

Article

A Highly Accurate and Efficient Statistical Framework for Short-Term Load Forecasting: A Case Study for Mexico

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Highlights

What are the main findings?

- This proposed short-term load forecast method is simple, effective, and highly accurate. It performs statistical-based hourly fine-tuning of day-ahead load forecasts presently carried out at Mexico's National Energy Control Center (CENACE).
- It has been efficiently implemented at the regional and zone levels and has been tested in several power system operating conditions, including extreme ones, showing consistently better results than those currently obtained in CENACE, with better error metric values in all cases.

What are the implications of the main findings?

- The proposed approach introduces a structured and systematic framework to transform an existing market-oriented load forecast, known in Mexico as Generating Unit Commitment for Reliability (GUCR), into an operationally meaningful hourly peak load forecast. This integration bridges two traditionally disconnected domains—market forecasting and real-time system operation—without requiring additional forecasting models, data sources, or computational infrastructure. This system-level integration constitutes an original contribution beyond simple statistical correction.
- Presently in CENACE, as with some control centers worldwide, there is no instant load demand forecast (MW) available for off-real-time operating strategies and for real-time operating processes. This proposed method meets this need without implementing a formal process, saving time, human, material, and financial resources. Indeed, it is much cheaper in terms of financial and time resources to implement than artificial intelligence-based load forecast methods, since load data preparation is not required. The framework was designed in one of CENACE's control centers and is now used in seven of them. It could be used in any other power system control center. The forecasts obtained with this framework could be a valuable tool for better decision-making regarding power system real-time operation in emergency or critical conditions, which could lead to applying load shedding or not.



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Abstract

Short-term load forecasting is fundamental for the effective and reliable operation of power systems. Very accurate forecasting methods often involve complex hybrid approaches that

combine statistical, physical, and/or intelligent techniques. In this work, we present an innovative, clear, and effective methodology for short-term hourly peak load forecasting that is both simple and highly accurate. The methodology is based on the load forecast used for electricity market purposes, together with fine-tuning dynamic estimation. As a case study, the methodology was applied and tested in Mexico's interconnected power system. It was implemented across various regions and at both regional and load-zone levels of this interconnected power system and, even under a variety of standard and extreme load conditions, achieved outstanding results.

Keywords: Centro Nacional de Control de Energía (CENACE); control area (GCR in Mexico); day-ahead; electricity market; load forecast; load zone; MAPE; Mexico; short-term forecasting; power systems

1. Introduction

Load demand forecast is crucial for any electric power system. It plays an essential role in long-, medium-, and short-term planning, depending on the forecast horizon. Additionally, it provides valuable information for decision-making processes related to electricity market management, planning, and real-time power system operations [1].

Short-term load forecasting ranges from one hour ahead up to seven to ten days ahead. In Mexico, the short-term load forecast for wholesale electricity market purposes is known as “load forecast for Generating Unit Commitment for Reliability (GUCR)”. GUCR refers to an operational forecasting product specifically designed to support unit commitment decisions under reliability constraints, that is, a reliable Mexico's National Interconnected Power System (MNIPS) load supply considering spinning and non-spinning reserves. GUCR focuses on hourly integrated energy (MWh/h) and prioritizes system security by ensuring sufficient generation availability and reserve margins. As a result, GUCR forecasts tend to be conservative and are optimized for operational reliability rather than for minimizing economic forecasting error.

This load forecast horizon covers 8 days ahead with an hourly resolution and is updated once a day. The energy load is forecasted in hourly integrated energy values.

MNIPS comprises seven control areas, known in Mexico as “Gerencias de Control Regionales” (GCRs). Figure 1a shows the geographical location of each one, and their geographical extent is described in Table 1.

The operation of MNIPS has become increasingly complex in recent years due to several factors. These include deficiencies in the infrastructure of the National Transmission Network (NTN) and its components, substations, transmission lines, transformers, and several types of static and dynamic compensation equipment, which have arisen from a lack of investment and construction delays. Furthermore, in the Gerencia de Control Regional Oriental (GCRORI), shown in Figure 1b, the geographical location, which includes coastlines along the Gulf of Mexico and the Pacific Ocean, greatly influences the region's load demand behavior. Meteorological phenomena such as cold fronts, heat waves, tropical storms, and hurricanes have a significant impact, causing the components of MNIPS to operate very close to the manufacturers' nominal limits. Hence, the power system has been operating more frequently in alert states established by CENACE to ensure safe operations and a continuous supply of electricity to meet demand. Thus, it is crucial to establish an hourly peak load reference value for the short-term future, ranging from a few hours to several days ahead, to enable the best decision-making in advance.

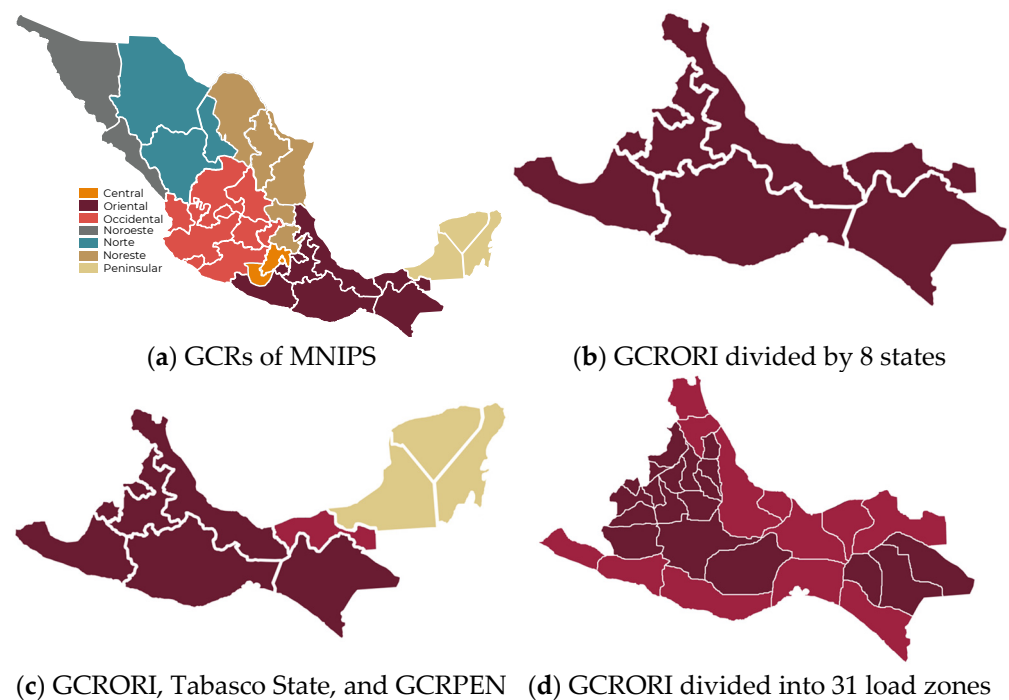


Figure 1. Regions where the proposed method has been used. (a) Seven GCRs of Mexico's National Interconnected Power System are shown in different colors. (b) The GCRORI is shown in dark cherry color. (c) GCRORI, Tabasco State, and GCRPEN are shown in dark cherry, lighter red, and beige, respectively. (d) The GCRORI's load zones located on the Gulf of Mexico and the Pacific Ocean coasts are shown in lighter red, and the rest of the GCRORI's load zones are shown in dark cherry.

Table 1. GCRs in MNIPS and their geographical extent.

GCR	Acronym	Geographical Extent (States)
Gerencia de Control Regional Central	GCRCEL	Hidalgo, Mexico City, and a portion of Morelos
Gerencia de Control Regional Oriental	GCRORI	Chiapas, Tabasco, Veracruz, Oaxaca, Puebla, Tlaxcala, Guerrero, and a portion of Morelos
Gerencia de Control Regional Occidental	GCROCC	Nayarit, Zacatecas, Jalisco, Colima, Michoacán, Guanajuato, Querétaro, Aguascalientes, and San Luis Potosí
Gerencia de Control Regional Noroeste	GCRNOR	Sonora and Sinaloa
Gerencia de Control Regional Norte	GCRNTE	Chihuahua, Durango, and a portion of Coahuila
Gerencia de Control Regional Noreste	GCRNES	Tamaulipas, Nuevo León, and a portion of Coahuila
Gerencia de Control Regional Peninsular	GCRPEN	Campeche, Yucatán, and Quintana Roo

Addressing this necessity, the Department of Evaluation and Statistics, GCRORI-DEE, created this proposed method by the end of 2023 and has been testing it since January 2024.

