Guidehouse
Outwit Complexity

Improvement 3 – IRP Forecast Support

Development of hourly customer class demand profiles by transmission planning area, 2024-2050

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LUMA

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Reference No.: 221964142
2024-04-18

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1. Executive Summary

Guidehouse developed an hourly demand forecast spanning fiscal years 2024-2050 for all of Puerto Rico (Puerto Rico-level) and for each of eight geographic regions of Puerto Rico, referred to as transmission planning areas (TPA-level). In addition to a base forecast, Guidehouse developed alternate high and low-demand scenarios to reflect forecast uncertainty. The forecast was developed by applying customer class demand profiles to forecasts of monthly energy consumption of the six customer classes (residential, commercial, industrial, agriculture, public lighting, and other authorities).

The monthly forecasts for the primary customer classes (residential, commercial, and industrial) are driven by macroeconomic and temperature conditions.[1] Guidehouse tested over 1,500 candidate model specifications for each class, selecting the model that provided the most accurate out-of-sample prediction of monthly energy consumption.[2] The results were consistent with the findings of the previous monthly forecast results developed by Guidehouse for LUMA as part of the Load Forecast Improvement 2.[3] In January 2024, Guidehouse updated the underlying monthly customer class energy forecasts to align more closely with the latest version of LUMA's Fiscal Plan Forecast.[4]

The annual sales forecast results are presented in Figure 1. The shaded bands indicate the range between the alternative high and low forecast scenarios.

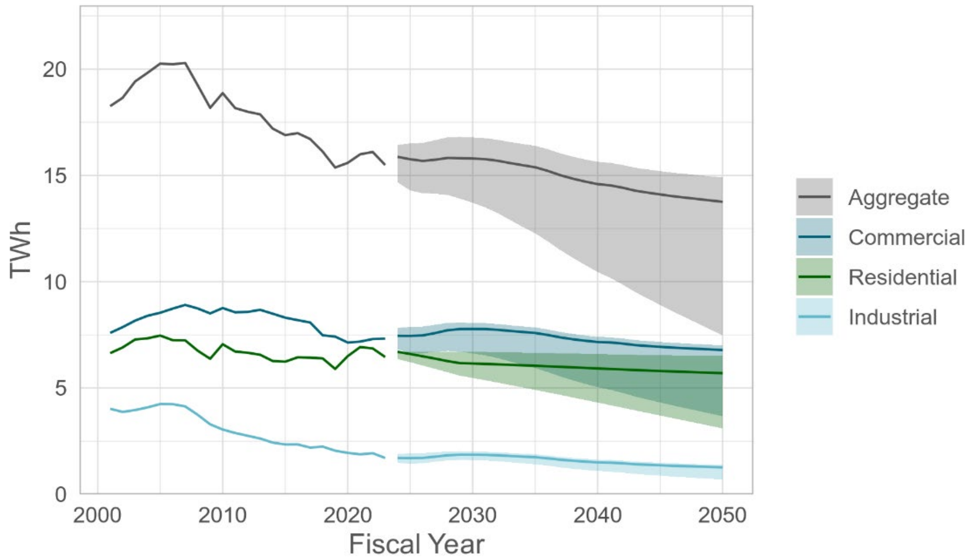
[1] The Improvement 3 forecast results are driven by macroeconomic and temperature conditions but *are not adjusted to account for future customer adoption of load modifiers*, including electric vehicle charging, distributed generation, energy efficiency, or demand response. Improvement 3 results are an "unadjusted" forecast. Impacts from distributed energy resource adoption, energy efficiency, etc. should be applied to the forecast as load modifiers.

[2] Subject to selection criteria as described in section 4, below.

[3] "Improvements" are defined scopes of work that fall within Guidehouse's larger load forecasting workstream. The goal of Improvement 2 was to estimate a new set of parameters to provide the unadjusted energy forecast that is part of the revenue forecast workflow.

[4] LUMA's Fiscal Plan Forecast undergoes continuous reevaluation and is updated as new data becomes available. The IRP forecast reflects the available data as of February 2024. Guidehouse expects that the Fiscal Plan Forecast will continue to be revised and differences will emerge between the two forecasts.

Figure 1. Annual Sales Forecast Results, Primary Customer Classes

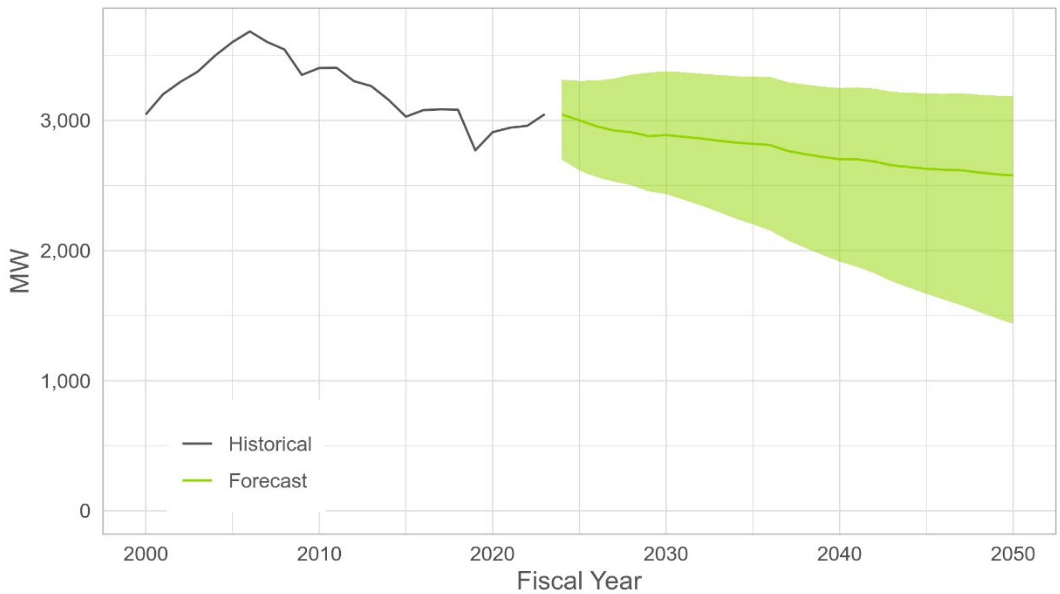


Source: LUMA, analysis by Guidehouse

Energy sales are projected to decline, consistent with forecasts of declining population and Gross National Product (GNP) in Puerto Rico. In the near term (2024-2026) residential sales are projected to decline more rapidly as the COVID-19-driven increase in residential consumption erodes. Sales are projected to increase somewhat between 2026 and 2029 driven by an increase in commercial and industrial consumption corresponding with temporary growth in forecasted GNP in the near term. Overall, aggregate sales fall from 16.2 TWh in FY2024 to 14.1 TWh in FY2050.

Figure 2 depicts the range of annual peak demand forecasts. Consistent with the sales forecast, peak demand is projected to decline from just above 3 GW in FY2024 to 2.6 GW in FY2050.

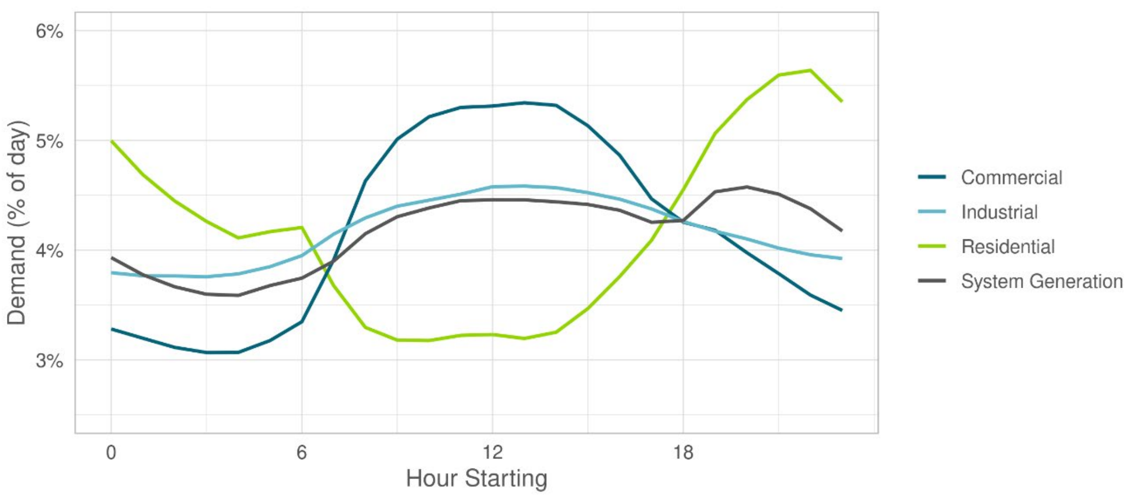
Figure 2. Annual Peak Demand, History and Forecast



Source: LUMA, analysis by Guidehouse

Class demand profiles from the most recent available pre-COVID-19 year (FY2019) were applied to forecast sales to derive estimated hourly demands. Figure 3 depicts average customer class and system demand profiles during summer weekdays.

Figure 3. FY2019 Customer Class and System Demand Profiles (Weekday, Summer)



Source: Guidehouse

Historically, LUMA's Puerto Rico-level peak demand typically occurs between 8 p.m. - 9p.m. driven by high evening consumption from the residential sector. Across forecast scenarios, the

Puerto Rico and transmission planning area[5] (TPA) peaks are projected to continue occurring during evening hours with the exception of the San Juan TPA. The San Juan TPA has a higher ratio of commercial to residential demand than the other seven TPAs. In San Juan, the high commercial demand produces an afternoon peak (1 p.m. - 2p.m.) coinciding with hours of high commercial demand.

[5] Transmission planning areas are the eight groups of municipalities that were defined to aid in the analysis of the transmission system and generation resources in the next LUMA IRP.

2. Introduction

In fall 2022, LUMA engaged Guidehouse to support the development of an hourly demand forecast which will be a key input to LUMA's Integrated Resource Plan (IRP). The hourly demand forecast (Improvement 3) is the third stage in a series of load forecasting improvements that LUMA has undertaken with support from Guidehouse. The goal of the broad set of improvements is to deliver a more accurate and useful forecast of monthly class-level consumption, and annual system peak demand. The motivation and strategy behind LUMA's load forecast improvements are outlined in greater detail in its Regulatory Long-Term Load Forecast Review report.[6]

The Improvement 3 demand forecast builds on the results from prior Improvements 1 and 2[7], and its primary outcome is to disaggregate the monthly long-term forecast for each customer class (residential, commercial, industrial, agriculture, public lighting, and other authorities) into an 8760 hourly forecast at the Puerto Rico and TPA levels from fiscal years 2024 to 2050.[8] Improvement 3 also includes additional high/low demand scenarios that reflect uncertainty about future economic and temperature conditions. The TPA level results are distinguished by eight TPA. The results can be used to identify the expected magnitude and timing of demand peaks at the Puerto Rico and TPA levels for both generation and distribution planning.

The Improvement 3 forecast results are driven by macroeconomic and temperature conditions but *are not adjusted to account for future customer adoption of load modifiers*, including electric vehicle charging, distributed generation, energy efficiency, or demand response. Improvement 3 results are an "unadjusted" forecast. Impacts from distributed energy resource adoption, energy efficiency, etc. should be applied to the forecast as load modifiers.

[6] Guidehouse, prepared for LUMA, *Regulatory Long-Term Load Forecast Review: Current State Assessment & Future Methods Recommendations*, June 2022
https://energia.pr.gov/wp-content/uploads/sites/7/2022/07/Motion-Submitting-Regulatory-Long-Term-Load-Forecast-Review-NEPR-MI-2021-0001.pdf

[7] Improvement 1 remediated historical monthly sales and hourly system generation data to address irregularities caused by billing system issues and electric service disruptions. Improvement 2 estimated a monthly sales forecast to be used for various purposes including revenue projection. See Appendices A and B for more information on these Improvements.

[8] LUMA's fiscal year calendar begins on July 1 of the prior year and ends on June 30. For example, fiscal year 2022 began on July 1, 2021.

3. Methodology and Data Overview

This section provides a summary of the approach and data used to develop the hourly demand forecast. A more detailed discussion of the individual elements of the approach may be found in Sections 4, 5, 6, and 7.

3.1 Methodology

Figure 4 provides a brief overview of the Improvement 3 approach.

Figure 4. Methodology Overview

Source: Guidehouse

1) **Update Monthly Sales Forecast.** Guidehouse expanded on the Improvement 2 monthly sales forecast by conducting additional econometric regression model testing for the primary customer classes (residential, commercial, and industrial) and incorporating a monthly sales forecast for secondary customer classes (agriculture, public lighting, and other authorities).

    - For each primary customer class, Guidehouse tested a broader set of candidate models using additional macroeconomic data.

    - For the secondary customer classes, Guidehouse adopted LUMA's existing long-term annual forecast and allocated the annual forecast values to month-interval values.

    The outcome of this step was a monthly energy forecast for the base scenario.

2) **Construct Class Demand Profiles.** Guidehouse constructed historical hourly demand profiles (FY2009 – FY2022) for each customer class using hourly rate-class data from historical rate-class load studies.[9]

3) **Develop High/Low Forecast Scenarios.** To account for forecast uncertainty, Guidehouse developed alternate high/low demand scenarios. The alternate scenarios were developed using three sources of uncertainty: variation in macroeconomic forecasts, variation in monthly average temperature conditions, and variation in the timing of historical annual peaks. Macroeconomic variation was derived from Moody's Analytics' Economic Forecast &

[9] Each of LUMA's six customer classes (residential, commercial, industrial, agriculture, public lighting, and other authorities) are comprised of one or more rate classes.

Historical Databases.[10] In February 2024, Guidehouse revised the low forecast scenariosfor the three primary customer classes to reflect a plausible future with energy demand continuing to decline along pre-COVID-19 pandemic trends. Specifically, the original low scenarios were adjusted by applying declining trends in average energy use per customer based on data from FY2011 – FY2019. In addition, Guidehouse revised the high forecast scenario for the residential customer class to understand the sensitivity of residential consumption when the COVID-19 "bump" in consumption persists indefinitely (i.e., through 2050).

