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Comparative Study of Forecasting Methods to Predict the Energy Demand for the Market of Colombia

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ABSTRACT

An important challenge for the energy sector worldwide is the selection of the best method for forecasting the energy demand of a country. This research addresses the Colombian electricity market, a developing country where power generation is predominantly hydroelectric. The goal is to compare commonly used and state-of-the-art methods to predict the general short-term demand. The selected methods are the long short-term memory (LSTM) network, the autoregressive integrated moving average (ARIMA) and Facebook Prophet. These methods were used to predict the hourly total electricity demand for Colombia for the next day (24 h). The cross-industry standard process for data mining methodology was partially used, excluding the deployment phase. The hourly time series considers data from 2022 to 2023. Models are evaluated using the root mean square error (RMSE) and the mean absolute percentage error (MAPE). Prophet had the best RMSE with 428.5 MW, followed by ARIMA (441.7 MW) and LSTM (541.3 MW). Prophet and ARIMA achieved the best MAPE (4.1%), outperforming LSTM (4.9%). Results shown that the hourly intraday energy demand of the Colombian market can be predicted accurately for both work and non-work days.

Keywords: Energy Demand, Forecasting, Colombia, Time Series, ARIMA, Long Short-Term Memory
JEL Classifications: Q47, C22, C520

1. INTRODUCTION

High energy demands around the world is causing negative effects on the environment; for example, (Sayed et al., 2021) highlighted some of these impacts, and (Sharifi et al., 2017) and (Patnam and Pindoriya, 2021) reviewed the literature in seeking solutions for the electricity market demand. These works show that in order to make solution proposals, it is important to characterize demand. (Ahmad et al., 2020) present an analysis of some of the demands of developed and developing countries to create policies and mechanisms that help mitigate the negative impacts of electricity market consumption. Artificial intelligence plays a leading role in the construction of demand prediction tools, and some proposals that can be highlighted are (Banik et al., 2021), (Shin and Woo, 2022) and (Mhlanga, 2023).

The forecasting of energy demand worldwide is a subject of great interest in the field of research, and selecting the appropriate forecasting is critical. (Shohan et al., 2022), (Shin and Woo, 2022) and (Pierre et al., 2023) present works that compare different methods for forecasting the demand for electricity and these studies concur that the best forecasts for their predictions were achieved using hybrid methods. In (Shohan et al., 2022) and (Shin and Woo, 2022), they do not work with data from hydroelectric markets. The data in (Pierre et al., 2023) come from various types of sources, but the hydroelectric market predominates with 40%.

Like the rest of the world, Colombia has a great interest in the construction of tools that support the actors of the system in the analysis and planning of day-to-day operations; some works in this regard include (Marín et al., 2023), (Caicedo-Vivas and Alfonso-Morales, 2023) and (Quiñones-Rivera et al., 2023). The price of electric power generation in Colombia is established through a process that has multiple components: Auctions in what is known as the Wholesale Energy Market (MEM), operation and maintenance costs, fuel prices, policies and regulations. XM (https://www.xm.com.co) is the company in charge of managing this market and of the operation of the national interconnected system. The price rate of this market is determined by a regulatory framework established by the Energy and Gas Regulation Commission (CREG).

Generally, the costs of electric energy are composed of generation, transmission, distribution and commercialization, with distribution and generation having the greatest impact on the unit cost of the tariff. The distribution tends to be a stable variable in time, unlike generation, which changes the most due to multiple factors. An important factor is consumption, which can be visualized for Colombia through the average demand curves (SINERGOX) generated by XM (https://www.xm.com.co/consumo/historicos-de- demand, accessed on 30 August 2024). Currently, Colombia predominantly hydroelectric energy, which generates more than 70% of the total energy demand, relies on similar to countries like for Brazil, Canada, and Norway, among others.

The price of electricity in Colombia is defined by a daily auction where generators present their offers of sale in price and quantity of energy for each hour of the following day. Additionally, distributors and large consumers present their demand forecasts in quantity and price for each hour of the following day. A tool that can predict the hourly demand the next day would be extremely valuable, allowing generators, distributors and consumers to better manage and plan their operations.

There are many models for forecasting the demand for electricity. In this paper, including the autoregressive integrated moving average (ARIMA), seasonal autoregressive integrated moving average (SARIMA), autoregressive moving average with eXogenous input (ARMAX), autoregressive fractionally integrated moving average (ARFIMA), LSTM network, Facebook Prophet, random forest (RF), extreme gradient boosting (XGBoost), support vector regression (SVR), support vector machine (SVM), gated-recurrent unit (GRU), bidirectional long short-term memory (BiLSTM), temporal convolutional network (TCN), histogram gradient-boosting regression (HGBR), light gradient-boosting machine regression (LGBMR), extra tree regression (ETR), ridge regression (RR), Bayesian ridge regression (BRR), and categorical boosting regression (CBR). In Tables 1 and 2, the references where these models are used and cited can be observed. Choosing which is the best and comparing them among each other is not an easy task; for this reason, in this study, the three most relevant to the problem were selected: Those that are most reported and those that yield the best forecasts in the literature. Like the forecasting models, the metrics used in the work were selected because they are the most reported in the literature.

In the literature, several works that compare different forecasting methods using time series have been reported. For instance, (Yamak et al., 2019). Studies the problem of predicting the price of Bitcoin through the ARIMA, LSTM and GRU models, they used MAPE and RMSE as comparison metrics and reported ARIMA as the best model with a MAPE of 2.76%. (Chaturvedi et al., 2022) conducted a study more similar to the study presented herein; they use a time series to predict the total and maximum monthly energy demand in India, and they generate long-term predictions for the subsequent 24 months using information from 2008 to 2018. Using SARIMA, LSTM, Recurrent Neural Network (RNN) and Facebook Prophet, the metrics for comparison were RMSE and MAPE, and reported Facebook Prophet as the best model with a MAPE of 3.3%.

The present work uses data from a predominant hydroelectric market to forecast the total electricity demand for the 24 h following a given day for Colombia. The methods used are Facebook Prophet, ARIMA and LSTM models, using the coefficient of determination (R^2), MAE, RMSE, MAPE and Symmetric Mean Absolute Percentage Error (SMAPE) as performance metrics for comparison. The results show that Prophet and ARIMA provide better average forecasts when taking all days of the week into account and for work days (Monday to Friday), whereas for nonwork days (holidays, Sundays and Saturdays), the model with the best average forecast is LSTM. The 95% confidence intervals clearly indicate that the results of the three models are good and can help the actors in the process analyse and optimize their operation plans.