In addition to prototype-level tests carried out in the GCRORI with forecasting models using an Long-Short Term Memory Neural Network (LSTM NN) [2,3] and Azure machine learning facilities [4], this different method has been developed in four stages:

1. First, this method was developed to address the urgent requirement for hourly peak load forecasts (in megawatts, MW) in the Eastern Region (GCRORI). The extreme heat waves of 2023 and 2024 led to a significant rise in load demand, particularly during the annual peak load season, which occurs in the spring and summer months in this region. During this period, the hourly peak load forecasts generated by this method can serve as valuable support for defining off-real-time operating strategies as well as real-time operational processes. The accuracy of these hourly peak load forecasts directly influences the effectiveness of both off-real-time strategies and real-time decision-making capabilities. At this stage, the application of the proposed load forecasting method was focused on the Eastern Region (GCRORI).
2. Second, due to the increasingly earlier peak load season, which occurred by the end of March 2025, it was essential to estimate the hourly instantaneous peak load for the state of Tabasco, highlighted in the red area in Figure 1c. This location is part of the GCRORI and borders the Gerencia de Control Regional Peninsular (GCRPEN), shown in the beige area of Figure 1c. Additionally, it was important to compute the peak load for the GCRPEN, considering the operating gate defined in this MNIPS zone (the Malpaso–Tabasco gate). Consequently, the methodology has been extended to include the GCRPEN [5], which corresponds to the region illustrated in Figure 1c.
3. Third, due to the excellent results, the approach was extended to the remaining GCRs of MNIPS. It is important to note that the Baja California Peninsula power system is part of Mexico's National Electric System (MNES), and thus, it is not included in MNIPS, as shown in Figure 1a.
4. Fourth, GCRORI's coastal load zones, highlighted in lighter red in Figure 1d, were incorporated into the forecasting algorithm, such that the scope of the framework was expanded to the load zone level. This decision was made because these areas have a high likelihood of being impacted by meteorological events such as tropical storms, hurricanes, and floods.

Despite the extensive literature and the wide range of methods applied to day-ahead load forecasting, such as neural networks [6–10], machine learning [11], deep learning [12], and Support Vector Machines [13–15], the forecasting method presented here is simple, effective, and accurate. It is based on a straightforward statistical algorithm that fine-tunes the integrated hourly energy demand forecast used for wholesale electricity market purposes, which is previously obtained and in Mexico is known as the “Generating Unit Commitment for Reliability” (GUCR) load demand forecast.

The term “Generating Unit Commitment for Reliability” refers to the fact that it considers all energy that will be consumed in the entirety of MNIPS, that is, the energy needs of all market-participant users (big industry, energy traders, exports, and imports), as well as the energy needs of non-market-participant users, network losses, and spinning and non-spinning generating reserves. This energy load forecast is projected from 1 to 8 days in advance with hourly resolution (MWh/h).

After each GCR of MNIPS calculates its GUCR energy load forecast using any methodology defined by CENACE [16], the resultant GUCRs are stored in the GCRORI's virtual server, where the proposed algorithm is applied to obtain the hourly peak load forecast. Thus, in this study, the baseline forecast corresponds to the load forecast used for GUCR. The proposed framework enhances the baseline by applying a statistical post-processing stage that adapts the GUCR forecast to an operation-ready instantaneous hourly peak load forecast with reduced systematic hourly bias.

Therefore, the contribution of this work is methodological rather than the proposal of a new base forecasting engine. The novelty lies in (i) targeting hourly instantaneous peak load (MW) as the operational variable of interest, rather than integrated hourly energy (MWh/h); (ii) introducing hour-dependent dynamic bias estimation through two factors, F_h and F'_h (introduced in Section 2), which are not fixed coefficients but are estimated from recent similar load profiles to capture systematic intraday discrepancies; (iii) providing a transparent post-processing framework that converts an existing GUCR forecast into an operation-ready peak load forecast.

The proposed load forecast approach's performance is evaluated by providing a multi-error evaluation analysis using error metrics additional to those used in CENACE to evaluate GUCR load forecast performance [16].

1.1. Current Problems

Currently, CENACE is encountering the following challenges:

1. There are currently no processes for real-time or intraday load forecasting of instantaneous load values.
2. Thus, there is currently neither an instant load forecast (MW) obtainable for real-time operational processes nor a definition process for off-real-time strategies. This type of load forecast has become increasingly essential due to the rising frequency of risky scenarios, high demand levels during the spring and summer seasons, the high temperatures recorded in Mexico in 2023 and 2024, and the threat that several tropical storms would evolve into hurricanes in 2025.
3. Nowadays, short-term GUCR load forecasts calculated in CENACE are for wholesale electricity market (WEM) purposes, not for power system operation nor for defining off-real-time operating strategies.
4. There is only a slight variation between hourly integrated load (MWh/h) and instant load (MW) values, but that small variation can be crucial in determining whether or not to implement load shedding during specific risk-operating conditions in real-time operations.

1.2. State of the Art

In the literature, many methods have been developed for day-ahead forecasting, such as expert systems, time series analysis, regression analysis, the similar-day approach, and different Artificial Intelligence (AI) techniques, such as Artificial Neural Networks (ANNs) in all their variations, Support Vector Machines (SVMs), Fuzzy Logic (FL), Genetic Algorithms (GAs), and hybrid methods [17]. However, the trend in recent research points more towards the application of artificial intelligence techniques than to pure statistical techniques. For example, some of the work published in recent years is described below according to the main approach used:

(A) Statistical-based day-ahead load forecasting methods

Even though there are well-defined statistical tools for load forecasting [18], in recent years, few works have been published for load forecasting using pure statistical methods. For instance, an approach based on Belief Functions Theory has been introduced and applied to load data in the residential sector in Canada, obtaining a Mean Absolute Percentage Error (MAPE) of 9% [19]. Also, a statistical approach based on an autoregressive integrated moving average model was used to forecast the daily load curve for weekdays in Mongolia, achieving a MAPE of 2.2% [20]. In another work, a comparison of the performance of the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Prophet models for hourly load forecasting of PJM Interconnection LCC data has been presented [21]. Another approach decomposes the load demand time series into a long-run linear trend, a seasonal

trend, and a stochastic trend, and it forecasts each using autoregressive techniques. The approach is tested with load data from Nord Pool, finding a MAPE of up to 1.9% [22].

(B) Artificial-intelligence-based day-ahead load forecasting methods

Forecasting models based solely on AI techniques are still under research, as shown by the following recent publications. A model based on LSTM NNs optimized by the gray wolf algorithm predicted 24 h microgrid energy consumption for a residential area in London with a MAPE of 8.69% and a peak prediction error of 1.33% [23]. Another intelligent model-based merging a Multi-Strategy Improved Sand Cat Swarm Optimization (MSCSO) algorithm with a Self-Attention Temporal Convolutional Network (SA TCN) was proposed and tested on the Panama power load dataset, obtaining $R^2 = 0.9830$ [24]. Also, a non-linear autoregressive neural network was used to forecast load patterns for different clusters of Irish household consumers, and the aggregated load was obtained by combining these results, finding an improvement in forecasting performance [25].

(C) Hybrid-based day-ahead load forecasting methods

Approaches that combine a statistical technique with an AI technique are the most common in the recent literature. For instance, most papers published in 2025 fall into this category, as shown in the following references. For example, a hybrid model based on LSTM NNs, clustering, and similar days was designed and tested using load data from a portion of the electrical system in Mexico, achieving MAPEs of up to 0.63% [2]. Moreover, a hybrid day-ahead forecasting method combining time series with machine learning algorithms such as a Conditional Generative Adversarial Network (CGAN), a one-dimensional convolutional neural network (Conv1D), and an LSTM NN achieved a MAPE of 4.4% [26]. Additionally, a complex hybrid approach combining the ARIMA method with Particle Swarm Optimization (PSO) and Support Vector Regression (SVR) was proposed and applied to a microgrid in northwest China [27]. Likewise, a model based on Empirical Mode Decomposition (EMD) and an LSTM NN was used for load forecasting across several sectors in Italy, yielding promising results [28]. Also, an elaborate method based on Variational-Mode Decomposition (VMD), Kernel Principal Component Analysis (KPCA), an extended long short-term memory neural network, and the informer model was designed and applied to load data in Australia, attaining a MAPE of 4.9% [29]. Furthermore, a model combining data clustering and dimensionality reduction schemes was proposed and applied to load data in California, achieving MAPEs of up to 2% [30]. Another model was introduced, where wavelet decomposition was applied to the data, followed by LSTM NN forecasting and tuning with XGBoost, achieving a MAPE of up to 1.3% [31].

In summary, many recent publications on load forecasting utilize either AI approaches or hybrid methods, enhancing forecasting accuracy while increasing model complexity [32–34]. The purpose of the proposed framework is to introduce a simple and straightforward yet highly accurate methodology for day-ahead load forecasting.

This work is structured as follows: In Section 2, we describe the proposed methodology. First, Section 2.1 highlights the difference between integrated hourly load values and instantaneous load values, which is fundamental to the methodology. Next, Section 2.2 presents the forecasting framework, followed by a description of the tool utilized in Section 2.3. In Section 3, we provide detailed results from applying the proposed methodology to MNIPS case study under different conditions. In particular, Section 3.1 describes the regional-level results in steady-state conditions, presenting examples from various regions for a 10-month period in Section 3.1.1 through Section 3.1.3. Then, Section 3.2 presents the results at regional level in atypical conditions, such as the blackout in Yucatan Peninsula (Section 3.2.1) and the impact of a cold front (Section 3.2.2). The results in load zones experiencing atypical conditions are presented in Section 3.3, such as the flood in the Poza Rica load zone and the

Day of the Dead festivities in the Puebla load zone described in Sections 3.3.1 and 3.3.2, respectively. Finally, Section 4 discusses the results, and Section 5 presents the conclusions of this work.