4) **Construct Hourly Puerto Rico-Level Forecast.** Guidehouse applied customer class demand profiles to the base and alternate scenario forecasts to project Puerto Rico-level hourly class demands for all forecast years (FY2024 - FY2050).

5) **TPA Allocation.** Guidehouse allocated the hourly Puerto Rico-level scenario forecasts to eight TPAs based on recent historical (FY2022) customer class sales within each TPA.

The Improvement 3 analysis was built on a foundation from Improvements 1 and 2, where the remediated historical data developed in Improvement 1 were used in all modeling steps.[11] Remediated historical sales data were used in the training and validation (out-of-sample testing) sets for the monthly sales regression analysis. Remediated hourly system generation data was used to calibrate the customer class demand profiles. The sales forecast update (methodology step one) was built on the regression analysis and monthly energy sales forecast from Improvement 2.[12]

3.2 Data

Table 1 contains a description of the most significant data items used in Improvement 3.

Table 1. Data Sources

Item	Source	Contents	Primary Application
Customer Class Energy Sales	Output from Improvement 1 (Data Remediation)	Historical monthly sales (MWh) for each of the three primary customer classes (residential, commercial, and industrial) Years: FY2009 – October of FY2024	Estimation of updated monthly sales forecast models
Historical System Generation	Output from Improvement 1 (Data Remediation)	Historical hourly aggregate electricity generation (MW) Years: FY2009 – October of FY2024	Development and calibration of historical hourly customer class profiles

[10] Moody's Analytics, *Economic Forecast & Historical Databases – Extensive Economic Information at the Global National and Subnational Levels*, accessed February 2023 https://www.moodysanalytics.com/-/media/products/Economic-Databases-Historical-Forecast.pdf

[11] See Appendix A for additional information about Improvement 1.

[12] See Appendix B for additional information about Improvement 2.

Item	Source	Contents	Primary Application
Historical Macroeconomic Data	Junta de Planificación de Puerto Rico (JPPR)	Historical Gross National Product (GNP); population; manufacturing employment	Estimate monthly sales regression models
Macroeconomic Forecast	Financial Oversight and Management Board for Puerto Rico (FOMB)	Single (base) forecast scenario of GNP and population	Forecasting monthly sales
Moody's Macroeconomic Data	Moody's Analytics	Historical and probabilistic forecast scenarios Gross domestic product (GDP); population; manufacturing employment; leisure and hospitality employment	Forecasting monthly sales
Historical Temperature Data	NOAA	Hourly temperature in San Juan region 2000 - 2022	Forecasting monthly sales Determine sensitivity of system peak to temperature conditions
Secondary Class Energy Sales Forecasts	LUMA	Long-term annual energy sales forecast (FY2023 – 2050) Short-term monthly energy sales forecast (FY2023)	Development of monthly sales forecast for secondary classes
Historical Rate Class Profiles[13]	LUMA	Single-year (8,760 hours) demand profiles for each rate class based on sampled meter study data from FY2009-2014	Development of historical customer class profiles
Technical & Non-technical Losses	LUMA	Loss Rates by transmission/distribution voltage level	Convert forecast sales at meter to generation requirement
Historical municipal level sales by class	LUMA	Historical monthly sales by customer class and municipality	Allocation of Puerto Rico-level forecast to TPAs

Source: Guidehouse

[13] Many of the profiles are from 2010. These are the best available, until data becomes available from the updated hourly load research sample that LUMA is currently collecting.

4. Approach to Update Monthly Sales Forecast

The first analysis step in the Improvement 3 approach was the development of an updated forecast of monthly energy sales for each customer class. Primary and secondary customer classes were handled separately.

For primary customer classes (residential, commercial, and industrial), Guidehouse developed the monthly sales forecast using the Improvement 2 regression analysis approach, which relied on macroeconomic indicators and temperature as independent variables. Improvement 3 included an extensive testing process that considered additional macroeconomic data, and a broader set of model specifications than had been reviewed in Improvement 2. Ultimately, the same forecast models selected in Improvement 2 were selected again in Improvement 3, which served to confirm the results of the more simplified analysis performed for Improvement 2.

For secondary customer classes (agriculture, public lighting, and other authorities), Guidehouse reviewed LUMA's existing forecast methodology and determined it provided a reasonable projection of energy consumption and was sufficient considering the small overall contribution to the total system load of these classes. Guidehouse adopted LUMA's existing sales forecast for these classes.

The Improvement 3 sales forecast results should be considered an unadjusted forecast. These forecasts do not account for the incremental adoption of distributed energy resources (i.e., distributed generation, distributed storage, energy efficiency and demand response), electric vehicle charging or other potential load modifiers, aside from those whose effects are implicitly included in the historical consumption data.

4.1 Regression Testing

The Improvement 2 sales forecast selection was limited to the forecast macroeconomic variables provided by FOMB.[14] For the Improvement 3 forecast, Guidehouse considered additional sources of macroeconomic data to assess the potential benefits of additional macroeconomic variables and to support uncertainty analysis as discussed in Section 6.1. LUMA obtained additional macroeconomic history and forecast data series from Moody's Analytics. Table 2 contains a list of the variables considered for inclusion in the primary customer class monthly sales forecast models.

Table 2. Variables Included in Candidate Regression Models

Item	Contents
Monthly Binary Variables	12 binary "dummies" to capture seasonal variation and other temporal effects.
Cooling Degree Days	Monthly aggregate cooling degree days (CDD) based on Puerto Rico average hourly temperature. Included in models both alone and interacted with monthly binaries.

[14] PREPA requires LUMA's revenue forecast to be derived from forecast macroeconomic variables provided by the FOMB.

Item	Contents
JPPR Macroeconomic Indicators	GNP ($Millions, 1954). A twelve-month moving sum of GNP. Manufacturing Employment (Thousands). Population (Thousands).
Moody's Analytics Macroeconomic Indicators	GDP Real (2012 USD) and nominal. Manufacturing Employment (Thousands). Leisure and Hospitality Employment (Thousands). Population Total vs. household count.
Electricity Price	$/kWh Historical average by fiscal year and customer class (residential, commercial, and industrial).

Source: Guidehouse

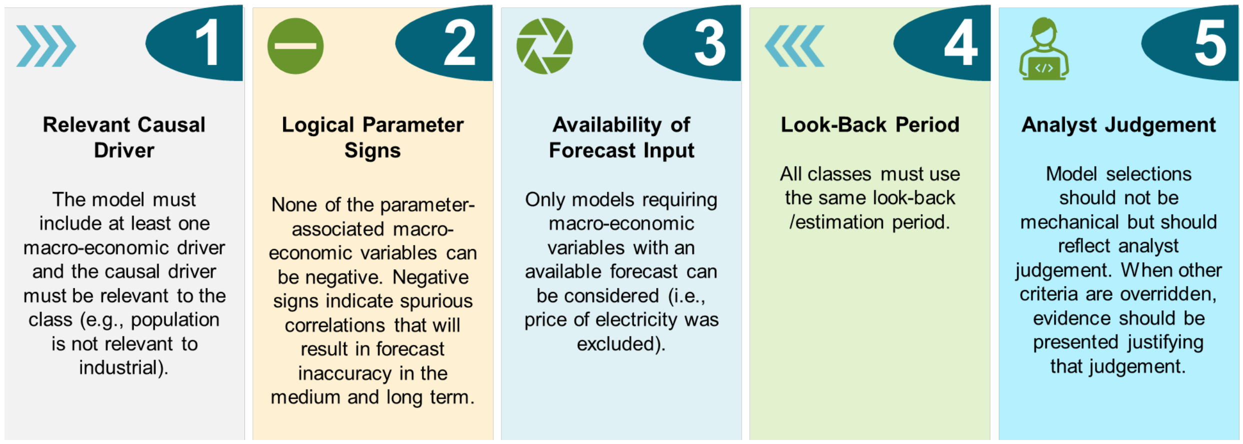
To determine which variables were the most accurate predictors of customer class demand, Guidehouse conducted an out-of-sample regression testing and validation procedure. Guidehouse defined 225 model specifications, each of which was a unique combination of the variables described in Table 2. Guidehouse also varied the number of years of historical data included in the training set to test alternative lookback periods. Combining 225 model specifications and eight alternative lookback periods, over 1,500 candidate models for each primary customer class were tested.

To evaluate the performance of the predictive models, Guidehouse excluded a period of recent monthly sales data from the model estimation data set and used it as an out-of-sample validation set. A year of predictions from each candidate model was compared against observed monthly sales from the 12 months prior to the beginning of the COVID-19 pandemic (March 2019 – February 2020).[15] Guidehouse selected the model that had the best out-of-sample performance subject to the additional selection criteria described in Figure 5.[16]

[15] COVID-19 resulted in a material, but short-lived, decline in commercial consumption, and a significant and sustained increase in residential consumption from FY2020 through FY2022.Despite a slight downturn in FY2023, preliminary data from FY2024 suggest a sustained increase in residential consumption compared to pre-pandemic trends.

[16] To assess performance, models were ranked in terms of the mean absolute error of their predictions compared to the actual data from the out-of-sample validation period.

Figure 5. Sales Forecast Regression Model Selection Criteria



Source: Guidehouse

4.2 Model Selection

Guidehouse found that models with the additional macroeconomic variables did not outperform the regression models selected in the previous Improvement 2 analysis. No candidate models had any meaningfully improved out-of-sample performance after applying the selection criteria. The regression models selected for Improvement 3 are the same as those selected for Improvement 2 and used for the revenue forecast filing with PREPA. In January 2024, LUMA's revenue forecast model specifications were revised to address emerging trends in post-COVID-19-pandemic energy consumption patterns. In February 2024, Guidehouse updated the Improvement 3 model specifications to align more closely with the revenue forecast model specifications.[17] The revised models include additional terms to account for changes in energy consumption patterns that occurred in recent years.

After selecting the final model specifications, Guidehouse re-estimated the selected models using the full historical period from the beginning of the selected lookback period (FY2011) through October of FY2024. The final commercial and residential models include variables for months impacted by COVID-19 consumption changes. The residential COVID-19 impact variable scales down linearly from 100% in 2020 to 0% by May of FY2028.[18] The embedded assumption is that the step-change increase in residential consumption that was correlated with the start of the COVID-19 pandemic is gradually declining and is assumed to disappear completely by May of FY2028. The commercial COVID-19 variable only applies in the months of March, April, and May of calendar year 2020 and has no direct impact on sales during the forecast period.

[17] Due to timing constraints, the underlying monthly customer class energy class forecasts do not completely align with the latest version of LUMA's Fiscal Plan Forecast. The Fiscal Plan Forecast was updated in March 2024, when the macroeconomic forecasts (e.g., Gross National Product and population) were provided to LUMA.

[18] The impacts of COVID-19 on electricity consumption in future years is uncertain. The scaling assumption of the COVID-19 impact variable reflects the Guidehouse forecast team's expectations based on trends in recent historical electricity sales.

The following sections describe the final monthly forecast models. Table 3 contains a key to the model specifications in the subsequent sections.

Table 3. Model Specification Key

Model Term	Definition
y_t	Class-level billed consumption (GWh) of residential customers in month of sample *t*.
$month_{m,t}$	A set of twelve binary variables capturing monthly seasonality. Each variable is equal to one when month of sample *t* is the *m*-th month of the calendar year and zero otherwise. For example, variable $month_{1,t}$ is equal to one when month of sample t is January, and zero otherwise.
CDD_t	Monthly cooling degree days observed in month of sample t. These are drawn from the National Weather Service as a monthly series for the San Juan Area.
GNP_t	A 12-month moving sum of the gross national product. This monthly series is derived from an annual series provided by the Junta de Planificación de Puerto Rico[19], supplemented (as necessary) by the FOMB.[20] The annual series is converted to monthly by dividing year-over-year (fiscal years) change in GNP by 12 and apply this increment in each month of the year.
Pop_t	Estimated total population by month, derived from annual values obtained by LUMA from the U.S. Census.
$COVIDwin_t$	A variable equal to one in the period beginning November of calendar year 2020 running through the end of April of calendar year 2021, and zero otherwise. This captures the impact of COVID-19 on consumption in the winter after the emergence of COVID-19.
$post2019_t$	A variable equal to one in calendar years 2020 through 2023, declining by 0.2 each May (beginning in May of calendar year 2024) until it reaches zero in May of calendar year 2028, and zero otherwise. As indicated by the monthly interaction and the subscripts on the associated summation, this applies only in the months from May through October of each year (i.e., it takes a value of zero in the period from November through April).
$CDD500_t$	A variable equal to the difference between observed (or forecast) CDD and 500. Average weather in the months to which this is applied (via the interaction with the monthly binary and its associated summation scripts) – June through October – CDD is on average always higher than 500. This variable is an attempt to better apply some weather sensitivity to the modeling.
$month_{m\in(5,10),t}$	A variable equal to one if month of sample *t* is either the fifth or the 10th month of the calendar year (May or October), and zero otherwise. That is, the parameter associated with the group of variables that begins with this one captures the post-2019 temperature-sensitive COVID-19 "bump" to residential consumption

[19] Junta de Planificación de Puerto Rico, *Tablas Apéndice Estadístico Del Informe Económico Al Gobernador 2021*, September 2022, "TABLAS-DE-APENDICE-ESTADISTICO-2021-1.xlsx" https://jp.pr.gov/apendice-estadistico-del-informe-economico-a-la-gobernador/

[20] The FOMB periodically provides LUMA with update forecast macroeconomic variables. The work in this document is based on the forecast provided to LUMA March 24, 2023.

Model Term	Definition
	for the months of May and October. The model assumes that this relationship is the same for both May and October.
$COVIDCOMtrans_t$	a variable equal to one in March, April, and May of calendar year 2020, and zero otherwise.
$indBinary_t$	A variable equal to one if month *t* is March of calendar year 2022 or later, and zero otherwise.
$\beta_{m,1}\ \beta_2$	Regression-estimated parameters (coefficients).

