Application of Shape Functions to the Calculation of an Annual Electricity Demand Forecast

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Abstract: - This work proposes a methodology to construct an electricity power demand annual profile using a novel model to reproduce the demand behavior during weekends and holidays. These days have the common characteristic that the demand decreases during the day, or weekend, and then increases again. This behavior is represented by a simple deterministic model that is systematically applied to a normalized hourly demand profile based on similar days, allowing a relatively fast construction of an annual profile that reflects the actual demand characteristics and is useful for load demand forecasting, and as support for other medium or long term analysis, such as electrical expansion planning or fuel economics planning. The electricity demand profile construction starts with hourly measurements of demand as input and a base profile is prepared with historical data from previous years. It is based on the characterization of the weekdays by normalization and grouping into several time periods along the year. The base profile made with normalized days is then shaped by functions that allow the characterization of the demand behavior during weekends and holidays. In this work, a shape function is a one-dimensional vector that multiplies a demand vector and modifies its data for an interval of interest, leaving the rest of the vector unchanged. For the case of weekend modeling, the shape function spans 7 days, centering the modification on the weekend and leaving the initial and final days unchanged. The shape function for a public holiday spans two days and does not modify all the two-day interval, preserving the initial part of the first day and the last part of the second day. The objective is to generate shape functions with a simple model that systematically represents the real demand with low computational effort. In this work, the shape functions for weekends and holidays are based on the gamma probability distribution. The shape functions approach does not explicitly consider the weather, but it implicitly considers stationarity effects by dividing the yearly time data into segments, each one with its own characteristic properties, which vary along the year. The shape functions methodology is demonstrated with the construction of a power demand forecast for the Mexican National Interconnected System for the year 2022.

Key-Words: - Demand forecasting, load forecasting, holiday load, annual electricity forecast, hourly forecast

Received: May 13, 2024. Revised: November 17, 2024. Accepted: December 13, 2024. Published: February 14, 2025.

1 Introduction

Electricity demand forecast is a key activity in several areas related to the energy market. From real-time load scheduling and one-day ahead unit commitment to expansion planning strategies for electrical generation systems, depending on the time horizon involved, the forecast is useful to support decision-making. Forecasts are commonly categorized as short-term, middle-term, and long-term, with their time span ranging from minutes to hours, hours to months, and one year to several years, respectively.

There is a diverse variety of techniques for demand forecasting, depending on the horizon time span. The most known are time series methods such as autoregression, autoregression with moving average, integrated moving average, and seasonal autoregressive integrated moving average. There are also exponential methods, single, double, and triple, depending on the type of data. A wide variety of artificial intelligence methods are also applied, such as neural networks, fuzzy logic, genetic algorithms, etc.

Among the mentioned forecasting methods, there are ARMA models for mid-term electric load forecast [1], or grey trigonometric models for demand forecasting [2], [3], [4], including a comparison of trigonometric with ARMA and exponential Holt Winters models, [3]. The application of Grey index models to short term forecast is described in [4].

For long-term peak load forecasting, [5] presents a comparison of Holt-Winters and Prophet models. Findings highlight the importance of precise long-term energy forecasting for informed policy decisions and infrastructure planning.

On more recent methods, [6] presents a comparative analysis of machine learning approaches for long-term and short-term electricity load forecasting. Among machine learning applications to short-term load forecast for different seasonal conditions, [7] applies SVM to process a season specific similarity concept.

On fuzzy logic techniques, among other applications, there is a system to forecast electricity load using learning machine techniques [8], and a combination of fuzzy entropy with neural networks for middle term load forecasting, [9]. A convolutional neural network model for load forecast in a smart grid is analyzed in [10]. A combination of neural networks with particle swarm optimization for short term load forecasting is documented in [11].

Decomposition methods are also used in power system forecasting. Decomposition of an aggregated load into sub-loads, and preparation of a forecast for each sub-load, where the sum is the aggregated load forecast is presented in [12]. A thorough literature review on time series decomposition methods in power systems forecasting is presented in [13]. It categorizes publications based on forecast aim, decomposition method, and comparisons with other techniques. According to this reference, most papers prefer multiplicative decomposition, followed by additive decomposition, and some use decomposition as an initial step in forecasting.

Similar day selection is another approach to obtain a forecast. This approach requires an expert or a method to select the appropriate days according to some specific conditions. An application using reinforcement learning for short-term load forecasting algorithm to remove the dependency on an expert to select similar days is found in [14].

Calendar holidays introduce a different behavior on the electric demand profile. Another short-term load forecast involving similar days for a day-ahead application focused on holidays was presented in [15].

A review of techniques for load forecasting can be found in the literature [16], [17] as well as discussion of advantages and disadvantages, [18]. Reference [19] is focused on methods for operation and planning.

A review of long-term hourly electricity demand forecast methods considering the evolving energy landscape is found in [20]. It identifies two main approaches: partial decomposition focusing on long-term trends and bottom-up methods aggregating hourly load profiles. The survey offers insights into diverse strategies and concludes with general recommendations for improving long-term load forecasting in dynamic power systems.

In this work, characteristics of similar days and decomposition methods are considered to construct the initial part of an hourly forecast for a one-year forecast. It commences with the normalization of the historical data for all seven weekdays. Once normalized, the shapes of the curves are compared so atypical days are readily identified and suppressed to obtain a representative shape over a period of time. With the seven representative days defined, a typical week is then constructed. A profile is built with typical weeks for several periods along the year. The obtained normalized profile has a straight aspect, it does not follow the power demand reduction on weekends and holidays. To account for the general behavior of demand, the profile is compensated with shape functions that provide the general tendency of the demand during a period of time, the weekend, for example. The shape function can be modeled and applied systematically to obtain a power demand profile close to the available data. Once a model is obtained, it can be applied to represent a future period of time and generate a forecast.

