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GOVERNMENT OF PUERTO RICO
PUERTO RICO PUBLIC SERVICE REGULATORY BOARD
PUERTO RICO ENERGY BUREAU

IN RE: IN RE: REVIEW OF T&D OPERATOR'S SYSTEM OPERATION PRINCIPLES	**CASE NO. NEPR-MI-2021-0001** **SUBJECT: Submission of "Regulatory Long-Term Load Forecast Review."**

MOTION SUBMITTING "REGULATORY LONG-TERM LOAD FORECAST REVIEW"

TO THE PUERTO RICO ENERGY BUREAU:

COME NOW LUMA Energy, LLC, and LUMA Energy ServCo, LLC, (jointly referred to as "LUMA"), through the undersigned legal counsel and respectfully submit the following:

1. On February 25, 2021, LUMA filed before this honorable Puerto Rico Energy Bureau ("Energy Bureau") a *Petition for Approval of LUMA's System Operation Principles* ("SOPs Petition") pursuant to LUMA's obligations under Section 4.1 of the Puerto Rico Transmission and Distribution System Operation and Maintenance Agreement dated as of June 22, 2020, executed by and among LUMA, the Puerto Rico Electric Power Authority and the Puerto Rico Public-Private Partnerships Authority.

2. Subsequently, after a series of procedural events and upon the request of the Energy Bureau, LUMA submitted to this Energy Bureau a revised SOP Section 3.3 and Figure 3-1 via *Motion in Compliance with Order Submitting Additional Information and Supplement Responses to Questions Posed in Technical Conference and Submitting Clarifications* filed with this Energy Bureau on May 14, 2021, and a revised version of the SOPs via *Motion in Compliance with Order*

Submitting Revised System Operation Principles, Phase I Draft Procedures and Additional Information, filed with this Energy Bureau on May 19, 2021.

3. On May 31, 2021, this Energy Bureau issued a Resolution and Order approving the SOPs subject to LUMA's compliance with several conditions listed in paragraphs 1 to 5 of Section IV therein ("May 31st Resolution and Order"). In what is relevant to this submission, this Energy Bureau directed LUMA to file within ninety (90) days "final versions of its Load Forecasting Procedures to include a description of power meter load data, load management, load forecast, and DER adoption models and weather normalization and peak allocation," ("Condition No. 3).

4. On August 25, 2021, this Energy Bureau issued a Resolution and Order (the "August 25th Resolution and Order") that included, among other matters, the following regarding the submittal of load forecasting procedures

> The Energy Bureau does not intend for LUMA to determine specific load projections for the system. Rather, Condition No. 3 requires LUMA to submit load forecasting **procedures** that set out the methodologies and the inputs needed to determine these projections when performing load forecasts. The load forecasting methodology is a core tool of any utility. However, utilities use different approaches when forecasting load. The Energy Bureau is seeking to examine LUMA's approach to projecting load.

August 25th Resolution and Order on page 5.

5. On September 13, 2021, LUMA submitted a motion entitled *Motion in Attention to Resolution and Order of August 25, 2021 and Request for an Agenda for the Virtual Technical Conference Scheduled for September 17, 2021* ("September 13th Motion"). In Section 3.0 of Exhibit 1 to the September 13th Motion, LUMA addressed the Energy Bureau's request regarding LUMA's load forecasting procedures. It explained that LUMA would implement a phased process to improve load forecasting and research functions, based on recommendations from its consultant Guidehouse Inc. ("Guidehouse"). At pages 5 through 6 of Exhibit 1, LUMA proposed

a timeline for said improvement process that included in Phase 2, a review of current and future methodologies.

6. LUMA hereby submits a document prepared by Guidehouse entitled "Regulatory Long-Term Load Forecast Review: Current State Assessment & Future Methods Recommendations" ("Long-Term Forecast Review") as Exhibit 1 to this Motion. The Long-Term Forecast Review involves the work done to fulfill Phase 2 of LUMA's approach to improving load forecasting processes.

WHEREFORE, LUMA respectfully requests that the Energy Bureau **take notice** of the aforementioned and **accepts** the Long-Term Forecast Review submitted as Exhibit 1 to this Motion.

RESPECTFULLY SUBMITTED.

In San Juan, Puerto Rico, this 30 day of June, 2022.

I hereby certify that I filed this motion using the electronic filing system of this Energy Bureau and that I will send an electronic copy of this motion to the attorneys for PREPA, Joannely Marrero-Cruz, jmarrero@diazvaz.law, and Katiuska Bolaños-Lugo, kbolanos@diazvaz.law.

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Exhibit 1

Regulatory Long-Term Load Forecast Review

Current State Assessment & Future Methods Recommendations

Prepared for:

LUMA

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Guidehouse Inc.

Reference No.: 217196
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guidehouse.com

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Acronym	Definition
A/C	Air Conditioning
AAGR	Annual Average Growth Rates
AMI	Advanced Metering Infrastructure
API	Application Programming Interface
ARIMA	Auto-Regressive Integrated Moving Average
BEA	U.S. Bureau of Economic Analysis
CAGR	Compound Annual Growth Rates
CDD	Cooling Degree Days
CEC	California Energy Commission
CHP	Combined Heat and Power
DER	Distributed Energy Resources
DG	Distributed Generation
DR	Demand Response
DSM	Demand Side Management
DTE	Detroit Edison Gas Company
ECMs	Error Connection Models
EE	Energy Efficiency
EMS	Energy Management System
ERCOT	Electric Reliability Council of Texas
EV	Electric Vehicles
FCA	Fuel Clause Adjustment
FOMB	Federal Oversight and Management Board
FQ	Fiscal Quarter
FTE	Full Time Employee
GC	Governance Committee
GDP	Gross Domestic Product
GNP	Gross National Product
HECO	Hawaiian Electric Company
HVAC	Heating Ventilation and Air Conditioning
IESO	Independent Electricity System Operator
IPP	Independent Power Producer
IRP	Integrated Resource Plan
LBNL	Lawrence Berkeley National Laboratory
LFR	Load Forecasting and Research
LSE	Load-Serving Entities
LTERP	Long-Term Electricity Resource Plans
MDM/S	Meter Data Management System
NOAA	National Oceanic and Atmospheric Administration
OLS	Ordinary Least Squares
OMS	Outage Management System
PG&E	Pacific Gas and Electric Company
PPCA	Purchased Power Charge Adjustment
PREB	Puerto Rico Energy Bureau

PREB	Puerto Rico Energy Bureau
PREPA	Puerto Rico Electric Power Authority
PV	Photovoltaic
QC	Quality Control
RASS	Residential Appliance Saturation Study
RTO	Regional Transmission Organization
SAE	Statistically Adjusted End-use
SAS	Statistical Analysis System
SCADA	Supervisory Control and Data Acquisition
SMUD	Sacramento Municipal Utility District
SRP	System Remediation Plan
SSCA	Supply Side Contract Administration
TOU	Time of Use
TP	Transition Period
UPC	Use-Per-Customer
VEE	Validation, Editing and Estimation
VP	Vice President

1. Introduction

In the fall of 2021, LUMA engaged Guidehouse to support the development and improvement of its long-term load forecasting process. The Annual Load Forecast is the long-term (20+ year) forecast used for projecting revenues, setting rates and rate-riders and is a key input to its Integrated Resource Plan.

The Annual Load Forecast is output once per year, with relatively near-term updates (the Quarterly Updates) performed three times per year to serve as inputs for the calculation of the Fuel Clause Adjustment (FCA) and Purchased Power Clause Adjustment (PPCA) rate riders. The load forecast is performed by the Load Forecasting and Research (LFR) team that is a part of LUMA's Regulatory department.

LUMA has commenced on an improvement process to its load forecasting procedures to deliver a more accurate and useful forecast of monthly class-level consumption, and annual system peak demand. This improvement process will also allow it to provide a Long-Term Load Forecasting Procedure to support the System Operation Principles as specified in Resolution and Order No. NEPR-MI-2021-0001.

LUMA has identified to PREB within LUMA's September 13, 2021 filing and September 17, 2021 Technical Conference, there are five phases of this work. The descriptions below are based on the phase details in the September 13, 2021 submission, updated to reflect the latest developments in LUMA's improvement planning.

1. **Phase 1 – Internal Governance and Organizational Design** – In progress. Formed with key internal stakeholders, providing a governance body *(referred to below as the "Governance Committee" (GC))* to initiate and provide input to ongoing development of Load Forecasting methodologies and practices and to ensure internal buy-in across the organization. LUMA has indicated in its submission to PREB that this phase has already commenced with a number of initial governance meetings having taken place and additional periodic future meetings have been scheduled.

