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Electrical Load Forecasting to Plan the Increase in Renewable Energy Sources and Electricity Demand: a CNN-QR-RTCF and Deep Learning Approach

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ABSTRACT

This research develops a new electric charge prediction method by using Convolutional Neural Networks with Quantile Regression (CNN-QR) combined with the Rainbow Technique for Categorical Features (RTCF) and using Deep Learning to create layers for the architecture of the neural network. This combination captures both local and global interdependencies within the load data. In particular, RTCF employs advanced natural language processing (NLP) techniques to convert several important categorical features into a single feature called "category," which is tailored to the various attributes of the Baja California Sur system, in Mexico, taking into consideration climatic conditions, local circumstances and a significant increase in energy consumption. Furthermore, this research compares CNN-QR with classical quantile regression and shows that CNN-QR works better at capturing sophisticated load patterns and producing probabilistic estimates. The above methodology uses hourly data from January 2019 to October 2020. The results obtained provide valuable information for policy formulation in the energy sector, specifically in the areas of load forecasting and expansion of renewable energy and electricity consumption. Finally, it is worth mentioning that the utilization of CNN-QR with RTCF not only improves the accuracy of load forecasting, but also provides a strategic framework for energy management and resource planning in dynamic energy systems, which demonstrates its substantial importance for market participants and authorities, as well as regulators.

Keywords: Electric Load Forecasting, Convolutional Neural Networks, Quantile Regression, Rainbow Technique for Categorical Features, Deep Learning
JEL Classification: C45, Q41, Q47, L94

1. INTRODUCTION

Electrical load forecasting is a crucial aspect of energy management that plays a central role in optimizing resource allocation and maintaining grid stability. Amid the increasing incorporation of renewable energy sources and the unpredictable nature of electricity demand, the need for robust and reliable forecasting methods has become extremely important (He, 2017). This study aims to satisfy this urgent requirement by proposing an innovative method combining Convolutional Neural Networks with Quantile Regression (CNN-QR) for electric load forecasting. Furthermore, this work presents the integration of the Rainbow Technique for Categorical Features (RTCF), a novel method aimed at improving forecast accuracy through categorical features.

Although widely used in load forecasting, traditional quantile regression algorithms provide probabilistic estimates at different quantile levels, but generally fail to capture the complex spatiotemporal patterns present in load data (He et al., 2020). In contrast, CNN have demonstrated an exceptional ability to recognize intricate patterns. Expanding on these characteristics, we emphasize that the CNN-QR approach combines the capabilities of CNN with Quick Response (QR) codes, resulting in a model that effectively replicates electrical charging patterns. Our proposal, designed specifically for the Baja California Sur (BCS) system, in Mexico, effectively captures local and global links in the data, resulting in a substantial improvement in prediction accuracy.

Incorporating the RTCF in our research is used to produce categorical features. This technique aims to combine various category elements into a single organized entity through a harmonization process. The RTCF improves our model by incorporating many category features from multiple points of view, providing a more complex and comprehensive understanding of the fundamental patterns that influence load forecasting (Reda, 2023). Finally, Deep Learning (DL) is used to create layers for the neural network and configure the complex architecture of the neural network for the BCS system.

The Mexican BCS system presents significant obstacles to effective load forecasting due to its distinctive characteristics, such as varied weather conditions and rapidly increasing energy demand. The goal of our research is to demonstrate the capabilities of CNN-QR to decipher complex loading patterns and provide extremely accurate probabilistic forecasts, particularly in comparison to conventional quantile regression techniques.

The main objective of this research is to analyze the performance of CNN-QR in electric load prediction. Additionally, the consequences of including the RTCF as a means of producing categorical features will be performed. This article aims to highlight the substantial improvements achieved by combining CNN-QR with RTCF using DL. This combination will not only show outstanding performance, but also confirm the effectiveness of the proposed methodology. This approach represents a substantial advance in the dynamic and intricate field of electrical load forecasting, providing crucial information to decision makers and stakeholders in the energy sector, facilitating better energy management and resource planning in complex energy systems.

The next sections of this investigation are organized as follows: section 2 presents a short review of the specialized literature, with specific emphasis on load forecasting approaches, quantile regression, convolutional neural networks, and feature creation methods; section 3 highlights the importance of load forecasting within a decentralized grid system while renewable energy generation continues to expand; section 4 provides a summary of the data gathering procedure and the categorical features; section 5 gives a comprehensive discussion on the specific steps and methods involved in the application of the RTCF; section 6 outlines the structure of the CNN-QR model; section 7 measures the effectiveness of the proposal and discusses the results obtained; and, finally, section 8 gives the conclusions.

2. LITERATURE REVIEW

This section provides a brief review of research in three critical domains: QR, CNN, and RTCF. First, QR has become increasingly popular in load forecasting because it can accurately represent the entire distribution of the target variable. This resource offers valuable data on several quantiles, allowing both central tendencies and extreme values to be estimated.

Most research has shown that quantile regression is effective in load forecasting. For the purpose of modeling positive asymmetrically distributed income data, the QR models are effective. These models provide practical statisticians and econometricians with significant insights (Saulo et al., 2023). For instance, Shi et al. (2021) use QR to forecast wind power probabilistically, demonstrating its ability to accurately represent uncertainty. Likewise, Guan et al. (2020) apply Gaussian process QR to achieve precise and resilient forecasts for probabilistic short-term load forecasting. Finally, Wang et al. (2019) develop a method using QR taking into account robustness, hence improving the effectiveness of load forecasting models.

On the other hand, CNN initially designed for image processing applications have proven to be effective in load forecasting because of its capacity to detect spatial and temporal patterns. These DL models have demonstrated potential in extracting pertinent characteristics and capturing intricate connections in load data. Multiple research projects have investigated the utilization of CNN in load forecasting. In order to improve the accuracy of traffic forecasting and real-time performance, the Dynamic Spatial-Temporal Adjacent Graph Convolutional Network (DSTAGCN) is able to efficiently capture the dynamic spatial-temporal dependencies that are present in traffic data (Zheng and Zhang, 2023). Likewise, Jin et al. (2021) develop an electric load forecasting model utilizing a DL network, showcasing the efficacy of CNN in accurately capturing load patterns. In this sense, Rafi et al. (2021) propose a convolutional long short-term memory neural network for load forecasting, which effectively combines the advantageous categorical features of CNN and recurrent neural networks. Finally, He et al. (2020) employed a 1-Dimensional convolutional neural network for day-ahead electric load forecasting, attaining precise and efficient forecasts.

Categorical Feature Generation Methods seek to improve the accuracy of load forecasting by extracting pertinent information or modifying the original characteristics. These approaches are capable of capturing seasonal patterns, trends, and other significant features of load data. Several studies have investigated techniques for generating categorical features in order to forecast load. The utilization of historical weather data in the proposed multi-feature data fusion technique improves the precision of electric car charging station load (Aduama et al., 2023). In this sense, Yao et al. (2000) perform the short-term load forecasting using a combination of wavelet transform and least squares support vector machine, which were optimized by an enhanced search method. Similarly, Shah et al. (2019) use singular spectrum analysis and support vector regression to accurately predict electric load, thereby capturing inherent patterns. Finally, Platten et al. (2020) apply statistical machine learning techniques to precisely estimate the energy efficiency of residential structures, emphasizing the effectiveness of feature generating approaches.

On the other hand, contemporary literature has integrated CNN with QR in load forecasting, capitalizing on the respective advantages of both methodologies. An effective improvement in load forecasting accuracy is achieved by the utilization of the proposed short-term power load forecasting approach (Wang and

Li, 2023). Also, Bracale et al. (2020) suggest a novel approach that integrates CNN with QR to enhance the accuracy of time series forecasting. Similarly, Zhang et al. (2019) develop a CNN model that uses QR to forecast short-term traffic flow. Likewise, Shi et al. (2018) applied a CNN based method for enhancing the resolution of magnetic resonance images using QR. These studies demonstrate the amalgamation of CNN with QR, exhibiting enhanced predictive accuracy in many fields.

The references offered provide a comprehensive and extensive summary of the literature on electrical load forecasting approaches covering CNN, QR, and RTCF. These tools are important for load forecasting, as shown below.

3. THE IMPORTANCE OF LOAD FORECASTING IN A DECENTRALIZED GRID SYSTEM WITH RENEWABLE ENERGY GROWTH

Mexico's energy sector is currently experiencing a significant change as it moves towards decentralized grid systems, accompanied by a strong effort to incorporate renewable energy sources. Mexico's Energy Transition Law supports this shift, with the goal of achieving a high percentage of electricity generation from renewable energy sources by 2024 (Enciso-Chávez, 2019). This growth represents both a broadening of energy sources and the emergence of new factors in energy management; decentralized renewable sources, including solar, wind, and hydro, will take a more crucial role.

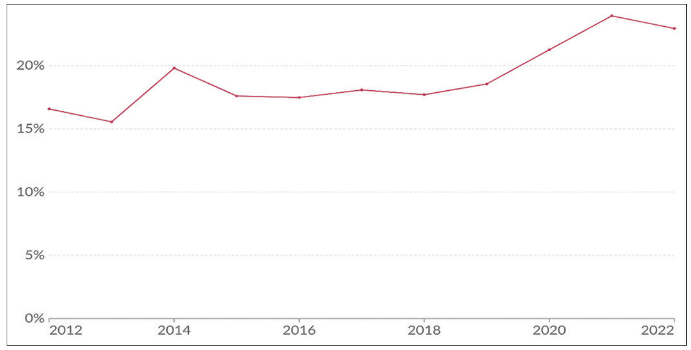
3.1. The Increasing Popularity of Renewable Energy in Mexico

Following the decentralization of Mexico's power market in 2014, there has been a significant increase in the capacity of renewable energy. As of 2022, the total power generation capacity of environmentally friendly energy plants exceeded 31,000 MW. This demonstrates a steady increase in capacity each year and highlights the country's dedication to adopting sustainable energy practices (Dieck-Assad and Carbajal-Huerta, 2017).

Figure 1 shows the proportion of energy generation derived from renewable sources in Mexico, showing its importance of the market decentralization that took place in 2014. Since 2014, there has been a noticeable and consistent increase, indicating the successful results of policy reforms and the growing ability of renewable energy sources to contribute to the national power supply. This development is evidence of Mexico's dedication to increasing its renewable energy sector.

The increase in renewable energy generation is attributed to various factors, such as legislative incentives, technological progress, increase in CO_2 emissions, and a societal transition towards more sustainable and environmentally friendly energy sources. The graph not only depicts these variables, but also illustrates Mexico's energy reform's progressive nature and its successful advancement towards a more environmentally friendly future.

Figure 1: Mexican share of electricity production from renewable energy



Source: Own elaboration with data from OurworldData.org/energy and Ember's Yearly Electricity Data (2022)

With respect to the significant increase in CO_2 emissions in Mexico, it is also necessary take immediate actions to improve environmental quality. Despite the awareness in Mexico that the increase in CO_2 emissions derived from industrial development (energy, transportation, construction, agriculture, etc.) is strongly linked to the consumption of non-renewable energy, few efforts have yet been made to achieve an energy transition each environmental stability (Mendoza-Rivera et al., 2023; Salazar-Núñez et al., 2020; 2022; Santillán-Salgado et al., 2020; Valencia-Herrera et al., 2020).

3.2. Obstacles in Predicting Power Demand for Distributed Power Systems

The decentralized grid, which consists of a combination of large-scale and dispersed generation, has distinct issues for load forecasting. Advanced forecasting approaches are required to handle the sporadic and fluctuating characteristics of renewable sources, such as solar and wind, which experience rapid variations in energy output and consumption patterns. Moreover, the growing number of small-scale renewable projects, motivated by the escalating power expenses and the need for dependable energy, introduces additional intricacies to energy management (Sultanuddin et al., 2022).

3.3. The Significance of forecasting in Maintaining Grid Stability and Efficiency

Accurate load forecasting is crucial for maintaining grid stability and operating efficiency in this decentralized environment with abundant renewable resources. It facilitates the efficient equilibrium of supply and demand, hence reducing the likelihood of power interruptions and minimizing energy inefficiency. Precise predictions are crucial for maximizing the allocation of renewable energy, diminishing dependence on fossil fuels, and guaranteeing a regular and dependable electricity provision (Raza et al., 2018).

3.4. Advancements in Technology for Predicting Load Demand

To address these difficulties, the energy industry in Mexico is utilizing state-of-the-art technologies in load prediction. The utilization of AI, machine learning, and big data analytics is growing in order to improve the precision and agility of forecasting models. These technologies enable the immediate processing and analysis of extensive datasets, enhancing the ability to estimate energy demand in a grid system that is abundant in renewable sources (Lakshminarayanan et al., 2021).

3.5. Implications for Policy and the Economy

Precise prediction plays a crucial role in developing energy regulations and directing investments in Mexico's electricity sector. It has a crucial role in decision-making processes concerning grid expansion, infrastructure upgrades, and the incorporation of new technologies. Furthermore, forecasting facilitates the synchronization of energy output with Mexico's overarching economic and environmental objectives, such as reducing emissions and advancing the adoption of electromobility (Fan et al., 2019).

As Mexico further embraces renewable energy in its decentralized infrastructure, the importance of load forecasting becomes more prominent. This forecasting is essential for guaranteeing effective energy management, upholding grid stability, and facilitating the nation's shift towards a sustainable energy future. Precisely forecasting electricity demand is not just a technical requirement, but also a strategic advantage that impacts all aspects of energy sector activities, ranging from policy development to daily grid administration.

4. NATURE OF THE DATA

This section presents a summary of the data utilized in the study, which was gathered from the BCS system. The dataset contains chronological records of electricity usage for every hour between January 01, 2019 and September 30, 2020. The National Energy Control Center (CENACE, the Spanish acronym for Centro Nacional de Control de la Energía) provides the data on electric demand or load and Local Marginal Price (LMP). Table 1 displays the information on the attributes utilized from the BCS System Dataset for load forecasting.

The load forecasting dataset comprises 15,336 observations. The variable Total_Demand reflects the aggregate power consumption per hour, measured in Megawatt-hours (MWh). A separate variable, Average_Pml, quantifies the mean value of the local LMP for the hour.

Table 1: Categorical features used in load forecasting from the BCS system dataset

Feature	Data type	Number of values	Unique values
Total_Demand	Real	15,336	
Average_Pml	Real	15,336	
Day_week	Nominal	7	7
Day_of_month	Nominal	31	31
Month	Nominal	12	12
Year	Nominal		2
Hour_of_day	Nominal	24	24
CDD	Real	15,336	
HDD	Real	15,336	
Season	Binary	2	2
Holiday	Binary	2	2

Source: Own elaboration with electrical load data from the BCS system

The dataset contains various nominal variables, including Day_week, Day_of_month, Month, Year, and Hour_of_day. The variable "Day_week" represents the day of the week, ranging from Monday to Sunday. The variable "Day_of_month" represents the day of the month, ranging from 1 to 31. The variable "Month" represents the month, ranging from January to December. The variable "Year" represents the year, which can be either 2019 or 2020. Finally, the variable "Hour_of_day" represents the hour of the day, ranging from 0 to 23.

The dataset additionally includes two temperature-related variables, namely CDD (Cooling Degree Days) and HDD (Heating Degree Days). CDD denotes the quantity of cooling degree days for the hour, which quantifies the amount of cooling needed during the summer months. HDD stands for heating degree days, a metric that quantifies the amount of heating needed during winter months. These factors are frequently employed in the energy sector to estimate energy demand and can be valuable for energy planning, weather prediction, architectural design, and energy efficiency studies. Furthermore, the dataset contains two binary variables, namely Season and Holiday. The Season variable denotes whether the hour falls within the dry season (November to April) or the wet season (May to October). The Holiday variable denotes the presence or absence of a holiday on a certain day.

The dataset comprises a total of 18 variables and 15,335 observations. The dataset was divided into a training set and a testing set using an 80/20 ratio. As a consequence, the test and validation sets consist of 3067 observations. Finally, this dataset offers a comprehensive and diverse range of data for load forecasting analysis. It includes numerous elements such as power demand, marginal pricing, temporal aspects, temperature-related variables, seasonality, and holiday effects.

5. RAINBOW TECHNIQUE FOR CATEGORICAL FEATURES

This section outlines the utilization of the RTCF approach on the categorical variables to produce a consolidated feature named "Category." The RTCF approach utilizes various categorical factors, such as Day of the "Week-Month-Season-Holiday-Hour" to generate phrases that represent the varied combinations. As an illustration, a sentence might read "Tuesday-January-Low-No-one."

In order to implement the RTCF approach, we begin by amalgamating the categorical variables to construct these phrases. Subsequently, we find that there are only 2537 distinct sentences present in the feature. We calculate the total number of occurrences for each sentence, with the maximum frequency being 20. Within the sentences that occur most frequently, there are four distinct sentences: "Sunday-March-Low-Holiday-one," "Thursday-January-Low-Holiday-one," "Wednesday-July-High-Holiday-one," and "Saturday-August-High-Holiday-one." Subsequently, we examine the correlation between these statements and the load. Under this framework, it is observed that the sentence with the lowest load has a frequency of 1. This sentence, "Saturday-April-Low-No-one," is related with a load of 166.75 MW. This sentence is categorized as label 0. Likewise, we attribute the phrase "Tuesday-August-High-Holiday-seventeen" to the peak demand, which reached a magnitude of 500.81 MW. Due to its repeated occurrence in the feature, we designate this statement with the category label 2536.

In order to include the RTCF approach into our research, we generate a Python dictionary and combine it with the load dataframe using the Pandas package. In addition, we investigate the correlation between load and various quantiles. Table 2 displays the load values for different quantiles, spanning from the 10^{th} to the 95^{th} percentiles. The load values corresponding to each quantile are shown in Table 2.

In addition, we analyze the connections between load and other characteristics for the 50^{th} percentile using the CNN-QR in order to predict the outcomes. The correlation matrices for each quantile, specifically highlighting the 10%, 30%, 50%, 70%, and 90% quantiles, as well as CDD, HDD, Average PML and the feature created using the RTCF approach (referred to as Category) are presented in Table 3.

Based on the correlation matrices, it is evident that the Category feature obtained using the RTCF approach is the most significant feature for all quantiles, except the 10% quantile. Moreover, the RTCF enables the efficient representation of categorical variables in a single feature, offering important insights into their correlation with the load. The Category characteristic holds substantial significance across different quantiles, underscoring its value for load forecasting analysis.

6. CONVOLUTIONAL NEURAL NETWORK-QUANTILE REGRESSION (CNN-QR) AND DEEP LEARNING

This section offers an elaborate description CNN-QR for load forecasting using Deep Learning. The architecture training method of the model is outlined as follows:

Table 2: Load by quantiles

Load	Quantile (%)
209.38	10
252.34	30
286.53	50
347.92	70
419.13	90

Source: Own elaboration with electrical load data from the BCS system.

a. Model Architecture: The model is built using the Deep Learning Sequential.
b. Application Programming Interface provided by the Keras toolkit.[1] The process commences with a Conv1-Dimensional layer that executes 1-dimensional convolution on the incoming data. The layer is composed of 128 filters with a kernel size of 3 and employs the ReLU activation function.
   Pooling Layer: After the convolutional layer, a MaxPooling1-Dimensional layer is added with a pool size of 2. This layer performs spatial dimension reduction on the output, thereby down sampling the characteristics extracted by the preceding layer. The purpose of the Flattening Layer is to transform the 2-dimensional output of the pooling layer into a 1-dimensional vector. This transformation pre-processes the data to be used in the following fully connected layers.
c. The flattened output is subsequently transmitted over two completely linked (dense) layers. The initial dense layer is composed of 128 units and employs the Rectified Linear Unit (ReLU) activation function. In addition, it utilizes L2 regularization with a coefficient of 0.001. The second dense layer contains a number of units that corresponds to the length of the quantiles array, which indicates the number of quantiles to be forecasted.
d. A Dropout layer is incorporated after the fully connected layers to address over-fitting. This layer employs a stochastic process to selectively deactivate a portion (specifically, 0.5) of the input units during training, therefore mitigating the network's overreliance on particular links.
e. The output layer consists of a dense layer with a number of units equal to the length of the quantiles array. This enables the model to generate predictions for multiple quantiles. The absence of an activation function in this layer allows it to produce unprocessed predictions.
f. The quantile loss function is a mathematical function used to measure the deviation between predicted and actual values at a specific quantile level. A user-specified loss function named quantile_loss is defined. The input parameters for this function include the quantile value (q), the genuine target values (y), and the anticipated values (pred). The quantile loss is computed to quantify the discrepancy between the anticipated quantile and the true target value. The function is designed to process computations in batches and outputs the average loss for each batch.
g. Model Compilation: The model is compiled utilizing the Adam optimizer, with a learning rate of 0.00001. The loss function is defined by utilizing a lambda function that calls the quantile_loss function with the specific quantile value (quantiles [0] in this instance).

1 Keras toolkit. Available at: https://pypi.org/project/keras-toolkit/

Table 3: Correlation matrices by quantile

Variable	Load, Quantile 10%	Load, Quantile 30%	Load, Quantile 50%	Load, Quantile 70%	Load, Quantile 90%
CDD	0	1	10	56	18
HDD	−4	2	−6	−27	−2
Average PML	29	16	17	21	23
Category	11	28	28	58	60

Source: Own elaboration with electrical load data from the BCS system

h. Model Training: The model undergoes training using the fit approach. The training data, consisting of X_train and y_train, is modified in order to align with the input shape required by the model. The training process consists of 300 epochs, with each epoch processing a batch size of 4. A validation split of 0.2 is used to assess the model's performance on a separate validation set while it is being trained. The training process can be stopped early using an early stopping callback (early_stopping) if the validation loss does not show any improvement.

The CNN-QR architecture encompasses convolutional, pooling, and fully connected layers, in addition to dropout regularization and a proprietary quantile loss function. The system is specifically tailored for load forecasting and its objective is to anticipate numerous quantiles concurrently, offering a comprehensive and precise assessment of the load.

7. MEASURING THE EFFECTIVENESS OF CNN-QR

This section provides a description of the experimental design and assessment criteria employed to evaluate the effectiveness of CNN-QR and standard Quantile Regression (QR) techniques on eight quantiles: 10%, 30%, 50%, 70%, and 90%. In order to carry out QR, we employed the statsmodels package, which enables the fitting of distinct quantile regression models for each specified quantile and offers model summaries for examination of the results.

The processed data frame comprises a single label, Demand, and four categorical features: CDD, HDD, Average PML, and Category. In order to divide the dataset into training and testing sets, we adhered to an 80/20 ratio. The implementation of QR was carried out utilizing the Statsmodels library. The estimations obtained through QR are provided below. The average quantile loss for each model on the test set is shown in the Quantile Regression column of Table 4.

Table 4: Quantile loss comparison

Quantile	CNN-QR	QR	Relative difference (%)
10%	8.84	39.00	−77
30%	19.02	25.01	−24
50%	11.08	21.50	−48
70%	7.17	24.28	−70
90%	8.70	34.34	−75

Source: Own elaboration with electrical load data from the BCS system

Table 4 presents a juxtaposition of quantile loss values for various quantiles, comparing the CNN-QR and QR approaches. The relative disparity between the two methods is also computed. The summary of findings is as follows:

a. CNN-QR obtains a quantile loss of 8.84 at the 10% quantile, while QR yields a quantile loss of 39.00. The comparative disparity between the two approaches is -77%, signifying a notable enhancement in performance of CNN-QR in comparison to Quantile Regression for this specific quantile.
b. CNN-QR obtains a quantile loss of 19.02 at the 30% quantile, whereas QR has a quantile loss of 25.01. In this case, the percentage change is a negative 24%.
c. CNN-QR achieves a quantile loss of 11.08 for the 50% quantile (median), whereas Quantile Regression yields a quantile loss of 21.50. As it can be seen, the percentage difference is a negative value of 48%.
d. CNN-QR obtains a quantile loss of 7.17 at the 70% quantile, whereas QR yields a quantile loss of 24.28. The percentage difference is -70%.
e. CNN-QR achieves a quantile loss of 8.70 for the 90% quantile, whereas Quantile Regression yields a quantile loss of 34.34. As shown in Table 4, the percentage change represents a decrease of 75%.

In summary, the findings indicate that CNN-QR consistently surpasses Quantile Regression in terms of quantile loss across different quantiles. The relative discrepancies span from −77% to −86%, demonstrating significant enhancements accomplished by CNN-QR in load forecasting accuracy when compared to QR.

In what follows, we analyze the detailed quantile regression results in the Tables 5-9. These tables provide critical insight into the relationship between key variables and load at various quantiles. The inclusion of this detailed statistical analysis enriches the understanding of the nuances of the predictive model

Table 5: 0.1 quantile regression results

Variable	Coef.	Standard Error	t	P >|t|	0.025	0.975
CDD	8.0337	0.268	29.966	0.000	7.508	8.559
HDD	62.7027	2.048	30.611	0.000	58.688	66.718
Average PML	0.0234	0.001	43.867	0.000	0.022	0.024
Category	0.0848	0.001	66.541	0.000	0.082	0.087

Source: Own elaboration with electrical load data from the BCS system

Table 6: 0.3 quantile regression results

Variable	Coef.	Standard Error	t	P > |t|	0.025	0.975
CDD	7.4558	0.211	35.302	0	7.042	7.87
HDD	78.8377	1.517	51.974	0	75.864	81.811
Average PML	0.0225	0	48.717	0	0.022	0.023
Category	0.0994	0.001	91.566	0	0.097	0.102

Source: Own elaboration with electrical load data from the BCS system.

Table 7: 0.5 quantile regression results

Variable	Coef.	Std. Err.	t	P > |t|	0.025	0.975
CDD	6.8901	0.214	32.157	0	6.47	7.31
HDD	103.6569	1.272	81.469	0	101.163	106.151
Average PML	0.0228	0	46.859	0	0.022	0.024
Category	0.1098	0.001	93.94	0	0.107	0.112

Source: Own elaboration with electrical load data from the BCS system

Table 8: 0.7 quantile regression results

Variable	Coef.	Standard Error	t	P > |t|	0.025	0.975
CDD	7.6231	0.304	25.059	0	7.027	8.219
HDD	143.5518	1.322	108.584	0	140.96	146.143
Average PML	0.0302	0.001	44.655	0	0.029	0.032
Category	0.1059	0.002	58.655	0	0.102	0.109

Source: Own elaboration with electrical load data from the BCS system

Table 9: 0.9 quantile regression results

Variable	Coef.	Standard Error	t	P > |t|	0.025	0.975
CDD	8.3107	0.442	18.821	0	7.445	9.176
HDD	132.6222	1.254	105.766	0	130.164	135.08
Average PML	0.0715	0.001	96.666	0	0.07	0.073
Category	0.0897	0.002	36.021	0	0.085	0.095

Note: Own elaboration with electrical load data from the BCS system

and demonstrates the robustness of our approach. Tables 5-9 corresponding to the regression results for each quantile are presented below.

From Table 5, we notice that the coefficient estimates for the variables CDD, HDD, Average PML, and Category are statistically significant at the 0.1 quantile. A one-unit increase in CDD is associated with an estimated increase of 8.0337 in Load, holding other variables constant. Similarly, a one-unit increase in HDD, Average PML, and Category is associated with estimated increases of 62.7027, 0.0234, and 0.0848 in Load, respectively.

Now, in Table 5, it can be observed that the coefficient estimates for the variables CDD, HDD, Average PML, and Category are statistically significant at the 0.3 quantile. It is worth noticing that a one-unit increase in CDD is associated with an estimated increase of 7.4558 in Load. In this case, a one-unit increase in HDD, Average PML, and Category is associated with estimated increases of 78.8377, 0.0225, and 0.0994 in Load, respectively.

The coefficient estimates for the variables CDD, HDD, Average PML, and Category are statistically significant at the 0.5 quantile. As it can be seen, a one-unit increase in CDD is associated with an estimated increase of 6.8901 in Load, keeping other variables constant. This implies that a one-unit increase in HDD, Average PML, and Category is associated with estimated increases of 103.6569, 0.0228, and 0.1098 in Load, respectively, as shown in Table 7.

In the case of Table 8, we notice that the coefficient estimates for the variables CDD, HDD, Average PML, and Category are statistically significant at the 0.7 quantile. This implies that a one-unit increase in CDD is associated with an estimated increase of 7.6231 in Load, holding other variables constant. Similarly, a one-unit increase in HDD, Average PML, and Category is associated with estimated increases of 143.5518, 0.0302, and 0.1059 in Load, respectively.

Finally, Table 9 show that the coefficient estimates for the variables CDD, HDD, Average PML, and Category are all of them statistically significant at the 0.9 quantile. We observe that a one-unit increase in CDD is associated with an estimated increase of 8.3107 in Load, maintaining other variables constant. Similarly, a one-unit increase in HDD, Average PML, and Category is associated with estimated increases of 132.6222, 0.0715, and 0.0897 in Load, respectively.

8. CONCLUSIONS

The research highlights the importance of load forecast accuracy amid the changing dynamics of Mexico's energy sector. Combining CNN-QR with RTCF using deep learning marks a major advancement in forecasting methodologies. These advances are particularly critical given the decentralized nature of the grid and the increasing integration of renewable energy sources. Our analysis of the Mexican BCS system has illuminated the effectiveness of these techniques. They skillfully capture complex spatiotemporal patterns, increasingly common due to the variable nature of renewable energy generation. The proposed forecasting method skillfully addresses the emerging challenges posed by the assimilation of renewable energy into the grid, a trend highlighted by the substantial increase in renewable electricity production since 2014.

The RTCF, with its ability to synthesize category characteristics, has proven its worth as an appropriate tool. It facilitates a broader representation of incoming data, allowing for a deeper understanding of underlying demand patterns. This improvement is vital for effective resource allocation and strengthening grid stability, especially in a system experiencing a significant increase in renewable energy. The implications of our findings are enlightening and promote the optimized utilization of energy resources and the establishment of reliable energy supply amidst the inherent fluctuations of modern energy systems.

In essence, this research presents a groundbreaking methodological approach for load forecasting within Mexico's BCS system. It imparts critical insights, underscoring the imperative need for sophisticated forecasting techniques in the face of renewable energy expansion and grid decentralization. The demonstrated efficacy of our proposal in delivering accurate and reliable forecasts positions them as pivotal contributions to the energy sector, steering stakeholders toward a resilient and sustainable energy future.

Finally, our study not only redefines the landscape of load forecasting in Mexico, but also signals a transformative step towards a skillful treatment of the complexities of modern energy systems, a beacon for future efforts in energy management and the formulation of policies.

REFERENCES

Aduama, P., Zhang, Z., Sumaiti, A. (2023), Multi-Feature Data Fusion-Based Load Forecasting of Electric Vehicle Charging Stations Using a Deep Learning Model. Energies, 16, 1309.

Bracale, A., Caramia, P., Falco, P., Hong, T. (2020), Multivariate quantile regression for short-term probabilistic load forecasting. IEEE Transactions on Power Systems, 35(1), 628-638.

Dieck-Assad, F., Carbajal-Huerta, E. (2017), Solar energy: Peaceful hope among nations. Journal of Business Case Studies, 13(4), 99-108.

Enciso-Chávez, N. (2019), Antecedentes, perspectivas y potencial de la energía solar fotovoltaica en la industria en Puebla, México. Revista de Energías Renovables. 3(9), 10-27.

Fan, R., Wu, H., Chang, X., Yang, C., Zhang, S., Zhao, J. (2019), A New Power Prediction Accuracy Evaluation Method of Renewable Energy Plant. In: 2019 IEEE Sustainable Power and Energy Conference (iSPEC). p610-612.

Guan, Y., Li, D., Xue, S., Xi, Y. (2020), Feature-fusion-kernel-based Gaussian process model for probabilistic long-term load forecasting. Neurocomputing, 426, 174-184.

He, H., Pan, J., Lu, N., Chen, B., Jiao, R. (2020), Short-term load probabilistic forecasting based on quantile regression convolutional neural network and Epanechnikov kernel density estimation. Energy Reports, 6(S9), 1550-1556.

He, W. (2017), Load forecasting via deep neural networks. Procedia Computer Science, 122, 308-314.

Jin, X., Zheng, W., Kong, J., Wang, X., Bai, Y., Su, T., Lin, S. (2021), Deep-learning forecasting method for electric power load via attention-based encoder-decoder with Bayesian optimization. Energies, 14(6), 1596.

Keras Toolkit (2021), Application Programming Interface Designed for Human Beings, not Machines. Available from: https://pypi.org/project/keras-toolkit [Last accessed on 2023 Oct 10].