2 Power Demand Profile Construction

Multiplicative decomposition is a technique for time series analysis and forecasting applications, [13]. These decomposition methods model the level, trend, and seasonality components from the input data, and the forecast is obtained as the product of each contribution. A similar concept is applied in this work, where a power demand profile is represented by a series of components for a given period of time, specifically one year. The power profile is assumed to be factorized into four components:

$$P^i = N_f\, S^i_{base}\, S^i_{nrml}\, S^i_{wknd}\, S^i_{hldy} \tag{1}$$

where

P^i	ith hourly element of the demand profile, with i varying from 1 to n, the total hours of the year.
N_f	Normalization factor, scalar
S^i_{base}	Base annual shape profile, nX1 vector
S^i_{nrml}	Normalized annual shape, nX1 vector
S^i_{wknd}	Weekend shape profile, nX1 vector
S^i_{hdy}	Holiday shape profile, nX1 vector

The normalization scalar factor N_f allows the integral of the profile to meet the total energy expected to be generated along the year.

The Mexican National Interconnected System (SIN) is composed by seven regions [21], and the total demand is the arithmetic addition of them. The data used in the present work corresponds to the preparation and conditioning of SIN information, and was collected and processed from public web pages, [22].

2.1 Base Annual Shape Profile

The input data to build a power demand profile is organized into yearly sequences of hourly measurements. The developed power demand profile is not an explicit function of weather, but it implicitly considers stationarity effects by dividing the year sequence into segments, each one with their own characteristic properties, which vary along the year. This profile provides the general shape of the demand curve and it is scaled to meet the energy generation during the year.

2.1.1 Computing the Base Shape Profile

The base annual shape profile sets the general aspect of the power profile. It is assumed that the shape of the demand curve for a given year resembles that of previous years, scaled according to some growth rate and subject to satisfy the proposed total energy to be generated. Given m years of data, the demand profile is computed as an average of the previous m years.

$$P_i = \frac{1}{m}\sum_{j=1}^{m} Q_i^j \qquad i = 1 \dots n \tag{2}$$

where n is the number of hours in a year: 8760 or 8784 if it is a leap year, and Q^j_i represents the ith element of the power demand profile for year j.

The plot of P_i would result on a curve with multiple peaks and valleys, as the demand peaks sometimes twice a day and has a minimum during the early hours of each day. P_i will be processed to generate a smoother annual shape.

A calendar year contains 52 weeks, plus one or two days depending if it is a leap year or not. Assuming hourly data, for a week there are 168 demand values. A new vector is defined as W_j, where j represents the jth week of the year and is defined as

$$W_j = \sum_i P_i \tag{3}$$

where

$$i = 168m - 167 \;\dots\; 168m \qquad if\ m < 52$$
$$i = 168m - 167 \;\dots\; 168m + 24 \qquad f\ m = 52$$

The summation involves adding 168 terms each week, except for the final week, which has one or two additional days to complete the year. The sequence of the 52 W_j values form a smoothed version of the power demand profile.

Figure 1 shows the power profiles W_j for the years 2017 to 2021. The length of the vectors is 52, the number of weeks in the year. Even when some smoothing was obtained by the summation of each week's demand, the general aspect is similar to a noisy hill that increases during the first semester and decreases during the second semester. The plot still contains multiple local peaks and valleys, and further smoothing can be achieved either by applying a smoothing algorithm such as Holt-Winters or simply performing a polynomial fit to the data. The latter approach will be used in this work.

The profiles of recent years can be averaged to obtain a representative profile, but because of the unique effect of the COVID-19 Public Health Emergency (PHE), the year 2020 is not accounted for as representative. For the construction of the 2022 example, it will be based on the 2021 data, therefore, the 2021 power profile will be scaled according to some factor to be defined later, to obtain a first gross power profile for 2022.

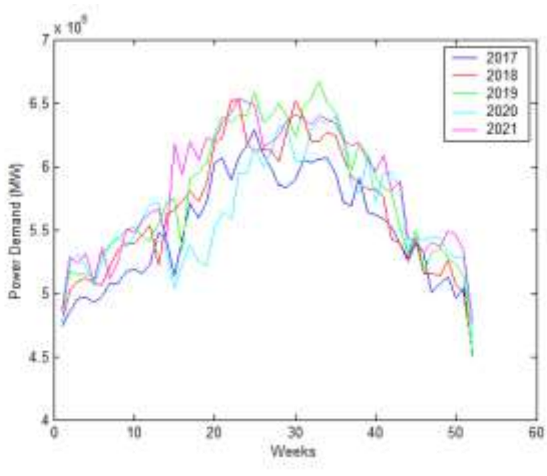

Fig. 1: Power demand profiles for 2017 to 2021

2.1.2 Total Annual Power Demand Projection

The integration of the power profile along one year produces the total demanded energy. An approximation to this integral is the sum of all the hourly power demand values per week. This sum can be written as the sum of all the partial sums W_i for a given year.

$$E = \sum_{i=1}^{n} W_i \quad where\ n = 52 \tag{4}$$

Figure 2 presents as small circles the area under the curve for the years 2017 to 2021. It is clear the effect of the COVID-19 PHE in 2020 and 2021. The green line represents a curve fit ignoring the 2020 data, and similarly, the red line represents a curve fit ignoring the 2020 and 2021 data. From the curves, an expected value for 2023 is the average of the red and green lines at 2023, and it is 3.1733X10^8 Wh.