2. **Phase 2 – Review Current and Future Methodologies** – **<u>Complete by June 2022</u>**. This phase involves both a detailed "As-Is" process documentation that identifies current data collection and forecasting processes and methodologies and a "To Be" process design that includes determination of future forecasting needs including methodologies and data required to meet those future forecasting needs. LUMA has indicated in its submission to PREB that this phase has already commenced and is anticipated to take until the end of Fiscal Year 2022 (June 30, 2022).

3. **Phase 3 – Establish Data Needs** – **<u>Complete by December 2022</u>** Identify data that are required to meet the future forecasting needs determined in Phase 2 and establish plans and timelines to start collecting the needed data.

4. **Phase 4: Process Design.** Completion date to be determined during Phase 2. Short-term and long-term initiatives, providing impacts to current processes, where possible using existing systems and data and developing long-term aligned processes across internal LUMA stakeholder needs, using new systems and processes. Long-term initiatives include establishing load forecasting and research capabilities and dedicated functions within the

organization.

5. **Phase 5: Build Capabilities.** Completion date to be determined during Phase 2. This may involve establishing and training for a centralized load forecasting function (across or within teams) that will be tasked with developing long-term load forecasts and enable the practice of load study or research.

Guidehouse's assistance on this engagement has been supporting LUMA with the first three of these phases. Guidehouse has, to date, provided LUMA with assistance in developing the GC charter, and a formal governance structure for reviewing and approving improvement activities undertaken by Guidehouse on LUMA's behalf.

This report fulfills the requirements of Phase 2:

- Review the current state approach to long-term forecasting employed by the LFR team,
- Contextualize these activities within the wider landscape of load forecasting within LUMA
- Identify a set of future methods that the LFR team should work to adopt for the Annual Load Forecast in the longer term; and,
- Map out a high-level transition roadmap from the current state to the recommended future methods.

This report is divided into the following sections:

1. **Introduction**. Introduces the report and articulates its structure.

2. **Load Forecasting at LUMA**. Provides the "As-Is" summary overview of the different load forecasting teams, their outputs, and the use-cases for those forecasts at LUMA.

3. **Long-Term Regulatory Forecast: Current State** . Describes in greater detail the current-state approach to long-term forecasting employed by the LFR team.

4. **Long-Term Regulatory Forecast: Future Methods**. Lays out Guidehouse's recommendations for a set of Forecast Principles that LUMA has adopted to guide its ongoing forecast development and describes a longer-term end-state of forecasting capabilities aligned with those Principles that LUMA will target implementing within approximately 7 - 10 years. This section provides the "To Be" long-term load forecasting process design.

5. **Future Methods: Transition Plan Road Map**. Provides a link between the current state and the recommended future methods. The purpose of this road map is to support the development and execution of more detailed workplans and evolving approaches toward the recommended future methods – the longer-term end-state.

Appendix A. These five sections of the main body of the report are followed by one Appendix: Appendix ,

Future Methods – Additional Detail & Examples. This appendix expands on the content of Section 4.

In this report, the term “long-term forecast” refers, unless otherwise explicitly stated, to the 20+ year Annual Forecast of billed energy consumption by customer class and coincident peak demand. A new version of this forecast projection is developed for the 20+ year forecast period once per year, using the process described in Section 3.2 of Section 3.

The Quarterly Updates (a set of updates providing a monthly forecast that is derived from the Annual Forecast) are sometimes referred to by the LFR team as the “short-term” forecast.[1] To avoid confusion with the very short-term forecasts (e.g., day-ahead) produced by System Operations, Guidehouse generally refers to these outputs as the Quarterly Updates, and not as a “short-term forecast”. The Quarterly Update outputs new forecast values for the remainder of the fiscal year using the process described in Section 3.1 of Section 3, but does not update forecast values for subsequent fiscal years.

[1] The Quarterly Updates are so called because they are produced by the LFR team on a quarterly basis. Each of these updates provides a forecast of monthly values.

2. Load Forecasting at LUMA

This section provides the "As-Is" summary overview different load forecasting teams, their outputs, and their internal use-cases at LUMA. The purpose of this section is to identify the load forecasting context within which the LFR team operates at LUMA.

In December of 2021, Guidehouse staff traveled to LUMA's headquarters and met with internal personnel from the following groups or departments:

- *Regulatory* – Load Forecasting and Research
- *Regulatory* – Grid Modernization
- *Regulatory* – Programs & Performance
- *Regulatory* – Supply Side Contract Administration
- *Utility Transformation* – Business Transformation
- *Utility Transformation* – System Operations
- *Engineering & Asset Management* – Substation and Feeder Level Planning
- *Customer Experience* – Customer Billing
- *Finance*

Over the course of these interviews, Guidehouse identified a list of existing and forthcoming load forecasts produced by members of the groups above and tied these to the existing and projected stakeholder use-cases for those forecasts. Guidehouse used this information to develop a high-level summary of forecast producers and users and a high-level profile of each forecast's characteristics (e.g., inputs, frequency). This summary was first presented to the GC at its February 2022 meeting and has been updated based on subsequent discussions with LUMA personnel for inclusion in this report that occurred between the original interviews (December 2021) and the end of April 2022.

In reviewing the forecasts described below, it is important to remember that different teams at LUMA produce forecasts for different purposes.

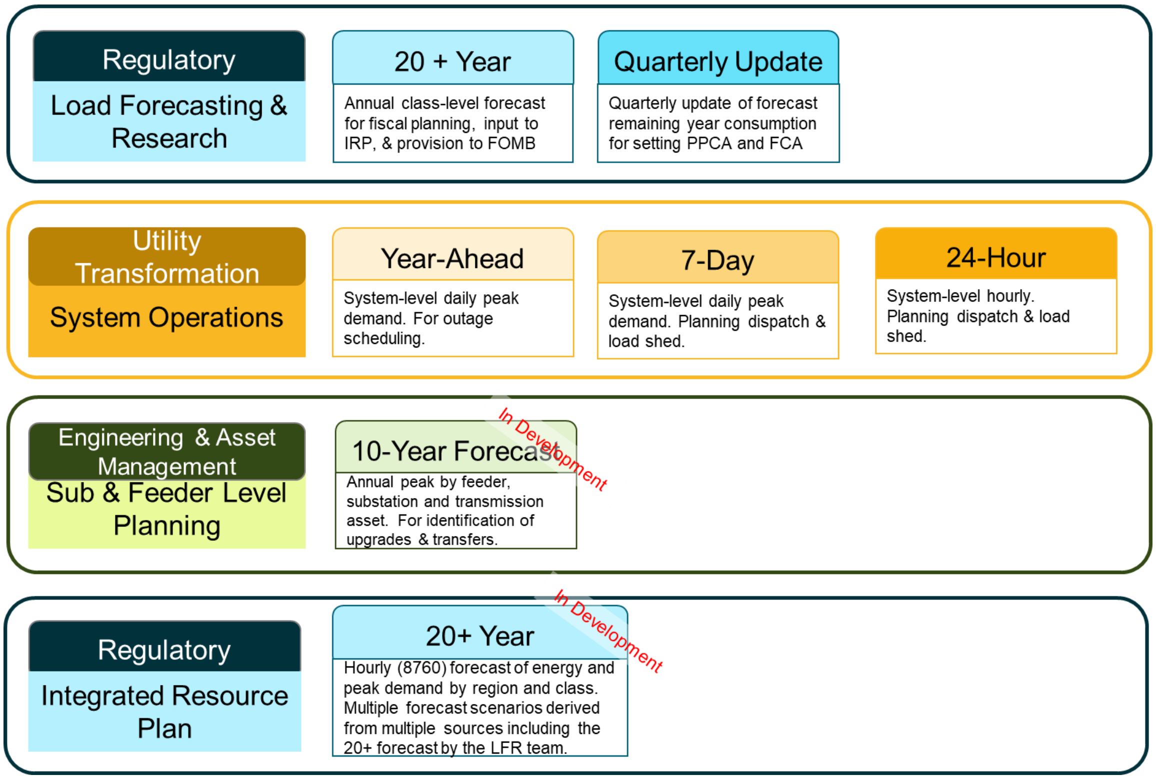
Engineering & Asset Management for example, projects non-coincident peak demand by asset in order ensure reliable service in emergency and extreme conditions (e.g., 90th percentile weather conditions). Regulatory, in contrast, projects class-level energy consumption and coincident peak demand under expected median (50th percentile) conditions in order to project expected revenues, and allocate system costs for the purposes of rate-setting. It would be neither desirable nor prudent for these forecast outputs to match each other.

All teams at LUMA undertaking load forecasting continue to review the data available to support the development of load forecasting activities for accuracy and completeness. As LUMA load forecasting teams come to better understand the constraints imposed by the data available, forecasting approaches, and the anticipated improvements to be applied to them, will continue to evolve.

2.1 Forecast Producers, Users, and Use-Cases

Three LUMA teams currently produce forecasts of electricity demand or production at LUMA, and a fourth is working to develop one. The four teams and the forecasts they produce are identified in Figure 1 below.