Source: Guidehouse

Residential Sales Model. The selected model estimates monthly residential energy sales as a function of monthly binaries, CDD, population, and COVID-19 effects. There are several terms used to detect various changes in consumption patterns related to COVID-19. The first COVID-19 term addresses impacts during the first winter after the COVID-19 pandemic outbreak. The latter two terms that include the post-COVID-2019 variable account for interactive effects of high temperature during summer months beginning in 2020. Historically, May and October have similar temperature conditions and consumption, so Guidehouse combined these into a single term to simplify the model.

$$y_t = \sum_{m=1}^{M=12} \beta_{1,m} month_{m,t} + \beta_2 CDD_t + \beta_3 Pop_t + \beta_4 COVIDwin_t$$
$$+ \sum_{m=6}^{M=9} \beta_{5,m} month_{m,t} \cdot post2019_t \cdot CDD500_t + \beta_6 month_{m\epsilon(5,10),t} \cdot post2019_t$$
$$\cdot CDD500_t + \varepsilon_t$$

Commercial Sales Model. The selected model estimates monthly commercial energy sales as a function of monthly binaries, CDD, interactions of CDD and monthly indicators, and GNP.

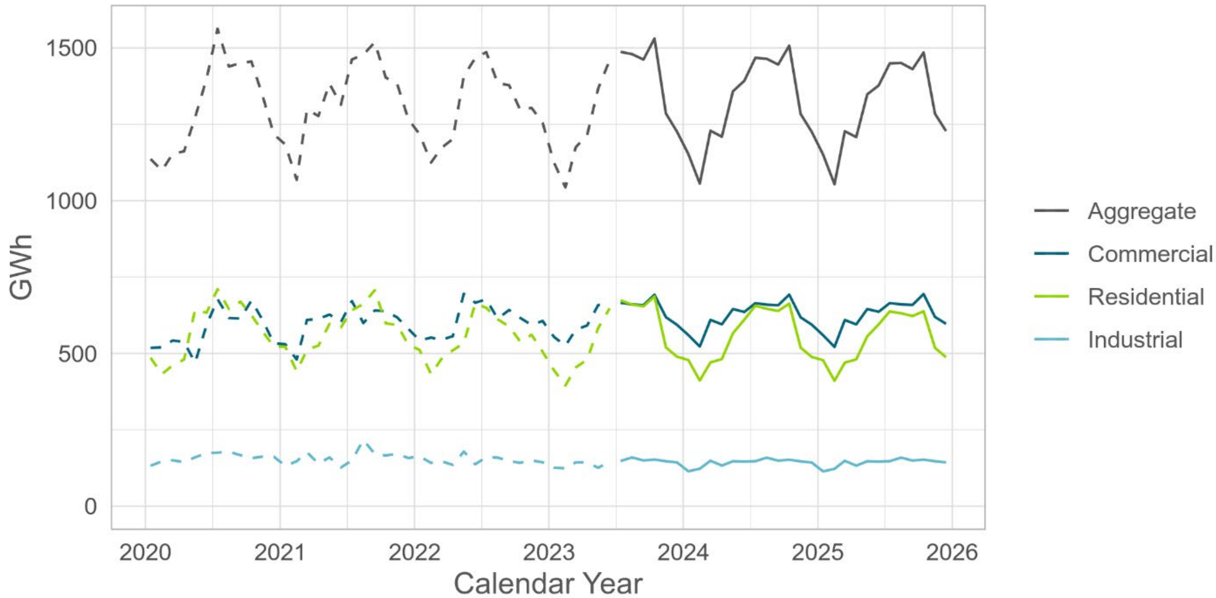
$$y_t = \sum_{m=1}^{M=12} \beta_{m,1} month_{m,t} + \sum_{m=1}^{M=12} \beta_{m,2} month_{m,t} \cdot CDD_t + \beta_3 CDD_t +$$
$$\beta_4 GNP_t + \beta_5 COVIDCOMtrans_t + \varepsilon_t$$

Industrial Sales Model. The selected model estimates monthly industrial energy sales as a function of monthly binaries and GNP.

$$y_t = \sum_{m=1}^{M=12} \beta_m month_{m,t} + \beta_2 GNP_t + \beta_3 indBinary_t + \varepsilon_t$$

Figure 6 depicts a sample of historical (dashed lines) and forecast (solid lines) monthly sales for each of the three primary customer classes.

Figure 6. Monthly Sales History and Forecast, Primary Customer Classes (2019-2025)



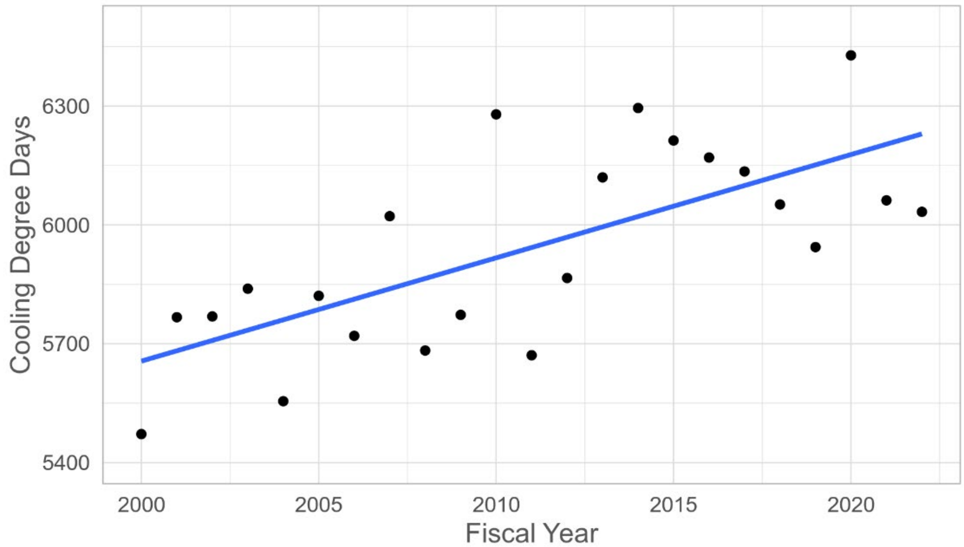
Source: LUMA, analysis by Guidehouse

4.3 CDD Projections

While reviewing historical CDD data from 2000-2022 for Puerto Rico, Guidehouse observed an apparent warming trend in annual CDD. Figure 7 depicts the historical annual values and estimated temporal trend. The observed trend is consistent with findings in peer-reviewed academic literature.[21]

[21] Khalyani, Azad Henareh; Gould, William A.; Harmsen, Eric; Terando, Adam; Quinones, Maya; and Collazo, James A. Climate Change Implications for Tropical Islands: Interpolating and Interpreting Statistically Downscaled GCM Projections for Management and Planning, American Meteorological Society, February 2016 https://www.researchgate.net/publication/293811670_Climate_PuertoRico_2016

Figure 7. Warming Trend in Historical CDD



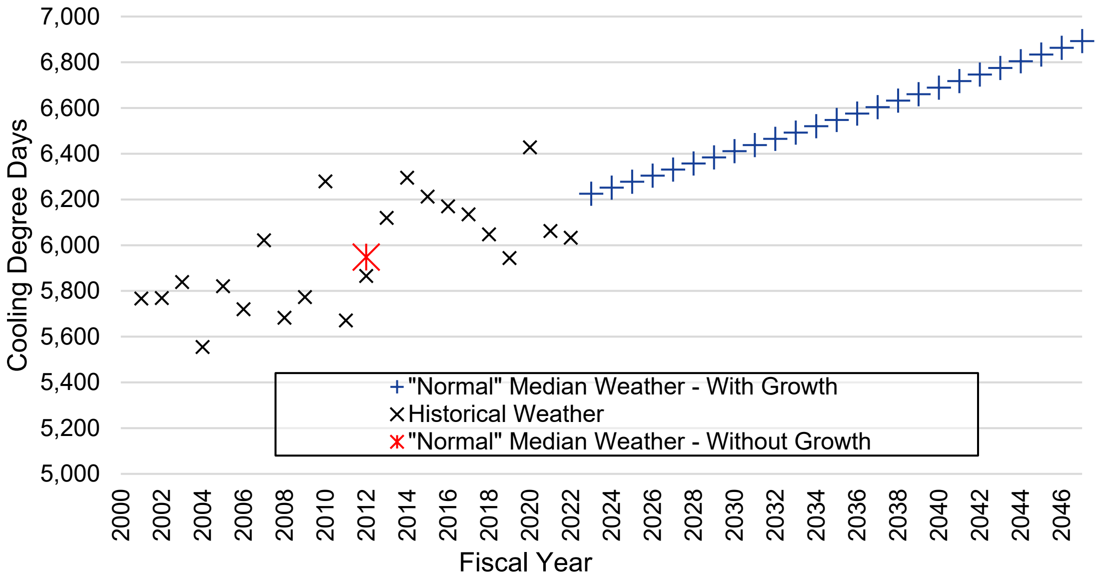
Source: NOAA, analysis by Guidehouse

Guidehouse incorporated the warming trend by applying an escalation to the monthly weather-normal CDD in the forecast period using a compound annual growth rate of 0.47%. This was slightly lower than, but consistent with the value used by the LUMA load forecasting research team in their previous forecasting (a CAGR of 0.68%).[22] In practice, a CAGR of 0.47% leads to an increase of approximately 28 CDD per year. Guidehouse applied the trend to historical CDD values to produce a projection of temperature outcomes for forecast years.

Figure 8 shows observed annual values of CDD (black x), the 50th percentile median value across the historical period (red cross with bar), and the trend-escalated “normal” (50th percentile) CDD applied in the forecast period (blue crosses).

[22] The LUMA team derived this growth rate from Khalyani et al. (2016)

Figure 8. Projection of Escalated "Normal" CDD



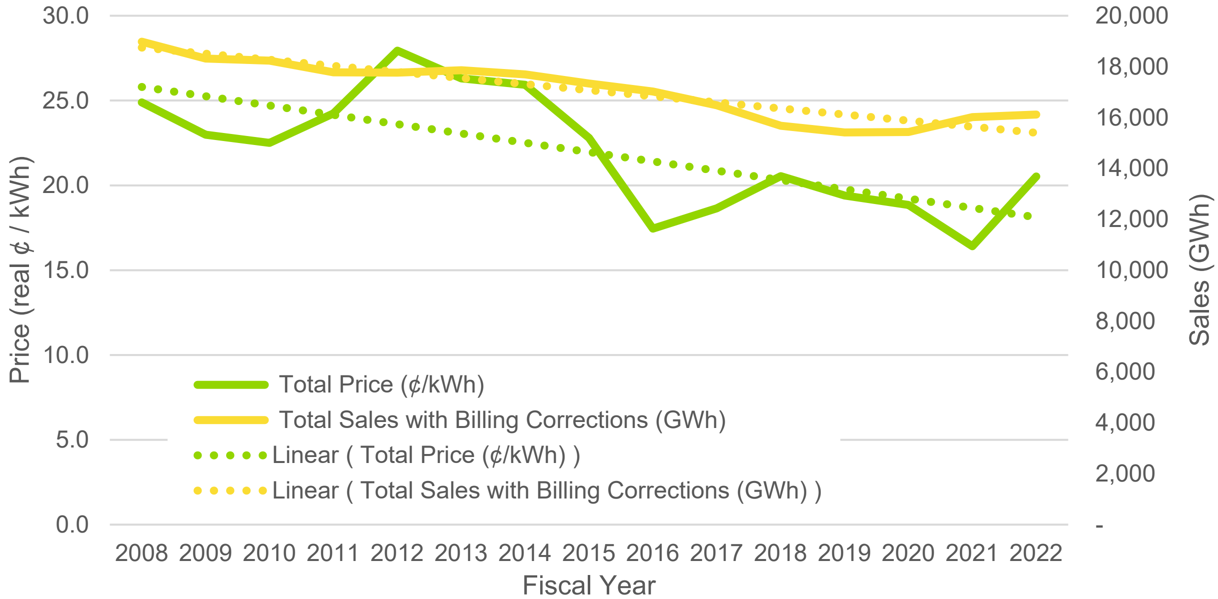
Source: NOAA, analysis by Guidehouse

4.4 Price Sensitivity Analysis

As a component of the sales forecast regression analysis, Guidehouse tested customer sensitivity to electricity price using data on annual average electricity price for each customer class.

Figure 9 depicts historical sales and price trends for the combined residential, commercial, and industrial classes.

Figure 9. Historical Price and Sales Trends



Source: LUMA, analysis by Guidehouse

Real (inflation adjusted) electricity price and sales both declined from 2008 to 2022. The declining trend is present for all the primary customer classes. The fact that price appears to be positively correlated with sales (the opposite of expectations) indicates that – compared with other factors driving both series – demand for electricity is relatively price-inelastic.

In the regression testing procedure, Guidehouse tested all candidate model specifications with and without electricity price as a predictive variable. Price provided no meaningful improvement in predictive accuracy.[23]

4.5 Secondary Class Forecast

After reviewing LUMA's internal forecast methodology for projecting the annual and monthly sales for secondary customer classes (agriculture, public lighting, and other authorities), Guidehouse determined it was sufficiently robust given the size of these classes. Guidehouse used the LUMA forecast of sales for these classes as an input for the Improvement 3 forecast.

Historically, secondary classes represent a relatively small contribution of LUMA's total sales. Secondary customer classes combined accounted for approximately 2% of total Puerto Rico energy sales in FY2022.