The general shape profile must be scaled to account for the expected total energy demand during the year. It will satisfy a forecast criterion based on previous years. For each previous year, the known hourly power profile is integrated to obtain the total energy demand during the year. Then the vector containing the power demanded over the years is analyzed to identify a tendency and the next year is extrapolated and the value is used as a normalization factor for the final power profile.

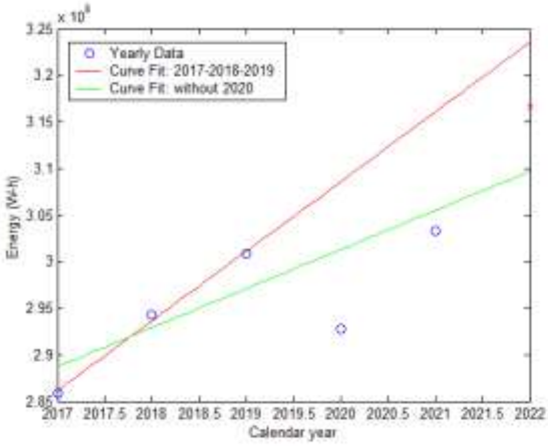

Fig. 2: Total energy demand for a year

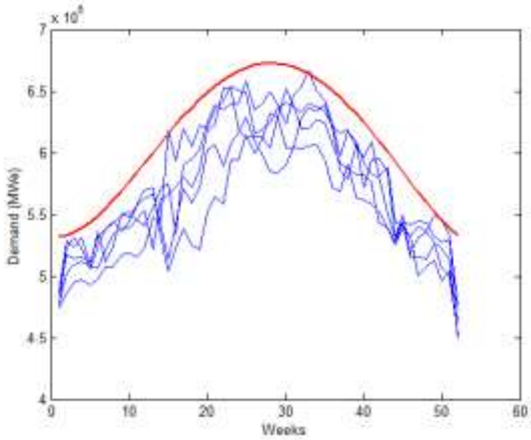

Fig. 3: Calculated smooth profile for the year 2022

The smoothed profile obtained in the previous section us now scaled to generate 0.31733 GWh, and Figure 3 shows the base annual shape profile for the 2022 demand. According to the expected growth rate of the demand, the area under this curve is slightly greater than those of previous years.

A figure of merit to evaluate a forecast is the Mean Absolute Percentage error (MAPE), and it is defined as:

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{A_i - F_i}{A_i} \right| \tag{5}$$

where A_i and F_i are the actual value and the forecasted value for time i. The MAPE is an average over a period of time, for the case of one day with hourly measurements, the summation will consider 24 terms. This figure of merit will be used to evaluate the forecast in the next sections.

2.2 Normalized Annual Shape Profile

For a given weekday, the day demand profile changes throughout the year. In winter, it has a minimum at about 05:00 AM, and a maximum at about 20:00 hrs. For summer, the profile develops two successive maximums at about 16:00 and 21:00 hrs. The behavior is cyclical, so at the end of the year, the profile shape for a given weekday is similar to that of the beginning of the year.

From the hourly annual data, the information is grouped depending on the day of the week, that is, all the Sundays, Mondays, etc. are grouped and normalized to obtain the weekday profile. To account for the variation of the day profile along the year, the profile is grouped into 4-week periods, obtaining 13 periods for a total of 52 weeks. An extra day is added to the last period to complete the 365 days of the calendar year. In case of a leap year, 2 days are added, instead. An average shape is computed for every weekday and group.

An atypical day has a different profile and it shifts the average shape from a typical representative value. Figure 4 shows the four normalized Mondays from a 4-week period. By inspection, the Monday shown as a magenta line has a different shape and corresponds to an atypical day, usually a holiday. The thick black line represents the average of all curves, and the thick green line represents the average of the remaining curves after the atypical day is discarded.

There may be a number of methods to detect atypical days, for example, cross-correlation. In this work, a MAPE is computed for each day taking as a reference the average shape. An arbitrary limit is used to discard a day, in this case, if the MAPE is greater than 2.5%, the corresponding shape is discarded.

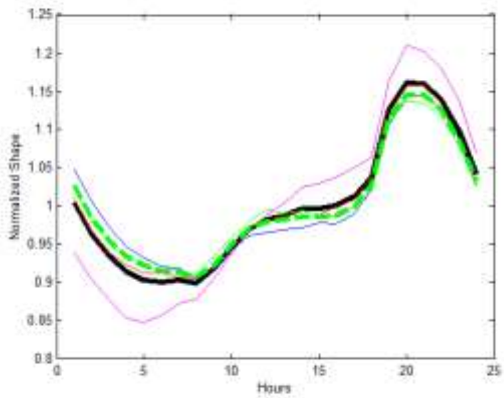

Fig. 4: Shape of Mondays during a period of four weeks

The green line in Figure 4 is considered the typical shape function for Monday for that specific period. If the same procedure is applied to all the other weekdays, then a complete typical week is constructed, as shown in Figure 5. The typical week represents a period of time, and it changes over the year. Figure 6 shows the typical week shape for the start, the middle, and the end of the calendar year. The start and the end of the year shapes are similar (winter), but the middle is different (summer). The shape for a weekday may gradually develop one or two peaks, depending on the season.