2. Materials and Methods

2.1. Difference Between Hourly Load Integrated Values and Instantaneous Load Values

Hourly integrated load values are calculated by integrating instantaneous power values over one-hour periods. Each hourly value, represented by the orange steps in Figure 2, is expressed in energy units (MWh) and results from integrating the instantaneous power values, shown as green values in Figure 2 and measured in power units (MW), over the duration of one hour (distance between dashed lines). Consequently, by performing this integration over a 24 h period, we obtain 24 hourly energy values. These energy values are essential for various wholesale electricity market processes, statistical analyses, and other applications. The unit of measurement is MWh, and to highlight that these values are derived from hourly integration, we denote them as MWh/h.

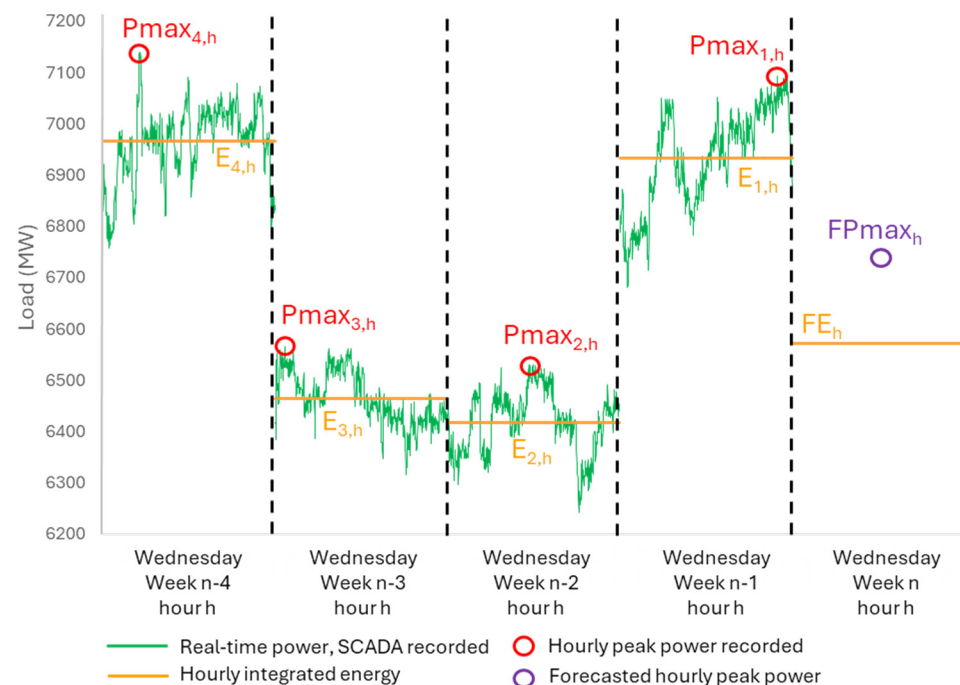


Figure 2. Hourly integrated energy (MWh/h), power values (MW), and hourly maximum forecasted power (MW) over time.

Instantaneous load values are obtained in real time directly from measurements of power system elements and represent the instantaneous power (MW). During each designated time period, multiple values can be recorded, such as one value per second or one value per minute, depending on the requirements. These instantaneous power values are essential for analyzing and defining operating strategies, as well as for real-time operating systems.

The differences among the hourly integrated energy (E , orange step, one single value per hour), instantaneous power (green lines, many values per hour), maximum hourly power or hourly peak load (P_{max} , red circle, one single value per hour), and hourly peak forecasted power (FP_{max} , purple circle, one single value per hour) are illustrated in Figure 2.

The difference between the orange step and the red circle values in Figure 2 can be crucial in determining whether to apply load shedding during critical operating conditions in the power system.

2.2. Forecasting Framework

The proposed load forecast method is a short-term forecast that relies on the energy predictions for Generating Unit Commitment for Reliability (GUCR), recorded power values from SCADA, and an algorithm that integrates these values. This approach allows for the fine-tuning of load forecasts for the upcoming hour and can extend up to eight days ahead. Consequently, the method generates hourly peak load (MW) forecasts from a megawatt-hour per hour (MWh/h) load forecast.

This proposed alternative forecasting method has both similar and different features regarding GUCR load forecast, which are described in Table 2.

Table 2. Comparison of similarities and differences between GUCR load forecast and the proposed Method.

	GUCR Load Forecast	Proposed Method
Same feature	Short-term load forecast	Short-term load forecast
Same feature	Hourly resolution	Hourly resolution
Different feature	MWh/h Units (hourly integrated values)	MW Units (maximum instantaneous value in each hour)
Different feature	It is updated only once a day at 17:00 h for the following 8-day period ahead.	1. It is updated only once a day at 17:00 h for the following 8-day period ahead. 2. It is updated every hour for the following one-hour ahead.

In CENACE, several methodologies [35] are used for GUCR load forecasts, including simple moving averages, similar days [16,35–37], and regressions. Each GCR uses the methodology to calculate the GUCR load forecast that best fit its needs, depending on its load profile behavior, geographical location, and its power system particularities. It is outside the scope of this work to detail the methodologies followed to obtain the GUCR load forecasts, but the following section will outline a general scope.

Once the GUCR load forecast is complete, the fine-tuning is performed in two stages:

1. Eight-day-ahead period;
2. One hour ahead.

The first stage corresponding to the eight-day-ahead tuning is performed as follows:

The conversion factor for the hour h , F_h , is computed using the energy consumption and maximum instantaneous demand profiles from four similar days prior to the day to be forecast, as follows:

$$F_h = \frac{1}{4} \sum_{d=1}^4 \frac{(Pmax_{d,h} - E_{d,h})}{E_{d,h}}, \quad (1)$$

where d refers to the day number, which ranges from 1 to 4, h is the hour of the day, spanning from 1 to 24, $Pmax_{d,h}$ is the maximum demand, and $E_{d,h}$ is the energy consumption during

hour h on a given day d . Thus, the maximum power forecasted (in MW) at day d in hour h , $FPmax_{d,h}$, is calculated by

$$FPmax_{d,h} = FE_{d,h} * [1 + F_h] , \quad (2)$$

where $FE_{d,h}$ is the forecasted energy (in MWh/h) in day d at hour h . All these values and its relationship are depicted in Figure 3.

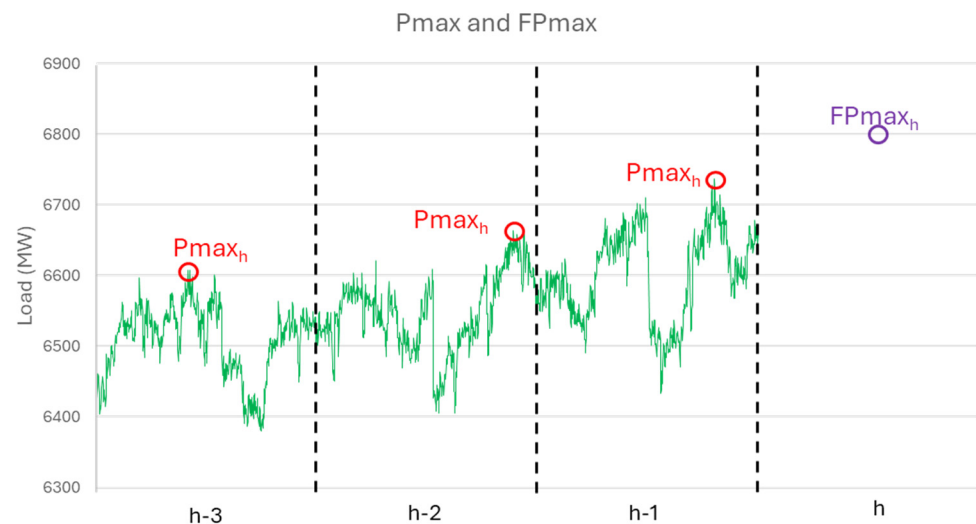


Figure 3. Hourly maximum power values ($Pmax$), hourly maximum forecasted power ($FPmax$) over time, one hour-period is the distance between dashed lines.

Then, the second stage corresponding to the one-hour-ahead tuning is performed as follows:

For every hourly energy forecast (MWh/h), another factor composed of the maximum hourly power recorded in the last three hours is applied, as follows:

$$F'_h = \frac{1}{3} \sum_{k=1}^3 (Pmax_{h-k} - E_{h-k}) , \quad (3)$$

where $Pmax_h$ is the maximum power in each of the previous three hours, and E_h is the energy forecasted in hour h .

Then, the factor is applied to the energy value forecast as follows:

$$FPmax_h = FE_h + F'_h , \quad (4)$$

where $FPmax_h$ is the maximum power forecasted for the following hour h , FE_h is the energy forecasted for the following hour, and F'_h is the tuning factor.

These variables are illustrated in Figure 3.

In both cases, the conversion factors F_h and F'_h of Equations (1) and (3) are not a fixed coefficient or a regression parameter. They are dynamically estimated hourly biases that capture the structural and time-dependent discrepancy between integrated energy demand and instantaneous maximum load, learned from recent similar operational profiles. This estimation differs fundamentally from classical similar-day methods or global regression models, which do not explicitly model this operational bias at the hourly level.

