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REDES NEURONALES PARA LA PREVISIÓN DE LA DEMANDA EN SISTEMAS DE DISTRIBUCIÓN PRIMARIA DE ENERGÍA

NEURAL NETWORKS FOR DEMAND FORECASTING IN PRIMARY POWER DISTRIBUTION SYSTEMS

Diaz Abimael [1]; Pruna Jhon [1]; Proaño Xavier [1]; Quinatoa Carlos [1]

[1] Department of Electrical Engineering, University Technical of Cotopaxi. Latacunga, Ecuador.
Correo: carlos.quinatoa7864@utc.edu.ec.

Resumen

Se desarrolló un modelo predictivo para analizar los perfiles de carga en redes de distribución eléctrica mediante redes neuronales artificiales. Se empleó una metodología mixta de análisis de datos, que combina enfoques cualitativos y cuantitativos. La recopilación de datos se realizó a intervalos de 15 minutos, generando 5856 registros de kilovatios (kW), kilovoltamperios (kVA) y kilovoltamperios reactivos (kVAr). El modelo se dividió en un 70 % de datos para entrenamiento (4099,2 registros) y un 30 % para validación (1756,8 registros). La arquitectura del modelo consta de tres capas: una capa de entrada, capas ocultas para análisis y una capa de salida. Se utilizó un modelo secuencial con una capa de entrada LSTM de 200 neuronas y una capa de salida densa con una sola neurona. El optimizador Adam y la medida de pérdidas mse se utilizaron para el entrenamiento. La función de activación utilizada fue lineal. Finalmente, el modelo demostró un error de pronóstico de ±3,57 % para el modelo 2 y de ±4,38 % para el modelo 3, lo que lo hace eficaz para la planificación eléctrica.

Palabras clave: Redes artificiales, modelo, LSTM, optimizador, distribución.

Abstract

A predictive model was developed to analyze load profiles in electric power distribution networks using artificial neural networks. A mixed data analysis methodology, combining qualitative and quantitative approaches. Data collection was performed at 15-minute intervals, generating 5856 kilowatt (kW), kilovolt-ampere (kVA) and kilovolt ampere reactive (kVAr) records. The model was divided into 70% data for training (4099.2 records) and 30% for validation (1756.8 records). The model architecture consists of three layers: an input layer, hidden layers for analysis and an output layer. A sequential model with a 200 - neuron LSTM input layer and a dense output layer with a single neuron was used. The optimizer Adam and the loss measure mse were used for training. The activation function used was linear. Finally, the model demonstrated a forecast error of ± 3.57% for model 2 and ± 4.38% for model 3, making it effective for electrical planning.

Keywords: Artificial, Networks, Model, LSTM, Optimizer, Distribution.

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1. Introduction

To begin with, it is mentioned that the efficient management of electricity demand peaks becomes crucial, facing challenges in the network. Strategies such as smart pricing and anticipatory control, however, are affected by consumer privacy [1]. The innovative strategy that detects utility maximization without the need-to-know specific details of the consumer's utility function [2] And, further that the study focuses on improving the accuracy of day-ahead electric forecasts through hybrid approaches such as the combination of Exponential Smoothing (EMA) and Long Short-Term Memory networks (LSTM) [3]. On the other hand, the electricity industry is moving towards a competitive environment, abandoning its monopolistic model. Accurate electricity price forecasting is crucial to mitigate risks and effectively manage energy resources.

Subsequently the use of Radial Basis Function Networks (RBFN), a more efficient way to train and forecast electrical loads, outperforming previous models based on Artificial Neural Networks (ANN) [4]. Focusing on economic factors and long-term demand, it offers a valuable tool for strategic planning of electric power generation [5].

The rising cost of energy, driven by the scarcity of fossil fuels, has accelerated the search for more sustainable sources. The integration of neural networks in electricity demand forecasting provides accurate and efficient results, enabling advanced and sustainable energy planning [6]. The evaluation of ANN against the Multiple Regression model (MRA) in daily forecasting becomes crucial for Ceilán Electricity Board (CEB) planning, looking for the optimal method with minimum Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and maximum R2 [7]. With more reason to improve the prediction of electricity demand using feedforward neural networks. Parallel-hybrid evolutionary algorithm Artificial Fish Swarm Algorithm (AFSA) Particle Swarm Optimization (PSO) Parallel-hybrid evolutionary algorithm (APPHE), which combines AFSA and PSO algorithms, is introduced, showing more satisfactory and faster performance compared to neural network training [8].