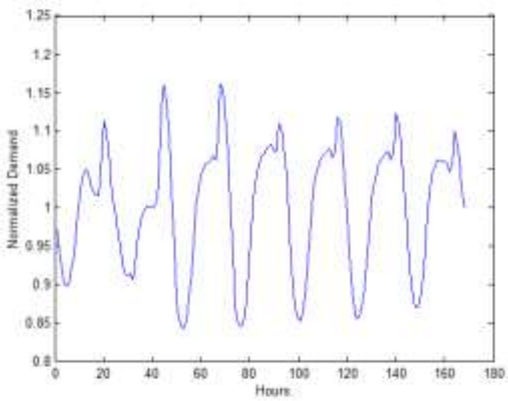

Fig. 5: A typical normalized week

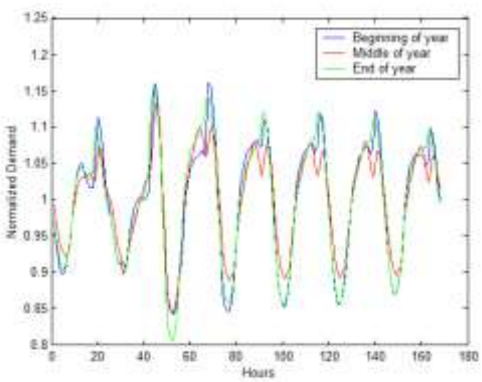

Fig. 6: A typical normalized week along the year

With the typical days already defined, and knowing the weekday that starts a target year to forecast, the days are arranged to generate an initial base profile S^i_{base} , shown in Figure 7.

Combining the results of the base S^i_{base} and the normalized S^i_{nrml} profiles (Figure 3 and Figure 7), the first two vector terms of Equation (1) are obtained, and Figure 8 shows the plot of the obtained power demand profile. Comparing this profile with actual data, it is possible to evaluate the error and obtain an insight of its characteristics. Figure 9 shows the MAPE for all the days of the year, this MAPE values were obtained by equation (5) averaging over 24 hours for each day. The average MAPE of all 365 days is 4.88%, and the standard deviation is 4.62% for this initial base power demand profile. The dashed red line represents two times the standard deviation.

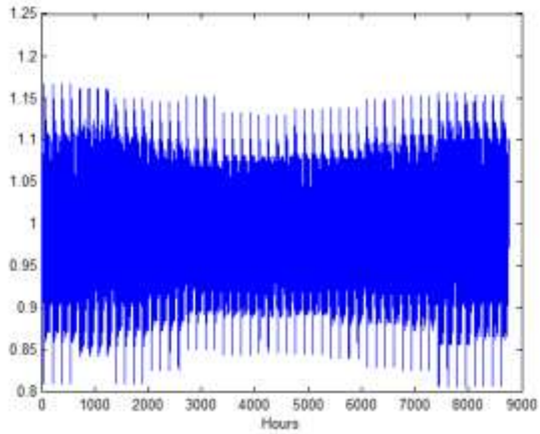

Fig. 7: Normalized profile built with typical weeks

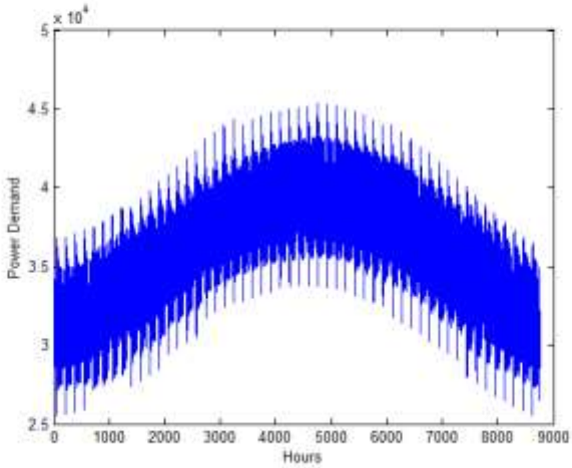

Fig. 8: Combination of the base and normalized profiles for 2022

Figure 10 shows the histogram of the MAPE values. The distribution is similar to hone-half normal distribution because of the absolute value of the MAPE formulation. The dashed red line represents two times the standard deviation.

Figure 9 shows a number of peaks on the MAPE values, these peaks are periodical and correspond to the MAPE for Saturdays and Sundays. This behavior suggests that a correction for the weekends is necessary to improve the demand profile.

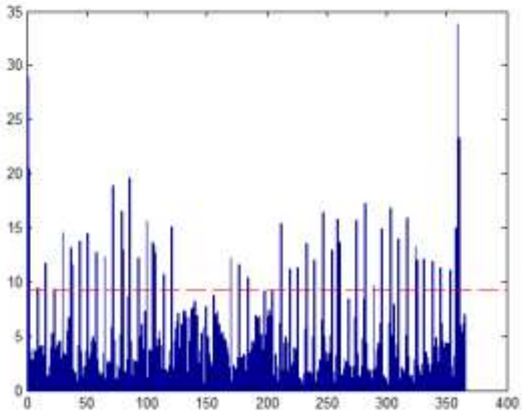

Fig. 9: Preliminary daily MAPE for 2022

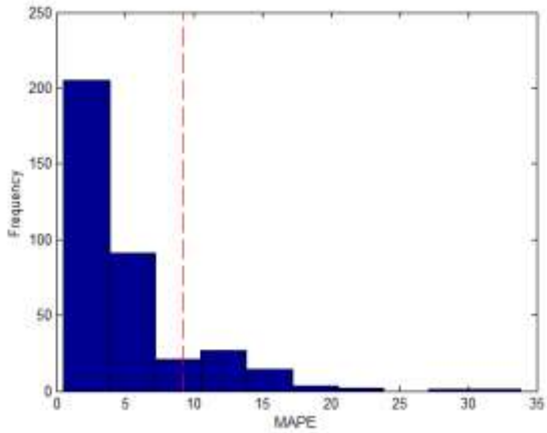

Fig. 10: Histogram for the 2022 MAPE

2.3 Weekend Shape Profile

The initial profile captures the shape of the different days of the week, but it does not capture the relative variation among those days, nor the demand decrease during a weekend. The daily MAPE plot shows a systematic and periodic error, this error is associated with the weekends. The term S^{i}_{wknd} of Equation (1) is now introduced to model the weekends and reduce this periodic error.