The forecasting performance of the proposed framework is evaluated using complementary error metrics. The three commonly used metrics to measure the performance of load forecasting models were used to quantify the accuracy of the proposed approach [38]. The average percentage error of the model across all real data is given by the Mean Absolute

Percentage Error (MAPE). The MAPE calculates the absolute difference between the real and the predicted N values and compute the mean of these quantities as

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{x_i - \hat{x}_i}{x_i} \right| \cdot 100\%, \quad (5)$$

where x_i and $\hat{x}_i$ are the real and predicted N values of the variable, respectively.

The average magnitude of the errors between the predicted and real values is given by the Mean Absolute Error (MAE):

$$MAE = \frac{1}{N} \sum_{i=1}^N |x_i - \hat{x}_i|. \quad (6)$$

This metric does not take into consideration the direction of the difference, i.e., whether there are overestimations or underestimations.

Also, there is the Root Mean Square Error (RMSE) that measures the mean difference between the real and predicted N values as

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (x_i - \hat{x}_i)^2}{N}}. \quad (7)$$

This metric more severely penalizes larger errors, and the better the prediction is, the lower the error is.

This multi-metric evaluation provides a scientifically rigorous assessment by capturing different dimensions of forecast accuracy. MAE quantifies the average absolute deviation in physical units (MW), offering a robust and interpretable measure of typical error. RMSE penalizes large deviations more heavily, making it particularly relevant for operational reliability, where large forecasting errors can have disproportionate impacts. MAPE evaluates relative error in percentage terms, enabling comparison across hours with different demand levels. Together, these metrics allow for a comprehensive and unbiased evaluation of both average accuracy and risk-sensitive performance, consistent with best practices in short-term load forecasting research.

2.3. The Tool (Web Interface)

The algorithm was created using Hypertext Preprocessor (PHP), an open-source programming language. It features an intranet web graphical interface that displays several graphs, with one graph dedicated to each GCR (Gerencia de Control Regional).

The PHP programming code is hosted on a local GCRORI virtual server. The algorithm uses the following data:

1. GUCR load forecast of each GCR: Each GCR transfers its GUCR forecast to the GCRORI virtual server. GUCR load forecasts are updated daily, every day of the year, by each GCR.
2. GUCR load forecast for each load zone of the GCRORI.
3. Real-time load data from SCADA for each GCR.

Then, Equations (1) and (2) are applied to the GUCR load forecast (in MWh/h) to obtain the tuned load forecast in MW for the following eight days ahead.

Afterwards, Equations (3) and (4) are then applied to the GUCR load forecast (in MWh/h) to obtain the tuned load forecast in MW for the following hour ahead.

Consequently, it is crucial to highlight that the proposed method does not require any additional resources compared to currently used methods, whether human, material, or financial. Figure 4 describes the complete process.

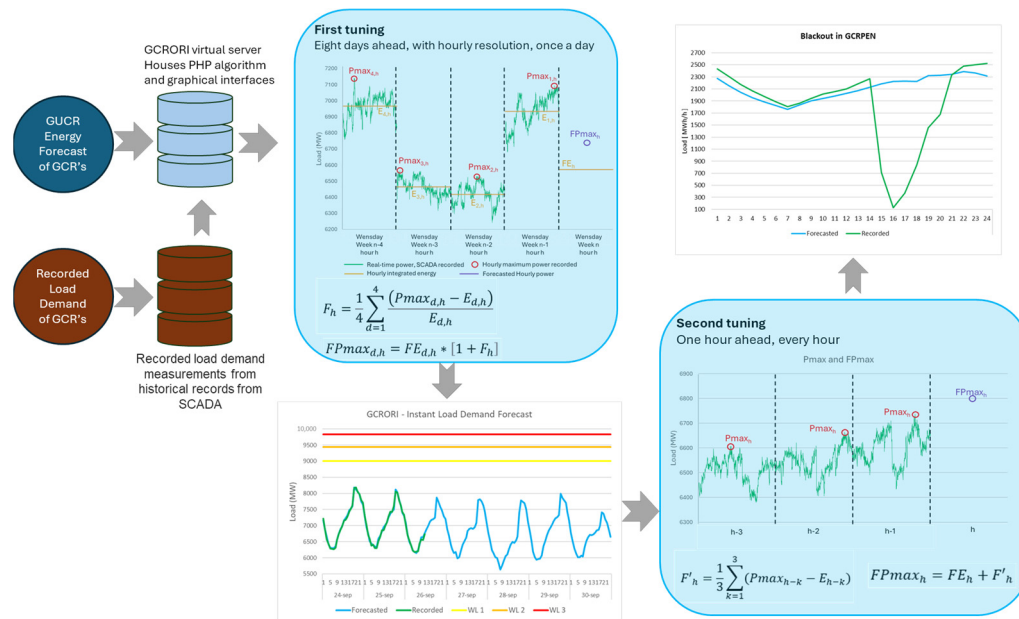


Figure 4. Proposed method description. Arrows show the data flow, and the two-steps tuning algorithm sequence execution. Graphs and equations are illustrative in this figure, they are described in other sections.

A set of graphs illustrates the two load profiles for each GCR: the recorded values (represented by a green line) and the forecasted values (shown as a blue line). Additionally, the graphs include warning values indicated by horizontal lines in yellow, orange, and red, labeled as WL1, WL2 and WL3, respectively. They correspond to high demand thresholds linked to predefined risk scenarios, that is, Warning Levels (WLs). These elements enable users to monitor load demand behavior—both recorded and forecasted—at any time. Figure 5a presents these details for a single GCR, while Figure 5b showcases the load profiles of multiple GCRs.

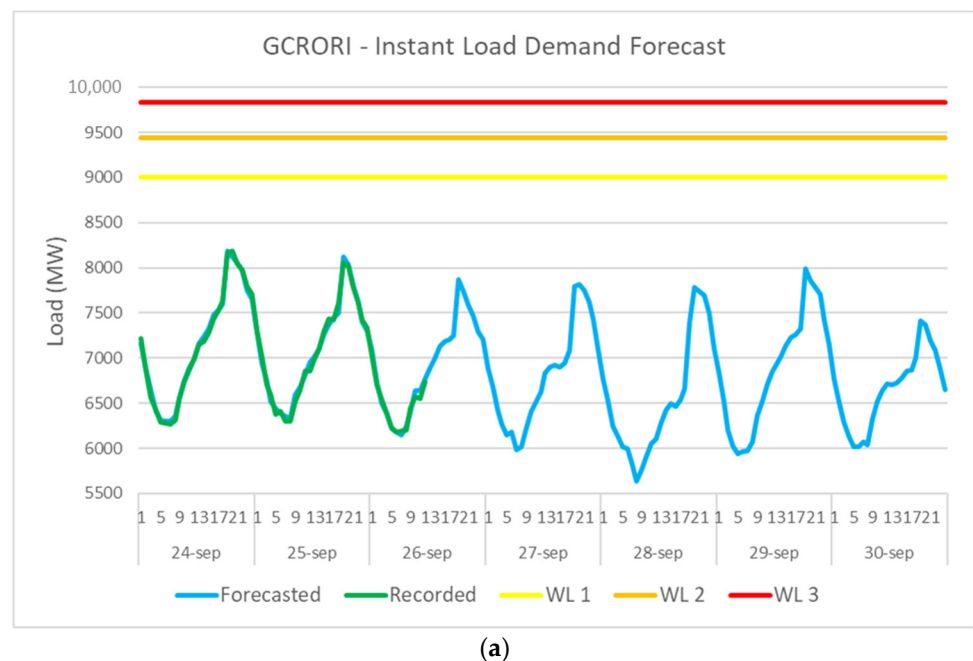


Figure 5. Cont.

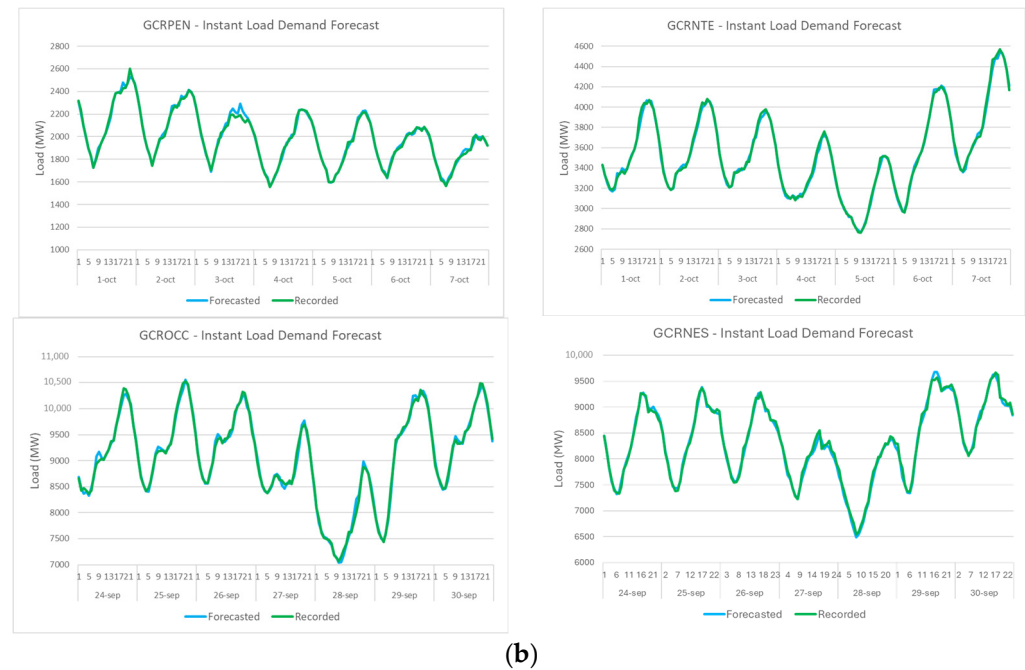


Figure 5. Graphics at intranet web graphical interface: (a) View of a single GCR. (b) Views of multiple GCRs.

3. Results

The results discussed in the following sections were obtained under various operating conditions of MNIPS. These results were gathered over different periods, in diverse circumstances, and at various operating levels, specifically at the regional (GCR) level and at the load zone level.

In this Results section, the load demand forecast that uses hourly integrated values (MWh/h) will be referred to as the “GUCR forecast.” In contrast, the load forecast generated by the proposed method, which utilizes hourly instantaneous peak values (MW), will be referred to as the “proposed method forecast” (PM forecast).

It is important to emphasize that the objective of this evaluation is not to benchmark the proposed framework against idealized offline forecasting models but to quantify its incremental operational value with respect to the baseline forecast currently used for wholesale electricity market purposes (GUCR). For this reason, performance is assessed through multiple complementary error metrics (MAPE, MAE, and RMSE) across different temporal aggregations and operating conditions, including extreme events. This evaluation strategy allows assessment of average accuracy, sensitivity to large errors, and operational robustness, which are the primary requirements in reliability-oriented forecasting contexts.

3.1. Results at GCR Level in Steady-State Conditions

3.1.1. The Eastern Region (GCRORI)

Figure 6 presents comparative load forecast monthly error metrics between GUCR and proposed method forecasts from January to October 2025 for the GCRORI. In this ten-month period, the monthly metric values show the proposed method’s consistently strong performance.

Figure 7 displays the forecasted and actual load demands for the week when the 2025 annual peak load demand in GCRORI was recorded, specifically from 18 May to 24 May. The peak load for the GCRORI in 2025 was recorded on 19 May at 21:00 h, reaching 9225 MW, which matches the value predicted by the proposed forecasting method. The MAPE for this week was 0.52%.

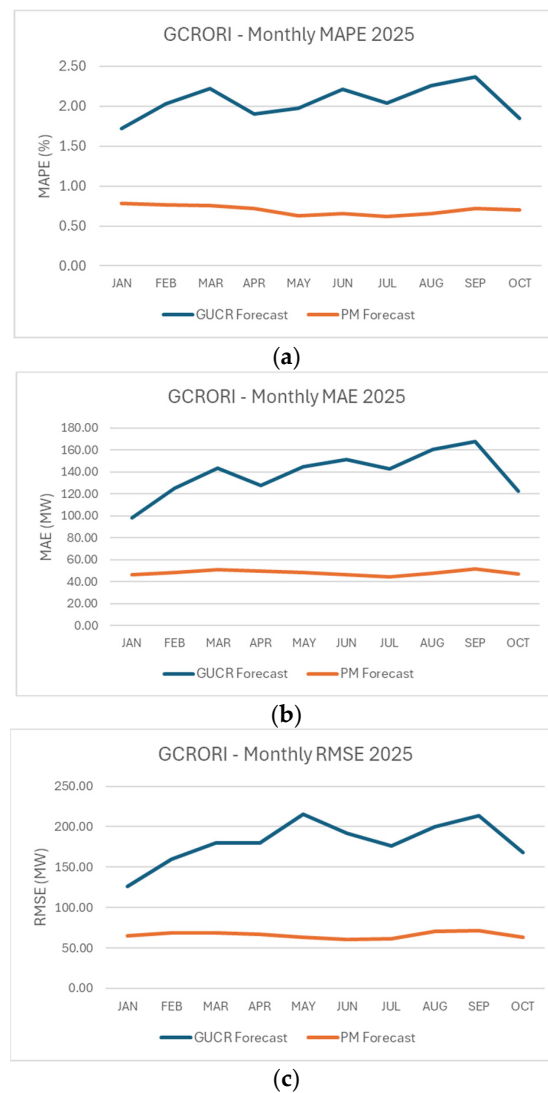


Figure 6. Monthly error metrics: (a) MAPE, (b) MAE, and (c) RMSE values up to October 2025 in GCRORI.

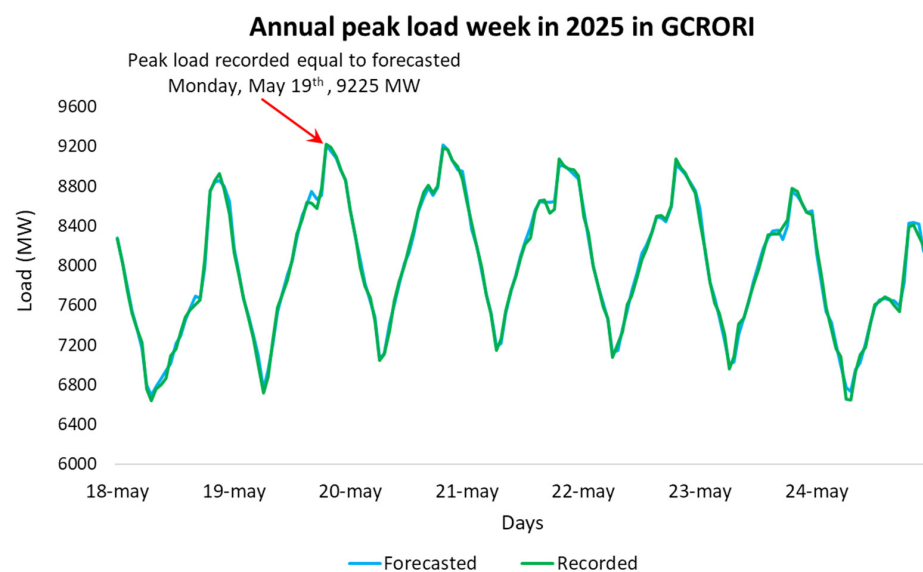
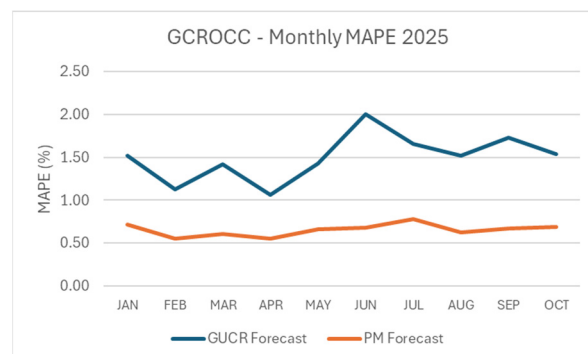


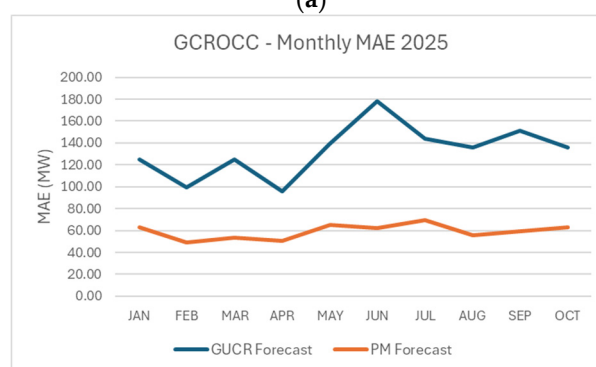
Figure 7. Annual peak load week in 2025 in GCRORI. The forecasted values with the proposed method and the recorded loads are displayed.

3.1.2. The Western Region (GCROCC)

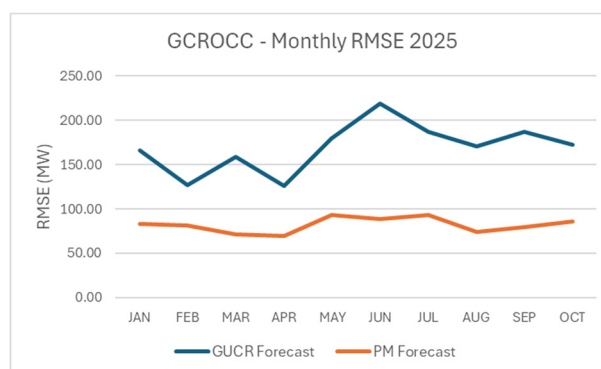
Figure 8 presents comparative load forecast monthly error metrics between GUCR and proposed method forecasts from January to October 2025 for the GCROCC. In this ten-month period, the monthly metric values show the proposed method's consistently better results compared to the GUCR forecast.



(a)



(b)



(c)

Figure 8. Monthly error metrics: (a) MAPE, (b) MAE, and (c) RMSE values up to October 2025 in GCROCC.

3.1.3. Other GCRs That Compose MNIPS

Tables 3–5 illustrates the difference in accuracy between the forecasts generated by the GUCR method and those produced by the proposed method (PM). Due to the proposed method being implemented gradually across the GCRs, Tables 3–5 show values from May to October 2025.

Table 3. Comparison of monthly MAPE values between GUCR load forecast and proposed method.

MAPE (%)	GCRCEL		GCRNTE		GCRNES		GCRPEN	
	GUCR Forecast	PM Forecast	GUCR Forecast	PM Forecast	GUCR Forecast	PM Forecast	GUCR Forecast	PM Forecast
MAY	2.10	0.99	2.21	0.69	3.20	0.95	1.93	0.81
JUNE	1.62	0.95	2.40	0.50	2.33	0.66	3.28	0.72
JULY	1.76	0.97	2.82	0.54	2.07	0.67	2.73	0.66
AUGUST	1.59	0.87	2.12	0.50	1.78	0.65	2.55	0.57
SEPTEMBER	1.68	1.14	2.81	0.57	2.62	0.70	3.32	2.14
OCTOBER	1.60	1.03	2.26	0.66	2.44	0.83	2.92	0.76

Table 4. Comparison of monthly MAE values between GUCR load forecast and proposed method.

MAE (MW)	GCRCEL		GCRNTE		GCRNES		GCRPEN	
	GUCR Forecast	PM Forecast	GUCR Forecast	PM Forecast	GUCR Forecast	PM Forecast	GUCR Forecast	PM Forecast
MAY	140.42	72.08	89.41	31.22	249.98	89.27	43.30	19.39
JUNE	108.95	67.44	103.14	23.13	196.49	60.31	70.84	16.05
JULY	112.60	67.92	110.64	22.49	172.26	60.53	60.55	15.01
AUGUST	98.87	59.61	92.63	23.05	158.91	61.96	56.78	12.78
SEPTEMBER	109.20	80.41	103.95	21.93	203.85	58.88	80.54	22.96
OCTOBER	106.23	73.75	71.29	21.94	177.87	65.61	56.78	15.27

Table 5. Comparison of monthly RMSE values between GUCR load forecast and proposed method.

RMSE (MW)	GCRCEL		GCRNTE		GCRNES		GCRPEN	
	GUCR Forecast	PM Forecast	GUCR Forecast	PM Forecast	GUCR Forecast	PM Forecast	GUCR Forecast	PM Forecast
MAY	182.58	92.59	125.58	42.91	331.25	179.97	54.71	47.14
JUNE	138.30	86.34	131.59	47.64	273.88	77.19	96.55	30.96
JULY	139.22	86.21	135.47	30.95	223.75	77.14	82.21	26.40
AUGUST	126.46	78.37	124.16	33.07	206.64	110.90	75.99	20.67
SEPTEMBER	139.45	108.53	135.37	30.29	302.13	73.94	161.12	109.05
OCTOBER	136.61	96.72	89.74	29.64	261.42	83.60	72.49	27.05

In Table 3, the monthly MAPE values for the GUCR forecast range from 1.62% to 3.32%. In contrast, the monthly MAPE values achieved with the proposed method range from 0.5% to 2.14%. The high MAPE value recorded for the GCRPEN in September was attributed to a total blackout that occurred on 26 September in the Yucatan Peninsula.

In Table 4, the monthly MAE values for the GUCR forecast range from 249.98 MW to 43.30 MW. In contrast, the monthly MAE values achieved with the proposed method range from 89.27 MW to 12.78 MW. The high MAE value recorded for the GCRPEN in September was attributed to a total blackout that occurred on 26 September in the Yucatan Peninsula.

In Table 5, the monthly RMSE values for the GUCR forecast range from 331.25 MW to 54.71 MW. In contrast, the monthly RMSE values achieved with the proposed method

range from 179.97 MW to 20.67 MW. The high RMSE value recorded for the GCRPEN in September was attributed to a total blackout that occurred on 26 September in the Yucatan Peninsula.

3.2. Results at GCR Level in Atypical Conditions

3.2.1. Peninsular Region: Blackout in Yucatan Peninsula (GCRPEN)

Blackouts in power systems are rare. However, on 26 September, at 14:18 h, a blackout occurred on the Yucatan Peninsula (GCRPEN), resulting in a loss of 2250 MW of load, which was fully restored by 21:00 h. Figure 9 shows the weekly load profile behavior and the accuracy difference between the GUCR forecast and the proposed method's forecast under this condition. The weekly MAPE value was 19.4% for the GUCR forecast, and weekly MAPE value was 7.0% for the proposed method's forecast.

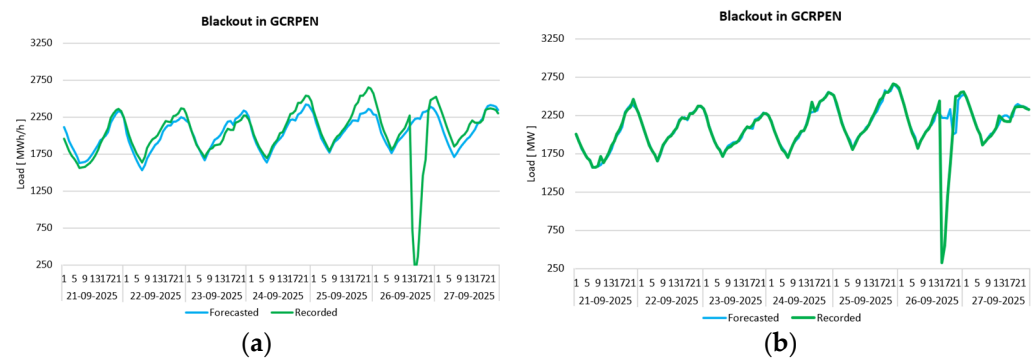


Figure 9. GCRPEN's daily load profiles during blackout week: (a) GUCR forecast; (b) proposed method forecast.

Table 6 shows the MAE and RMSE values for the same week.

Table 6. Comparative GCRPEN's weekly error metric values during blackout week.

	GUCR Forecast			PM Forecast		
	MAPE (%)	MAE (MW)	RMSE (MW)	MAPE (%)	MAE (MW)	RMSE (MW)
GCRPEN	19.40	134.04	298.46	7.00	51.42	221.85

Moreover, Figure 10 illustrates the load profile for that day and the differences in accuracy between the forecasting methods. The MAPE for the GUCR forecast was 111%, while the proposed method achieved a MAPE of 44%.

3.2.2. Impact of Cold Front Number 13 on Some GCRs

Due to Mexico's geography, meteorological phenomena do not strike in the same way or with the same intensity across the different GCRs. For this reason, cold front number 13, forecasted by the Comisión Nacional del Agua (CONAGUA), struck the GCRNTE, GCRORI, and GCRPEN from 10 November to 12 November, as shown in Figure 11.

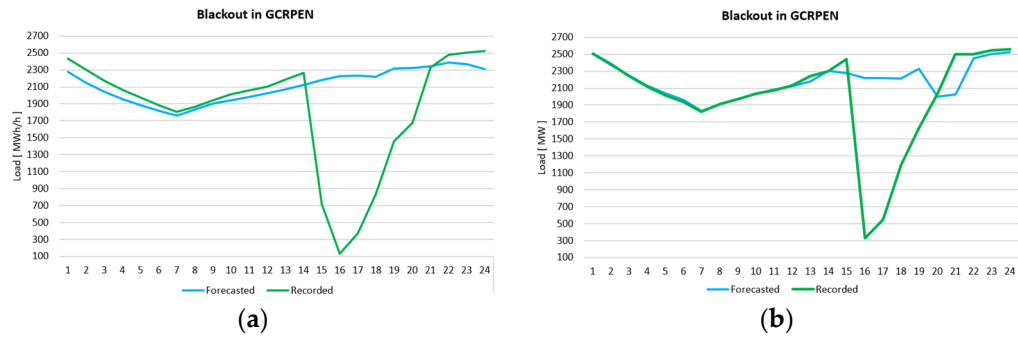


Figure 10. GCRPEN’s load profile on blackout day: (a) the GUCR load forecast and (b) the load forecast using the proposed method.

Table 7 shows the MAE and RMSE values for the same day.

Table 7. Comparative GCRPEN’s error metric values for blackout day.