LUMA's forecast approach for the smaller classes is based on a static linear extrapolation of historical sales. This approach reflects an assumption that secondary class sales will remain relatively constant across years. This approach is consistent with the approach taken in

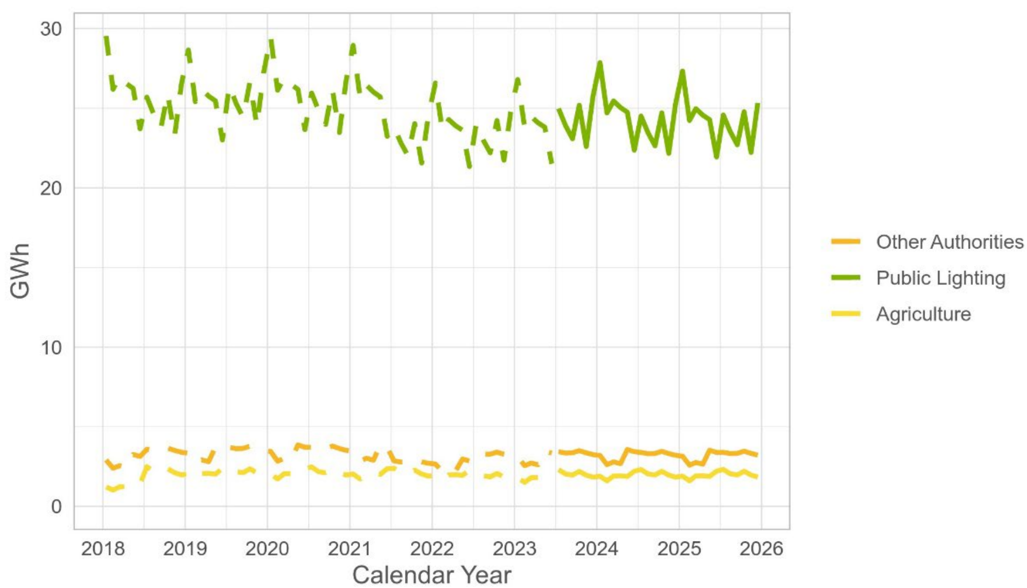
[23] Generally, the models that included price produced greater errors when predicting on the out-of-sample test set. In the rare cases that price models had comparable error metrics to the selected models, the price models were excluded due to the other selection criteria (e.g., illogical parameter sign as described in section 4.2).

PREPA's previous IRP filing in 2018. Guidehouse compared a back-cast using LUMA's secondary class forecast method against actual historical sales for the secondary classes. The back-cast error (mean absolute error) was 0.2% of historical total electricity sales, well within an acceptable margin of error.

Guidehouse reviewed the LUMA forecast methodology, the historical data, and the relative contribution of these secondary customer classes. Due to the relatively small magnitude and historical stability of secondary class sales, Guidehouse concluded that forecast models based on linear extrapolations of historical sales were sufficiently robust for use in Improvement 3.

For each secondary customer class, Guidehouse allocated LUMA's annual energy sales forecast into a monthly interval forecast based on LUMA's near-term (1-year) monthly sales forecast. Figure 10 depicts a subset of the monthly forecast results for the secondary customer classes.

Figure 10. Monthly Sales History and Forecast, Secondary Customer Classes



Source: LUMA, analysis by Guidehouse

5. Approach to Construct Customer Class Demand Profiles

After developing the monthly sales forecast, the next step in the Improvement 3 analysis was to develop hourly demand profiles for all six customer classes. Guidehouse developed profiles for each customer class using the available historical rate-class hourly demand profiles. The available profiles were relatively dated, having been defined using source data from within FY 2009 – FY2014.[24] To update the profiles, Guidehouse used a regression approach to predict historical rate class profiles for all historical years and calibrated the results to the hourly system generation profile.

After constructing calibrated demand profiles for the full historical study period (FY2009 – 2022), Guidehouse tested them to identify which historical profile year would provide the most representative demand profiles for hourly allocation of forecast monthly sales.

In coordination with LUMA, Guidehouse also developed estimates of customer class loss rates that could be applied to scale up meter-level demands to a generation-level supply requirement.

5.1 Constructing Historical Class Profiles

For each rate class, LUMA provided a one-year, hour-interval (8,760) demand profile drawn from a series of metering studies conducted between FY2009 and FY2014. To aggregate rate-class profiles into the customer-class level profiles required for forecasting, it was necessary to obtain rate-class profiles for a consistent set of historical years. It was also important to update the profiles to account for changes in system-level demand patterns between FY2009 and FY2022.

Guidehouse used historical hourly system generation data to estimate the relationship between hourly rate class demand and system generation. The regression model took the following form:

$$y_t = \sum_{m=1}^{M=12} \sum_{k=1}^{K=4} \sum_{h=1}^{H=24} \beta_{mkh} \cdot SysGen_t \cdot Month_m \cdot DayType_k \cdot Hour_h + \varepsilon_t$$

Where:

y_t is the natural log of the rate class demand profile value in hour t normalized to observed monthly consumption of the month in which hour *t* falls.

$SysGen_t$ is the natural log of the system generation profile value in hour t.

$Month$ is a set of binaries, one for each calendar month.

[24] Most of the rate-class profile data was from FY2009 – FY2011. The age of the data represents a source of uncertainty in the forecast. LUMA is currently planning a project to develop updated class demand profiles.

$DayType$ is a set of binaries, one for each of four categories: (1) non-holiday weekdays, (2) holidays and weekends, (3) peak weekdays, and (4) peak holidays and weekends.[25]

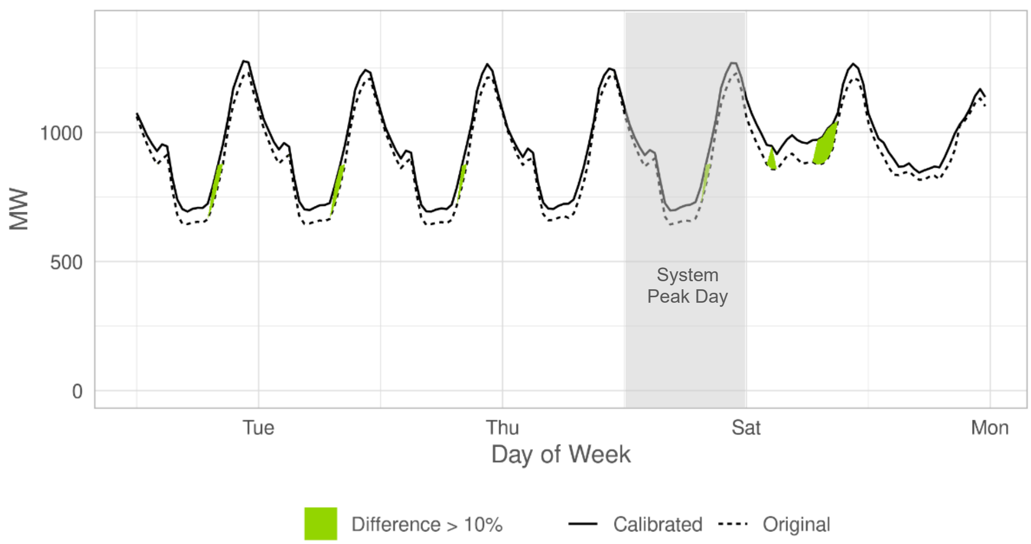
$Hour$ is a set of binaries, one for each hour of the day.

β_{mkh} is the set of regression coefficients uniquely defined for each hour h of day type k in month m.

Using the estimated regression parameters, Guidehouse predicted hourly demand for each rate class throughout the historical study period (FY2009 - FY2022). Guidehouse aggregated the rate-class profiles to produce customer class profiles.

Guidehouse then calibrated the profiles to the historical remediated monthly class-level sales and to hourly system generation. Figure 11 depicts a sample of the residential class profile before and after calibration to the system generation profile.

Figure 11. Profile Calibration Adjustment – Residential Profile Sample (August 23-29, 2021)



Source: Guidehouse

5.2 Profile Selection

After developing hourly customer profiles for all years in the historical period of analysis, Guidehouse selected a single historical year to provide a representative set of projected customer class demand profiles.

The principal criterion Guidehouse considered in the selection of the historical profile year was predictive accuracy. Guidehouse's selection of the historical profile year was determined by that

[25] A day was considered a peak day if it was among the top four system peaks occurring on a weekday or top two system peaks occurring on weekend day in terms of aggregate system peak separately within each month.

which provides the most accurate prediction of peak demand in a historical back-cast relative to other candidate profile years.

To test the predictive accuracy of candidate profile years, Guidehouse applied the demand profiles from each year in FY2019 - FY2022 (the candidate years) to historical sales from 2010-2022. Guidehouse compared the resulting predicted peak demand to actual historical system peak generation. The magnitude of the predicted system peaks was consistent across the four candidate profile source years.

However, the *timing* of the predicted system peaks varied, in turn meaning that the relative contributions of the classes to peak varied. Historically, LUMA's system peaks have occurred between 8 p.m.–9 p.m. and are largely driven by the peak in residential demand. In the profile testing procedure, some source profiles predicted historical annual peaks during afternoon hours, during periods with high *commercial* demand.

Demand profiles from FY2019, when applied to historical sales, produced an evening peak (8 p.m. - 9 p.m.) in all historical years, which was consistent with hourly system generation history. Each of the other profile source years candidates (FY2020 - FY2022) produced predicted peaks occurring during afternoon hours (2 p.m.–4 p.m.) in some historical years of the back-cast. The poor predictive performance of the FY2020 - FY2022 profiles in the back-cast may be explained in part by changes in consumption patterns related to COVID-19. Profiles from FY2020 - FY2022 may not be reflective of consumption patterns in future years when COVID-19 impacts have diminished.

For this reason, Guidehouse used the FY2019 class demand profiles to forecast.

5.3 Customer Class Profiles

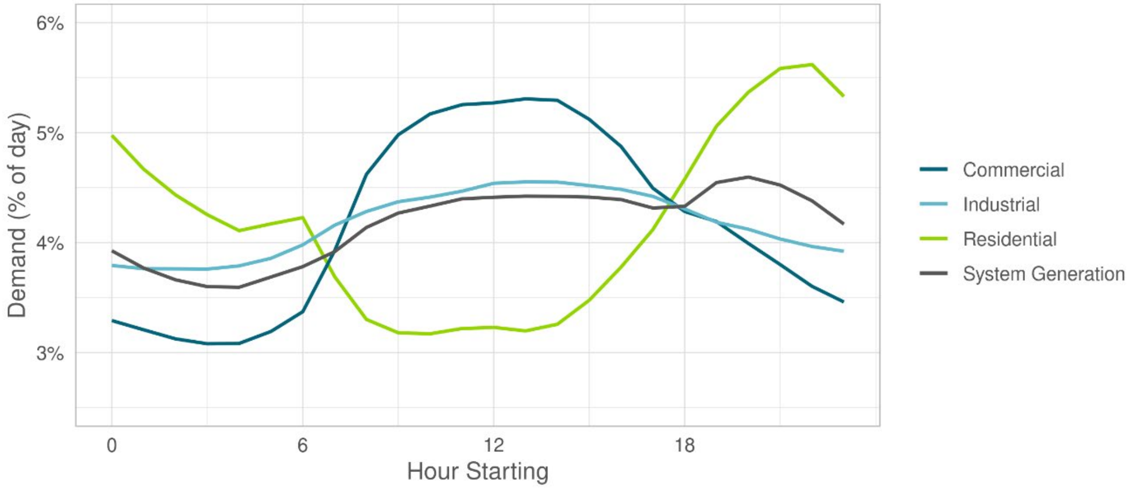
Figure 12 depicts average customer class load shapes by season (summer vs winter) and day type (weekday vs weekend/holiday). The load shapes are consistent across the winter and summer seasons.

The industrial profile (the light blue line) is relatively flat throughout the 24-hour period though industrial demand is slightly higher between 8 a.m. and 6 p.m. on weekdays than in other hours. Commercial demand (dark blue line) is relatively low at night and high between 9 a.m. and 3 p.m. Residential demand (light green) is low during the day and peaks between 9 p.m. and 10 p.m. The residential demand profile peak may be driven by residential air conditioning load.[26]

The average daily peak in the aggregate system profile occurs between 7 p.m.–9 p.m. and appears primarily driven by residential class demand. Every annual peak demand (i.e., peak generation output) since FY2002 has occurred between 8 p.m.–10 p.m.

[26] Based on conversations with LUMA staff, Guidehouse understands that it is common for Puerto Rico residents to use ductless air conditioning units in bedrooms and to use them primarily in the evening.

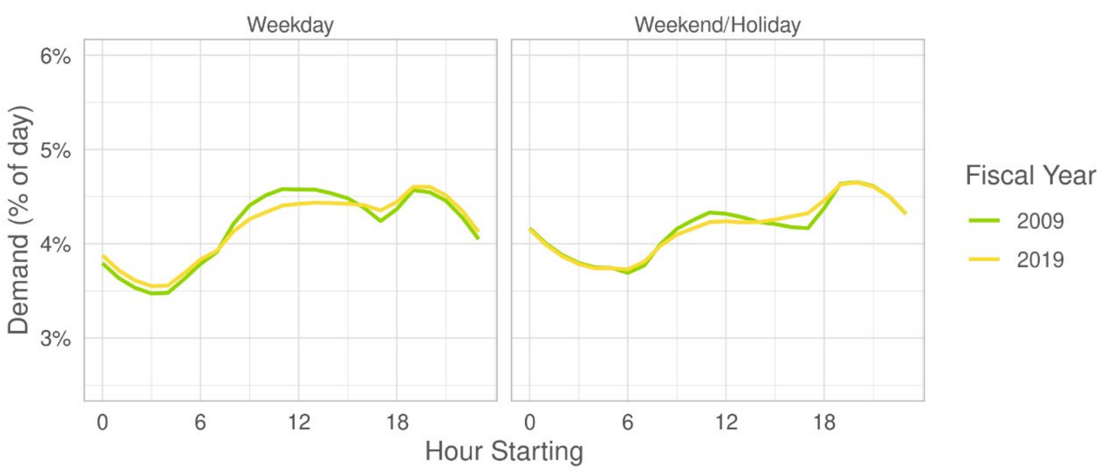
Figure 12. FY2019 Customer Class and System Demand Profiles (Weekday, Summer)



Source: Guidehouse

Figure 13 depicts average system-level demand profiles in FY2009 and FY2019. Over time, consumption during mid-day hours (8a.m. - 3p.m.) has declined and consumption in the late afternoon and evening (4p.m. - 10p.m.) has increased slightly. These changes may be the result of increased adoption of air conditioning and by the decline in Commercial sales, which contribute a greater share of mid-day demand.[27]

Figure 13. Change in Historical System Demand Profile, FY2009 vs FY2019



Source: LUMA, analysis by Guidehouse

[27] In FY2009 commercial sales were approximately 30% higher than residential sales, but in FY2022 they were only about 6% higher.