2.3.1 Weekend Modeling.

As seen previously, the daily MAPE plot for the preliminary forecast profile has periodic peaks associated with weekends. Figure 11 shows the effect of the weekend on the power profile. The preliminary profile (blue) does not show a decrease in the real demand during the weekend (red).

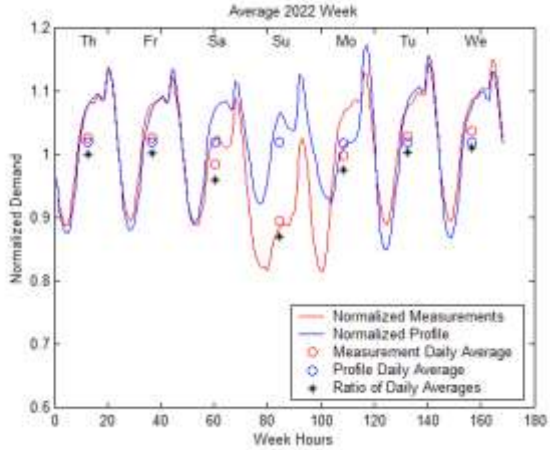

Fig. 11: Comparison of a normalized weekend with an actual weekend.

For the average week of a given period of four weeks in the year, Figure 11 shows the plot of the normalized measurements and the normalized profile as red and blue line plots, respectively. The blue and red circles correspond to the power profiles' daily average, respectively, and are plotted every noon. The black asterisks represent the ratio of the daily averages. It is observed a tendency on the shape described by the asterisks, a smooth temporary reduction followed by a recovery of the daily average ratios. By inspection, the asterisks resemble an inverted normal distribution, but it is not symmetrical, so a better representation would be an inverted gamma distribution. Therefore, the following function is postulated to shape the weekend behavior:

$$S_{wknd}(x) = 1 - Kf(x) \tag{6}$$

Where f(x) is a Gamma distribution, [23]

$$f(x) = \frac{x^{\alpha-1}e^{-x/\beta}}{\beta^{\alpha}\Gamma(\alpha)} \tag{7}$$

Here, a shape function $S_{wknd}(x)$ is proposed as one minus a gamma distribution function. This function tends to one for x values located far from the mean value, therefore if it multiplies a power profile, it will affect only elements located relatively close to the mean, depending on the variance. Figure 12 shows the shape function fitted to the power demand data plotted as small black circles in Figure 11. The fitting of the average values for each day is shown only to illustrate the concept of defining a function that shapes the weekend profile. For a better shape function calculation, a fitting is performed over all the hourly data points. The distribution mean and the variance control the shape and are chosen to fit the values inside a period of three days. The gain sets how deep the depression of the curve will be.

For a Gamma distribution with parameters α and β, the expected value is αβ and the variance is $\alpha\beta^2$ [23], its density function can be algebraically rearranged to show a clear dependency on mean and variance, two key parameters that provide physical insight and facilitate the curve fitting to power data. Therefore, equations (7) and (6) are rewritten as

$$f(x) = \frac{x^{\left(\frac{E^2}{V}-1\right)} e^{\frac{-Ex}{V}}}{\left(\frac{V}{E}\right)^{\frac{E^2}{V}} \Gamma(\frac{E^2}{V})} \tag{8}$$

$$S_{wknd}(x) = 1 - K\left[\frac{x^{\left(\frac{E^2}{V}-1\right)} e^{\frac{-Ex}{V}}}{\left(\frac{V}{E}\right)^{\frac{E^2}{V}} \Gamma(\frac{E^2}{V})}\right] \tag{9}$$

where V is the variance and E is the expected value.

To illustrate the application of equation (9) to the weekend demand modeling, a period of 4 consecutive weeks from the 2021 demand measurements was selected, and the four-week period profile was averaged and is shown in Figure 12 as the red line. Similarly, the normalized profile is averaged and plotted with a blue line. The average value for each week day is computed, and their ratios are presented as black circles. Those black circles shape-out a depression that is modeled as a shape function according to Equation (9). The determination of variance, gain and mean is based on the interpretation of the depression width, height and location along the x axis, respectively.

Given the fact that for a normal distribution, 95% of the area is located in the range from minus two to plus two standard deviations, a fast estimation of the variance is obtained assuming the gamma distribution is similar to a normal one. From Figure 12 most of the distribution should be located between hours 50 and 110 over a span of 4 standard deviations. Then (110 – 50) /4 should be an approximate value of the standard deviation. This gives a rough initial estimate of the variance as 225 to start tuning the fit to equation (9). The tuned shape function is shown as the green line in Figure 12.