Figure 1. Forecast Producers and Their Outputs



Source: Guidehouse & LUMA

The "20+ Year" forecast produced by the LFR team and identified in the figure above is also referred to in this document as the "long-term" forecast and, more formally, the Annual Forecast. Unless otherwise explicitly noted, all references to the long-term forecast or the Annual Forecast indicate this 20+ year forecast of customer class billed consumption and system-level peak demand.

The Utility Transformation and Engineering & Asset Management departments are themselves the primary users of the forecasts they produce. Engineering & Asset Management, for example, uses their load forecast[2] to determine any electric system upgrades necessary to accommodate future loads, Electric Vehicle (EVs), maintain system reliability and for planning infrastructure requirements, load transfers.

[2] Note that the Engineering & Asset Management forecast is a projection of asset demand under extreme peak conditions – an estimate of system design criteria – rather than (as is the case for the LFR forecasts) an attempt to project average conditions and demand.

The Utility Transformation uses their forecast for planning outages (year-ahead forecast) and daily dispatch and load shed events.

The LFR team's forecasts, in contrast, are currently used by (or will be used by) several different "clients" both internal and external to LUMA. These use-cases are summarized in Table 1.

Table 1. "As-Is" Current State Users of LFR Team's Forecasts

User(s)	Forecast Used	Use-Case
Regulatory	Annual Forecast and Quarterly Updates	Regulatory teams use the first three months of the Annual Forecast and the subsequent Quarterly Updates to calculate the FCA and PPCA rate riders on a quarterly basis. These forecast values are also inputs to its PROMOD software modeling, which in turn outputs the estimated average fuel cost over that period. These outputs are used to update the riders.
Regulatory Finance	Annual Forecast	Regulatory leads the development of a revenue forecast based on the Annual Forecast (LFR 20+ Year), working closely with Finance to align on assumptions and methods. Once top-line revenue forecast is identified, Finance builds a bottom-up budget, calibrated to allocated top-line revenue forecast.
[FUTURE USER] Utility Transformation	Annual Forecast	This team is also responsible for providing load modifiers for forecast adjustment (EVs, Distribution Energy Resources (DERs), Demand Side Management (DSM)) and reviews the base[3] Annual Forecast as part of that work The Energy Bureau is currently procuring a baseline study and potential study which will inform load modifiers in the future
[FUTURE USER] Regulatory	Annual Forecast	The Integrated Resource Plan (IRP) team will use the LFR team's long-term Annual Forecast as an input for the development of the integrated resource plan forecast.
[EXTERNAL USER] Financial Oversight and Management Board of Puerto Rico (FOMB)	Annual Forecast	The FOMB uses the Annual Forecast to forecast for the Fiscal Plans restructured debt payments for the next 40 years.

Source: Guidehouse & LUMA

Siemens has historically been responsible for the development of LUMA's IRP and used the Annual Forecast as an input for the long-term fuel and purchase power costs. This responsibility will remain with Siemens until another IRP is approved by the Energy Bureau.

Additionally, in conversations with the various teams as part of Guidehouse's on-site visit, the representative from the Customer Experience – Customer Billing indicated an interest in exploring the use of the Annual Forecast in its workflows, though no firm plans are in place at present to do so.

[3] The "base" Annual Forecast is what is forecast by the LFR team *before* applying adjustments for load modifiers without significant historical precedent (DERs, EVs, and DSM). See Section 3 for more details.

2.2 Forecast Profiles by Producer

The section above identifies and provides a summary of those teams at LUMA that produce and use load forecasts, and what they are used for. In this section, a profile of each load forecast is provided, identifying each forecast's primary data providers (sources), level of granularity, core approach, key inputs, and frequency of updates. Table 2 provides a high-level profile of the characteristics of the load forecasts prepared by the Regulatory: the LFR team, and the IRP team. Additional details related to the LFR team forecasts are contained in Section 3.

The LFR team forecasts are described in their current state here and are reflective of the approach used in the most recent forecast development cycle.

Table 2. "As-Is" Current State Regulatory Forecast Teams' Forecasts

	Load Forecasting & Research (LFR)		IRP
Forecast	**Quarterly Updates**	**Annual Forecast (20+ Year)**	**20+ Year** *(under development, details below subject to change)*
Data Sources	System Operations, Finance, Customer Experience (Billing), LFR	System Operations, Finance, Customer Experience (Billing), FOMB, Siemens, National Oceanic and Atmospheric Administration (NOAA)[4]	LFR, Engineering & Asset Management, others TBD[5]
Granularity	Monthly, by customer class	Monthly (base only) and annual (adjusted by load modifiers: EVs, DERs, etc.), by customer class (where applicable)	Hourly (8,760) energy forecast by region, and customer class. Hourly peak demand by region, and, subject to availability of data, customer class. TBD.
Core Approach	Trend analysis of generation output and conversion to consumption with historic efficiency and allocation factors.	Application of forecast inputs (weather, Gross National Product (GNP), etc.) to 2018-estimated regression parameters adjusted to reflect incremental growth of load modifiers (EVs, Distributed Generation (DG), etc.)	A range of forecasts will be developed. One of the forecasts will be based on the application of load profiles and asset-level data to updated LFR Annual Forecast to deliver disaggregated, probabilistic forecast. TBD
Key Inputs	Generation data, monthly billed consumption by class, previously developed forecast values	Generation data, monthly billed consumption by class, forecast macroeconomic inputs (population, GNP, manufacturing employment), estimated regression parameters, LFR-developed forecast of Cooling Degree Days (CDD)[6]	LFR forecast, historic hourly and sub-hourly substation data[7], forecast macroeconomic inputs
Updates	Three times per year, prior to the second, third, and fourth quarter of the fiscal year.	Once per year	Once per year (TBD)

Source: Guidehouse & LUMA

The IRP team forecast, in contrast, is still in development and is described here prospectively. As the different teams involved, including the IRP consultant, in the development of this forecast work with the data and resources available, the specifics of this approach are likely to evolve, and the description noted here should be understood to be preliminary and subject to change. For example, some uncertainty exists as to how much the LFR Annual Forecast will be used as an input to the IRP and how much work developed for the IRP will be used as an input to the LFR Annual Forecast, going forward.

[4] Monthly cooling degree days are obtained from the National Oceanic and Atmospheric Administration (NOAA)'s National Weather Service:

NOAA, National Weather Service, *Climate – NOWData – San Juan, PR,* Accessed June 2022.

https://www.weather.gov/wrh/Climate?wfo=sju

[5] "To be determined" (TBD). Currently under development and details subject to change.

[6] Cooling degree days (CDD)

[7] LUMA personnel are still conducting a quality review of the available substation data and have not yet determined to what degree it may be appropriate to use in the development of forward-looking analyses.

Table 3 contains the characteristics of the load forecasts prepared by the Systems Operations team. As noted in this table there are several internal activities ongoing to further develop the forecasting capabilities of this team (e.g., procurement of an Energy Management System (EMS), re-alignment of 90-day forecast, etc.)

Table 3. "As-Is" Current State Systems Operations Forecasts

	System Operations		
Forecast	Year-Ahead	7-Day	24-Hour Ahead
Data Sources	Supervisory Control and Data Acquisition (SCADA)[89]		
Granularity	Daily, system-level	Daily, system-level	Hourly, system-level
Core Approach	Average of prior two years, by day of year, informed by analyst judgement	Trend analysis with weather adjustments as warranted, and analyst judgement.	
Key Inputs	Historical daily peak generation output	Recent historical hourly output data, historical peak demand values, and weather	
Updates	Once per calendar year	Daily – rolling 7-day outlook period	Daily

Source: Guidehouse & LUMA

Table 4 provides the characteristics of the load forecast currently under development by the Sub & Feeder Planning team

[9] Supervisory Control and Data Acquisition (SCADA, legacy and current source). An Energy Management System (EMS) is being procured to support this work.

Table 4. "As-Is" Current State Engineering & Asset Management Forecast

	Sub & Feeder Level Planning
Forecast	10-Year Forecast *(under development, details below subject to change as available data are reviewed for quality)*
Data Sources	Pi Server software/SCADA[10], NOAA, LUMA weather stations[11]
Granularity	Annual peak demand, to the extent possible, by upstream (sub-station & transmission) asset and potentially by feeder.
Core Approach	Connection requests (1 – 3 years), trend analysis, weather normalization, and engineering judgement.
Key Inputs	Historic feeder and upstream asset annual peak demands and weather data where available
Updates	Annual by calendar year

Source: Guidehouse & LUMA

[10] Significant limitations exist in the data available and under review, most significantly only a single phase ("B" phase) substation demand is metered suggesting significant remedial action and strong assumptions required before these data can be used to forecast asset-level demand.

[11] LUMA weather station data are still being assessed for quality, but preliminary investigations indicate that many LUMA (legacy PREPA) weather stations are not functioning and that significant gaps exist in the data recorded by those stations that are still functioning.