Lakshminarayanan, M., John, N., Channegowda, J., Raj, A., Naaz, F. (2021), Devising High Fidelity Synthetic Data using Generative Adversarial Networks for Energy Storage Systems. In: 2021 IEEE Mysore Sub Section International Conference (MysuruCon). p202-205.

Mendoza-Rivera, R.J., García-Pérez, L.E., Venegas-Martínez, F. (2023), Renewable and non-renewable energy consumption, CO_2 emissions, and responsible economic Growth with environmental stability in North America. International Journal of Energy Economics and Policy, 13(4), 300-311.

Platten, J., Sandels, C., Jörgensson, K., Karlsson, V., Mangold, M., Mjörnell, K. (2020), Using machine learning to enrich building databases-methods for tailored energy retrofits. Energies, 13, 2574.

Rafi, S., Nahid-Al-Masood, Deeba, S., Hossain, E. (2021), A short-term load forecasting method using integrated CNN and LSTM network. IEEE Access, 9, 32436-32448.

Raza, M., Mithulananthan, N., Li, J., Lee, K. (2018), Multivariate ensemble forecast framework for demand prediction of anomalous days. IEEE Transactions on Sustainable Energy, 11, 27-36.

Reda, K. (2023), Rainbow colormaps: What are they good and bad for? IEEE Transactions on Visualization and Computer Graphics, 29(12), 5496-5510.

Salazar-Núñez, H.F., Venegas-Martínez, F., Lozano-Díez, J.A. (2022), Assessing the interdependence among renewable and non-renewable energies, economic growth, and CO_2 emissions in Mexico. Environment Development and Sustainability, 24(11), 12850-12866.

Salazar-Núñez, H.F., Venegas-Martínez, F., Tinoco-Zermeño, M.A. (2020), Impact of energy consumption and carbon dioxide emissions on economic growth: Cointegrated panel data in 79 countries grouped by income level. International Journal of Energy Economics and Policy, 10(2), 218-226.

Santillán-Salgado, R.J., Valencia-Herrera, H., Venegas-Martínez, F. (2020), On the relations among CO_2 emissions, gross domestic product growth, energy consumption, electricity use, urbanization, and income inequality for a sample of 134 countries. International Journal of Energy Economics and Policy, 10(6), 195-207.

Saulo, H., Vila, R., Borges, G., Bourguignon, M., Leiva, V., Marchant, C. (2023), Modeling income data via new parametric quantile regressions: Formulation, computational statistics, and application. Mathematics, 11, 448.

Shah, I., Iftikhar, H., Ali, S., Wang, D. (2019), Short-term electricity demand forecasting using components estimation technique. Energies, 12(13), 2532.

Shi, J., Liu, Q., Wang, C., Zhang, Q., Ying, S., Xu, H. (2018), Super-resolution reconstruction of MR image with a novel residual learning network algorithm. Physics in Medicine and Biology, 63(8), 085011.

Shi, K., Zhao, W., Li, T., Wang, Z., Liu, Z., Feng, Y. (2021), Probability Prediction of Short-Term Wind Power Based on Quantile Regression Forest and Variable Bandwidth. In: Conference: 2021 IEEE/IAS Industrial and Commercial Power System Asia (IandCPS Asia). p1206-1213.

Sultanuddin, S., Suganya, A., Ahmed, M., Shanmugasundaram, V., Adhikary, P., Sajith, S. (2022), Hybrid Solar Energy Forecasting with Supervised Deep Learning in IoT Environment. In: 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES). p1-6.

Valencia-Herrera, H., Santillán-Salgado, R.J., Venegas-Martínez, F. (2020), On the interaction among economic growth, energy-electricity consumption, CO_2 emissions, and urbanization in Latin America. Revista Mexicana de Economía y Finanzas Nueva Época, 15(4), 745-767.

Wang, N., Li, Z. (2023), Short term power load forecasting based on BES-VMD and CNN-Bi-LSTM method with error correction. Frontiers

in Energy Research, 10, 1076529.
Wang, Y., Gan, D., Zhang, N., Xie, L., Kang, C. (2019), Feature selection for probabilistic load forecasting via sparse penalized quantile regression. Journal of Modern Power Systems and Clean Energy, 7, 1200-1209.
Yao, S., Song, Y., Zhang, L., Cheng, X. (2000), Wavelet transform and neural networks for short-term electrical load forecasting. Energy Conversion and Management, 41(18), 1975-1988.
Zhang, W., Yu, Y., Qi, Y., Shu, F., Wang, Y. (2019), Short-term traffic flow prediction based on spatio-temporal analysis and CNN deep learning. Transportmetrica A: Transport Science, 15(2), 1688-1711.
Zheng, Q., Zhang, Y. (2023), DSTAGCN: Dynamic spatial-temporal adjacent graph convolutional network for traffic forecasting. IEEE Transactions on Big Data, 9(1), 241-253.