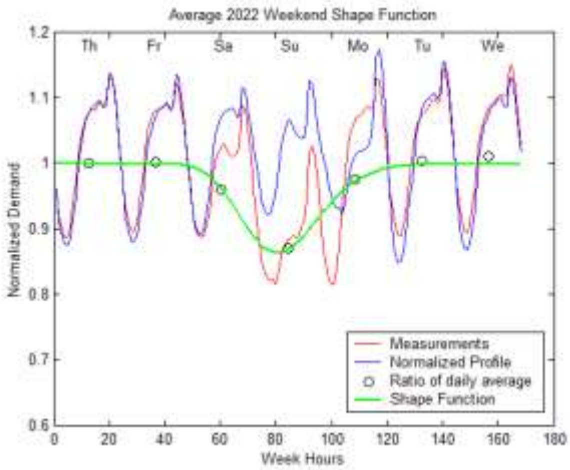

Fig. 12: Example of shape function for a weekend

2.3.2 Weekend Profile Construction

The example case of the previous section was presented as an illustration of the shape function application. For the actual profile construction, the selection of parameters for the shape functions are not based only on daily averages, but on all the 24 points of each day.

The S^i_{wknd} profile is therefore composed of a successive application of the shape function along the annual profile with a periodicity of seven days. A segment of the resulting profile is shown as a green line in Figure 13.

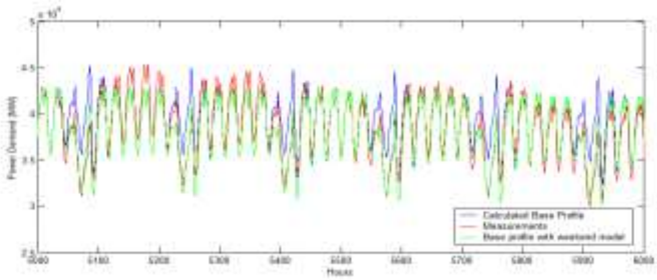

Fig. 13: Effect of the weekend shape profile S^i_{wknd}

Figure 13 shows a typical segment of the annual profile. The weekend compensation model works very well to reproduce the minimum values on Saturday nights, and reproduces well the Sunday nights, with some overestimation. In general, the model does a good job of representing the weekend reduction of power demand.

With the weekend model, the average MAPE is reduced from 4.88 to 3.84 %. Similarly, the standard deviation is reduced from 4.62 to 2.91%. Figure 14 shows the daily MAPE and Figure 15 shows the histogram. Compared with Figure 9 and Figure 10, the MAPE of Figure 14 and Figure 15 is more concentrated into the 2 standard deviations region.

DOI: 10.37394/232016.2025.20.4

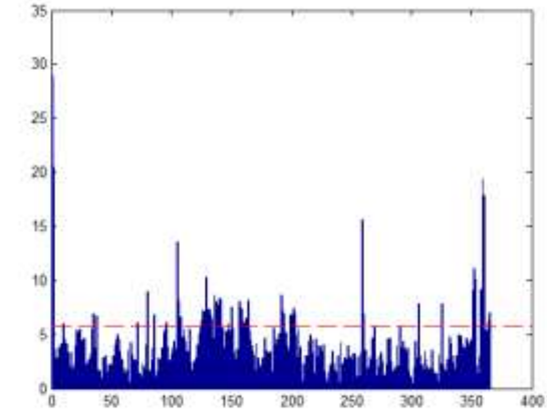

Fig. 14: MAPE for weekend compensated power demand profile

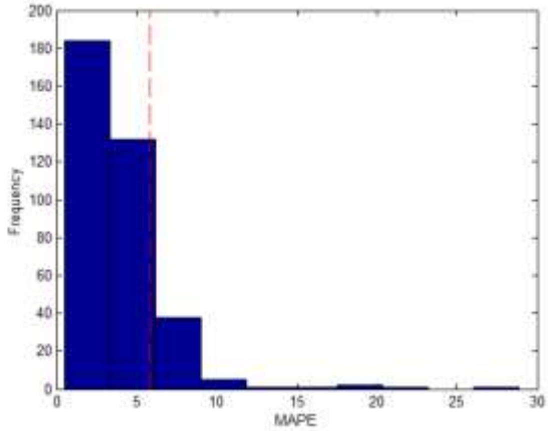

Fig. 15: MAPE histogram for weekend compensated power demand profile

2.4 Holiday Shape Profile

The demand behavior observed during the weekends is similar for public holidays, where the span of measurements affected by Eq. (9) is limited to one day. The Holy Week can also de described using a bigger time span.

2.4.1 General Holiday Modeling

Every calendar holiday can be modeled using the same approach with a compensation shape function. Figure 16 shows a holiday example, Friday September 16, where the blue line is the real demand, the red line is the base profile and the green line is the base profile with the application of a shape function. A time span of 48 hours bounding September 16 and 17 is represented as vertical dashed lines. It can be seen that the load reduction spans more than Friday, affecting also the early hours of the next day. The effect of the shape function is to allow the profile to follow the real demand. This function is prepared with an adaptation of equation (9) over a time span of 48 hours. For this case, the adaptation is achieved with the statistical parameters: mean 20.0, variance 200.0, and gain 4.5. The effect on the last 12 hours is small.

There are some special days that do not closely behave like a holiday, such as May 10th (Mother's Day) and December 12 (a religious holiday), important in Mexican society. For these days the gain of the shape function is reduced to 50% of that of a standard holiday. As a result of analyzing the error values along the profile, it was found that when a holiday occurs during a weekend, it is not necessary to be modeled because all the weekend days are compensated by the weekend model and an additional compensation would result in an over-damping of the profile.

The shape function for all the year S^{i}_{hldy} contains the individual shape functions for each of the calendar year holidays.