This is crucial given the depletion of natural resources and the need to develop alternative energies. In forecasting the future distribution of electricity demand in Taiwan as a fundamental part of planning for the efficient use of electricity [9]. It is worth remembering that the accuracy of the electric charge is essential in meteorological conditions. It is proposed to use a single hidden-layer artificial neural network optimized with techniques such as Particle-swarm-optimization (PSO) and Genetic algorithm optimization (GA) to improve the training convergence and uniqueness of the solution in strategic electrical planning [10]. Incidentally, electricity load forecasting, divided into short, medium and long term, has experienced an increase in short-term forecasting due to the deregulation of the electricity sector. The application of methods, such as stacked autoencoders and convolutional NRA, promise planning and cost reduction [11]. In other words, the energy sector often lacks predictability, but the use of natural sources and user demand can improve in the short term.

In order to predict overall demand, computational intelligence models are evaluated and compared, optimizing results through high-performance computing infrastructure [12]. Then electricity requires management, given the unpredictability of the electrical load, daily forecasting is crucial. RNA, especially the multilayer perception model, stands out as an effective tool for this purpose, outperforming traditional methods such as Autoregressive integrated moving average (ARIMA) and Multiple linear regression (MLR) in speed [13]. It is necessary to emphasize that electric power is essential, the importance of short-term load forecasting in power systems [8]. RNAs are presented as a tool for analyzing and predicting electricity consumption, considering temporal factors, providing a solution for three-phase electric power [14].

Finally, the power grid has evolved into a smart grid with technologies such as advanced metering and artificial intelligence [15]. Digital twins, supported by statistical and deep learning techniques, enable efficient management and accurate demand forecasting, improving grid performance in a smart infrastructure [16].

2. Materials and Methods

2.1 Previous Data

The first step in the idea is gathering freight data in November and December of 2022. This data will be processed to use only the specific information needed for the creation of the neural network, focusing on power and time parameters. The system in Table 1 collects data every 15 minutes, generating a set of 5856 data including kilowatts (kW), kilovolt amperes (kVA) and kilovolt amperes reactive (kVAr).

Finally, the study will also focus on the assessment of the results achieved and on the comparison with other approaches to analyse the electrical charge distribution [17].

Table 1. *Data base*

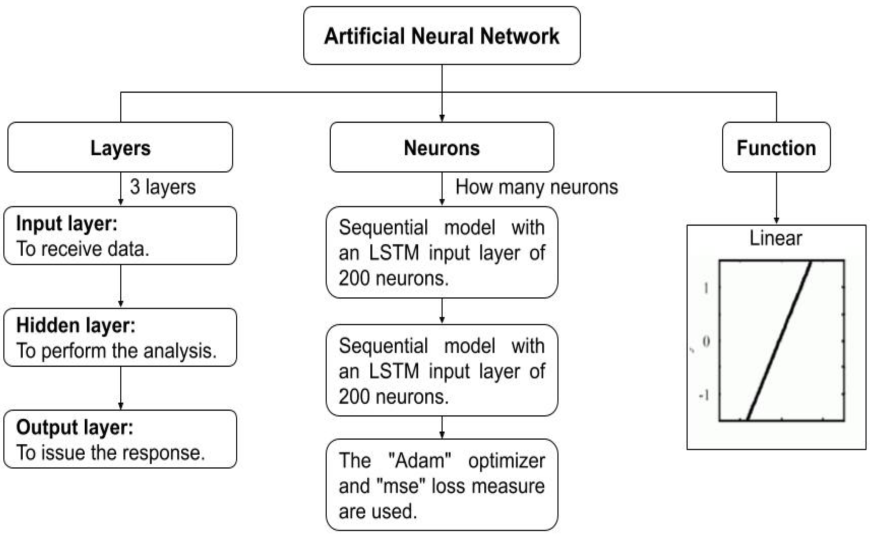
Data	Train	Validate
5856	70% of 5856	30% of 5856
	= 4099.2	= 1756.8

In general, an RNA architecture composed of sets of neurons (layers) divided into three groups is proposed:

- Input layer for receiving data.
- Hidden layers for analysis.
- The output layer to issue the response.