	GURC Forecast			PM Forecast		
	MAPE (%)	MAE (MW)	RMSE (MW)	MAPE (%)	MAE (MW)	RMSE (MW)
GCRPEN	111.07	420.00	745.22	44.00	261.07	583.27

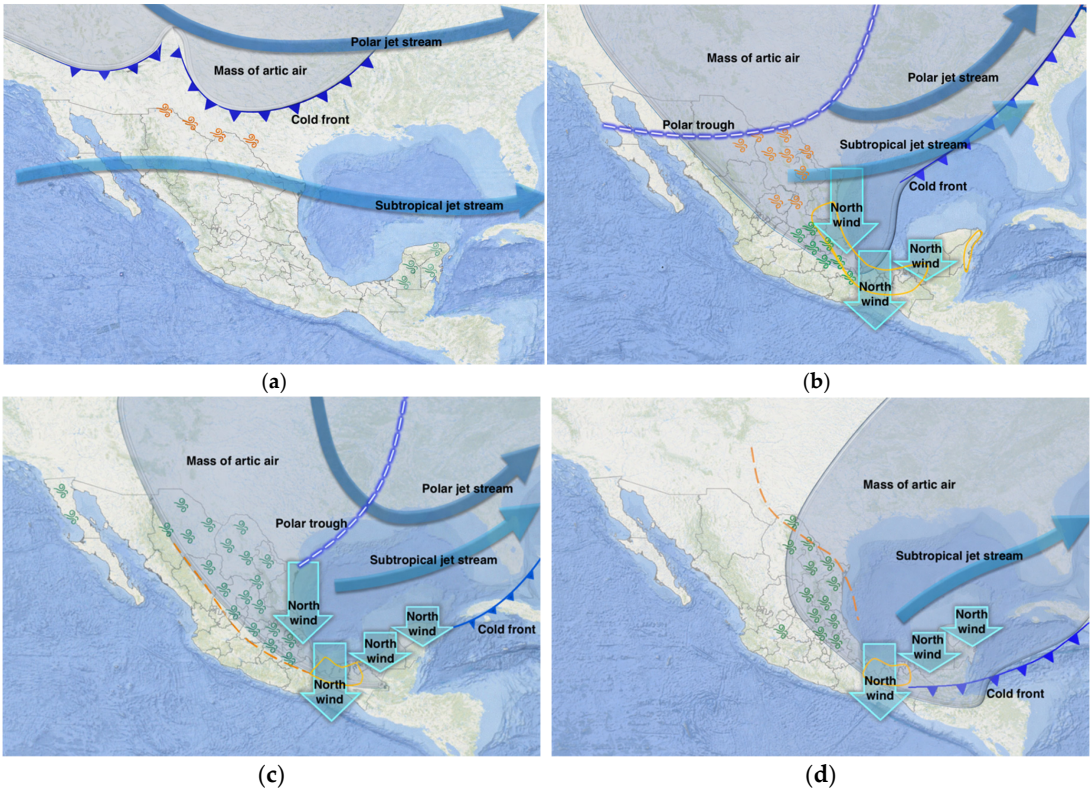


Figure 11. The impact of cold front number 13 on GCRNTE, GCRORI and GCRPEN along with its development from November 8 to 11, 2025, are illustrated in figures (a–d). Wind gusts ranging from 40 to 60 km/hr are indicated by green symbols, while those between 60 and 80 km/hr are represented by orange symbols. The orange dotted line indicates a low-pressure trough, while the solid yellow line illustrates heavy rain (>25 mm).

The difference between the GUCR forecast and the proposed method’s forecast for each GCR is illustrated in Figure 12.

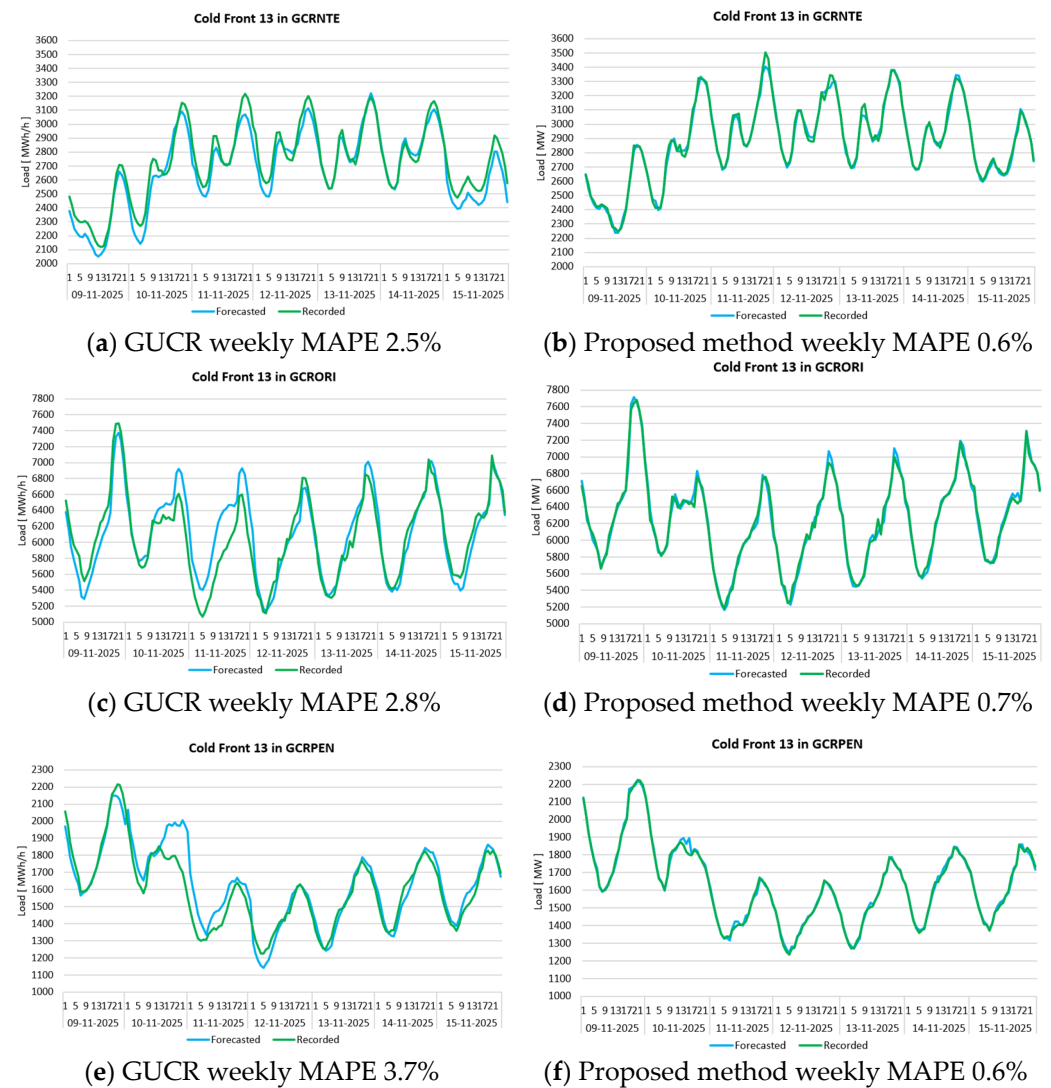


Figure 12. Impact of the cold front on load profiles and accuracy differences between the GUCR and the proposed forecasting method.

Table 8 shows metric errors between both forecast methods in these three GRCs.

Table 8. Comparative error metric values for cold font 13 in GCRORI, GCRPEN, and GCRNTE.

	GUCR Forecast			PM Forecast		
	MAPE (%)	MAE (MW)	RMSE (MW)	MAPE (%)	MAE (MW)	RMSE (MW)
GCRORI	2.80	164.85	211.24	0.70	43.99	57.53
GCRPEN	3.7	58.39	83.97	0.6	9.93	14.48
GCRNTE	2.5	67.76	80.61	0.6	18.9	25.75

3.3. Results at Load Zone Level in Atypical Conditions

The proposed method has also been tested at the load zone level. In particular, the GCRORI's 31 load zones are illustrated in Figure 13. The following examples correspond to two of the GCRORI's load zones: Poza Rica and Puebla.

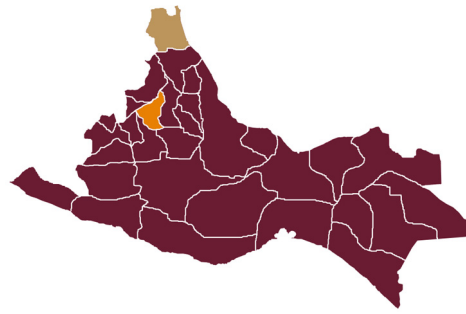


Figure 13. The GCRORI's load zones. The Poza Rica load zone is represented in brown, while the Puebla load zone is shown in orange.

3.3.1. Poza Rica Load Zone

From October 7th to 11th, this load zone experienced significant flooding caused by heavy rainfall. Figure 14 illustrates the accuracy difference between the GUCR forecast (Figure 14a) and the forecast produced by the proposed method (Figure 14b). The GUCR forecast has a MAPE of 34.0%, while the proposed method demonstrates improved performance with a MAPE of 2.19%.

It is important to emphasize that the more critical the operating condition in the power system, the more important the load forecast accuracy is due to the decisions to be taken in the real-time operation process.

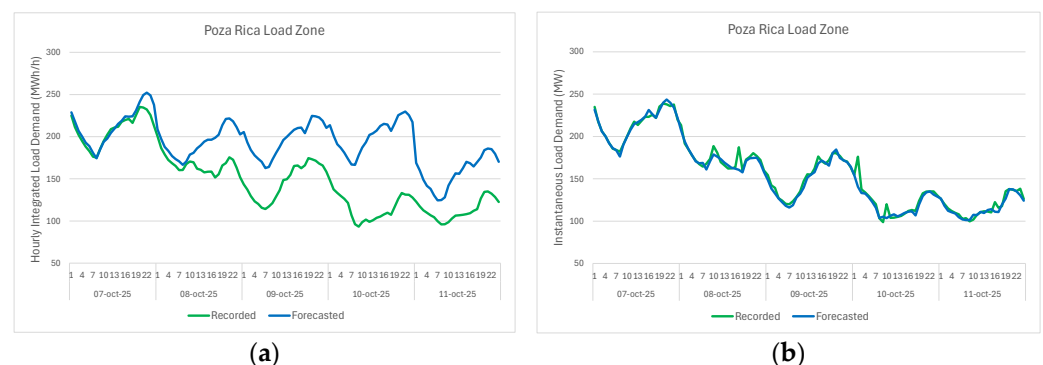


Figure 14. Forecasted and recorded loads for Poza Rica load zone on flood days. (a) GUCR forecast. (b) Proposed method's forecast.