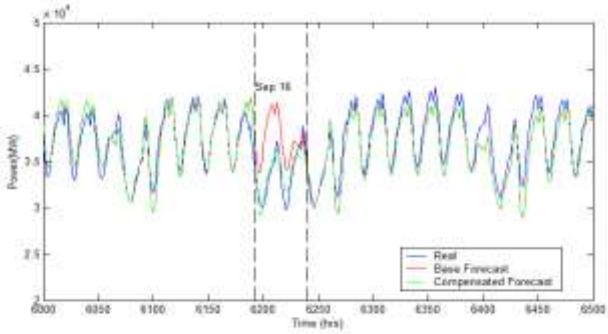

Fig. 16: Example of Holiday: September 16 (Friday)

2.4.2 Holy Week Modeling

The Holy Week reflects a clear effect on the power profile. The decrease in the demand for this period is similar to the weekend model, but the demand decrease spans more than two days. For this case, a shape function for a total length of seven days is prepared. Figure 17 shows the shape function for the Holy Week, which has a length of 168 hours, it is obtained from Equation (9) with a mean of 85, a variance of 300, and gain of 5.0. The plot shows that the first day is practically unchanged, as well as the last day. Figure 18 shows the effect of the Holy Week shape function, which is integrated into S^{i}_{hldy} .

2.4.3 Other Considerations

The demand decreases during the last days of the year and the first days of the next year. The shape function in this case is divided into two segments. Christmas is similar to a holiday, and it is modeled with a two-day span shape function.

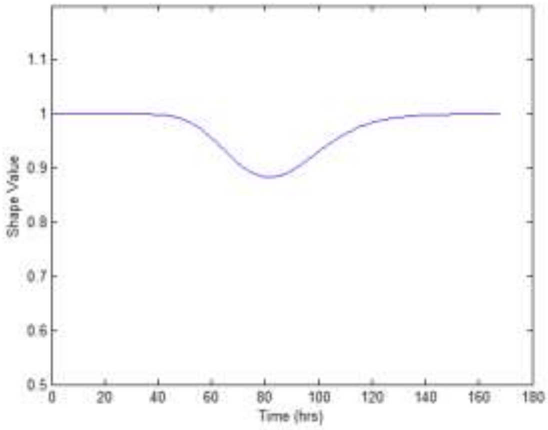

Fig. 17: Shape function for Holy Week

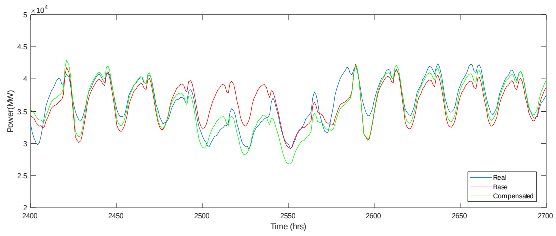

Fig. 18: Demand during Holy Week

3 Final Results

The final power profile involves all terms of Equation (1). All the multiplicative compensation profiles have the effect of reducing the demand, and also reducing the area under the curve. After all the multiplicative compensations are considered, the whole profile is scaled to meet the expected generation energy. Figure 19 shows the finished demand profile for 2022 (red) as well as the real profile (blue).

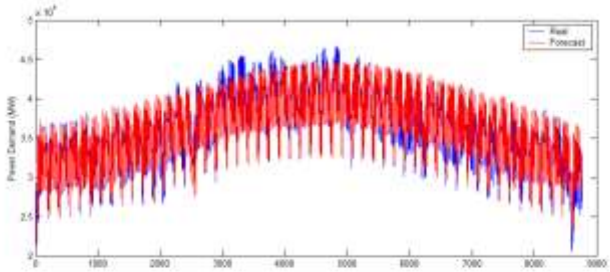

Fig. 19: Calculated Demand Power profile for 2022

Considering the calendar holidays, the average MAPE of all daily MAPEs of the final profile is 3.28%. Figure 20 shows the daily MAPE results. The standard deviation is 2.38%

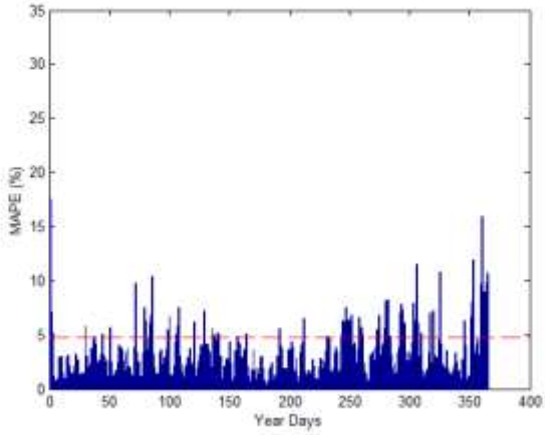

Fig. 20: MAPE for weekend and holiday compensated profile

Figure 21 shows the histogram of the MAPE. The red line at 4.75% represents two times the standard deviation.

By classifying the year's days into Mondays, Tuesdays, etc., it is possible to find the MAPE for each specific day of the week. Figure 22 shows the average MAPE for all the 52 Mondays, Tuesdays, etc. Sundays present the highest error in the forecast.