In this research it is described in Figure 1 below:

Fig. 1: *Artificial neural network*

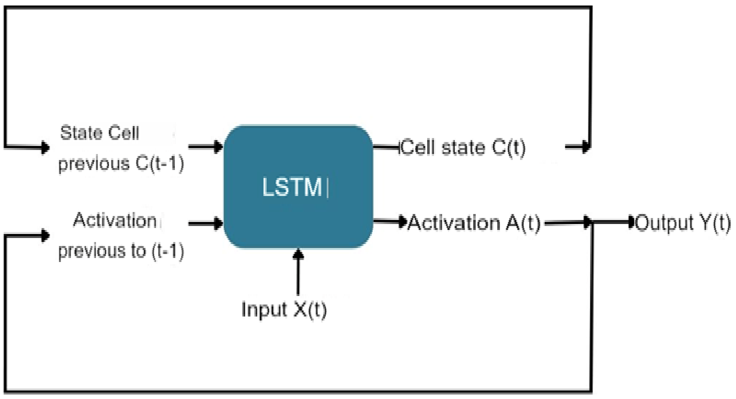


2.2 LSTM Networks

Long-term and short-term memory (LSTM) constitute a special category within recurrent networks. The distinguishing feature of recurrent networks is their ability to retain information by incorporating loops in the network structure, essentially allowing them to remember previous states and use this information to determine the next state. This property makes them particularly suitable for dealing with temporal sequences. While conventional recurrent networks can model short-term dependencies, then relations close in time sequence can capture long-term dependencies, thus manifesting a type of extended memory [18].

In Figure 2 a recurrent neural network LSTM is composed of key components: the memory represented by the values of C, the outputs represented by H, the inputs by X, and the resulting outputs by Y. Specific operations designed to discard obsolete information, update the memory with relevant information, and compute the new hidden state of the memory are performed [19].

Fig. 2: *Schematic types of neural networks*



2.3 How to Train a Neural Network

By feeding the input data into a deep neural network which consists of an initial 100-unit LSTM layer and a subsequent 50-unit layer anticipation is accomplished. To control overfitting, the dropout technique is applied after every layer. Lastly, a conclusive probability is provided by a dense layer with a single unit and sigmoid activation.

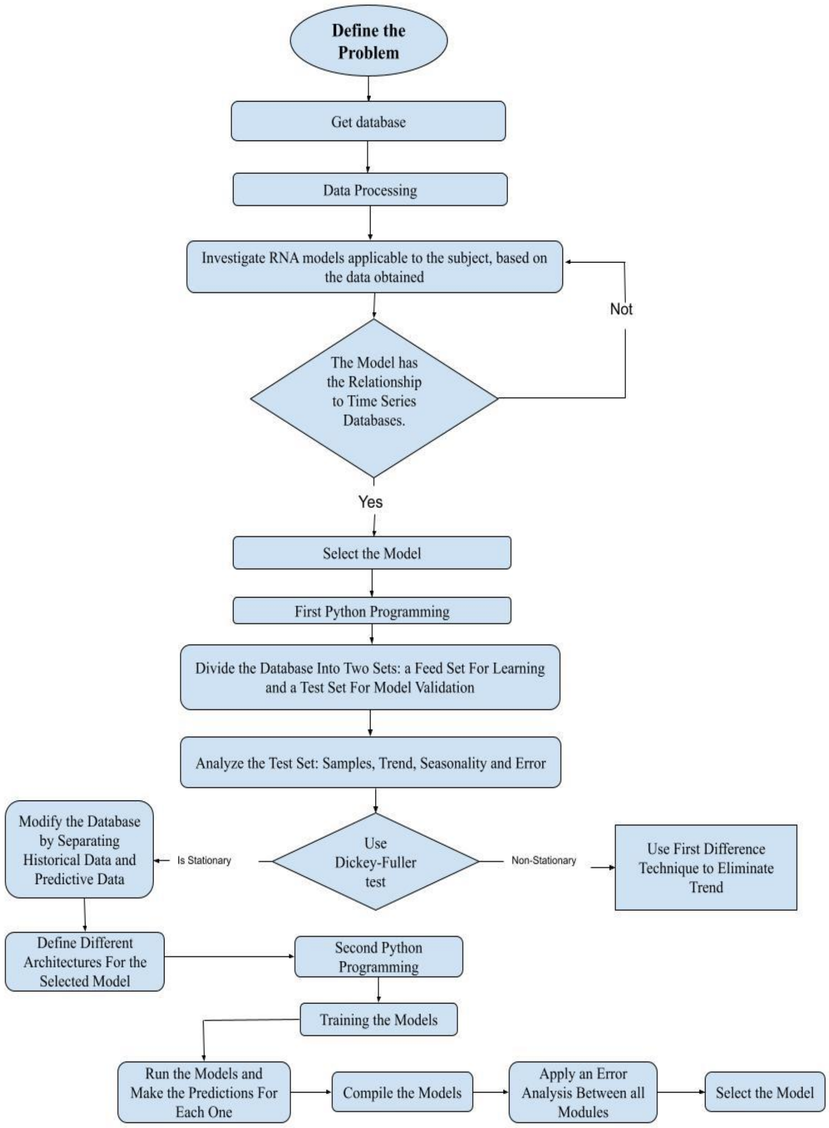
It is crucial to put this network through a training procedure in order to get reliable predictions. Training is developed as an iterative learning process, where data instances, specific segments of inputs, are presented to the network along with their known correct outputs. Each instance is introduced individually, adjusting the weights associated with the input values at each layer accordingly [20]. This process is repeated several times with various batches of data until the weights are adjusted well enough to accurately predict the correct label (or probability) for any given input sample.

2.4 Procedure

The approach suggested to accomplish the goals centers on applying artificial intelligence techniques to create a prediction model. This approach aims to improve the forecasting capability of electric load profiles in electric power distribution networks. The investigation of artificial neural network models related to time series databases is proposed with the purpose of making predictions of load profiles in electric power distribution networks [21]. The aim is to define an appropriate model that satisfies the key aspects to ensure an accurate assimilation of the historical data relevant to this study.

In order to assess the created model's efficacy in properly predicting demand patterns in electrical load profiles, an evaluation of its performance will be conducted using several error metrics. Figure 3 shows the diagram model. The text addresses the lack of research on electrical load profiles on primary feeders of a specific distribution structure, highlighting the importance of understanding and optimizing performance in this area. The application of deep learning models and the use of available data to develop more effective strategies for electrical management of the distribution network is proposed.

Fig. 3: *Neural network prediction model.*



The need to examine data to determine the optimal sampling frequency and normalize it between 0 and 1 to facilitate its input to the neural network is highlighted. In addition, it is suggested to split the data into training and test sets, implement additional preprocessing techniques such as anomaly detection, and use matrices to transform the data and build a prediction model. The importance of considering additional variables such as climatic factors to improve model accuracy is emphasized. Models such as Vanilla and Stacked LSTM with different configurations in layers and neurons are proposed to identify the optimal combination to maximize performance. Subsequently, the flexibility of adjusting the number of iterations for neural network training is mentioned, highlighting the computational cost associated with this process [22]. It is suggested to explore optimization strategies and advanced training techniques, such as transfer learning, to improve computational efficiency. It is suggested that efficiency be assessed in relation to variations in the number of iterations and that the best possible balance between computing cost and accuracy be found. Finally, the evaluation of models using error metrics such as MAE, MSE and R^2 is described, as well as the possibility of exploring the visualization of results using time series plots to identify patterns and areas of improvement in the prediction of electrical load profiles.

3. Results

After completing the training of the LSTM models, we proceed to make predictions for a period of 7 days and evaluate their agreement with the test set. Figure 4 is an example of the kilowatt variable of the first LSTM model. Although its performance is acceptable, it is observed that the trend is downward and does not faithfully reproduce the test set.

Then, the second model is presented in Figure 5, where it is possible to notice that it fits more effectively to the test set, and its trend is very close.

The third model, which incorporates a hidden layer and is visible in Figure 6, yields a similar result to the second LSTM model.

Looking at Figure 7, it is clear that in the fourth model the neural network is overtrained, which causes several errors in its predictions. Due to this reason, this model is excluded from the analysis. It is essential to emphasize the importance of avoiding overfitting in the process of learning models, as it can significantly compromise their ability to make accurate predictions in real-world situations.

In conclusion, all models can be observed compared only with the training data. This is reflected in Figure 8.

3.1 Analysis of Results

Fig. 4: *Prediction of the first LSTM model*

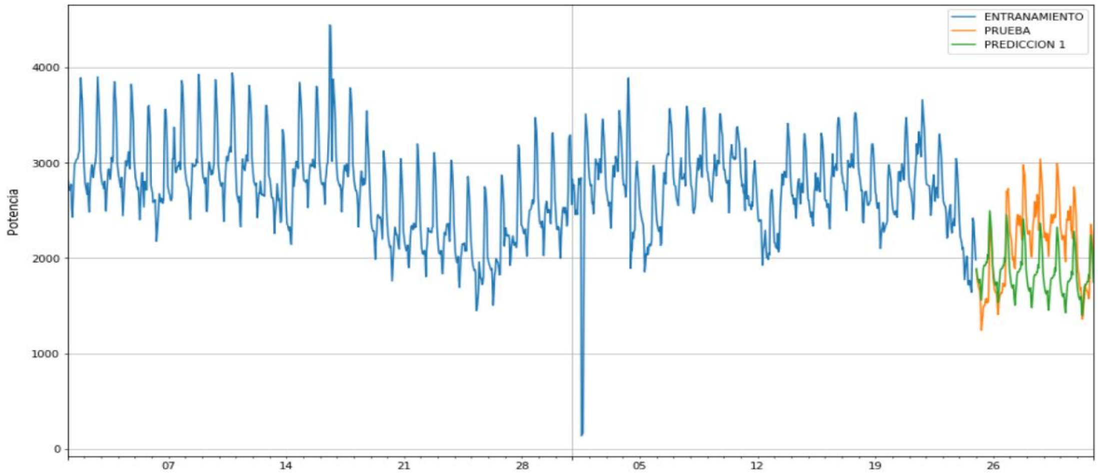


Fig. 5: *Prediction of the second LSTM model*

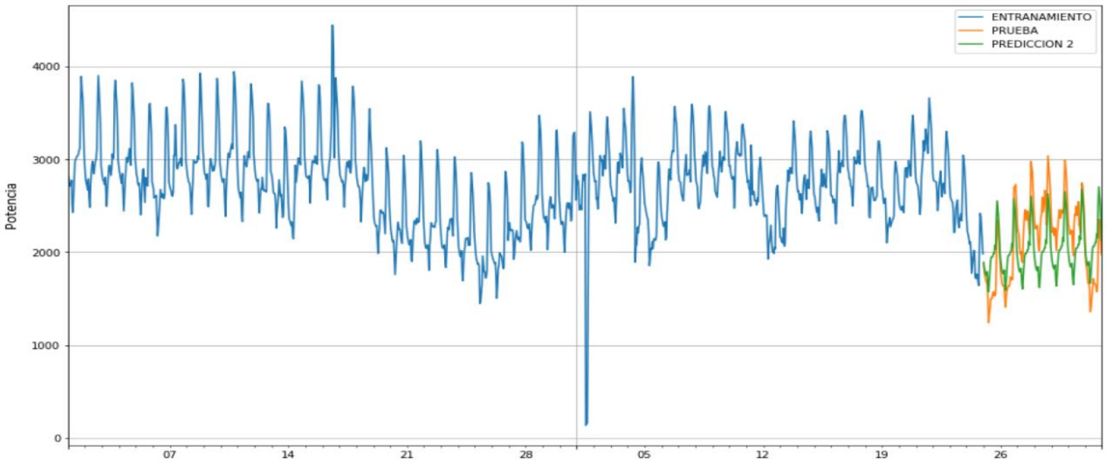


Fig. 6: *Prediction of the third LSTM model*

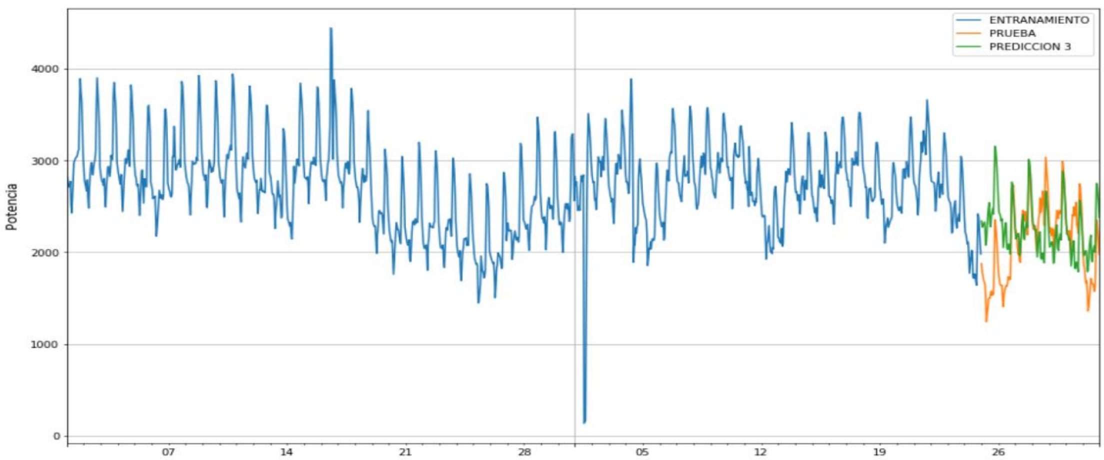


Fig. 7: *Prediction of the fourth LSTM model*

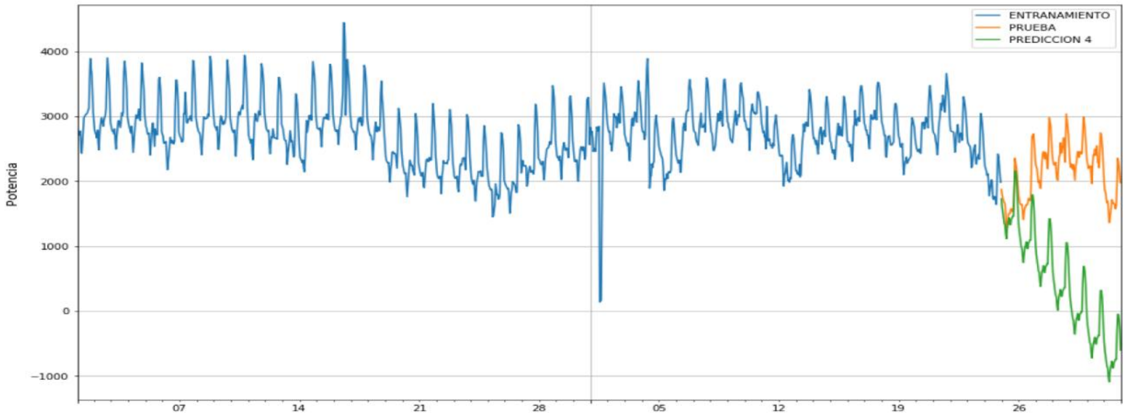
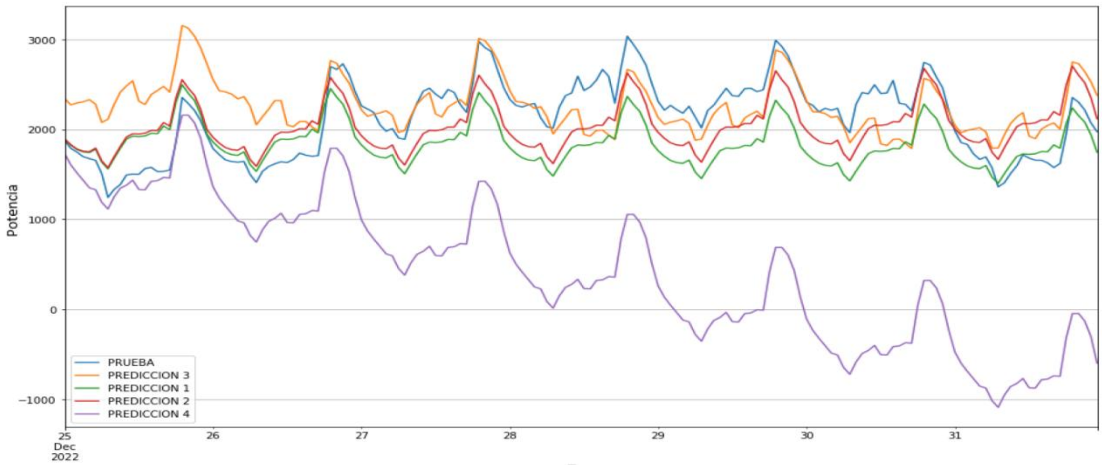


Fig. 8: *LSTM model predictions*

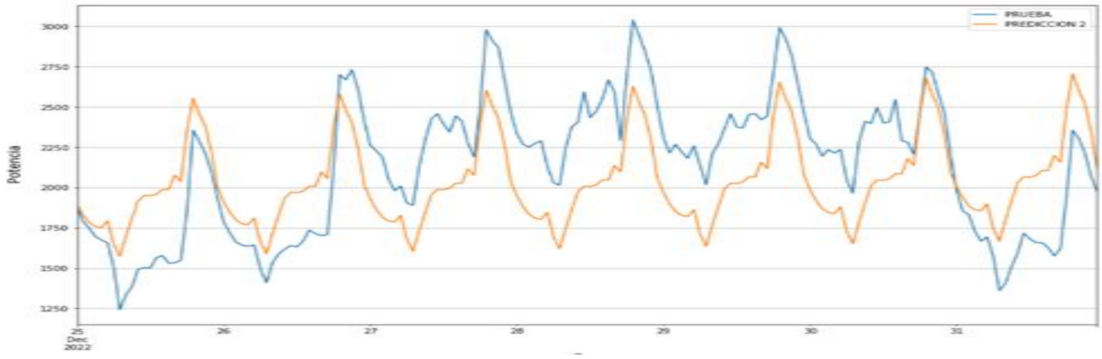


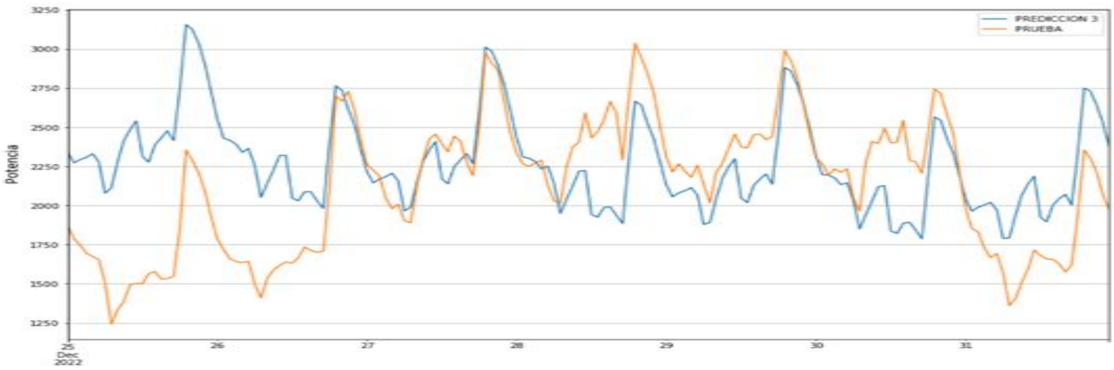
3.2 Technical Validation of Results

After compiling all the models, as shown in the previous section, it could be noted that the second and third models were the best fit to the time series of load profiles. For this reason, both models are directly compared with the test set to analyze their similarities. This process is depicted in Figure 9.

In order to make an appropriate choice of the prediction model, evaluations are carried out using various types of errors. The Mean Absolute Error (EAM) provides insight into the accuracy of the model without considering the direction of the error, while the Mean Squared Error (ECM) addresses this issue by squaring the error, thus avoiding biases in decision making.

Fig. 9: *(a) Model 2 LSTM predictions; (b) Model 3 LSTM predictions*





Likewise, the coefficient of determination (R2) provides information on the variability of the model and the quality of the prediction fit.
The analysis of Table 2 reveals that, although model #2 presents a lower EAM compared to model #3, it is crucial to keep in mind that negative and positive errors can influence the choice of model. Consequently, the ECM suggests that model #3 exhibits a lower value, indicating a more accurate fit. In addition, the R2 metric points out that both predictions are close to zero, indicating similar behavior between both models. When examining the maximum errors of each model, it is highlighted that the prediction of model #3 is considerably higher, leading to the choice of the second model with only one input layer and one output layer.

Table 2. *Error analysis*

Data	EAM	ECM	R2
Model #2	318.45 Kw	347.09 Kw	0.31
Model #3	343.78 Kw	437.75 Kw	-0.09

Finally, to verify the probability accuracy of the two models investigated, the first 10 samples of the test set are examined, analyzing the variability in the predictions, the percentage of hits for each model.

Table 3 indicates that model #2 presents a forecast error of ± 3.57%, while model #3 has an error of ± 4.38%. This approach allows a deeper evaluation of the reliability and consistency of each model in terms of predictions, providing valuable information about its performance in specific situations of the test set.

Table 3. *Errors in model analysis*

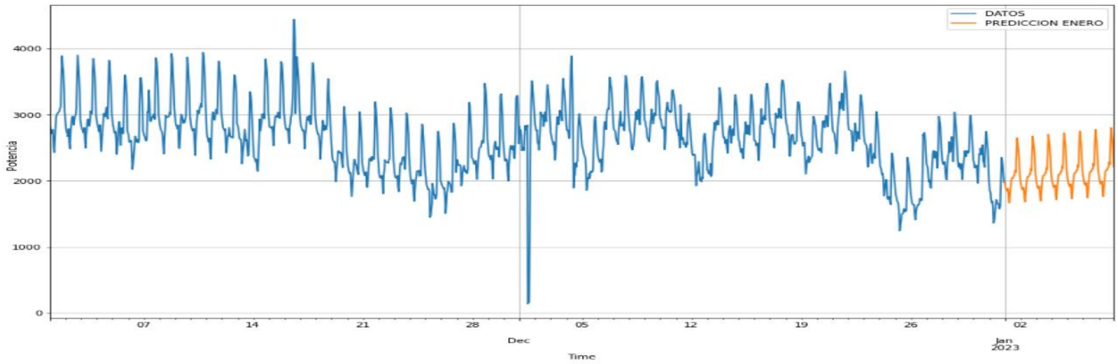
Model	Probability of success
Model #2	± 3.57%
Model #3	± 4.38 %

3.3 Evaluation of impacts or results

Once the model has been chosen, it is trained using the entire data set to make predictions of future samples. Following the same criteria established during the development of this project, the prediction for the next 7 days of January 2023 is carried out.

In Figure 10, it can be seen that the prediction retains the same periodicity with similar peaks in kilowatts, although it exhibits a more linear trend. This behavior is attributed to the limitation of the data set, since its reduced size does not allow it to capture more accurately the periodicity of the time series.

Fig. 10: *LSTM model predictions*



4. Conclusions

LSTM networks are capable of generating predictive models very close to the test values, ensuring the ability to forecast future samples for electrical planning. This load profile prediction study has evidenced the usefulness of LSTM networks; however, it is crucial to consider a data preprocessing that adapts them to the needs of the model.

Although this project has not addressed the computational cost associated with LSTM network training and search in layer and neuron selection, it is important to note that high-performance servers are required to perform these tasks. By transforming and processing the time series database, the data needed to train deep learning models, such as neural networks, were obtained. This involved adjusting the data to an appropriate sampling frequency, scaling it between 0 and 1, and subsequently splitting it into training and test sets. In addition, various statistical methods, such as the Dickey- Fuller test and the first difference technique, were applied to evidence the stationarity of the time series. These results confirm the need for the model to be complex in order to forecast the data accurately. The choice of using recurrent neural networks to analyze electrical load profiles on primary feeders of a power distribution network appears to be the most effective option to achieve a predictive approach. This is due to the ability of these networks to process sequential data, understand complex patterns in the data, and their ability to self-regulate and adapt to changes in the environment

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