The remainder of this paper is organized as follow. In Section 2, relevant works are discussed. Section 3 presents the materials and methods used to develop the present work. In Section 4, a description of the methodology used is presented. Section 5 contains an analysis and discussion of the results. And finally, Section 6 presents the conclusions and future work.

2. RELATED WORKS

Currently, in the field of energy demand management, there is great interest in the prediction and characterization of energy demand. This task is a crucial step for addressing environmental, economic, and energy security problems and guaranteeing a safe and sustainable future, which can be seen in (Sayed et al., 2021). In this section, works related to the problem of predicting electricity demand and prediction techniques that utilize data or models are discussed.

(Kim and Cho, 2019) presents a deep learning model to predict electrical energy consumption and categorized the studies related to the topic into three tapes of models: Models based on statistics, models based on machine learning and models based on deep learning. Their model was a novel proposal that combines a convolutional neural network (CNN) and LSTM network. For their proposal, they used a multivariate time series with real preprocessed data of 4-year residential consumption (16-December-2006-November 26, 2010). These data were presented in 1-minute units collected from a household in France, and the algorithm used a 60-min window to predict the next 60 min. The results of the model were compared with those of

Table 1: References for electricity demand forecasting in Colombia

Reference	Methods	Time series	Metrics	Data	Best model
(Diaz et al., 2019)	Set Membership	Electricity demand, hourly	RMSE and MAPE	Quebradanegra - Colombia, February 2014 to February 2016	Standard Set Membership
(Collazos et al., 2020)	Artificial Neural Networks	Electricity demand, day	RMSE and MAPE	XM, 2000 to 2017, Colombia	Bayesian Regularization
(Grimaldo-Guerrero et al., 2021)	Linear Regression	Gross domestic product (GDP) and electricity demand (ED), yearly	Akaike information criterion (AIC) and R^2	Electricity Demand XM and GDP Banco de la República 2021, Colombia	Multivariable Models
(Marín et al., 2023)	Functional Data Analysis (FDA), ARIMA and ARFIMA	Electricity demand, hourly	MAPE	XM 2010 to 2019, Colombia	FDA-ARIMA
(Quiñones-Rivera et al., 2023)	ARMAX and NN-ARMAX	Demand for electrical products, monthly	MAPE, R^2 and RMSE	Colombian Manufacturing Companies, 2013 to 2020	NN-ARMAX
(Caicedo-Vivas and Alfonso-Morales, 2023)	LSTM and XGBoost	Electricity demand, hourly	RMSE and MAPE	Operator in Colombia, 6 June 2009 to 31 October 2021, not publicly available	LSTM

other machine learning methods in terms of the mean square error (MSE), RMSE, the mean absolute error (MAE) and MAPE. The results revealed better predictions for the proposed model than those of the other methods. In this study, residential consumption data were analysed.

In contrast, (de Oliveira and Cyrino Oliveira, 2018) investigated the demand of entire countries. In that work the goal is to predict the monthly demand of different parts of the world (developing and developed countries) for 24 months in advance. The proposal combines different bootstrap decomposition and aggregation techniques (bagging) to simulate new time series, and the exponential smoothing methods ARIMA and SARIMA were used. For the analysis and comparison of the results, MAPE, sMAPE, RMSE and the Theil coefficient of inequality (TIC) were used. This study identified bagging methodologies, particularly the Moving Blocks Bootstrap (MBB) and the proposed Remainder Sieve Bootstrap (RSB) procedure, as the best models, achieving a MAPE of 1.3%.

(Shin and Woo, 2022) demonstrated the applicability of machine learning for forecasting energy consumption and showed that traditional econometric approaches can outperform machine learning when there are fewer unknown irregularities in time series; however, machine learning may work better with irregular and unexpected time series data. In the literature, there is also a strong representation of studies that employ assembly methods; of these, (Farsi et al., 2021) combined an LSTM model and a CNN model to analyse short-term load forecasting, (Shohan et al., 2022) combined LSTM with Prophet, (Sulandari et al., 2023) proposed linearity (EnL) and nonlinearity relationships (EnNL), and (Pierre et al., 2023) combined ARIMA with LSTM.

As in the rest of the world, in Colombia, there is also interest in this topic, below are some recent works that are considered relevant in the forecast of energy demand for Colombia. In (Diaz et al., 2019), using the set membership technique, the 24-h demand of a given day was predicted for the municipality of Quebradanegra using data from February 2014 to February 2016. The study did not show any comparison with another technique and did not use exogenous variables. In (Collazos et al., 2020), an artificial neural network in which a Bayesian regularization network algorithm was implemented to predict daily energy consumption in Colombia using daily consumption data from the years 2000 to 2017; however, exogenous variables were not used to make predictions. (Grimaldo-Guerrero et al., 2021) presented an analysis of the relationship between electricity demand and economic growth; in their model, they included 12 variables of the economic sector defined by the Bank of the Republic of Colombia and reported that their best model used linear regression with 5 of the 12 variables defined to carry out the forecast.

More recent works that forecast energy demand in Colombia include the following. In (Marín et al., 2023), functional analysis of time series (FDA) was used to characterize the electricity demand in Colombia using hourly data for every day of the week from May 2010 to May 2019. This work made predictions using the DFA, ARIMA and ARFIMA methods for the 24 h of a given day without exogenous variables. (Quiñones-Rivera et al., 2023) aimed to evaluate demand forecasting models to determine whether the use of exogenous factors and machine learning techniques is better than univariate statistical models are. The case study aimed to manage the demand of manufacturing companies in Colombia and used monthly information between 2013 and 2020. Finally, (Caicedo-Vivas and Alfonso-Morales, 2023) used LSTM results in a prediction of 7 days with a granularity of 1 h for a department in Colombia. The authors reported that the week with the best MAPE was 1.65%, and the week with the worst MAPE was 26.22%. The data used for this study were not in the public domain, and the study did not include exogenous variables.

The studies listed above for Colombia did not forecast the daily demand for the next 24 h of a given day for all the demand in Colombia. If there were related studies, comparisons were made in the results section. Table 1 lists some of the works found in the literature on electricity demand in Colombia. This table provides the citations, the methods used, the type of time series used in the study, the metrics used for the comparison of the models, the data used and the best model considered by each author. The methods used in this study were also used in the literature, as were the metrics for the evaluation of the models.

Table 2: Benchmarks with more than one forecasting model using time series

Reference	Methods	Time series	Metrics	Data	Best model
(Masum et al., 2018)	ARIMA and LSMT	Electric load, day	RMSE	Great Britain, Poland and Italy	LSTM
(de Oliveira and Cyrino Oliveira, 2018)	Bagging ARIMA and Exponential Smoothing	Mid-long term electric energy consumption, monthly	ASM, sMAPE, RMSE and TIC	Canada, France, Italy, Japan, Brazil, Mexico and Turkey	Remainder Sieve Bootstrap
(Khan and Osińska, 2021)	Fractional-order Grey Model and ARIMA	2019 statistical review of world energy, yearly	MAPE and MSE	Brazil, Russia, China, India, and the Republic of South Africa (BRICS)	ARIMA
(Banik et al., 2021)	Random Forest, Ensemble Learning, Boosting and XGBoost	Electricity load, hourly, weekly and monthly	R^2 and RMSE	Tripura in India	Ensemble RF-XGBoost
(Farsi et al., 2021)	ARIMA, LSTM, and Parallel LSTM-CNN Network.	Hourly load consumption	MAPE, R^2 and RMSE	Germany and Malaysia	Parallel LSTM-CNN Network
(Zhao et al., 2021)	GRU, LSTM, RNN, TCN, CNN+LSTM and Transformer	Day-ahead load forecasting	MAPE	Australia	Transformer network
(Chaturvedi et al., 2022)	SARIMA, LSTM RNN and Facebook Prophet	Monthly energy demand, monthly	MAPE and RMSE	India	Facebook Prophet
(Panagiotou and Dounis, 2022)	RNN, ANFIS, and LSTM	Energy consumption, hourly	MSE, R, R^2, MAPE and CI	Hospital Building's Energy Consumption	ANFIS LSTM
(Henzel et al., 2022)	Naive Methods, Linear Regression, LSTM, and the Facebook Prophet Method	Energy consumption, hourly	MSE and MAPE	Digital-Twin Model of the Building	Facebook Prophet
(Shohan et al., 2022)	ANN, LSTM, Facebook Prophet and LSTM-Facebook Prophet	Hourly load demand, hourly	MAPE, R^2, SSE and RMSE	Florida	LSTM- Facebook Prophet
(Ribeiro et al., 2022)	ARIMA, SVR, Random Forest, XGBoost, RNN, LSTM, and GRU	Energy consumption, hourly	RMSE, MAPE and MAE	ESCO (Energy Service Company) Ireland	XGBoost
(Shin and Woo, 2022)	Random Forest, XGBoost and LSTM	Energy consumption, monthly	RMSE and MAPE	Korea	LSTM and Random Forest
(Sulandari et al., 2023)	ARIMA, Exponential Smoothing, Facebook Prophet, Neural Networks, and Proposed Ensemble Methods	Generation of electricity, hourly	MAPE and RMSE	US, Ontario, England, Wales and Australia	Proposed Ensemble Methods
(Pierre et al., 2023)	ARIMA, LSTM, GRU, ARIMA-LSTM, and ARIMA-GRU	Electricity demand, hourly	MAPE and RMSE	Benin Electricity Company (CEB)	Hybrid Approach
(Koukaras et al., 2024)	HGBR, LGBMR, ETR, RR, BRR, CBR	Energy consumption, hourly	R^2, RMSE, CVRMSE, NRMSE and MAE	ITI/CERTH Smart House, Thessaloniki (Greece)	HGBR, LGBMR

To broaden the coverage of the research, studies that compare more than one forecasting method to predict the demand for electricity in different parts of the world were reviewed, and a table was constructed that relates and compares some of these investigations. Table 2 contains bibliographic references, methods used in the research, the type of time series, the metrics that were used for the evaluation of the models, the type of data source and, finally, the model that the authors considered as the one with the best result in the investigation.

As shown in the previous table, there is currently great interest in the study of the demand for electrical energy worldwide. This summary highlights that many models have been proposed to solve this problem. This problem has been addressed from the perspective of the prediction of devices and households to countries using time interval ranges from hours to years, and many metrics to evaluate these models. However, MAPE and RMSE are the most commonly used metrics, and among the models reported with the best results, LSTM is predominant. For this reason, in this study, we used the ARIMA, LSTM and Prophet models as the models to address the stated problem and MAPE and RMSE as metrics for comparing the models.

3. MATERIALS AND METHODS

3.1. ARIMA

The ARIMA model has been one of the most commonly used models in time series forecasts for energy demand, as shown in (Suganthi and Samuel, 2012). That used ARIMA for predictions in countries such as Turkey, Spain, Lebanon, etc. More recently, (Kuster et al., 2017) presented a literature review that included ARIMA within the forecasting models for electricity demand. In that review, many works that used ARIMA were discussed, and the model was deemed generally appropriate for short- and very short-term predictions.

Recent use of ARIMA can be found in (Kaur et al., 2023) and (Kontopoulou et al., 2023). There is still much interest in the ARIMA model, as this model is among the most accepted because of its precision, flexibility and reliable results. A reviewed of the scientific literature on the comparison of ARIMA algorithms and machine learning applied to predicting problems in time series, is (Kontopoulou et al., 2023). This review concludes that ARIMA prevails in some cases due to the nature of its application, specific data sets, and has significantly lower computational demands than ML models.

The ARIMA model is a statistical model used to analyse and predict time series and works by combining three main components:

- Autoregressive (AR): This component uses the past observations of a time series to predict future values. It is based on the idea that past values in the series can influence future values. This component can be expressed as follows:
  $$y_t = c + ø_1 y_{t-1} + ø_2 y_{t-2} + _{...} + ø_p y_{t-p} + \epsilon_t, \quad (1)$$
  where y_t is the current value, c is a constant, ϵ_t is the error term in time t, and $ø_{1,}\ ø_{2,...,}\ ø_{p}$ are the coefficients of the AR model.
- Moving average (MA): This component uses residual errors from previous predictions to predict future values. It focuses on the relationship between the current error and the errors in previous periods of time. The MA component of order q can be expressed as follows:
  $$y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + _{...} + \theta_q \epsilon_{t-q}, \quad (2)$$
  where μ is the mean of the time series; $\theta_{1,}\ \theta_{2,...,}\ \theta_q$ are the coefficients of the MA model; and $\epsilon_{t,}\ \epsilon_{t-1,...,}\ \epsilon_{t-q}$ are the error terms.
- Integration (I): This component refers to the number of differentiations necessary to make a time series stationary. Stationarity implies that the mean and variance of the series are constant over time. The integration component of order d involves differentiating the time series d times to make it stationary. If y_t is the original series, the differentiated series y'_t is obtained as:
  $$y'_t = \Delta^d y_t, \quad (3)$$

where Δ is the difference operator; for the case of d = 1, this would be $y'_t = y_t - y_{t-1}$.

The ARIMA model is a combination of the AR and MA components applied to differentiated series:

$$\Delta^d y_t = c + ø_1 \Delta^d y_{t-1} + ø_2 \Delta^d y_{t-2} + \ldots + ø_p \Delta^d y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + _{...} + \theta_q \epsilon_{t-q}, \quad (4)$$

The ARIMA model is adjusted to the time series data by identifying the ARIMA parameters (p, d, q), where p defines the order of the autoregressive component, d the number of differentiations necessary to make the series stationary and q the order of the moving average component.

The model adjustment process involves the selection of the optimal values of p, d and q, generally through techniques such as visual inspection of autocorrelation (ACF) and partial autocorrelation (PACF), as well as the evaluation of information criteria such as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

3.2. Facebook Prophet

Prophet is a time series forecasting procedure based on an additive model and has been used to forecast energy demand, as shown in (Chaturvedi et al., 2022) and (Henzel et al., 2022). The model is defined in (Taylor and Letham, 2018), a time series is broken down into three parts: trend, seasonality and holidays. The model can be expressed as follows:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t, \quad (5)$$

where y(t) is the time series that is decomposed into g(t), which is the part of the model that captures the long-term trend (growth or decrease), s(t) is the part of the model that captures seasonality (patterns are periodic), h(t) captures the changes due to the relevant days for the series (holidays), and ϵ_t represents the error or random noise.

Prophet offers two options to model the trend, linear growth, represented as:

$$g\ (t) = (k + a(t)t) + b, \quad (6)$$

where k is the growth rate, a(t) is the function that allows changes in the trend (growth at different points in time) and b is the intercept. The other way to model the trend is logistics growth, which can be modelled as:

$$g(t) = \frac{C}{1 + \exp(-k(t-m))} \quad (7)$$

where C is the capacity of the time series, k is the growth rate and m is the time where half the capacity is reached. Seasonality s(t) is modelled by periodic functions (sines and cosines) and is expressed as:

$$s(t) = \sum_{i=1}^{N} \left(a_i \cos\left(\frac{2\pi i t}{P}\right) + b_i \sin\left(\frac{2\pi i t}{P}\right) \right) \quad (8)$$

where P is the period of seasonality (annual, monthly, or weekly) and a_i and b_i are the coefficients of the sine and cosine functions, respectively. The holidays h(t) seek to model specific days of the problem domain through binary indicators, which are represented as:

$$\mathrm{h}(t) = \sum_{k=1}^{K} \left(\lambda_k I(t \in H_k\right) \quad (8)$$

where H_k is the set of dates of the holidays and λ_k is the effect of holiday k. Finally, the noise ϵ_t captures the random variations in the data that are not explained by trend, seasonality, and holidays. These assume that ϵ_t follows a normal distribution with zero mean.

3.3. LSTM Network

The general idea of the operation of an LSTM network is to keep the information of the past for analysis during long periods of time during training, which is done by means of a memory cell that retains its state over time. At each time step, the memory cell interacts, and this cell always receives data from the previous cells C_{t-1} and h_{t-1} and the current time x_t. To change the state of the memory cell, the Forget Gate function is used, which is responsible for deciding what information is relevant in the memory cell. The Input Gate function is used to decide what new information will be part of the new state of the memory cell. The Cell State Update function is used to update the state cell, and the Output Gate function is responsible for determining what part of the information in the memory cell should be used to construct the output. In general, the equation that defines an LSTM can be summarized as follows:

$$f_t = \sigma(W_f [h_{t-1}, x_t] + b_f), \quad (9)$$

$$i_t = \sigma(W_i [h_{t-1}, x_t] + b_i), \quad (10)$$

$$\tilde{C}_t = \tanh(W_C [h_{t-1}, x_t] + b_C), \quad (11)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t, \quad (12)$$

$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o), \quad (13)$$

$$h_t = o_t * \tanh(C_t), \quad (14)$$

where f_t, i_t, and i_t are activation vectors at time t; W_f, W_i, W_c and W_o are the weights of the gates; σ is the sigmoid function; h_t is the hidden state at time t; x_t is the input at time t; b_f is the bias of the forgetting gate; $\tilde{C}t$ is the vector of candidate values for the update of the time t cell; C_t is the state of the cell at time t; and b_i, b_c and b_o are the biases of the entry and exit gates.

3.4. Metrics

As shown in Tables 1 and 2, the metrics MAE, RMSE, MAPE, SMAPE and R^2 are the most commonly used metrics in the literature; as such, they are used in the present work. These metrics are defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - x_i\right|, \quad (15)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - x_i\right)^2}, \quad (16)$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{y_i}\right|, \quad (17)$$

$$SMAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{\left|y_i - x_i\right|}{\frac{\left(\left|y_i\right|+\left|x_i\right|\right)}{2}} \quad (18)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - x_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}, \quad (19)$$

where y_i is the observed value, x_i is the prediction of the models, $\bar{y}$ is the mean of the observed value and n is the total number of observations.

4. METHODOLOGY

Currently, several methodologies, such as the Team Data Science Process (TDSP), Simple Explore Modify Model Assessment (SEMMA) and Cross-Industry Standard Process for Data Mining (CRISP-DM), are widely used in pattern discovery processes, as shown in (Azevedo and Santos, 2008), (Palacios et al., 2017), (Plotnikova et al., 2020) and (Schröer et al., 2021). One of the common elements in those studies is that, in general, CRISP-DM is the most commonly used methodology. The construction of hybrid methodology is currently growing to fill methodological gaps, with the implementation phase having more opportunities for improvement, as shown in (Díaz Álvarez et al., 2022).

In this paper, CRISP-DM was used as a framework, but the entire framework was not used since the implementation phase was not carried out. The stages of understanding the business, understanding the data, and preparing the data were developed, as were the modelling phase and evaluation phase. Each phase is described below.

4.1.Understanding the Business

In Colombia, the CREG establish is a regulatory framework for energy production. The Colombian market has two types of consumers, regulated and unregulated. Unregulated markets or large consumers (consumption of 55 MWh or more) negotiate their rates directly with traders, defining a more competitive market. The regulated market or small consumers are controlled by the CREG, and distribution is manged through a daily auction mechanism, MEM. The steps defined for the daily auction are the following:

- Power generators present their sales offers in terms of price and quantity of electricity for each hour of the following day, which sets the price.
- Distributors and large consumers present their demand forecasts in terms of quantity and price for each hour of the following day, determining the demand.
- At 6 pm the day before, the daily market closes, and XM collects the sales offers and demand forecasts.
- XM, through an optimization algorithm, determines the equilibrium price where supply and demand are equal; with this method, the price that must be paid for each hour of energy is defined for the following day.

- Power is allocated from the lowest bids until all the anticipated demand is satisfied, and generators with bids less than or equal to the equilibrium price will be able to generate electricity and sell power.
- Finally, XM publishes the results of the process where each generator is assigned the price and amount of energy for each hour for the next day to be generated.

Taking into account this process, it is important to know the daily energy demand (hourly) in advance so that the actors in the process can analyse and optimize their operations. The present work focuses on the electric power market in Colombia and seeks to predict the 24-h power demand each day.

4.2. Understanding the Data

A total of 19,704 records of the daily demand per hour from January 1, 2022, to April 31, 2024, for Colombia were used to forecast the 24 h of the next day. The information is in the public domain and was taken from the official XM website (https://sinergox.xm.com.co/dmnd/Paginas/Historicos/Historicos.aspx, accessed on 30 August 2024). The time series is visualised in graph 1 and some of its descriptive statistics are presented in Table 3.

In Figure 1, the blue plot shows the real demand, and the red plot shows the rolling average of data. Since there is no trend in the rolling average plot (red plot), the data is stationary. Since the ARIMA model was used to make the prediction, the stationarity of the series was checked via the Dickey–Fuller test (ADF), which was used to determine if the time series had a unit root. For the null hypothesis (H_0), if the time series has a unit root, the series is not stationary, and for the alternative hypothesis (H_1), if the time series does not have a unit root, the series is stationary. As a result of the test, the P = 0.01, indicating that the series was stationary; therefore, the null hypothesis was rejected.

Regarding the descriptive statistics in Table 3, it can be said that the data distribution, the mean (9,082,670) is slightly lower than the median (9,145,344), indicating that the distribution is nearly symmetrical, though with a slight leftward skew, as confirmed by the skewness of −0.0617. The median lies between the first and third quartiles, suggesting that the data is relatively well-balanced, with half of the values concentrated in the interquartile range (between 8,111,609 and 10,030,525). The standard deviation of 1,151,236 reflects a moderate level of dispersion around the mean, indicating considerable variability in the time series.

Analyzing skewness and kurtosis, the skewness of −0.0617 points to a slightly left-skewed distribution, meaning that some lower extreme values may be pulling the mean slightly leftward, but this skewness is very mild, implying that the data is distributed almost symmetrically. The kurtosis of 2.0014, which is below 3 (the reference value for a normal distribution), indicates a platykurtic distribution, meaning thinner tails and a less pronounced peak compared to a normal distribution. This suggests a lower incidence of extreme values (outliers) in the series.

The time series exhibits an almost symmetrical distribution with a slight leftward skew. This means that values are relatively well distributed around the mean and median, with a slight tendency towards lower values. The standard deviation indicates significant, though not excessive, variability. The low kurtosis suggests there is not a significant number of extreme values or outliers, which is a sign of stability in the data. In summary, the time series appears to be well distributed, with a slight skew towards lower values and a lower likelihood of extreme events, suggesting that there are no large fluctuations or dramatic spikes in the data.

The series had no missing data, and its values were within the expected ranges. Since the ARIMA model was used to make the prediction, the stationarity of the series was checked via the Dickey–Fuller test (ADF), which was used to determine if the time series had a unit root. For the null hypothesis (H0), if the time series has a unit root, the series is not stationary, and for the alternative hypothesis (H1), if the time series does not have a unit root, the series is stationary. As a result of the test, the P = 0.01, indicating that the series was stationary; therefore, the null hypothesis was rejected.

4.3. Data Preparation

In this phase, the suggestions made by (Khan et al., 2022) were considered. In that study, the authors performed a cleaning and preprocessing phase before designing a neural network, deleting atypical records, replacing missing data and normalizing the data. For the data in this study, outliers were necessary because they contain important and real information of the time series, necessary for the prediction and for that reason they were not eliminated, there were no missing data, and only the data for the proposed LSTM model were normalized between values of 0 and 1 (there are no negative values). The objective was to guarantee that all the data were in the same range of values.

The proposed LSTM model follows a univariate + multistep approach. Therefore, to create the training dataset, a sliding window is defined over the hourly demand time series, where each window corresponds to a sample to be evaluated. Each sample contains 24 past hours as input and the following 24 h as the output to be predicted. For ARIMA and Prophet, the data were not scaled. For all the proposed models, 15,763 examples were used for training, 1,970 examples were used for validation, and 1971 examples were used for testing.

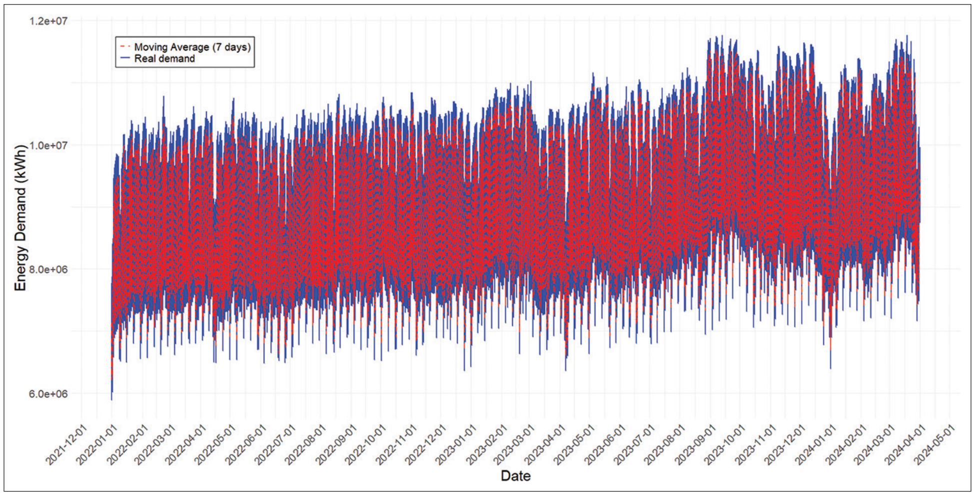
4.4. Modelling and Evaluation

The LSTM network was built using a univariate and multistep approach. It was univariate because there was only one variable (energy demand) for its construction, demand from the previous 24 h, and it was multistep because the forecast was for the following 24 h. The model had 128 hidden cells, 200 epochs, and

Table 3: Descriptive statistics of the time series

Minimum value	First quartile	Median	Mean	Third quartile	Maximum value	Standard deviation	skewness	kurtosis
5,888,025	8,111,609	9,145,344	9,082,670	10,030,525	11,759.099	1,151,236	−0.0617	2.0014

Figure 1: Time series of energy demand between 2022 and 2024 for Colombia



a batch size of 256, and MSE was used for the training stage as an error adjustment metric with a learning rate of 5e-5.

Through an exploratory analysis of the time series and the use of autocorrelation (ACF) and partial autocorrelation (PACF) graphs, the hyperparameters of the ARIMA model were modified and defined as: 4 lags were considered for the AR component, 1 was differentiated to make the serial series (I), and 4 lags in the MA component constituted the best model of all the candidates. For the Prophet model, tests were conducted on the change points and growth-related hyperparameters. However, the adjustments proved to be insignificant, and the hyperparameters were ultimately left at their default values. Based on the analysis presented in Tables 1 and 2, the metrics used to evaluate the models were R^2, MAE, RMSE, MAPE and SMAPE.

5. RESULTS AND DISCUSSION

This section presents the results and discussion of the work through three comparative tables, organized according to the previously defined rubrics for evaluating the three proposed models. Table 1 analyzes the complete set of results, Table 2 focuses on the results obtained for working days, and Table 3 examines those for non-working days (public holidays, Saturdays, and Sundays). Each table is accompanied by a graph illustrating all the predictions from each analysis, and, finally, a graph is provided showing the prediction intervals for a specific day. The evaluation data, which are the hourly predictions each day using the proposed models, correspond to the months of January, February and March of 2024.

The comparison of the three proposed models with the defined metrics and the results of the predictions for all days of the week can be observed in Table 4. We observe that Prophet and ARIMA perform very similarly across most metrics, with ARIMA having a slight edge in terms of R^2, MAPE, and SMAPE. Both models show strong predictive capabilities with minimal differences. LSTM, on the other hand, has lower performance compared to Prophet and ARIMA, with significantly higher errors across MAE, RMSE, MAPE, and SMAPE. This suggests that LSTM

Table 4: Comparison of average metrics for all days of the week

Model	R^2	MAE	RMSE	MAPE	SMAPE
Prophet	0.92	**377520.16**	**428455.65**	0.0414	0.0407
ARIMA	**0.93**	382061.51	441660.45	**0.0406**	**0.0403**
LSTM	0.85	461964.11	541297.02	0.0487	0.0491

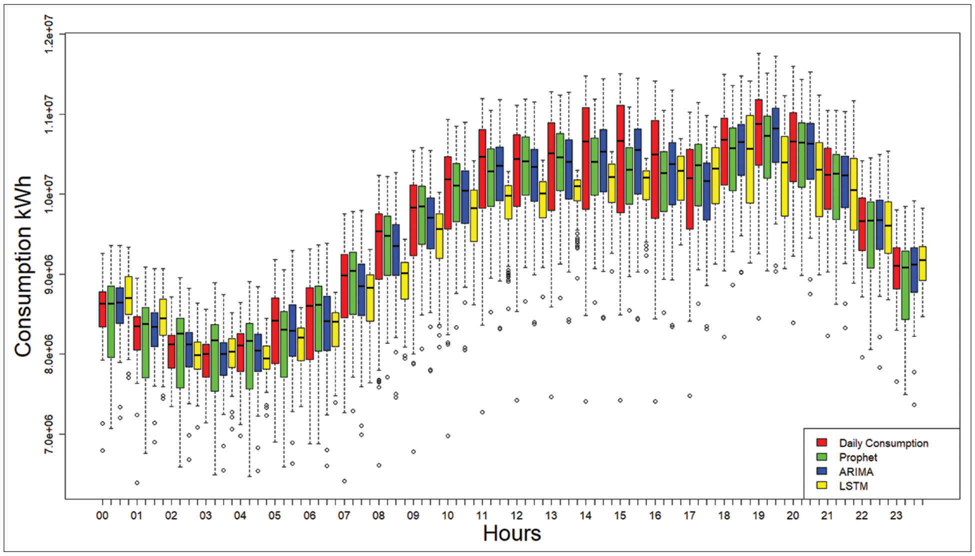
Bold value represents best result in the metric

may not be as well-suited for this particular dataset or time series, or it might require further tuning or more data to improve its accuracy. Overall, ARIMA is marginally the best model based on this analysis, but Prophet provides nearly identical performance and could be an equally viable choice depending on the specific application. LSTM, while typically effective for time series forecasting, is underperforming relative to the simpler statistical models in this case.

Comparison of the results of the evaluation of each model with the expected values for each day of the week can be seen in Figure 2. In this Figure we find on the Y-axis the total consumption in kWh and on the X-axis each of the hours of the day with their respective consumption predictions for each proposed model and the actual consumption. For each hour of the day we find four boxplots, in red all the real consumptions of the evaluation interval, in green all the predictions made with Prophet, in blue the predictions with ARIMA and in yellow the predictions with LSTM. In each boxplot you can visualize the quartiles, medians and outliers for each hour of the day for all predictions and the values to be predicted. it is evident that the LSTM makes predictions systematically below the real values and the predictions generated via Prophet and ARIMA; in general, the three models represent very well the trend of daily demand per hour in the country.

When the forecasts are analysed by work days, discarding holidays, Sundays and Saturdays, it is observed that, in general, all the forecasting methods underestimate the real value. The LSTM forecasts values below the real value and presents the worst results in terms of the studied metrics, as shown in Table 5 and Figure 3.

Figure 2: Comparison of the evaluation results from each model with the expected values for every day of the week



In general, as observed in the comparison of the metrics, the three models make good predictions, where Prophet and ARIMA are a little better and very similar. When the demand for energy increases, the three methods tend yield underestimated predictions as can be seen in the medians of the boxplots in Figure 3.

Table 5: Comparison of business day metrics

Model	R^2	MAE	RMSE	MAPE	SMAPE
Prophet	**0.98**	**304198.07**	346990.55	0.0312	0.0315
ARIMA	0.98	304392.05	**346578.04**	**0.0303**	**0.0313**
LSTM	0.89	465118.77	542533.50	0.0462	0.0479

Bold value represents best result in the metric

When the forecasts for non-work days (holidays, Sundays and Saturdays) are analysed, the LSTM method is slightly better than the other two methods, as shown in Table 6. The LSTM method has the lowest R^2 but the best results in the rest of the metrics (MAE, RMSE, MAPE and SMAPE).

In Figure 4, the three methods tend to overestimate the real value for the hours of greatest demand, with the LSTM method having the best forecast among the three and ARIMA which has the greatest overestimations according to the medians of the boxplots. Unlike Figures 1 and 2, as seen in Figure 4, in terms of the real values for higher demand, no outliers are identified in the boxplots. It is important to highlight that when comparing the hours of work days with non-work days, we find that work days are those with the highest average consumption and for this reason the models are affected in their forecasts.

To further interpret the results, Figure 5 presents the 95% confidence intervals (CI) for the forecasts of the three models on January 3, 2024. The red line represents the actual data, while the blue, green, and orange lines represent the CIs for the forecasts from the Prophet, LSTM, and ARIMA models, respectively. In this graph, we can observe that the ARIMA model demonstrates the highest stability and accuracy in terms of error variability, while the Prophet and LSTM models exhibit greater variability, which may suggest that, under certain circumstances, these models are less reliable.

Analyzing the 95% confidence intervals based on the forecast averages in Figure 6, it is evident that ARIMA once again shows the least variability in its prediction errors, with a narrower confidence interval. Prophet displays a moderately wide confidence interval, indicating some variability in its prediction errors, but it captures the trend well with smooth curves. LSTM also reflects the trend over time but has the widest confidence interval of the three models, suggesting higher variability in its prediction errors.

The ability to accurately forecast electricity demand in Colombia for the next 24 h is crucial for multiple stakeholders within the energy sector. For system operators like XM, it allows for real-time balancing of supply and demand, ensuring grid stability. Generation companies can optimize production, especially those using variable energy sources, while energy retailers and distributors can adjust their purchasing and distribution strategies to minimize costs and maintain system reliability. Large industrial consumers benefit from adjusting their usage patterns based on anticipated demand, while government regulators, such as the Energy and Gas Regulatory Commission (CREG), use this information to shape energy policies that ensure market efficiency and long-term grid stability.

Investors and developers of renewable energy projects rely on demand forecasts to assess project feasibility and guide investments. Market participants, including traders, can anticipate price fluctuations and make informed decisions, while consultants and researchers use this data to conduct market studies and develop energy models. Even small consumers may indirectly benefit through dynamic pricing mechanisms, which allow them to reduce costs by adjusting their consumption. Overall, accurate demand forecasting improves operational efficiency, informs strategic decision-making, and enhances the sustainability of the energy system.

Figure 3: Comparison of the evaluation results from each model with the expected values for work days

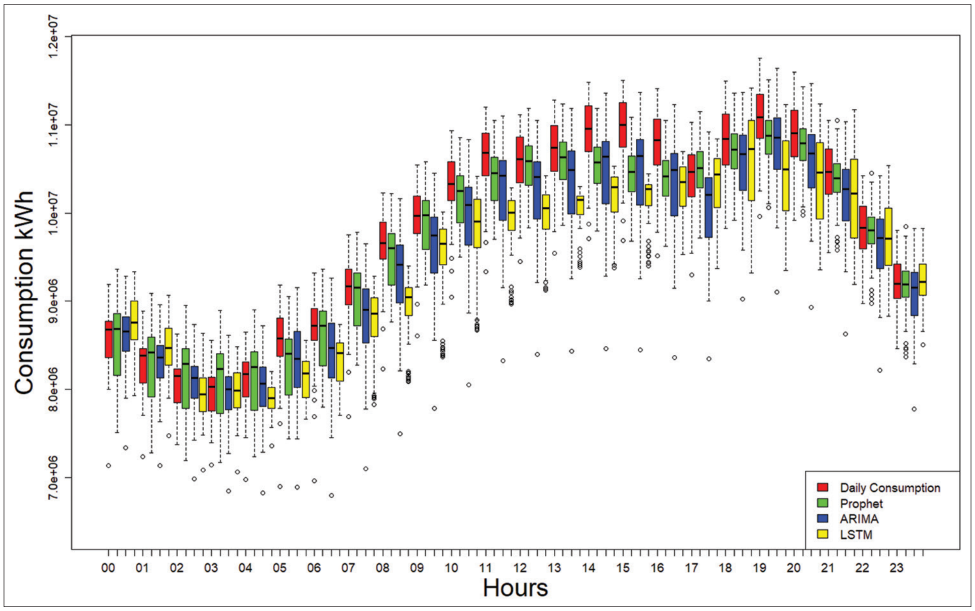


Figure 4: Comparison of the evaluation results from each model with the expected value for non-work days

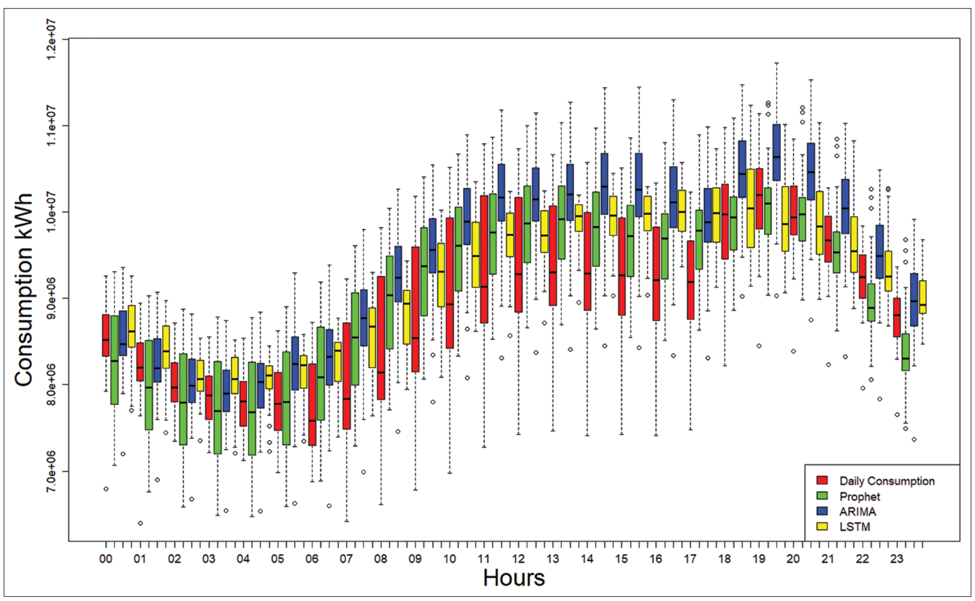


Figure 5: 95% confidence intervals for a given day

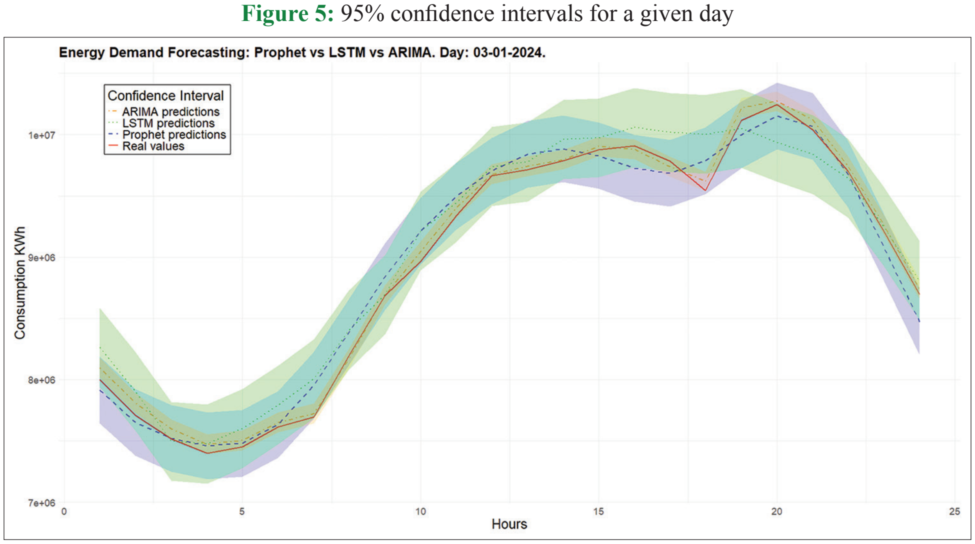


Figure 6: 95% confidence intervals for averages of the results

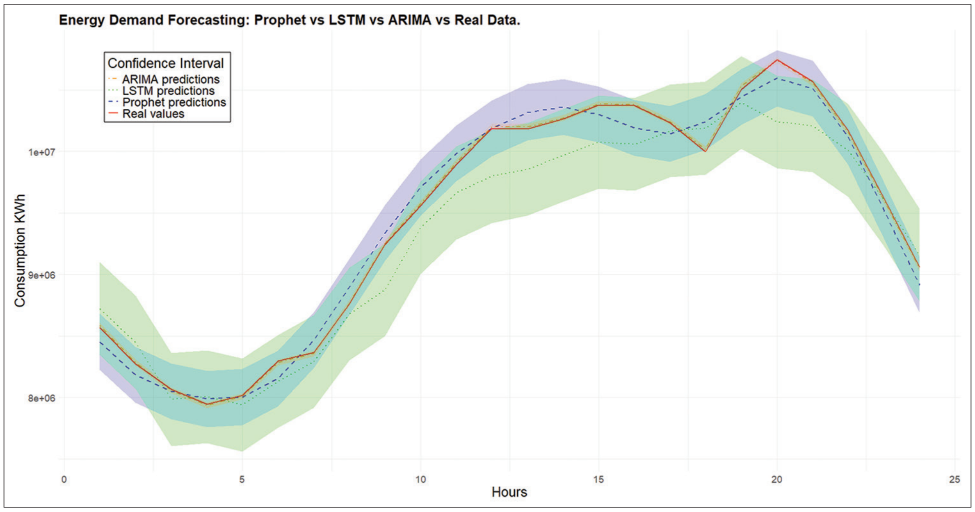


Table 6: Comparison of the metrics for non-work days

Model	R^2	MAE	RMSE	MAPE	SMAPE
Prophet	0.81	519433.88	586130.04	0.0612	0.0587
ARIMA	**0.84**	532389.50	625690.92	0.0604	0.0577
LSTM	0.78	**455858.31**	**538903.83**	**0.0535**	**0.0514**

Bold value represents best result in the metric

6. CONCLUSION

The ability to predict Colombia's electricity demand with accuracy over short time horizons offers critical advantages to system operators, generation companies, retailers, distribution entities, industrial consumers, regulatory bodies, investors, market traders, and even small consumers. This information improves operational efficiency, informs strategic decision-making, reduces costs, and supports the overall reliability and sustainability of the electrical grid. As evidenced in the literature cited in this study, the prediction of electricity demand is of vital importance for the development of a country. In addition, finding the appropriate method to carry out this prediction is a research task of great interest. For this reason, the objective of this work was to carry out a comparative evaluation of the ARIMA, LSTM and Prophet methods for predicting the total electricity demand of Colombia within 24 h of a given day. The models were trained and evaluated, using 19704 hourly daily demand records from January 1, 2022, to April 31, 2024. As a result, the models yielded better predictions for business days than nonbusiness days and both combined. The results also showed a systematic underestimation in all the predictions made.

In the evaluation of the model through 95% CIs, it was evident that, in general, all the models were within CIs and retained the trend of the data to be predicted. The three models generally presented good results and can be used to predict the total electricity demand of Colombia for 24 h after a given day with the data provided by XM without using exogenous variables in a predominantly hydroelectric market. When analysing the three models, the best performing model is LSTM and the ARIMA and Prophet models present similar results based on performance metrics.

In future work, specific models for work and nonwork days should be built, the results of each model should be analysed, and the results should be compared with those of other similar studies. Another element that can be analysed is the inclusion of other exogenous variables specific to a predominantly hydroelectric market, with the purpose of evaluating whether these variables improve the prediction of demand. According to the results of the evaluated models, for peak hours, there is an underestimation of demand; therefore, analysing the peak hours where there is greater demand can help to improve the predictions. Finally, as evidenced in the literature, many studies have proposed the use of assemblages of methods to improve predictions. It is necessary to validate whether data from a predominantly hydroelectric market also produce better results.

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