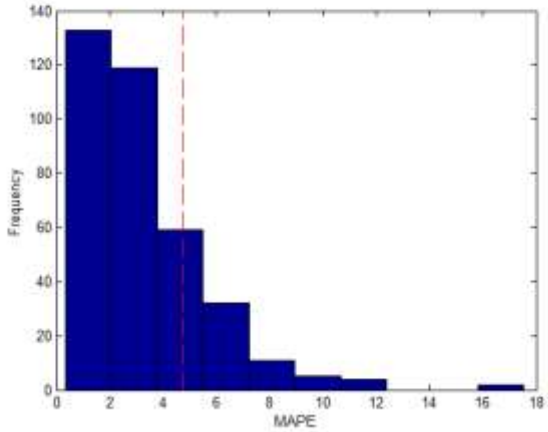

Fig. 21: MAPE histogram for power demand preliminary profile

The load duration curve is useful for electricity generation planning. Because it is defined by sorting the hourly demand profile from highest to lowest values, it provides additional information such as how many hours loads will have a value in a given power interval, [24]. The distribution of loads provides the planner information for determining the proper mix of base, intermediate, and peaking capacity.

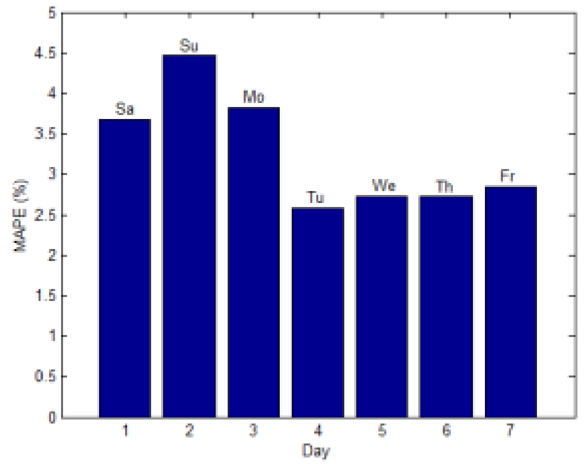

Fig. 22: Average MAPE by day of the week

Figure 23 shows the load duration curve for the constructed and the real 2022 profile. The computed load duration curve tends to be higher than the real one. This is due to the overestimation of the total area under the 2022 profile (see the projection for 2022 in Figure 2). If the estimated profile is scaled according to the real area, the curves would almost match.

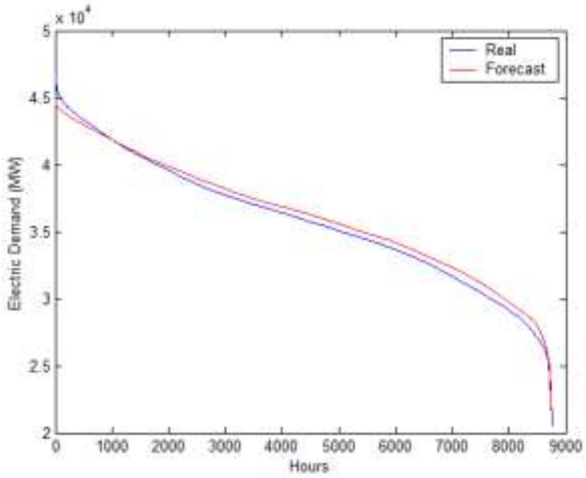

Fig. 23: Load duration curve comparison

The resulting model considers a generic weekend model that is applied to all 52 weeks of the year, a holiday model to model holidays, and a half-holiday model to handle special dates such as Mother´s Day. Each model involves a fitting of equation (9) using three statistical parameters. Therefore, the final model for the year profile keeps the number of tuning parameters to a minimum of 9, which are manually adjusted based on the historical data.

For the application to construct the 2022 demand profile, all the multiplicative shape profiles of Equation (1) contribute to reducing the demand forecast error, and the MAPE was progressively reduced from 4.88% for the base profile to 3.84% with the weekend model, and finally 3.28% with the weekend and holiday models.

All the programming for the power demand profiles was developed in Matlab, [25].

4 Conclusions and Future Work

The present work describes the calculation of a yearly power demand estimation using profiles to shape a normalized power demand curve. These profiles are: a base annual shape that provides the general tendency of the annual power demand curve; a normalized annual shape, that provides demand details for each week of the year; a weekend shape profile, to model the demand decrease during weekends; and a holiday shape profile, that compensates for the demand decrease during holidays.

The weekend compensation profile is computed using a multiplicative function that allows the modeling of the demand decrease effect observed on Saturdays, Saturdays, and part of Mondays. This effect is systematically applied to all weekends of the year.

Grouping the annual data into 4-week periods allows us to implicitly consider weather conditions. The resulting power profile contains the basic information expected in a forecast and can be systematically constructed with low computational effort.

The constructed power profile takes into account expected components, such as weekends, holidays, and Holy Week characterization. The results are satisfactory and show it is possible to build a yearly profile with an average MAPE of less than 4%. An example hourly power profile with an average daily MAPE of 3.3% was achieved for the 2022 power demand profile.

Results show a tendency of the MAPE to be higher during weekends. Because this work computes and applies a unique weekend shape function for all 52 weeks of the year, additional work could be conducted to analyze the adequacy of the weekend gamma statistical parameters for different periods of time along the year. Having variable statistical settings throughout the year could improve the forecasts for weekends. Furthermore, the adaptation of the statistical parameters for the shape functions was made manually. A better calculation of these statistical parameters could be achieved using an optimization algorithm to minimize an error expression or applying techniques such as machine learning or artificial intelligence (AI).

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

- Miguel Cecenas-Falcon contributed with the conceptualization, the methodology, and part of the writing.
- Uriel I. Lezama-Lope contributed with formal analysis, validation and part of the writing.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding other than the provided by the author's institution of adscription was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare.