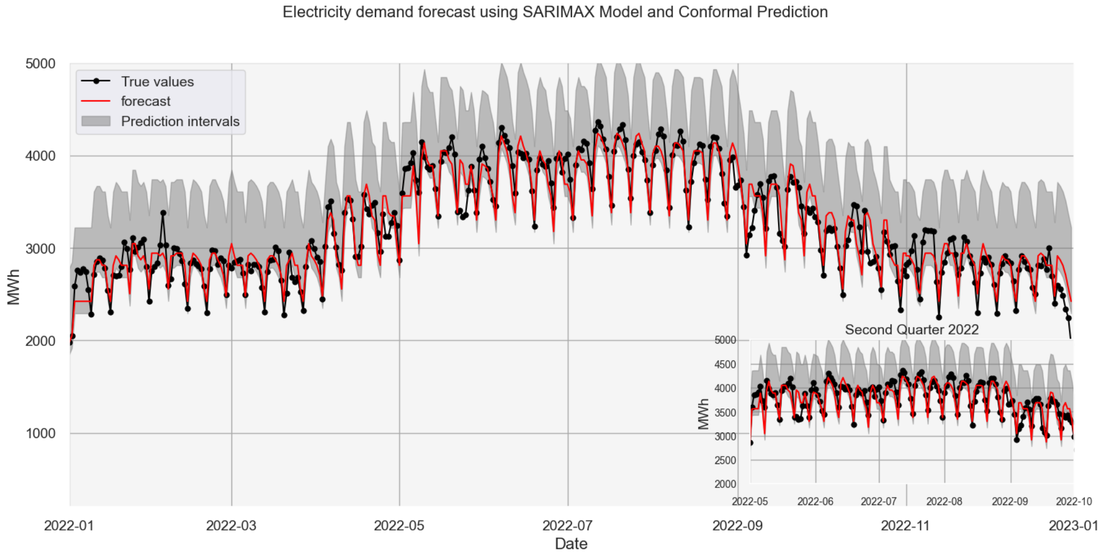
α = Significance level

3 RESULTS

The result of the prediction generated with the SARIMAX model compared to the measured and reported electricity demand values by CENACE for the year 2022 is shown in figure 8.

Figure 8

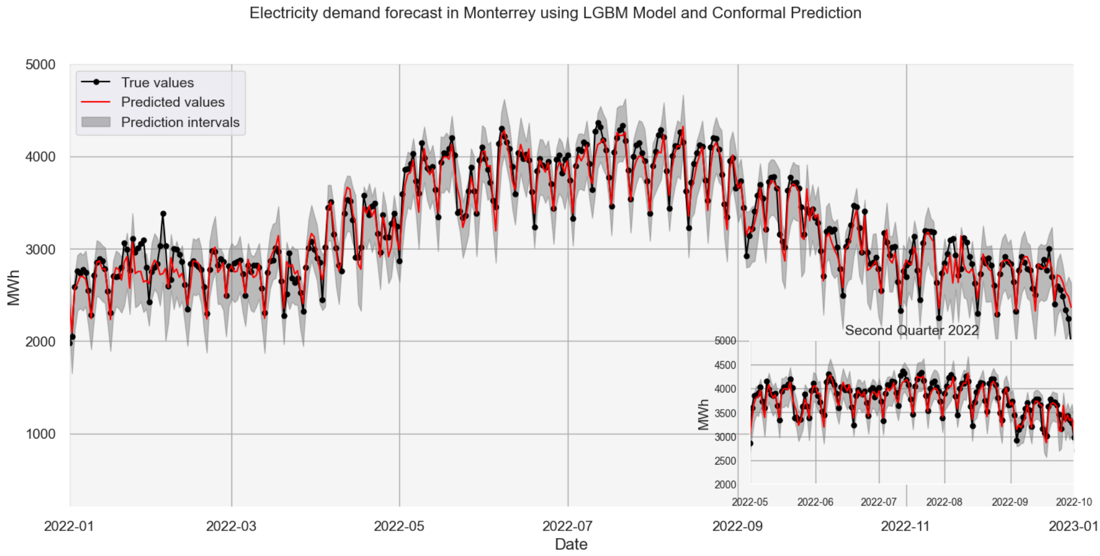
Actual electricity demand data compared to predicted values using SARIMAX model along with prediction intervals. Inset figure shows the interval from May thru October.



The result of the prediction generated with the LGBM model compared to the measured and reported electricity demand values by CENACE for the year 2022 is shown in figure 9.

Figure 9

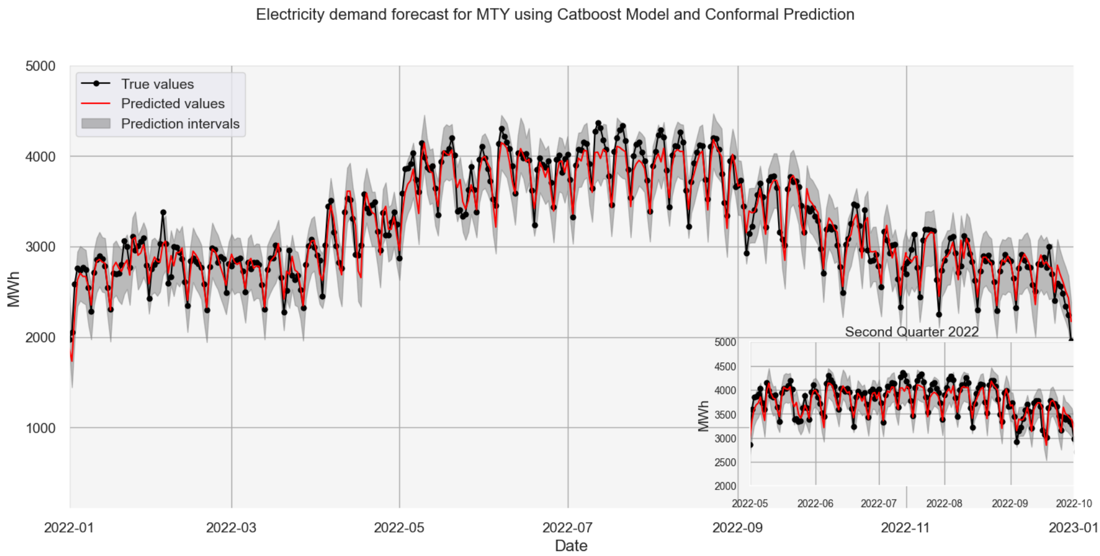
Actual electricity demand data compared to predicted values using LGBM model along with prediction intervals.



Finally, the prediction results from using CatBoost model are shown in Figure 10.

Figure 10

Actual electricity demand data compared to predicted values using CatBoost model along with prediction intervals.



The values of the different statistical metrics calculated for the three models as well as for the prediction intervals using conformal prediction framework are shown in table 5.

Table 5

Statistical metrics for the three models analyzed in this work along with the metrics for prediction intervals evaluation calculated by conformal prediction framework.

Metric	SARIMAX	LGBM	CatBoost
MAPE (%)	4.56	2.94	2.65
MAE	143.38	91.67	84.16
MSE	34,336.34	15,371.50	12,691.79
RMSE	185.30	123.98	112.66
R2	0.89	0.95	0.96
Coverage (%)	77.05	100	100
Validity	0.72	0.25	0.26
Sharpness	908.36	592.24	589.41
Interval score	909.13	700.74	701.10

4 DISCUSSION

Considering the performance evaluation of all three models, the metrics reveal that the SARIMAX model exhibits notably higher Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) values in comparison to the other two models, indicative of larger forecast errors. The modest coefficient of determination (R^2) value of 0.22 suggests a diminished capacity of this model to elucidate the variance within the dataset.

Despite having a higher coverage percentage in contrast to the CatBoost model, the SARIMAX model demonstrates considerably elevated sharpness and interval score metrics, signifying inadequate calibration and wider prediction intervals. Figures 8, 9, and 10 visually depict comparative plots for the three models, thereby substantiating the strong limitations encountered by the SARIMAX model in accurately predicting electricity demand, notably during the second quarter of the year (spanning April to October 2022). This discrepancy could be related to the SARIMAX model's reliance on presumptions regarding the data adhering to a specific stochastic process.

As evident from figure 8, temporary fluctuations related to seasonal variations in the time series, poses challenges for the SARIMAX model to effectively capture them. In contrast, the prediction intervals generated by the LGBM and CatBoost models encompass the actual values across the entire temporal span, thus underscoring their supremacy over the SARIMAX model within this particular context. Furthermore, it is discernible that the LGBM model exhibits marginally elevated MAPE, MAE, MSE, and RMSE values compared to the CatBoost model, indicative of slightly augmented forecast errors. Nevertheless, it maintains worthy overall performance. Notably, the LGBM model shows a superior coverage percentage, suggesting its prediction intervals encapsulate a greater proportion of the actual values.

Additionally, it outperforms the CatBoost model in terms of validity, sharpness, and interval score metrics, thereby implying enhanced calibration and precision. Conversely, the CatBoost model demonstrates even more robust performance, as evidenced by the MAPE value of 1.85%, RMSE of 30.67, and coefficient of determination of 0.9. Furthermore, the evaluation metrics pertaining to prediction intervals corroborate the CatBoost model's superiority as the foremost forecasting model, with the highest coverage, narrowest width, and lowest interval score. In summation, the SARIMAX model exhibits the least favorable performance overall, while the LGBM model occupies an intermediary position, displaying performance akin to CatBoost but slightly inferior in terms of coverage and interval score. Considering that in the literature the reported MAPE value for complex models (DL and hybrid) ranges between 0.4% and 3% (Scheidt et al., 2020), the MAPE values obtained in our case study with LGBM and CatBoost models are both within this range, confirming that these models can be reliably used for the prediction of electricity demand in Mexico's MEM. Evidently, we propose the use of CatBoost model for forecasting as per the statistical metrics obtained.

Table 6 shows the comparative evaluation of the MAPE error obtained with the LGBM and CatBoost models compared to other models used by other working groups for different electric markets (Park et al., 1991), (Sigauke & Chikobvu, 2011) and (Torres et al., 2022), as well as compared to a model called Naïve, one of the simplest prediction models. This model is widely used as a benchmark for more advanced prediction models.

Table 6

LGBM and Catboost models' benchmarking with Naïve model and compared to other models Zreported in literature.

Model	MAPE (%)
Catboost (this work)	2.65
LGBM (this work)	2.94
Naïve (Benchmarking)	5.90
SARIMA-GARCH (Sigauke & Chikobvu, 2011)	1.42
LSTM (Torres et al., 2022)	1.45
ANN (D. C. Park et al., 1991)	3.39

From this comparative, it is observed that the MAPE value of 2.94% and 2.65% obtained with the LGBM and CatBoost models respectively for this work is among the lowest values, only preceded by the SARIMAX-GARCH and LSTM (DL) models. However, unlike those two models, the LGBM and CatBoost models are much simpler, more computationally efficients and provide equivalent precisions.

5 CONCLUSIONS

The results of the prediction of the daily demand for electricity in the wholesale market in Mexico for a day-ahead scheme were presented, defining as adjustment variables the days of the week and the month of data registration. Three models named SARIMAX, LGBM and CatBoost were proposed for the prediction, with a better performance obtained for the CatBoost model with a MAPE of 1.85%. The advantages of this model are that it requires less training time, as well as less memory use and computational resources compared to other more complex models such as those based on neural networks or DL, so it is more attractive for use in real-time predictions that can be useful to the different participants of the MEM. It is necessary to continue analyzing improvements to the model considering some additional exogenous variables such as weather conditions, fuel costs, the country's economic activity, among others.

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