Table 9 shows metric errors between both forecast methods in the Poza Rica load zone due to flooding in this five-day period.

Table 9. Comparative error metric values for flood in Poza Rica load zone.

	GURC Forecast			PM Forecast		
	MAPE (%)	MAE (MW)	RMSE (MW)	MAPE (%)	MAE (MW)	RMSE (MW)
POZA RICA	34.00	42.84	51.89	2.19	3.30	5.60

3.3.2. Puebla Load Zone

Due to the Day of the Dead festivities that took place over the weekend in 2025, there were significant changes in the recorded load across several load zones during that period. For instance, Figure 15 shows the accuracy difference between load forecasts. Figure 15a shows the GUCR load forecast accuracy, with a weekly MAPE of 7.8%. Figure 15b shows the proposed method's load forecast accuracy, with a weekly MAPE of 0.9%.

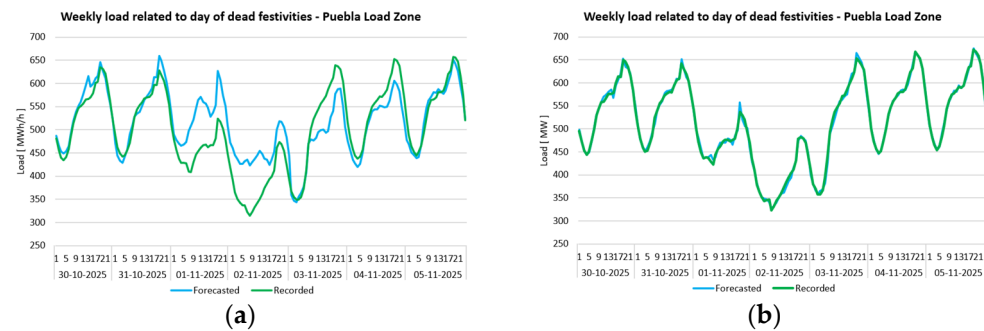


Figure 15. Forecasted and recorded loads for Puebla load zone during Day of the Dead festivities in 2025: (a) GUCR forecast. (b) Proposed method's forecast.

Table 10 shows metric errors between both forecast methods in the Puebla load zone due to Day of the Dead festivities.

Table 10. Comparative error metric values in Puebla load zone due to Day of the Dead festivities.

	GURC Forecast			PM Forecast		
	MAPE (%)	MAE (MW)	RMSE (MW)	MAPE (%)	MAE (MW)	RMSE (MW)
PUEBLA	7.80	35.59	47.65	0.90	4.53	5.85

4. Discussion

Unlike most studies that evaluate forecasting accuracy under normal conditions, the proposed method has been validated using real operational data from Mexico's National Interconnected Power System in steady-state conditions and during extreme events, including blackouts, heat waves, cold fronts, flooding, and holiday-induced demand anomalies. The demonstrated robustness and transferability across regions and load zones further reinforce the methodological contribution.

In all these scenarios, the MAPE values were superior to those obtained using the GUCR load forecasting method, which has already demonstrated its robustness. Nevertheless, there are further directions to follow in future research, such as the following:

- Although this method successfully forecasts hourly instantaneous peak load, it can be adjusted to predict hourly instantaneous minimum load, which would be beneficial during low-demand periods like holidays or the winter season.
- The current proposed method includes only the coastal load zones and the main load zones in the GCRORI. However, in the future, we may incorporate all 101 load zones of MNIPS into this method. As an intermediate step, adding all coastal load zones of MNIPS would enhance the forecasting accuracy for load zones during severe meteorological events.
- This method has been applied to all GCRs that compose MNIPS; it could also be applied to the Baja California peninsula power system to reach nationwide use, that is, Mexico's National Electric System (MNES).
- This method can also be applied in any other power system control center. As mentioned earlier in Section 2.2, the only requirements are a prior load forecast, recorded real-time load data stored in SCADA, and this algorithm.

5. Conclusions

Most existing statistical, machine learning, and hybrid approaches focus on forecasting hourly integrated energy demand (MWh) for market and planning purposes. In contrast,

the proposed framework explicitly targets the hourly instantaneous peak load (MW), which is the key variable for real-time operation, emergency assessment, and load-shedding decisions. The explicit formulation and forecasting of hourly instantaneous peak load from integrated energy forecasts represents a novel problem framing that we have not found in the existing traditional load forecasting literature.

This study demonstrates that a simple statistical post-processing framework can substantially enhance the operational usefulness of short-term load forecasts without introducing additional base forecasting models. By explicitly targeting hourly instantaneous peak load and incorporating hour-dependent dynamic bias estimation, the proposed approach captures systematic intraday discrepancies that are not addressed by conventional similar-day methods or static regression-based corrections. The results confirm that this methodology provides a transparent, robust, and computationally efficient pathway to improve reliability-oriented load forecasting in practice.

From a statistical perspective, the stability and reliability of the proposed framework are supported by its consistent performance across multiple error metrics and operating regimes. The simultaneous reduction in MAE, RMSE, and MAPE observed across regions, load zones, and extreme events indicates not only improved average accuracy but also controlled error dispersion and robustness against large deviations. In particular, the sustained RMSE reductions during atypical conditions such as blackouts, cold fronts, floods, and holiday-induced demand anomalies demonstrate that this method maintains stable behavior under non-stationary operating conditions. This multi-metric consistency provides quantitative evidence of model stability and error robustness, which are essential requirements for short-term load forecasting in power system operation.

The research performed in this work shows that the proposed load forecast method is easy to use, effective, and highly accurate, consistently yielding better results than the GUCR baseline used for comparison. Additionally, this method offers an instant peak load demand forecast (MW) without requiring a specific real-time load forecasting process or additional human, material, or financial resources, thereby saving on costs.

Author Contributions: Conceptualization, L.C.L. and T.A.C.; methodology, L.C.L. and T.A.C.; software, T.A.C.; validation, L.C.L. and T.A.C.; formal analysis, L.C.L. and M.B.; investigation, M.B. and G.R.-C.; resources, M.B. and G.R.-C.; data curation, L.C.L. and T.A.C.; writing—original draft preparation, L.C.L.; writing—review and editing, L.C.L. and M.B.; visualization, M.B.; supervision, L.C.L. and M.B.; project administration, M.B.; funding acquisition, M.B. and G.R.-C. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Some MNIPS and MNES load demand data are freely available in the Centro Nacional de Control de Energía database (<http://cenace.gob.mx>) (accessed on 2 November 2025). GCR load data and load zone data is part of the statistical information used for several internal purposes in CENACE and is not available for public access. These datasets are kept in every GCR and in CENACE's corporate office databases. Data presented in this publication are only for academic purposes.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ANN	Artificial Neural Network
CENACE	Centro Nacional de Control de Energía
CGAN	Conditional Generative Adversarial Network
CONAGUA	Comisión Nacional del Agua
Conv1D	One-dimensional Convolutional Neural Network
DAM	Day-Ahead Market
DEE	Departamento de Evaluación y Estadística
EH	Extended Horizon
EMD	Empirical Mode Decomposition
FL	Fuzzy Logic
GAs	Genetic Algorithms
GCR	Gerencias de Control Regional
GCRCEL	Gerencia de Control Regional Central
GCRORI	Gerencia de Control Regional Oriental
GCROCC	Gerencia de Control Regional Occidental
GCRNOR	Gerencia de Control Regional Noroeste
GCRNTE	Gerencia de Control Regional Norte
GCRNES	Gerencia de Control Regional Noreste
GCRPEN	Gerencia de Control Regional Peninsular
GUCR	Generating Unit Commitment for Reliability
KPCA	Kernel Principal Component Analysis
LCC	Limited Liability Company
LSTM NN	Long Short-Term Memory Neural Network
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MNIPS	Mexico's National Interconnected Power System
MNES	Mexico's National Electric System
MSCSO	Multi-Strategy Improved Sand Cat Swarm Optimization
MW	Instant value units for active power load
MWh/h	Energy value units for active power load, obtained by integrating instant values in a one-hour period
NTN	National Transmission Network
PHP	Hypertext Preprocessor
PJM	Pennsylvania–New Jersey–Maryland
PSO	Particle Swarm Optimization
PM	Proposed Method
RMSE	Root Mean Squared Error
SARIMA	Seasonal Autoregressive Integrated Moving Average
SA TCN	Self-Attention Temporal Convolutional Network
SCADA	System Control Acquisition Data
SVM	Support Vector Machine
SVR	Support Vector Regression
VMD	Variational-Mode Decomposition
WEM	Wholesale Electricity Market
WL	Warning Levels
XGBoost	Extreme Gradient Boosting

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