5.4 Loss Rates

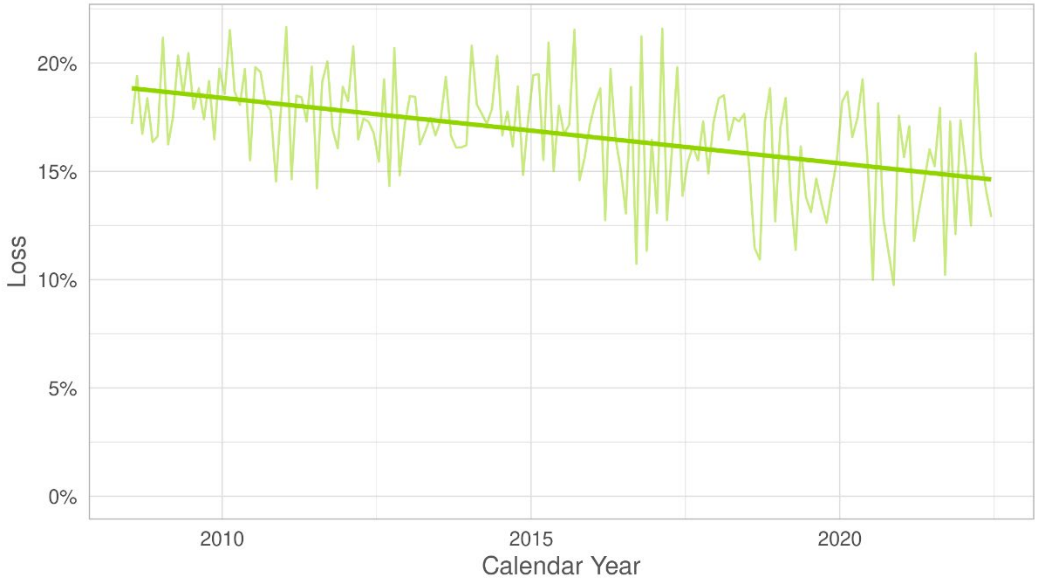
The last component of the demand profile development was the estimation of loss rates to account for the portion of the gross generation that is not billed due to transmission and distribution losses, generation plant auxiliary loads, consumption at LUMA/PREPA facilities, power theft, and consumption from other unknown users. Guidehouse applied loss rates to translate monthly sales and demand profiles at the meter into estimates of hourly generation requirements.

In the following section,we use the following terms:

- **Non-technical loss, which includes:**
  - Loss attributed to power theft
  - Loss attributed to unbilled consumption from unknown users
- **Net technical loss, which includes:**
  - Transmission loss
  - Substation Loss
  - Primary distribution loss
  - Secondary distribution loss
- **Gross technical loss, which includes:**
  - All items included in net technical loss (as noted above)
  - Auxiliary load consumption at power plants
  - Consumption at LUMA/PREPA facility (own-use)
  - Consumption from other unbilled and known legitimate users
- **Total loss, which includes:**
  - Non-technical loss
  - Gross technical loss

Figure 14 depicts historical total loss rates from FY2009 through FY2022. Guidehouse derived the loss data in the figure from system generation and sales data outputs from Improvement 1. From FY2009 to FY2022, total loss rates in LUMA's service territory declined from approximately 18% to 15%.

Figure 14. Historical Total Loss Rates



Source: LUMA, analysis by Guidehouse

Guidehouse used data, provided by LUMA, on non-technical and net technical loss by transmission and distribution voltage level to produce bottom-up estimates of customer class loss rates. Guidehouse applied a calibration adjustment to convert the net technical loss estimates to gross technical losses consistent with the top-down estimates from historical aggregate sales and generation data. Table 4 contains estimates of non-technical loss rates, net and gross technical loss rates, and total loss rates by customer class.[28]

Table 4. Customer Class Loss Rates

Customer Class	Non-Technical Loss (A)	Net Technical Loss (B)	Gross Technical Loss (C)	Total Loss (A + C)
Residential	3.7%	10.3%	15.2%	18.9%
Commercial	2.5%	7.7%	11.6%	14.1%
Industrial	1.0%	3.3%	5.2%	6.2%
Agriculture	3.7%	10.3%	15.2%	18.9%
Public Lighting	3.7%	10.3%	15.2%	18.9%
Other Authorities	0.9%	3.0%	4.7%	5.6%

Total loss is the difference between electricity at the generation source and metered sales.
All loss columns are defined as percent of electricity output at the generation source.

Source: Guidehouse

28 Class loss rate estimates are differentiated based on transmission/distribution voltage level. Residential, agriculture, and public lighting share common loss rates because LUMA provided data indicating that all customers in these classes are served by secondary distribution voltage.

6. Approach to Develop Alternative Forecast Scenarios

To account for uncertainty in the demand forecast that is a result of uncertainty in the forecast of macroeconomic conditions, temperature, and system peak demand. Guidehouse developed a range of high and low demand scenarios. Guidehouse incorporated four sources of variation.

1) **Variation in macroeconomic conditions.** Guidehouse applied a set of alternative macroeconomic forecast scenarios from Moody's Analytics FOMB-forecast macroeconomic variables to construct a set of alternative input macroeconomic conditions for which demand scenarios could be estimated. Alternative economic scenarios from FOMB were not available. The range between the low and high macroeconomic forecasts from Moody's Analytics was narrow. To better reflect a plausible lower bound, Guidehouse applied an additional adjustment to the low demand scenarios for the three primary customer classes and to the high demand scenario for the residential class.

2) **Variation in average monthly temperature conditions.** Guidehouse used the distribution of historical temperature to construct high and low demand scenarios reflecting variation in monthly CDD.

3) **Other peak variation.** Guidehouse applied an additional adjustment of +/- 170 MW to system peak demand in the high/low temperature scenarios to account for short-term local weather conditions and other factors that might influence peak demand without significantly impacting average monthly CDD. The magnitude of this adjustment was selected based on the distribution of historical peak demand.

4) **Historical declining trend in per-customer energy use.** Guidehouse applied an additional adjustment to the alternative low-demand forecast to reflect a scenario with use-per-customer returning to pre-pandemic trends. Use-per-customer declined for all major classes (residential, commercial, industrial) during the pre-pandemic period (2011-2019).

5) **Persistence increase (i.e., COVID-19 "bump") of residential consumption.** Guidehouse applied an additional adjustment to the alternative high-demand forecast for the residential customer class to account for the uncertainty in the persistence of the COVID-19 "bump" in residential consumption. This high-demand forecast assumes that the effect persists indefinitely (i.e., through 2050).

The first three of these items were applied to both high and low demand scenarios. Item four applies only to the low demand scenarios for the three primary customer classes. Item 5 applies only to the high demand scenario for the residential class. Items 1, 2, 4, and 5 influence average hourly demand via the monthly sales forecast. The third source of variation was applied as an adjustment to the hourly demand values on peak days.

6.1 Macroeconomic Scenarios

Guidehouse developed the high and low macroeconomic scenarios based on a set of economic forecasts from Moody's Analytics. The Moody's scenarios were defined as follows:[29]

1) **Scenario 0 (S0) – Upside 4th percentile**. This is the economic scenario with the highest economic growth. It is used in the high-demand scenario.

2) **Base – 50th percentile.** This is the core economic scenario used for base forecast.

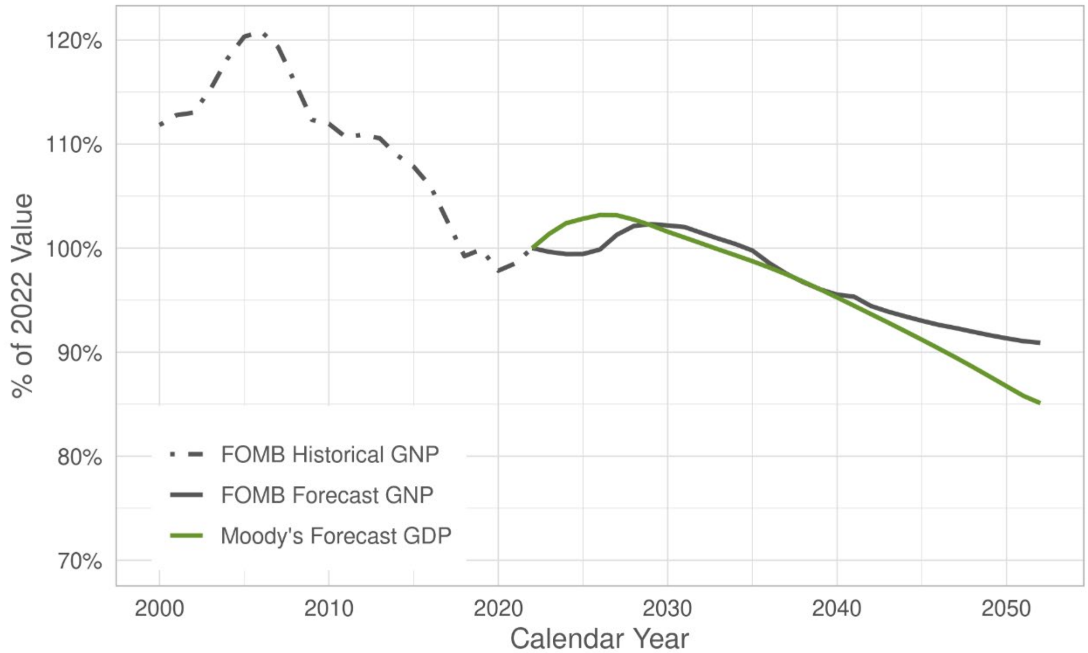
3) **Scenario 4 (S4) – Downside 96th percentile.** This is the economic scenario with the lowest economic growth. It is used in the low-demand scenario.

Upon review of the Moody's base scenario GDP forecast compared to the FOMB GNP forecast, Guidehouse and LUMA observed that the forecasts followed similar general trends. However, the FOMB forecast appears to reflect more specific local information about expected economic conditions. As a result, Guidehouse used the FOMB forecast as the base economic scenario and calibrated the Moody's high/low economic scenarios to be centered around the FOMB scenario. The calibration adjustment preserves the relationship between LUMA loads and FOMB macroeconomic forecasts while simultaneously utilizing the relative variation in the original Moody's scenario forecasts.

Figure 15 depicts a comparison of the FOMB GNP forecast and the Moody's GDP forecast, normalized to their 2022 value. Figure 16 depicts a comparison of the population forecasts. Over the longer term, the forecasts follow parallel trends. In the near term (2023-2027), the Moody's GDP scenario reflects more optimistic growth expectations. The variation in the trajectory of the FOMB GNP forecast appears to reflect more specific local knowledge about economic conditions.

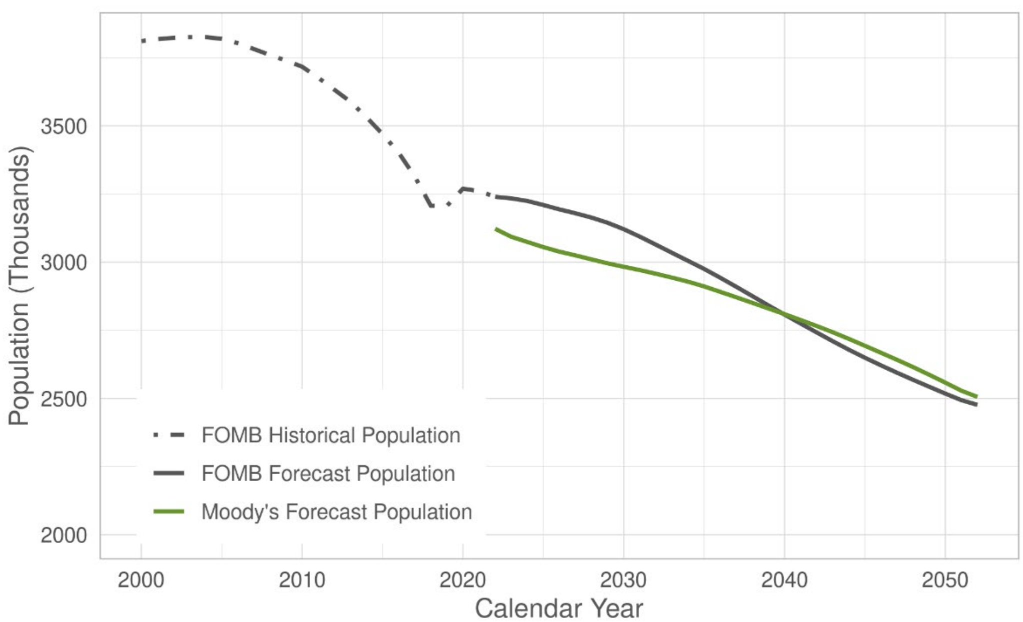
[29] There are additional Moody's Analytics scenarios: S1 (Upside 10th percentile), S2 (Downside 75th percentile), and S3 (Downside 90th percentile). These scenarios fell between scenarios S0 and S4 and provided little additional value.

Figure 15. Economic History and Forecast Comparison, FOMB GNP vs. Moody's GDP



Source: FOMB and Moody's Analytics

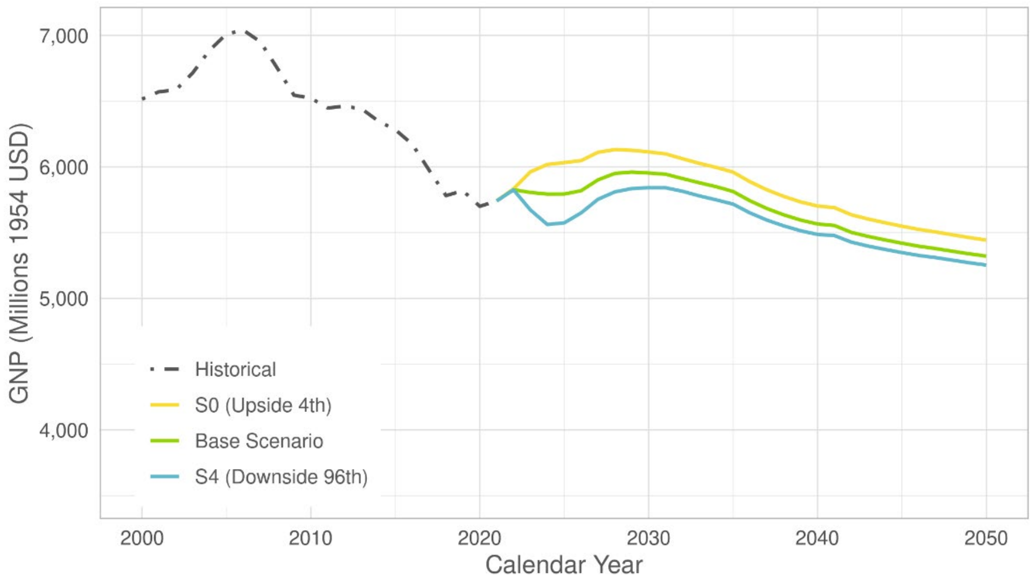
Figure 16. Population History and Forecast Comparison, FOMB vs. Moody's



Source: FOMB and Moody's Analytics

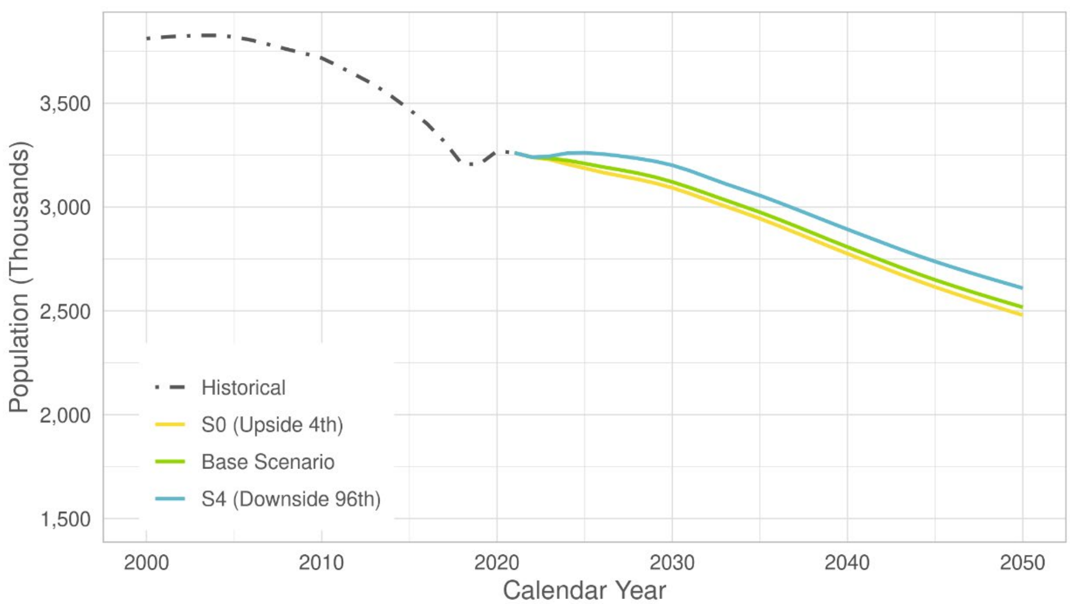
Figure 17 and Figure 18 depict the range of the Moody's Analytics economic scenario forecasts.

Figure 17. GNP Forecast Scenarios



Source: FOMB and Moody's Analytics, analysis by Guidehouse

Figure 18. Population Forecast Scenarios



Source: FOMB and Moody's Analytics, analysis by Guidehouse

Guidehouse observed two noteworthy characteristics of the scenarios.

First, despite the nominally wide range of the scenarios' probabilistic definitions (4th to 96th percentile), they exhibit a relatively narrow range of economic outcomes.

Second, the population forecasts vary across the scenarios with a relationship that is counter to the scenario definitions (upside/downside). For example, the S0 (4th percentile upside) scenario has the highest GNP, but the lowest projected population in all forecast years. Moody's Analytics provided context for this dynamic by explaining that the scenarios reflect high/low growth assumptions at the national level, so the dynamics in Puerto Rico are downstream of economic dynamics at the U.S. country level.[30] Put another way, as national GDP rises, Puerto Rican migration to the continental U.S. increases (reducing population), but since Puerto Rican GDP is tied to national GDP, it rises even as population declines.

The narrow 'within-variable' ranges combined with the countervailing trends in GNP and population across the economic scenarios, lead to the relatively narrow range of demand forecast results that can be attributed to economic uncertainty.

6.2 Temperature Scenarios

Guidehouse developed high and low temperature scenarios by applying alternative CDD projections to predict monthly customer class sales. Guidehouse took all historical weather years 2000-2022 and applied the CDD escalation as described in section 4.3 above. Then, Guidehouse applied the escalated monthly CDD projection from each historical year to each forecast year. Finally, Guidehouse selected the temperature scenario that produced the highest and lowest system level peak demand and labeled them the high/low temperature scenarios.

Due to the limited sensitivity of customer class consumption to CDD and the limited range of historical temperatures, the range of sales between the high and low temperature forecasts is narrow.

6.3 Other Peak Variation

The temperature scenarios reflect variation in average hourly demand due to variation in average monthly CDD, but they do not reflect the full impact of short-term weather events that may have an outsized impact on peak demand despite a relatively small impact on average monthly CDD. Beyond temperature variation, there may be other factors that influence peak demand that are not fully captured by variation in aggregate macroeconomic conditions and normal temperature.

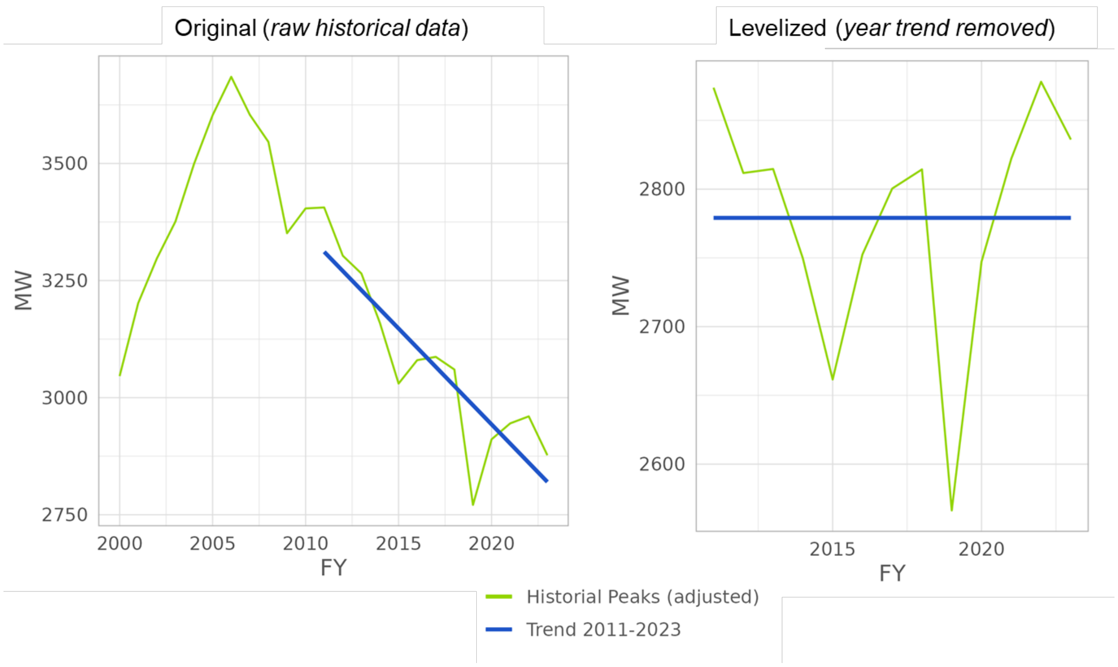
To account for these additional sources of variation in peak demand, Guidehouse applied an adjustment to the high and low demand scenarios. Guidehouse determined the magnitude of the adjustment by estimating the distribution of variation in historical peaks after controlling for temporal trends between FY2011 and FY2022. Figure 19 depicts historical annual peak

[30] Moody's Analytics provided the following explanation for the counter-intuitive population forecast dynamics:

> "The upside shock to GDP in the S0 and S1 scenarios that results from quickly diminishing supply chain issues and much lower COVID-19 cases, hospitalizations, and deaths outweighs the downside shock to population. U.S. GDP is about 6% above the baseline by the end of 2024 in the S0 scenario and about 2.5% above the baseline in the S1 scenario by the end of 2024. The strength in the U.S. economy encourages faster out-migration from Puerto Rico, creating a downside shock to Puerto Rico's population. This downside shock to population ensures that the upside shock to GDP in Puerto Rico is less than nationally. For example, Puerto Rico's GDP is about 4% above the baseline by the end of 2024 in the S0 scenario and about 1.5% above the baseline in the S1 scenario by the end of 2024."

demand before and after adjustment to account for the temporal trend. The results indicated that peaks ranged by +/- 170 MW.[31]

Figure 19. Historical Annual Peak Demand Before and After Temporal Trend Adjustment

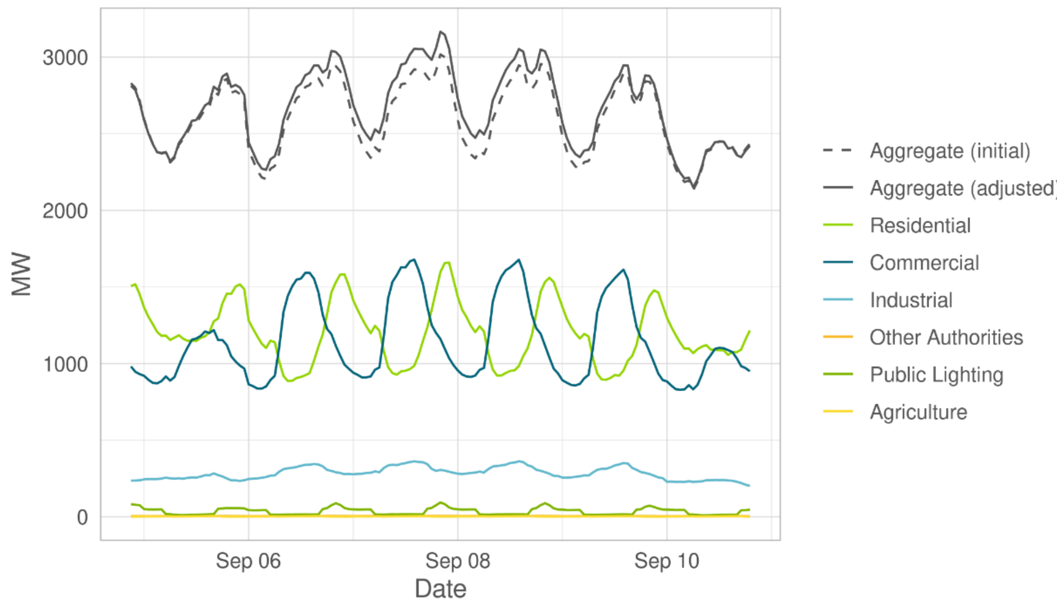


Source: LUMA, analysis by Guidehouse

Guidehouse applied the adjustment of 170 MW in the system peak hour and ramped the adjustment linearly from 0 to 170 over a period of +/- 72 hours from the peak hour. The adjustments were allocated to customer classes in proportion to their original demand. Figure 20 depicts the aggregate demand profile before and after peak adjustment along with the underlying customer class demand profiles for a sample forecast year.

[31] A range of +/- 170 MW approximately aligns with the 95th percentile confidence interval of the mean assuming the theoretical distribution of peak demand in any given year is normally distributed.

Figure 20. High Scenario Peak Adjustment, FY2023



Source: Guidehouse

Although this additional peak variation may not necessarily be driven by weather conditions, Guidehouse embedded the additional peak variation within the high/low temperature scenarios to avoid expanding the total number of alternative scenarios.[32]

6.4 Modified Low and High Demand Scenarios

The alternative low and high demand scenarios are intended to reflect extreme yet plausible outcomes for energy demand in Puerto Rico. Due to the limitations of the economic data described in section 6.1, Guidehouse determined that it was prudent to modify the low-demand scenario for the three primary customer classes to account for the possibility that energy demand returns to pre-pandemic trends. Due to uncertainty about the persistence of COVID-19 consumption impacts, Guidehouse also modified the high-demand scenario for the residential class to reflect an assumption that post-COVID-19 consumption increases continue indefinitely.

6.4.1 Modified Low Demand Scenarios

For each of the primary customer classes, Guidehouse estimated the declining trend in use-per-customer (UPC) between FY2011 and FY2019. Guidehouse estimated a simple linear trend in monthly UPC using data on historical monthly sales and customer counts by class. Table 5 contains the estimated historical kWh trend for each class.

[32] After applying the peak adjustment, Guidehouse recalibrated the class demand profiles to maintain alignment with the monthly sales forecast.

Table 5. Annual Trend in Energy Use-per-Customer FY2011 - FY2019

Customer Class	Trend (UPC per Month)	% of Average Monthly UPC*
Residential	-0.4 kWh	0.11%
Commercial	-6.1 kWh	0.11%
Industrial	-229.0 kWh	0.08%

** Average Monthly UPC was calculated based on average UPC between FY2011 and FY2019*

Guidehouse estimated the incremental decline in consumption for each class by applying the UPC trends in Table 5 to LUMA's internal forecasts of customer populations. Guidehouse produced the final low-demand scenarios by applying the UPC trend adjustment to the low-demand scenario including the sources of demand variation described in the prior sections, 6.1, 6.2 and 6.3.

6.4.2 Modified High Demand Scenario

In the core residential forecast scenario, Guidehouse assumed that the post-COVID-19 increase in residential consumption will gradually decay (at approximately 20% per year) until residential consumption patterns revert to the historical conditional mean patterns by May of calendar year 2028. However, the persistence of this consumption effect remains uncertain. The continued appearance of increased residential consumption during the recent summer of calendar year 2023 could be a result of extreme weather, or some combined effect of weather and the post-2019 consumption change.

Guidehouse modified the residential consumption forecast in the high demand scenario, imposing an assumption that post-COVID-19 consumption effects persist indefinitely (i.e., through 2050).

7. Puerto Rico Level Forecast and TPA Allocation Approach

The sections below describe the approach used to construct the Puerto Rico-level forecast and allocate the system-level forecast to TPAs.

7.1 Puerto Rico Level Forecast

To construct the aggregate, Puerto Rico-level forecast, Guidehouse normalized the selected (FY2022) customer class demand profiles by converting each hour from MW to a percent of monthly aggregate demand. Then, Guidehouse applied the normalized profiles to the forecast of sales in each month. The results were 18 total scenarios: six economic scenarios (S0 upside 4th, S1 upside 10th, Base, etc.) combined with three temperature scenarios (Low, Base, High) spanning all forecast years (FY2023 through FY2050).

When the FY2022 calendar months did not align with the forecast year calendar, the Guidehouse team recycled days (24-hour demand profiles) based on day-type (weekday vs weekend/holidays). For example, in 2022 there were 22 weekdays in May, but in 2023, there will be 23. In such cases the Guidehouse team applied the customer class demand profiles from the first weekday in May 2022 to both the first and last weekday in 2023.

7.2 TPA Allocation

Guidehouse allocated the Puerto Rico-level aggregate hourly forecast scenarios to TPA level forecasts proportional to customer class sales in each transmission planning area in FY2022. The transmission planning areas are defined as groups of municipalities. Figure 21 displays a map of the eight transmission planning areas.

Figure 21. Map of Municipalities by Transmission Planning Areas

Source: LUMA

Guidehouse reviewed historical annual sales in each TPA to assess regional differences in the distribution of customer classes. Figure 22 depicts the distribution of energy consumption by customer classes across historical years in each of the TPAs. Out of the eight TPAs, the most significant difference relative to the Puerto Rico as a whole and the other regions is San Juan. Commercial consumption is a much greater share of overall consumption in San Juan (65%) compared to the other TPAs (25-45%). Residential consumption contributes a lower percentage of total demand in San Juan (~30%) compared to other TPAs (40-50%).

Figure 22. Transmission Planning Areas; Distribution of Consumption by Class

Source: LUMA, analysis by Guidehouse

8. Results and Recommendations

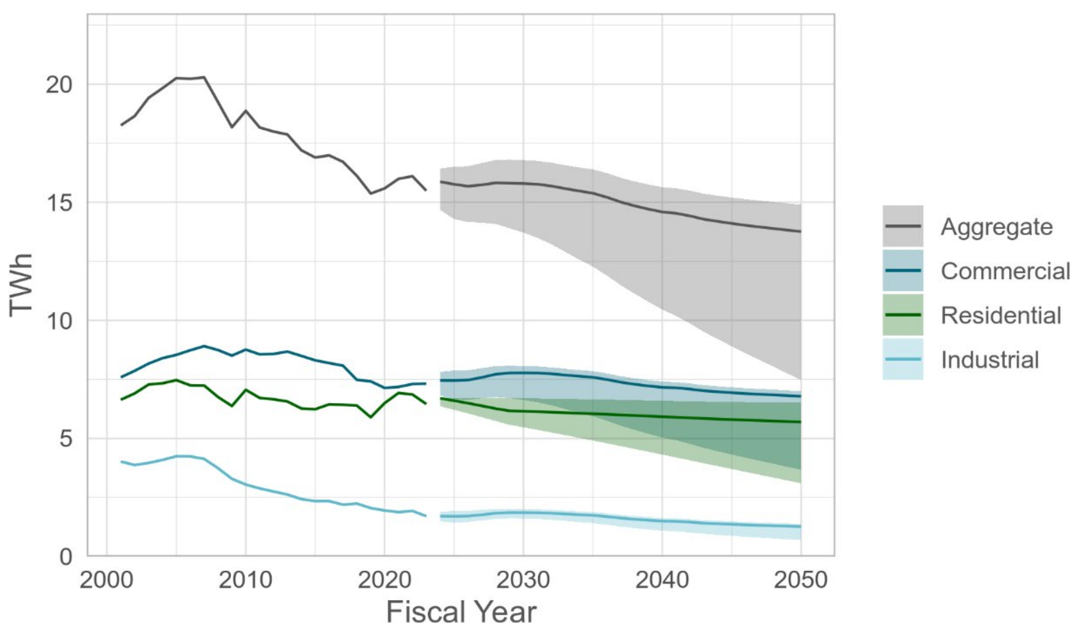
The following sections describe the results of the Puerto Rico-level forecast, scenario forecasts, and TPA-level forecasts. Annual forecast energy values – Puerto Rico-level generation, sales, and peak demand – are available in Appendix C.

8.1 Puerto Rico Level Forecast Results

Figure 23 depicts historical and forecast annual sales (TWh) for the aggregate system and primary customer classes. Over the long run, forecast energy sales decline, continuing a similar trajectory to recent history. However, in the near term (2023-2026) there is a steeper decline in residential demand as the consumption impacts of COVID-19 are expected to fade. From 2026 to 2029, there is a slight increase in sales, driven by projections for temporary growth in GNP between 2025 and 2030.

The shaded ranges above and below the forecast lines indicate the range of the high and low demand scenarios. The range between the core and high demand scenario forecasts is narrow for the commercial and industrial sectors, reflecting the narrow range of the underlying economic forecasts and temperature conditions. The low demand scenario diverges more significantly from the core scenario, following a similar trend as the historical period from FY2011 through FY2019.

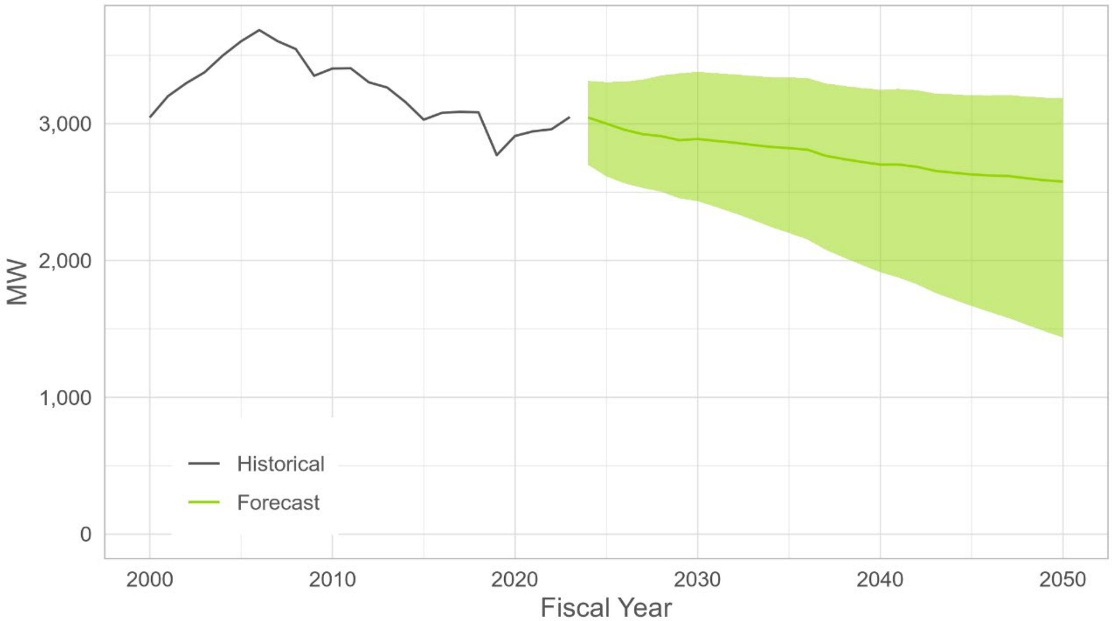
Figure 23. Annual Sales History and Forecast Results



Source: LUMA, analysis by Guidehouse

Figure 24 depicts historical and forecast annual system peak demand. Forecast annual peak declines from just over 3 GW in FY2024 to 2.6 GW in FY2050.

Figure 24. Annual Peak Demand Forecast Results

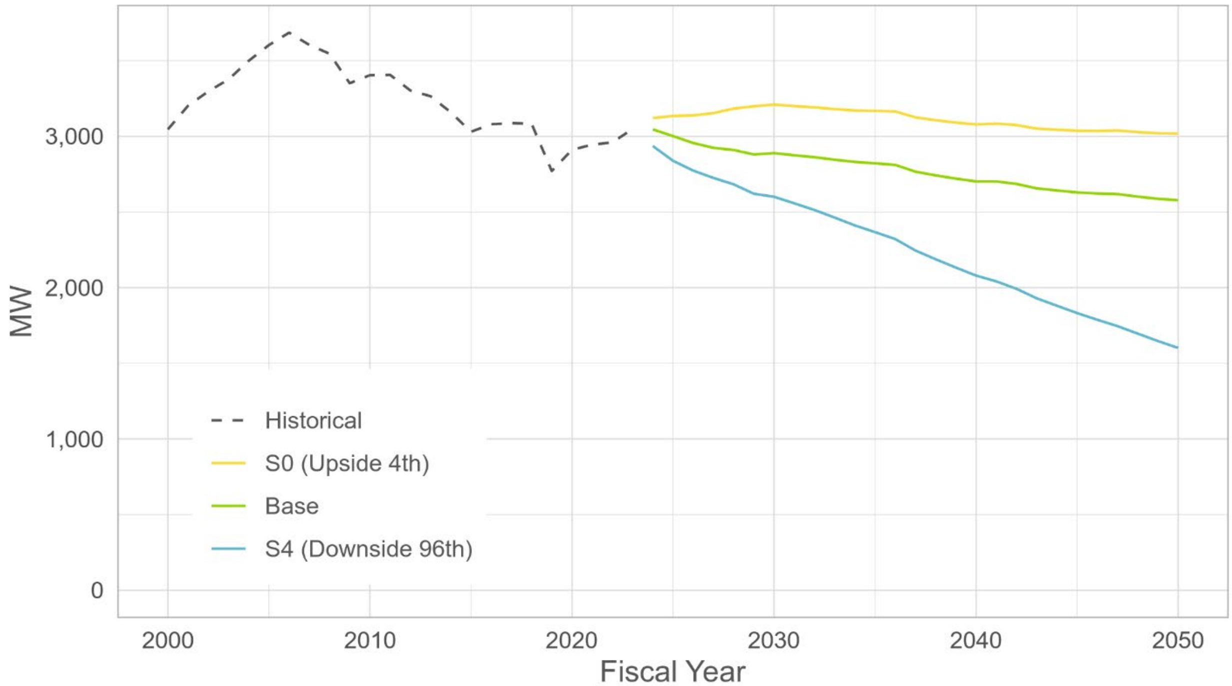


Source: LUMA, analysis by Guidehouse

8.2 Scenario Forecast Results

Figure 25 depicts the range of economic forecast scenarios including the modification to the low demand scenarios for the three primary customer classes and the high scenario for the residential class, as described in section 6.4, and holding the temperature scenario constant (base temperature).

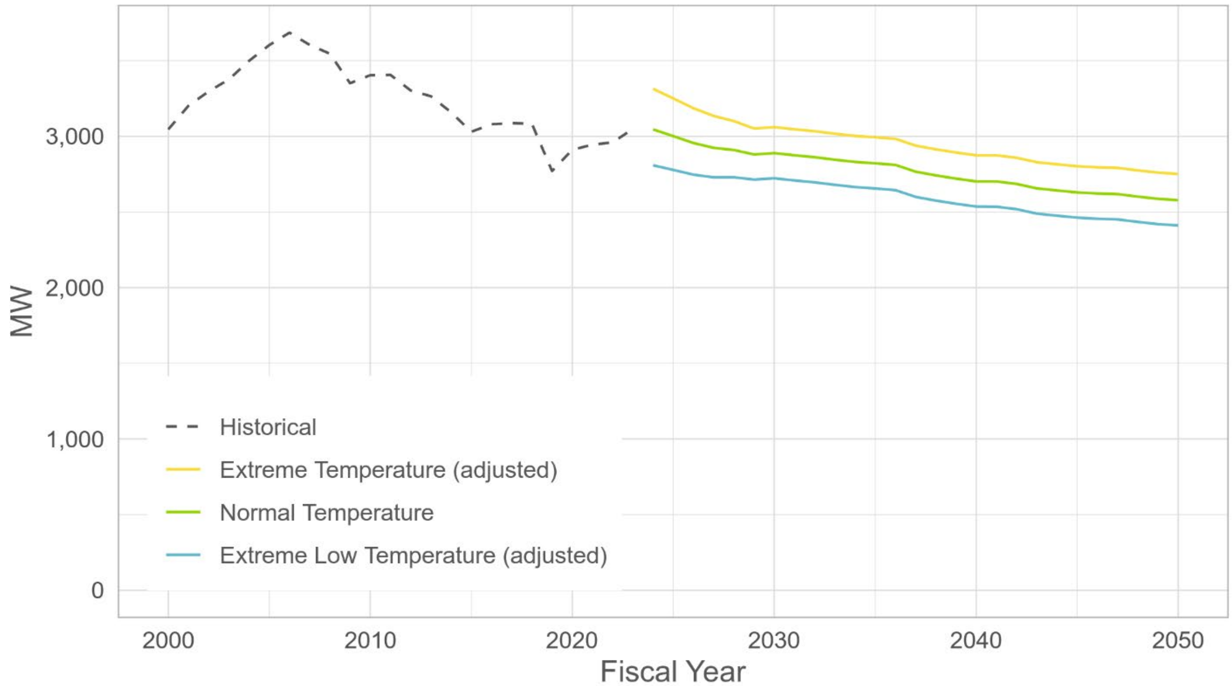
Figure 25. Annual Peak by Economic Scenario



Source: LUMA, analysis by Guidehouse

Figure 26 depicts the range of peak demand temperature forecasts holding the economic scenario constant (base economic scenario). The central forecast scenario reflects the core temperature forecast. The high and low scenarios reflect alternative temperature scenarios with the adjustment for additional uncertainty about annual peak demand outcomes (as described in section 6.3).

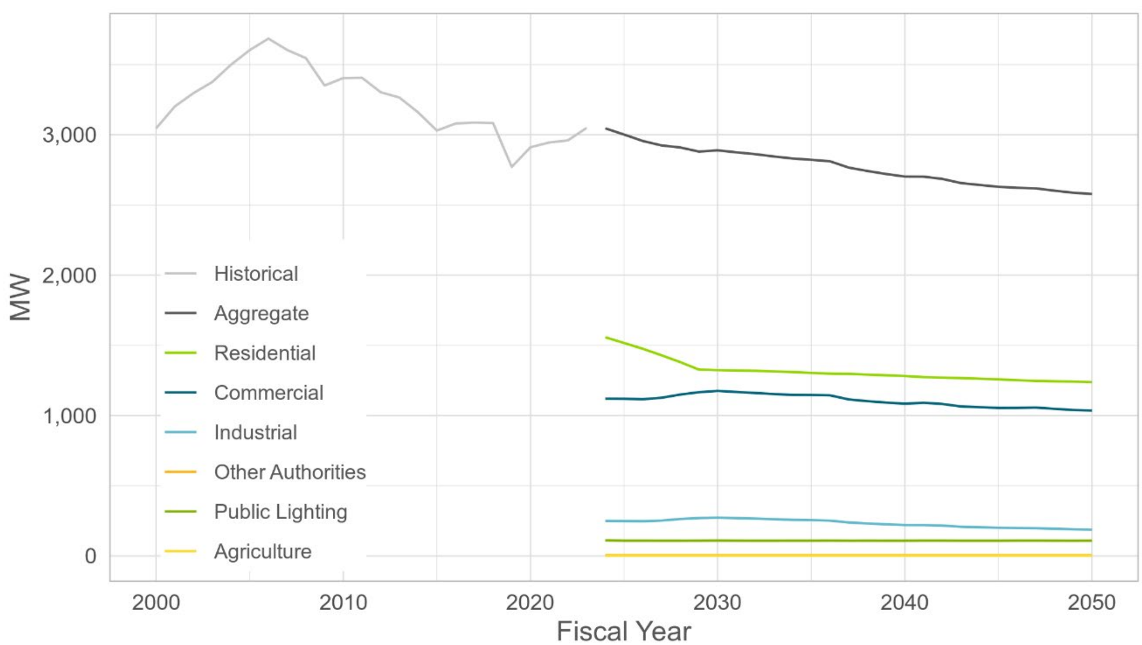
Figure 26. Annual Peak by Temperature Scenario



Source: LUMA, analysis by Guidehouse

Figure 27) depicts annual system peak demand and customer class coincident demand during the system peak hour in each forecast year.

Figure 27. Annual Aggregate and Coincident Class Peaks – Base Scenario



Source: LUMA, analysis by Guidehouse

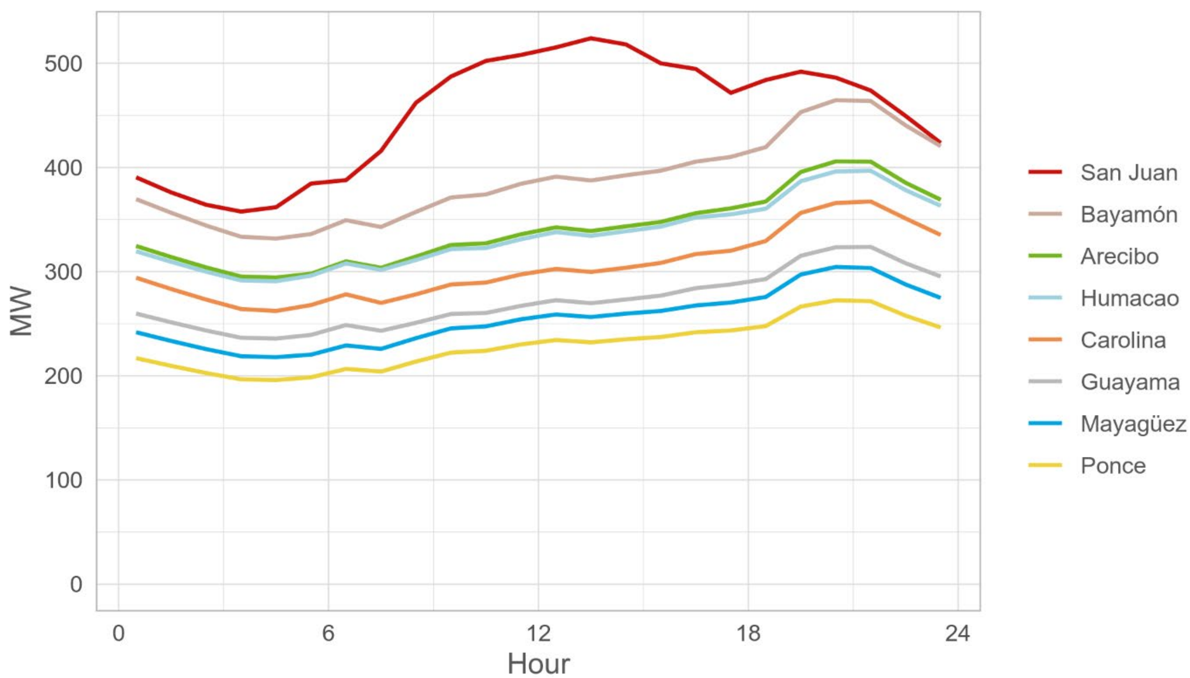
Across the range of economic scenarios, the system peak consistently occurs, as it has done for the previous 20 years, during evening hours (8p.m. – 9p.m.) and is driven by residential demand. The residential sector has the greatest electricity demand during the peak coincident hour.

8.3 TPA Level Forecast Results

Guidehouse allocated hourly Puerto Rico-level customer class demand to TPA level results for the eight TPAs. Figure 28 depicts the peak-day demand profile for each TPA.

Seven of the eight TPAs (all except San Juan) have demand profiles that approximately coincide with the Puerto Rico level peak day profile. In San Juan, due to the large share of consumption by the commercial customer class, the peak in the San Juan TPA occurs between 12 p.m.–1 p.m.

Figure 28. TPA Level Peak Day Demand Profiles



Source: Guidehouse

8.4 Recommendations

As a result of the Improvement 3 analysis, Guidehouse identified the following recommendations for LUMA to consider in future analyses and planning efforts.

Develop Updated Demand Profiles. The most recent hourly customer class demand data that was available was collected between 2009 and 2014. A majority of the profiles were over a decade old. We recommend that LUMA develops updated hourly demand profiles for each customer class.

Consider Potential for Bi-modal Peaks. In the core Puerto Rico-level forecast scenarios the annual system peak is projected to continue occurring during evening hours (8 p.m.–9 p.m.) during periods with high residential class demand. However, in the San Juan TPA and the Puerto Rico-level forecast in sensitivity cases using demand profiles from alternate source-years, annual peak demand occurs during midday hours (12 p.m.–1 p.m.) during periods with high commercial demand and low residential demand.

The timing and class contributions to the two alternative peak periods have implications for the implementation of demand management programs. For example, if LUMA were to conduct demand response to address local distribution constraints in the San Juan TPA, LUMA should consider targeting the commercial-driven afternoon peak. Alternatively, if LUMA were instead conducting demand response to address Puerto Rico-wide capacity constraints, it should target the residential-driven evening peak.

Consider Impacts of Distributed Generation on Forecast Peaks. The adoption of load modifiers including distributed generation (e.g., solar photovoltaic systems) and electric vehicle charging are likely to influence demand during system peaks in future years. Increased solar adoption is likely to reduce demand during midday hours. The impact of electric vehicle charging is uncertain. However, if electric vehicle charging is concentrated during evening hours, it would exacerbate the current evening peak period.

Periodically Update Assumptions about Residential COVID-19 Effects. Guidehouse in consultation with LUMA's Load Forecasting and Research team, assumed that the increased residential consumption attributed to COVID-19-related effects would disappear by FY2025. Although informed by what appears to be a gradual decline in this effect in FY2022, this is a highly speculative assumption and should be updated as more observed consumption data become available.

Consider Alternate Sources for Economic Scenario Forecasts. The economic forecast scenarios from Moody's Analytics exhibit some counterintuitive characteristics. Notably, the high GDP forecast scenarios have lower population projections than the lower GDP scenarios. Communication with Moody's revealed that these dynamics are a result of the fact that Moody's high/low economic scenarios are defined in terms of country level (i.e., US) outcomes. For future forecast scenario analysis, it would be preferable to identify a source for economic scenarios defined specifically in terms of outcomes in Puerto Rico.

Appendix A. Improvement 1 Results Memo

This memo contains a summary of the methodology and results of Improvement 1 – Data Remediation.

LUMA LF Imp 1
Summary Memo 202

Appendix B. Improvement 2 Results Presentation

This PowerPoint presentation contains a summary of the methodology and results of Improvement 2 – monthly sales forecast. The contents reflect the final reported results as December 20, 2022. In coordination, Guidehouse and the LUMA load forecast team made updates to the Improvement 2 outputs after completion of this presentation. Guidehouse used the latest data from Improvement 2 that was available at the time of writing (updated March 2024) in the Improvement 3 analysis. The data in this Improvement 2 presentation may not be an exact match of the data used in Improvement 3.

LUMA_Improvement
2 Reporting 2022-12

Appendix C. Monthly Sales Forecast Update Memo

The attached memo provides a detailed description of the sales forecast model revisions that were applied in January and February of 2024. The model specifications described in this memo are consistent with those used to forecast residential, commercial, and industrial consumption for Improvement 3, as described in section 4.2, above.

LUMA LF Forecasts
January 2024 Updat

Appendix D. Historical and Forecast Annual Energy

The following table contains annual electricity generation, sales, and system peak for FY2010 - FY2050 for the three forecasting scenarios (e.g., Base, Low Scenario, and High Scenario). From FY2010 to FY2023, the values reflect historical actuals based on the remediated sales and generation data (results of Improvement 1). The FY2024 - FY2050 data are the results of the Improvement 3 forecast for the three scenarios. The annual peak values reflect demand at the generator. They have been scaled up to account for total loss rates.

Table 6. History and Base, Low Scenario, and High Scenario Forecasts; Annual Generation, Sales, and Peak

Group	Fiscal Year	Generation (TWh)	Sales (TWh)	Annual Peak (MW)
Historical Actual	2010	23.59	19.24	3,404
	2011	22.66	18.53	3,406
	2012	22.28	18.36	3,303
	2013	21.96	18.22	3,265
	2014	21.36	17.56	3,159
	2015	20.91	17.26	3,030
	2016	20.91	17.36	3,080
	2017	20.29	17.09	3,087
	2018	19.72	16.45	3,084
	2019	18.43	15.73	2,771
	2020	18.91	15.96	2,911
	2021	18.98	16.33	2,945
	2022	19.23	16.44	2,960
	2023	18.55	15.84	3,049
Base Forecast	2024	19.18	16.21	3,046
	2025	19.04	16.10	3,001
	2026	18.95	16.02	2,956
	2027	19.01	16.09	2,924
	2028	19.10	16.18	2,910
	2029	19.08	16.17	2,880
	2030	19.06	16.15	2,889
	2031	19.03	16.12	2,875
	2032	18.94	16.05	2,862
	2033	18.81	15.94	2,845
	2034	18.70	15.84	2,831
	2035	18.59	15.74	2,822
	2036	18.39	15.57	2,811
	2037	18.16	15.37	2,766
	2038	17.98	15.21	2,742

Group	Fiscal Year	Generation (TWh)	Sales (TWh)	Annual Peak (MW)
	2039	17.82	15.07	2,720
	2040	17.68	14.95	2,702
	2041	17.61	14.89	2,702
	2042	17.49	14.78	2,685
	2043	17.33	14.64	2,656
	2044	17.22	14.55	2,642
	2045	17.12	14.46	2,629
	2046	17.03	14.38	2,622
	2047	16.95	14.31	2,618
	2048	16.87	14.25	2,602
	2049	16.79	14.18	2,587
	2050	16.72	14.12	2,578
Low Scenario Forecast	2024	17.88	15.09	2,699
	2025	17.45	14.72	2,615
	2026	17.30	14.61	2,564
	2027	17.26	14.59	2,530
	2028	17.19	14.54	2,503
	2029	16.97	14.37	2,455
	2030	16.76	14.19	2,434
	2031	16.50	13.97	2,391
	2032	16.18	13.70	2,347
	2033	15.80	13.38	2,298
	2034	15.42	13.05	2,246
	2035	15.06	12.75	2,201
	2036	14.63	12.37	2,155
	2037	14.15	11.97	2,079
	2038	13.73	11.61	2,022
	2039	13.33	11.26	1,968
	2040	12.94	10.93	1,915
	2041	12.62	10.67	1,876
	2042	12.25	10.35	1,827
	2043	11.84	9.99	1,764
	2044	11.48	9.69	1,715
	2045	11.12	9.39	1,667
	2046	10.77	9.09	1,623
	2047	10.44	8.81	1,580
	2048	10.11	8.53	1,531
	2049	9.77	8.24	1,483
	2050	9.44	7.96	1,438

Group	Fiscal Year	Generation (TWh)	Sales (TWh)	Annual Peak (MW)
High Scenario Forecast	2024	19.92	16.86	3,290
	2025	20.00	16.93	3,304
	2026	20.03	16.95	3,308
	2027	20.18	17.09	3,323
	2028	20.33	17.22	3,353
	2029	20.35	17.24	3,368
	2030	20.32	17.22	3,380
	2031	20.28	17.18	3,370
	2032	20.20	17.11	3,361
	2033	20.08	17.00	3,350
	2034	19.97	16.91	3,341
	2035	19.88	16.83	3,338
	2036	19.70	16.67	3,335
	2037	19.48	16.47	3,295
	2038	19.30	16.32	3,277
	2039	19.15	16.18	3,261
	2040	19.02	16.07	3,249
	2041	18.97	16.03	3,255
	2042	18.85	15.93	3,245
	2043	18.71	15.79	3,222
	2044	18.61	15.71	3,215
	2045	18.53	15.64	3,208
	2046	18.45	15.57	3,207
	2047	18.38	15.51	3,210
	2048	18.32	15.45	3,199
	2049	18.25	15.40	3,192
	2050	18.18	15.33	3,190

Source: Guidehouse Analysis