3. Long-Term Regulatory Forecast: Current State

This Section summarizes the current state ("As-Is") approach used by the LFR team to project the Annual Forecast and the Quarterly Updates. These are sometimes referred to internally by the LFR team as the "medium and long-term forecast" and the "short-term" forecast (respectively).

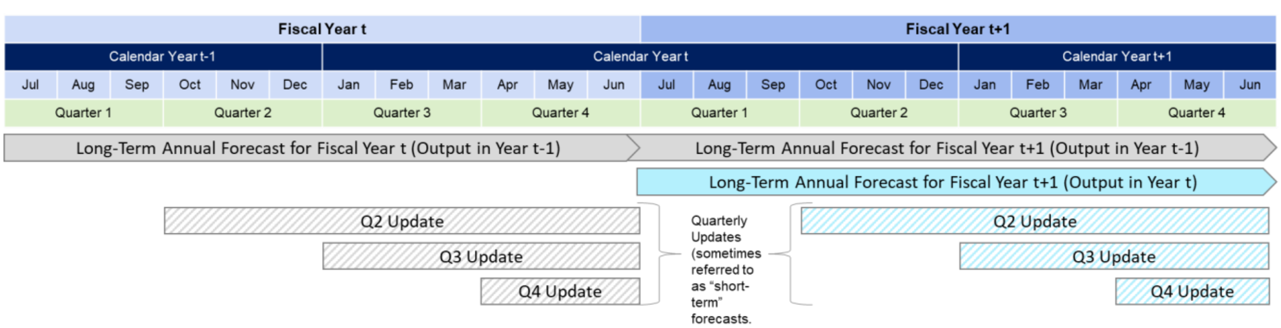
The Quarterly Updates provide input values for the quarterly updates to the FCA and PPCA rate riders. The Quarterly Updates are also used internally by the Finance department and for cash-flow reporting to the FOMB for Puerto Rico. The Quarterly Update is completed in the month preceding each fiscal year quarter.

The Annual Forecast provides input values for setting the Initial Budget (LUMA's budget for the subsequent fiscal year), and for the PREPA fiscal plan. Both the "base" forecast (without the application of any load modifiers) and the final adjusted Annual Forecast (the base forecast, adjusted for load modifiers such as EVs, distributed generation, etc.) are provided to Siemens and to the Supply Side Contract Administration (SSCA) team. The SSCA team applies these outputs (and fuel and plant availability projections provided by PREPA and the Independent Power Producers (IPPs)) to its PROMOD software model to project fuel needs for the next fiscal year. Siemens uses these values to run the approved IRP plan with the Siemens developed model and to project fleet dispatch and fuel costs for the subsequent 19 years (following the first-year projection delivered by the SSCA team). The Annual Forecast is typically completed by April or May in each year.

Each of the subsequent two sections of this section summarize the modeling and data processing currently applied by the LFR team to estimate these forecasts. The content has been developed from (1) a series of in-person and virtual interviews conducted by the Guidehouse team, and (2) a detailed review of the LFR team's Excel workbooks that generate the forecasts. In addition to the information provided in this section, Guidehouse has supported the drafting of the "Load Forecasting Process" procedural document that describe the process in greater detail than provided here.

The forecasts developed by the LFR team are all in relation to the fiscal, and not the calendar year. LUMA's fiscal year runs from the beginning of July until the end of June and is divided into four quarters. The periods covered by each of these forecasts are summarized in Figure 2.

Figure 2. LUMA "As-Is" Long-Term Annual Forecast and Quarterly Updates Schedule



Source: Guidehouse & LUMA LFR team

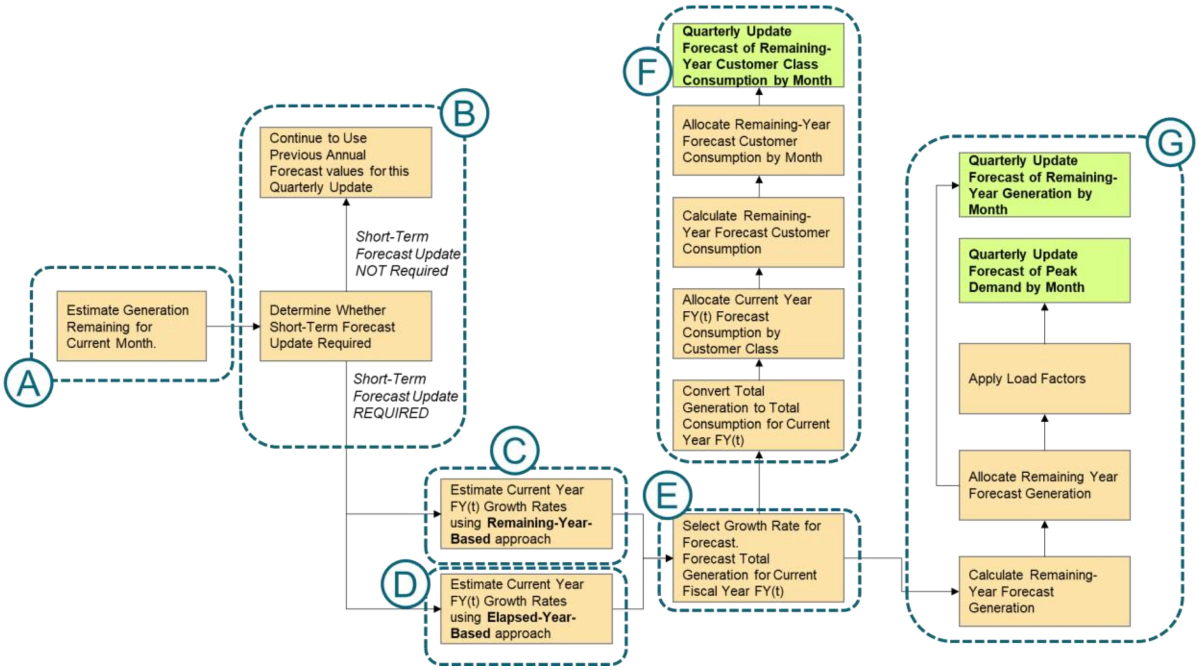
3.1 Quarterly Updates

The Quarterly Updates deliver a forecast by month of:

- Consumption by customer class.
- Total generation requirements.
- Total system peak demand.

These are provided for the remainder of the fiscal year (i.e., the Quarterly Updates do not impact the forecast annual values for subsequent fiscal years). Figure 3 contains high-level summary of the key steps in the process used to estimate the three required outputs, represented as green boxes in the process flow. A description of each step (identified by the letters A through G in Figure 3) is also provided.

Figure 3. Summary of Current State Quarterly Updates Process



Source: Guidehouse & LUMA LFR team

The Quarterly Updates, if required, are output three times a year, in the month immediately prior to the start of the subsequent Fiscal Quarter (FQ): September (prior to FQ2), December (prior to FQ3), and March (prior to FQ4). No quarterly update is performed for FQ1 – the monthly forecast values for this period are drawn directly from the outputs of the Annual Forecast that begins July 1 (the start of FQ1).

The seven steps for generating the Quarterly Update are:

A. Current Month Generation. A key decision in the process flow requires a comparison of fiscal year-to-date observed/actual monthly energy generation values and forecast monthly generation values. The purpose of this step is to scale up generation values in the current month (the month in which the update is performed) to ensure a complete set of monthly "actuals" for this comparison.

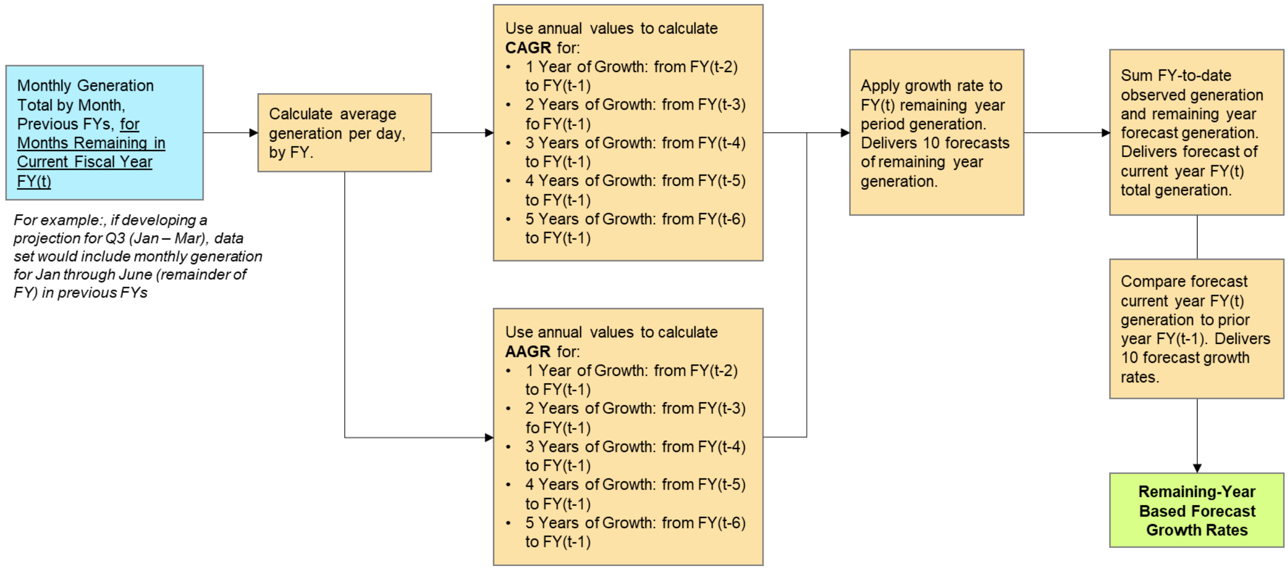
B. Decision: Quarterly Update Approach. The Quarterly Update is either drawn directly from the most recent monthly output of the Annual Forecast or estimated using observed generation data.

- No update to Annual Forecast monthly projected generation values is required if two conditions hold: a) the absolute forecast error for the year-to-date projected generation requirements is less than 3% and b) no updates were performed in earlier FQs of the same year.
- If both conditions are true, projected monthly values from the Annual Forecast are used.
- If one or both conditions are not true, the LFR team update its projection of monthly consumption by class, generation output, and system peak demand according to the steps below.

C. Estimate Remaining-Year Based Growth Rates. When an update is required, it is estimated by projecting annual growth in generation output, subtracting year-to-date generation, and allocating the difference across the remaining months of the year. Two sets of growth rates are considered as possible drivers for the Quarterly Update: the "remaining-year" based growth rates (described in the bullets immediately below), and the "elapsed-year" based growth rates (described in Step D). The details of this step are illustrated in Figure 4 below.

- The first set of growth rates considered for updating the forecast of monthly generation are the "remaining-year" based growth rates.
- The remaining-year growth rates are the historical Compound Annual Growth Rates (CAGR) and Annual Average Growth Rates (AAGR) observed historically for the period remaining in the current year over five different windows of time: the most recent year's growth, the most recent two years' growth, etc.
- This delivers 10 possible annual growth rates as contenders for use in projecting the Quarterly Update.

Figure 4. Step C Process Detail

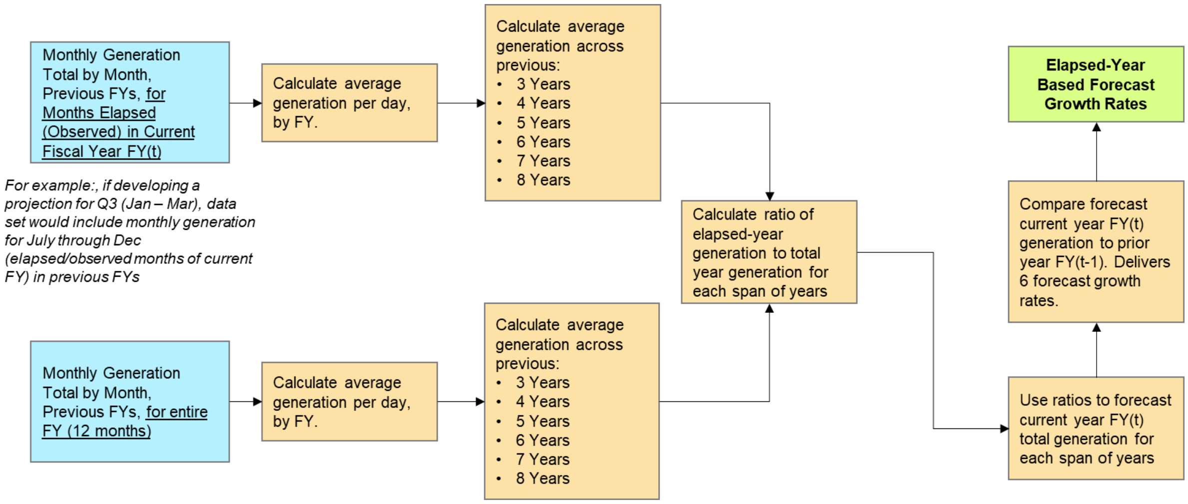


Source: Guidehouse & LUMA LFR team

D. Estimate Elapsed-Year Based Growth Rates. The second set of growth rates considered for use in updating the forecast of remaining year generation output (and consequently customer billed consumption and total peak demand) is developed using the "elapsed-year" approach. The details of this process are illustrated in Figure 5, below.

- Historical average daily generation for the elapsed year months in previous years is compared to average daily generation across the entire year in previous years.
- The ratio of these two values is applied to average daily generation for the period elapsed in the current year to deliver a projected annual generation value and calculate a growth rate.
- Six growth rates are calculated in this way, each based on a different look-back window: one averaging daily generation across three years, another across four years, etc.

Figure 5. Step D Process Detail



E. Select Growth Rate and Forecast Current Year Generation. The 16 growth rates generated in steps C and D are compared to the total growth in generation output of all complete months in the fiscal year-to-date compared to the same months in the prior fiscal year.

- Of the 16 growth rates, that which is closest to, but less than, this observed growth rate (i.e., the growth in generation output of all complete months in the fiscal year-to-date compared to the same months in the prior fiscal year) is selected.
- The selected growth rate is applied to the previous fiscal year's generation output to develop an updated forecast of generation output for the entire current fiscal year.

F. Project Remaining-Year Consumption by Month.

- The historical contribution of each class's consumption to total billed consumption is used to allocate generation output by class, and a historical efficiency factor (capturing losses between the generator and the meter) is applied to convert this to forecast annual consumption value for the entire fiscal year.
- Forecast total year consumption by class is subtracted from observed billed consumption by class in the fiscal year-to-date to deliver the total forecast customer consumption for the remaining months of the year, which is then allocated across the months based on the historical distribution of class-level consumption by month.
- This delivers the Quarterly Update forecast of remaining-year customer class consumption by month.

G. Project Remaining-Year Generation and Peak Demand.

- Total observed generation output in the year-to-date is subtracted from the updated forecast total generation for the current fiscal year (estimated in step E) to deliver forecast generation output for the remainder of the fiscal year.

- Monthly allocation factors estimated in EViews are used to spread the remaining-year forecast generation output by month. This delivers the Quarterly Update forecast of remaining-year generation by month.
- Month-specific load factors are applied to the updated monthly generation output forecast. This delivers the Quarterly Update forecast of system peak demand by month.

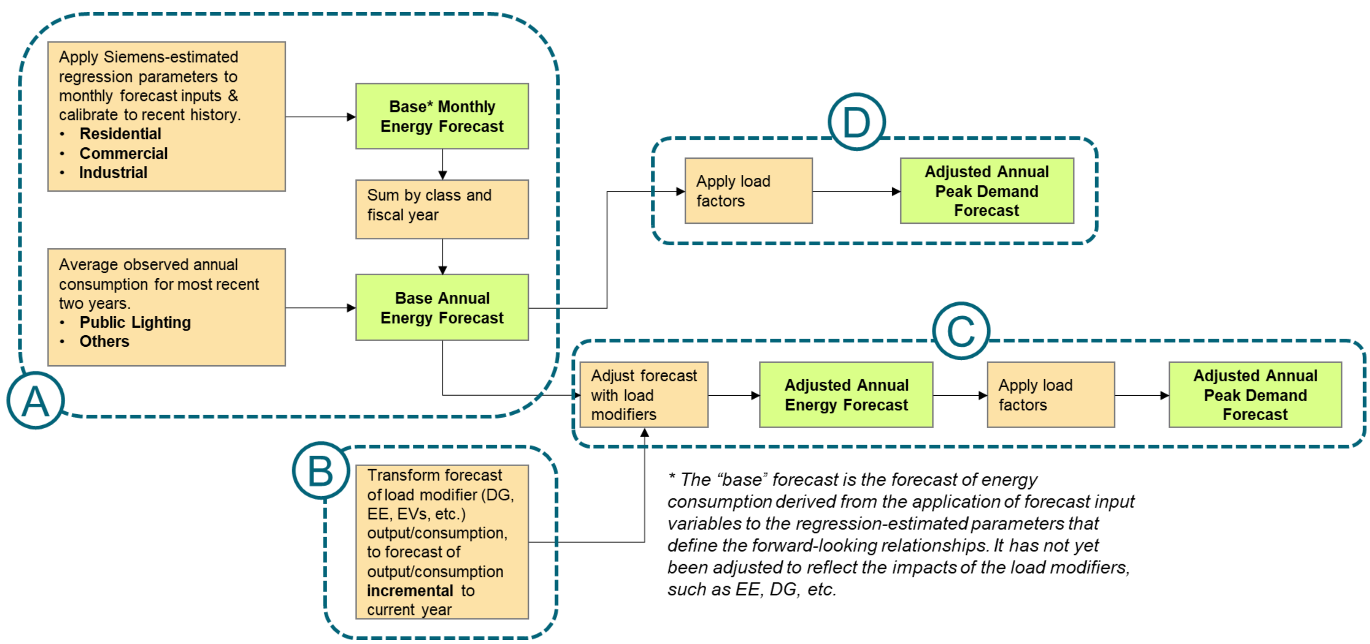
3.2 Annual Forecast

The Annual Forecast is performed once per year, and provides five forecast outputs:

1. Base[12] monthly energy consumption, by customer class.
2. Base annual energy consumption, by customer class
3. Base annual peak demand, by class, and at the system level.
4. Adjusted (for the incremental effects of the load modifiers) annual energy consumption, by customer class
5. Adjusted annual peak demand, by class, and at the system level

Figure 6, illustrates the key steps in the process used to estimate the required outputs, represented as green boxes in the process flow. A description of each step (identified by the letters A through D in Figure 6 is provided below.

Figure 6. Current State Annual Forecast Process



Source: Guidehouse & LUMA LFR team

[12] The "base" forecast is the forecast of consumption prior to the application of load modifiers that adjust forecast consumption for forecast incremental: EV consumption, Distributed Generation (DG) production, cogeneration Combined Heat and Power (CHP) production, and Energy Efficiency (EE) or Demand Side Management (DSM) energy savings.

A. Base Annual Energy Forecast.

- CDD are forecasted by applying a growth rate[13] to the most recent observed annual CDD value.
- For residential, commercial and industrial classes, forecast macroeconomic variables (the "macros") provided by the Puerto Rico Fiscal Agency and Financial Advisory and approved by the FOMB, calendar variables and forecast CDD developed by the Load Forecasting and Research team are applied to regression parameters provided by Siemens, last estimated in 2018.
- This delivers a forecast monthly consumption series for the three customer classes. These levels are differenced to transform the forecast consumption into forecast growth (i.e., the value in month t+1 is subtracted from the value in month t).
- This series of differences is applied to the most recently observed value do deliver the base (i.e., not reflecting the impacts of incremental future EV consumption, Energy Efficiency (EE)/DSM, DG and Combined Heat and Power (CHP) production) monthly energy forecast.
- The monthly base level forecast by customer class is aggregated by fiscal year to deliver the base annual energy forecast for residential, commercial, and industrial customers.
- For Public Lighting, Agriculture, and Other Authorities, averages of previously observed annual consumption values are used as forecast values. This delivers the base annual energy forecast for these classes.

B. Prepare Load Modifier Forecast. In this step forecast some of the load modifiers (EVs, DG, and CHP) are processed such that adjustments are applied based on *incremental growth* in the given load modifier. This is to ensure that the impacts of load modifier adoption trends embedded in the historical observed are not double-counted in the forecast period.

C. Adjust Base Forecast and Forecast Adjusted Peak Demand.

- The load modifiers are applied to the base forecast of annual consumption by class.
- This delivers the adjusted annual energy consumption forecast by customer class.
- Allocate annual class-level consumption by tariff/rate-class based on the historic consumption and apply load factors to estimate annual peak demand by rate class.
- Sum peak demand across all tariff/rate-classes and customer classes and calculate the year-over-year growth rate.
- Apply this growth rate to the most recently observed annual peak demand (derived from hourly generation data) to deliver the annual adjusted peak demand forecast.

[13] The CDD growth rate is derived from a 2016 paper projecting temperature changes for Puerto Rico (*citation may continue on next page):*

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

D. Forecast Base Peak Demand

- Allocate the annual class-level base forecast (i.e., not considering the impacts of the load modifiers) consumption as derived in Step A by tariff/rate-class based on the historic consumption and apply load factors to estimate annual peak demand by rate class.
- Sum peak demand across all tariff/rate-classes and customer classes and calculate the year-over-year growth rate.
- Apply this growth rate to the most recently observed annual peak demand (derived from hourly generation data) to deliver the annual base peak demand forecast.

4. Long-Term Regulatory Forecast: Future Methods

In Section 3 the Guidehouse team documented the current state of LUMA's long-term forecasting approach. The goal of this section is to identify – at a high level – the end-state to which this group should strive to achieve in seven to ten years.[14] The section that follows this Future Methods section connects these two points in time – the current state and the future methods – and provides an initial, and high-level, conceptual "road-map" that LUMA should consider as it evolves from the current to its final state.

Although the focus of Guidehouse's review and recommendations is squarely on Regulatory LFR group's long-term system-level forecast of energy consumption and peak demand (the Annual Forecast), Guidehouse notes that as increasingly granular metering data become available to long term forecasting and distribution planning groups, the practical distance between these two groups' forecasting methods and requirements will shrink.

Therefore, increased collaboration and information sharing between these groups – beginning now – will help to avoid potential inconsistencies in the inputs[15], assumptions and methods used by the two planning functions. The need for increasing alignment of forecasting work across these functional areas is explicitly addressed in the sections that follow, though the primary perspective adopted is that related to the development of the regulatory long-term load forecast and the LFR team.

The sections that follow address the LUMA LFR team's future methods across two key areas:

- **Long-Term Forecast Principles**. In this section we define the Principles approved and adopted by the LUMA Load Forecasting Governance Committee. The Principles are the rules to which the long-term forecast should adhere – that will guide the LUMA LFR team's selection of future methods and approaches. The load forecast Principles may be thought of as a set of aspirational outcomes or goals – a "North Star" of longer-term improvements – that will guide forecast development.

- **Processes, Technology, People** . This section describes a set of future methods, consistent with trends in the electricity distribution utility industry and in alignment with the Principles that could be in place within the next seven to ten years. The description of methods is at a relatively high level to avoid being too prescriptive. Guidehouse's purpose here is to articulate a set of end-state methods that align with the Principles[16] and provide motivation for a long-term transition plan or road-map (see Section 5) while still providing the LFR team with the flexibility to develop approaches that maximize the value of the available data.

[14] Guidehouse believes that all of the future methods outlined in this section may be put in place in this time span, subject to the availability and provision of the funds and resources (human and material) to enable them. The Guidehouse team notes, however, that doing so is a significant undertaking with many interdependencies. As LUMA continues to assess the quality of the data available and collect new data, the planning horizon identified here should be periodically re-examined in the context of other on-going changes to the environment in which LUMA operates and revised if required.

[15] It has already been noted, but is worth re-stating here, that because the two processes project different outcomes – (distribution planning projects extreme scenarios, the Regulatory LFR team projects *average* scenarios) differences in input values and some assumptions between the two functions are inevitable.

[16] These methods may change and evolve as the Principles evolve and are approved by the GC.

To summarize, we have worked carefully to avoid being too prescriptive in our recommendations. Load forecasting is, at LUMA especially, but also in the utility industry more generally, a fluid and evolving practice. The LFR team must be allowed a significant amount of discretion and flexibility in the details of forecast implementation and evolution to ensure that the methods developed and adopted are optimally suited to the data available and to the conditions in which the forecast must operate.

4.1 Long-Term Forecast Principles

Load forecasting Principles are a set of rules or goals that define the characteristics that the Regulatory LFR team's forecast should exhibit in the longer term.

The Principles are the "North Star" of forecasting development at LUMA and are intended to provide structure to evolutionary decision-making: does the proposed change in the forecasting method improve its alignment with the principles? If yes? – proceed. If no? – reconsider.

The Principles are summarized in Figure 7 below, and spelled out in greater detail in the table below that.

Figure 7. Long-Term Forecast Principles: the "North Star"

Source: Guidehouse

Each of these Principles is described in greater detail in Table 5, below.

Table 5. Forecast Principles: Additional Context

Forecast Principle	Additional Context
Principle 1: The long-term load forecast must be a function of causal relationships.	• Unlike in the very short-term[17], causality is very important for long-term forecasts. Economic growth, for example, is one driver of electricity load growth. Modeling such causality is essential to maintaining alignment with the appropriate view of the future driving other major planning decisions on the island. • The testing of causal relationships (i.e., independent variables) for inclusion in the forecast must include the testing of variables that capture macroeconomic fluctuations (e.g., Gross Domestic Product (GDP)), customers costs (e.g., the price of power), and weather. • A purely machine learning/artificial intelligence approach – which may be implemented without specifying causality – is therefore unsuitable for the long-term forecast.[18] • Estimated causal relationships used to project the forecast should be re-visited (e.g., re-estimated or re-tested) annually.
Principle 2: The long-term forecast must explicitly address uncertainties through scenario and/or other analyses.	• It is vital to ensure that the sensitivity of forecast demand can be explored using scenarios or stochastic methods, to better understand the uncertainty associated with the forecast. This requires reasonable estimates of the causal relationships that drive load growth, and an understanding of the estimated uncertainty associated with those relationships and the underlying variables such as economic activity, energy prices and weather. Put differently, a single point estimate forecast is insufficient for planning purposes. • Uncertainties related to the adoption of EVs, and DERs (which may include distributed generation Photovoltaic (PV) and CHP, EE, Demand Response (DR), and storage), population growth, as well as to economic growth, and extreme weather events must be addressed. • Uncertainty may be addressed through scenario analysis, estimation of probabilistic outcomes, stochastic simulation, or some combination of these different techniques. • When scenario analysis is used[19] they should be defined by the Regulatory LFR team in consultation with the GC to ensure that the scenario input assumptions chosen are reflective of internal stakeholders' planning needs and uncertainties.
Principle 3. The long-term forecast must be temporally and geographically granular.	• Outputs must be temporally granular to capture intra-daily peak migration. The long-term forecast should output an hourly projection of demand. This may be particularly important when exploring areas of uncertainty (e.g., forecast adoption of EVs, storage, etc.)

[17] In this case "short-term" is meant to indicate day-ahead or week ahead forecasting, for which pure time-series or machine learning techniques (which are generally cause-agnostic) may be used.

[18] Such techniques are used successfully in the industry for short run forecasting, (e.g., 1 hour to two weeks ahead) and may still be used in long-term forecasting, for example to assist with developing some types of customer load profiles. However, for long-term forecasting they cannot be used without also including some set of interpretable causal estimated relationships.

[19] For example, when probabilistic techniques are inappropriate because the joint probability density function of several independent variables (e.g., extreme weather events and DG adoption) is unknown.

Forecast Principle	Additional Context
	• Outputs must be geographically granular[20] to reflect regional variation in the forecast adoption of major load modifiers (e.g., EVs, DER) and so support distribution planning. Geographic granularity is required to allow for the longer-term alignment of the regulatory and distribution planning load forecasting techniques and assumptions (where such alignment is desirable). • Inputs must be granular in time, geography, and major end-uses. This is vital for capturing structural changes (adoption of EVs, DG, storage), market interventions (DSM, rates), or the effects other policy-driven interventions, and to ensure that the effects of such changes are not “double-counted”. For example, annual trend variables may capture some growth trends in some structural drivers, and care must be taken to ensure that this is accounted for when load modifier adjustments to the base forecast to reflect structural changes.
Principle 4. All teams conducting forward-looking load analyses within LUMA should use a consistent set of data sources and align on input assumptions, subject to the specific end-user needs of the projection or forecast.[21]	• As noted above in Principle 3, Regulatory LFR team personnel should work with other groups within LUMA to align both sets of forecasts within a common framework where advisable to do so. • While LUMA works towards a consistent load forecasting framework, every effort should be made to ensure that input assumptions and input forecast (and historical) values should align across different forecasts where it is reasonable that they do so. • *Such alignment may not always be desirable*, but where assumption or inputs are not aligned, they should be identified and justified. For example: using average (50th percentile, or 1-in-2 weather) weather in the case of an energy forecast used for projecting revenue, versus using extreme weather (e.g., 90th percentile, or 1-in-10 weather) in the case of asset-specific non-coincident peak demand forecasting for investment planning.
Principle 5. The performance of past forecasts must be recorded, monitored and assessed consistently and transparently.	• All historical forecasts should be maintained in a common database or set of tables such that they remain easily accessible to the Regulatory LFR team on an ongoing basis. • At each forecast cycle update (e.g., on an annual basis), updated observed “actuals” should be added to the database, comparisons made with historical forecasts, and a summary analysis of that comparison appended to annual forecast reporting such that historical performance is explicitly considered each cycle. • At each forecast cycle update observed values of the forecast input variables (e.g., macroeconomic variables, weather variables) should be applied to the most recently used forecast model to obtain a “forecast” that is conditional on the historically observed input values in a forecast period. A comparison of these values with observed values will enable the forecast team to more precisely identify drivers of forecast imprecision.

[20] Forecast granularity in time, geography, and even major end-uses is possible within the 10-year time frame assumed for this report. This is highly dependent, however, on the rapid deployment of metering to a load research sample as soon as possible following the identification of data needs as part of Phase 3 of LUMA’s improvement plan (see Section 1) and the selection of a representative set of sites to which to deploy them.

[21] Different teams at LUMA produce forecasts for different purposes. Transmission and distribution teams, for example, project non-coincident peak demand by asset in order ensure reliable service in emergency and extreme conditions (e.g., 90th percentile weather conditions). Regulatory teams, in contrast, projects class-level energy consumption and coincident peak demand under expected median (50th percentile) conditions in order to project expected revenues, and allocate system costs for the purposes of rate-setting. It would be neither desirable nor prudent for these forecast outputs to match each other.

4.2 Processes, Technology, People

This sub-section defines, at a high level, a set of methods that will deliver on the requirements of the Principles laid out above. These “Future Methods” are intended to be the outcome of extensive development and evolution by the LFR team, its management and internal stakeholders following a seven to ten-year development period. There should be no expectation that the methods below can be put into practice in the short-term. It should also be noted that the details of the Future Methods will likely evolve as LUMA continually assesses further information on the needs of the system and its customers.

The Future Methods cannot be implemented in a vacuum. The end-state forecasting *process* that delivers on the Principles will require the adoption of new tools, or *technology*, and will need to be operationalized by the right team of *people*, supported by the appropriate approvals and governance structure.

To present a complete high-level view of the future methods, this sub-section is divided into the three area perspectives identified immediately above:

- **Processes**. This section describes the types of modeling, input data. workflow, and performance monitoring that should be part of the future load forecasting process, as it evolves to an end-state that delivers on the Principles above.

- **Technology**. This section describes the technology required to support the forecast development methods laid out in the Processes section. More specifically, this section will address the tools required to support the data collection, analysis and storage needs of the methods defined in the Process section.

- **People**. This section describes the management, organizational, and governance structure required to support the Processes, as well the skills, training, and structured continuous improvement needed to leverage the Technology and implement the improved Processes.

Each of these perspectives have been further sub-divided in the sections below to ensure that the entire scope of the LFR team’s future methods is addressed.

The future methods laid out here are sufficiently specific to define the needs of the transition roadmap described in Section 5, but sufficiently high-level to allow the GC and LFR team some flexibility in its development. The reality is that the choices made by the GC and LFR team for the future methods development will be defined in response to evolving constraints and opportunities in each of the three areas.

The methods adopted in the Processes component will be defined by the skills (People), data, and analytic tools (Technology) available. The tools (Technology) will be selected to serve the needs of the methods (Process). The skills development and governance structure (People) will in turn be defined by the Process and Technology components. Development will need to be measured and systematic, and the future methods must be defined such that the LFR and the GC have sufficient flexibility to meet the challenges of development as they arise.

4.2.1 Processes

The “processes” component of the future methods is the core of the future methods. It is the analytics process selected to develop the long-term forecast of customer energy consumption and peak demand that will dictate the technology and tools required, and how the team responsible for its output must be developed and managed.

To help articulate the process needs succinctly but comprehensively, Guidehouse has divided this element of the future methods into three components:

- **Data Input and Workflow** This section identifies the way data input sourcing should be established to ensure consistency of assumptions across teams producing forward-looking projections of energy or demand, and the way in which the LFR team’s modeling must be flexible to the requirements of different internal (and potentially external) stakeholders. The focus of the data warehousing discussion in this section is on the warehousing of exogenous inputs (e.g., weather, etc.). Warehousing of consumption and demand data is addressed in Section 4.2.2.2, and the warehousing of outputs and results is addressed in Section 4.2.1.3)

- **Load Modeling.** It is in this component that process development is most central to the end-state future methods to be employed by the LFR team. This section addresses the development of use-per-customer modeling for customer load profiles, geographic granularity, and probabilistic and scenario analysis to address uncertainty associated with weather and other structural load drivers.
- **Performance Monitoring & Output Data Warehousing.** This section lays out the kinds of internal Quality Control (QC) methods that should be adopted by the LFR team to catch errors in code development and application. This section also discusses the way in which historical forecasts and the estimated relationships that drive them should be preserved and re-examined on an ongoing basis to allow for continuous improvement.

4.2.1.1 Data Input and Workflow

LUMA's forecasting process should, in the future, make use of a common, comprehensive set of exogenous inputs that can be accessed by the LFR team (and other teams developing forward-looking analyses and outputs) from its chosen development environment. The process should also include a flexible workflow that can enable iterations of different sets of inputs (to serve different internal clients) quickly and with a minimum of "manual" adjustments.

Input Integration

The inputs we refer to here are not demand or energy consumption inputs (the warehousing of which is addressed in greater detail in Section 4.2.2), but the exogenous historical inputs required to estimate the relationships that drive the forecast and the exogenous forecast inputs applied to those relationships that will deliver forecast output values.

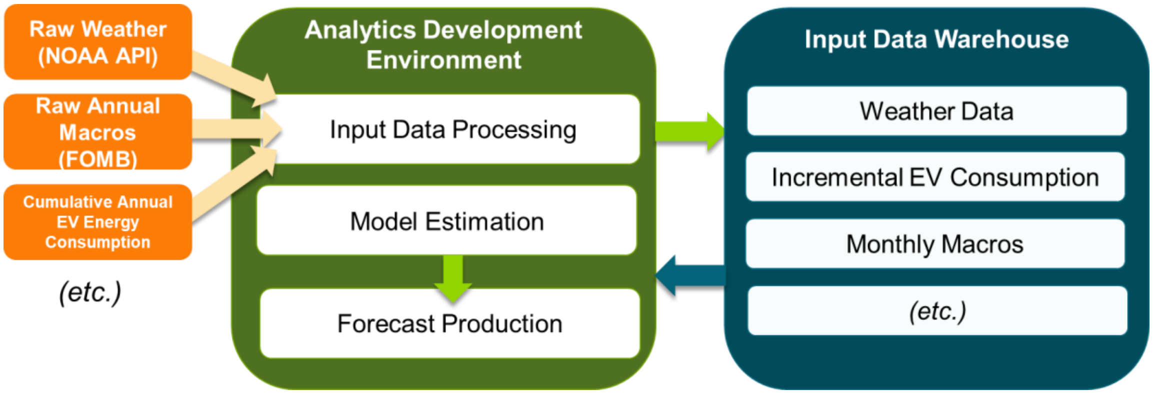
Regardless of the degree to which forecasting and forward-looking analyses become aligned , it is important for the credibility and consistency of LUMA's projections that all such projections use a consistent set of exogenous inputs and assumptions.[22] To do so requires a single storage repository for each set of data, a regular schedule of data updates, and a clear line of responsibility for delivering (and advertising) those updates. Such data repositories should be indexed clearly and available through a single portal – a "one-stop shop". This should be a data warehouse[23], but may, if circumstances and constraints dictate it, simply be a guide to the locations of the various required databases.

Figure 8 presents a highly stylized illustration of how work might flow between the analytics development environment and the input data warehouse.

[22] Note that there is a significant difference between "consistent" and "identical". A sub-station-specific projection (for instance) would likely make use of weather only from the most proximate weather stations, whereas a system-wide projection might use some blended mix of stations. The crucial point (in this example) is that the *source* (e.g., NOAA's API) is to be the same and that the localized weather values should be embedded in those of the blended value.

[23] A data warehouse is a repository of structured data: these are data prepared and processed (not "raw") to serve as inputs to further analysis.

Figure 8. Stylized Workflow for Input Data Warehouse



Source: Guidehouse

Such a design makes referencing straightforward and sourcing consistent, allowing for greater integration of workflows across teams, and making collaboration more efficient. The most crucial inputs to forward looking analyses that should be accessible in this manner include historical and forecast: weather data, macroeconomic data, electricity prices, customer counts and population, EV counts (by location), and DERs.

In some cases (for example customer counts or forecast EV adoption) the “inputs” so centrally indexed may be the outputs of analyses undertaken by different teams. In such cases, when values are revised or updated, previous versions should be archived but remain accessible in case they are later required for reconstructing (or deconstructing) previously developed forecasts or projections.

Weather data may be collected from the NOAA Application Programing Interface (API)[24] or any other reliable source of hourly historic weather data at regular intervals and processed (addressing outliers, measurement errors, missing values, etc.) into clean hourly series of temperature, humidity, cloud cover, etc. Processing of such data may also include aggregations (to ensure consistent aggregation procedures). This process may be automated, but if so, automated outputs should be subject to regularly scheduled (e.g., monthly) inspections by qualified analysts. The management of this process should be shared across teams, with clear lines of responsibility identified such that there exists sufficient redundancy in the monitoring and output of these values.

Macroeconomic data collection and processing (as required) should likewise be assigned to a cross-team group (if relevant) responsible for compiling macroeconomic data from the various sources used (e.g., the FOMB, Moody’s, U.S. Bureau of Economic Analysis (BEA), etc.) and developing the “canonical” input data set (or data sets) that should be used consistently across the organization. As with the weather data team, redundancy in staffing here is important (in addition to the careful documentation of processes and decision-making) to ensure the retention of institutional memory of processes in the face of inevitable team attrition.

All input data (e.g., projected EE achievement from potential studies, EV adoption, DER production, etc.) sets available through the data portal or hub used to make such data available

[24] Application programming interface. NOAA’s API allows users to query historical weather data interactively from NOAA’s servers.

to LUMA personnel (the LFR team and others) should be subject to a similar set of development, maintenance and staffing protocols, for the reasons outlined above.

Input Selection Flexibility

It has already been established, in the Load Modeling section above, that the LFR team will develop and output multiple scenarios using the same basic forecasting framework or structure. As additional use-cases are desired by the GC and depending on the degree to which forward-looking analysis becomes integrated and centralized in an evolved LFR team, it is likely that increasing demands may be placed on that team to output alternative scenarios, filtered (e.g., geographically or customer-type-specific) outputs, or alternative output forecast distributions.

The architecture and workflow adopted by the LFR team must be such that running such alternative outputs, whether on an ad hoc or regularly scheduled basis, can be performed quickly, with a minimum of "manual" inputs all preferably in a single location that can also act as documentation for the scenario explored.[25] This is vital for ensuring consistency and quality in the outputs. There must not, for example, be hard values or scenario-specific case/when or if/else logic embedded in the core model that require manual updates for different scenarios. Each manual intervention carries with it the possibility of user error, and user error is (eventually) inevitable, and so minimizing and centralizing all user inputs is critical for maintaining model stability and accuracy.

The specifics of the approach to developing a uniform input "form" will depend entirely on the architecture adopted by the LFR team, but as much as possible the goal should be to have a single control object or list of objects that can centrally updated when a novel or alternative run of the model is required.

4.2.1.2 Load Modeling

Load modeling refers to the process of modeling electricity use for the purposes of forecasting energy consumption and demand (particularly peak demand), and is further divided into six parts:

- *Projecting Residential and Commercial Demand and Energy in a Use-Per-Customer Framework.* Outlines the need for LUMA LFR team to migrate to a Use-Per-Customer (UPC) times number of customers approach in the residential and commercial sectors, with a further breakout of key segments that have distinct load profiles within each sector.
- *Projecting Industrial, Public Lighting, and Other Sector Demand and Energy*. A UPC times customer count approach is typically not appropriate for very large customers (industrial or large government installations) or those with trend-stable loads (e.g., public lighting). These sectors may require simpler trend-based or expert opinion/customer information-driven approaches

[25] Described below as a kind of input "form", any such summary of major inputs and assumptions used for a given scenario should also include a concise narrative related to the scenario being requested, describing its purpose, particularly any downstream use of the outputs by other teams or functions within LUMA.

- *Estimation of System Peak Demand Using Hourly Generation Data.* In the long term, LUMA will have either Advanced Metering Infrastructure (AMI) or sufficient load research interval data from which to model and forecast system peak demand. In the interim, moving to the use of hourly generation data will provide more accurate peak demand[26] forecasts than continuing to apply peak coincidence factors to customer class forecast energy sales.
- *Geographic Granularity.* Addresses how increased geographic granularity may be addressed through separate models, and the implications for providing support for distribution planning efforts.
- *Load Forecast Uncertainty* Describes how load forecast uncertainty associated with more policy-driven or global macroeconomic factors can be addressed via scenario analysis, as well as potentially more sophisticated probabilistic approaches to address forecast uncertainty.
- *Intra-Annual Forecast Updates.* Quarterly updates to the long-term forecast are prudent, and recommended, but should be consistent with the Annual Forecast development framework including review and approval by the GC.

Additional detail and examples for each set of recommendations for the future methods described here can be found in Appendix , below.

<u>Projecting Demand and Energy in a Use-Per-Customer Framework</u>

In the long-term end-state, the LUMA LFR team's long-term forecast should, for the residential and commercial sectors be output as a function of a customer type forecast and a UPC profile forecast. This style of forecast approach is already quite common, used, for example[27], by National Grid[28], Pacific Gas and Electric Company (PG&E)[29], Portland General Electric[30], Avista[31], and many others. Figure 9, as an example, shows Avista's forecast residential customer and residential UPC growth in the near and longer term.

[26] This recommendation is predicated on the assumption of the accuracy of the historical hourly system-level generation data. LUMA continues to review the quality of the data available and may need to adopt a different approach depending on the findings of its review.

[27] References are provided for the first citation of a given example, but not repeated thereafter.

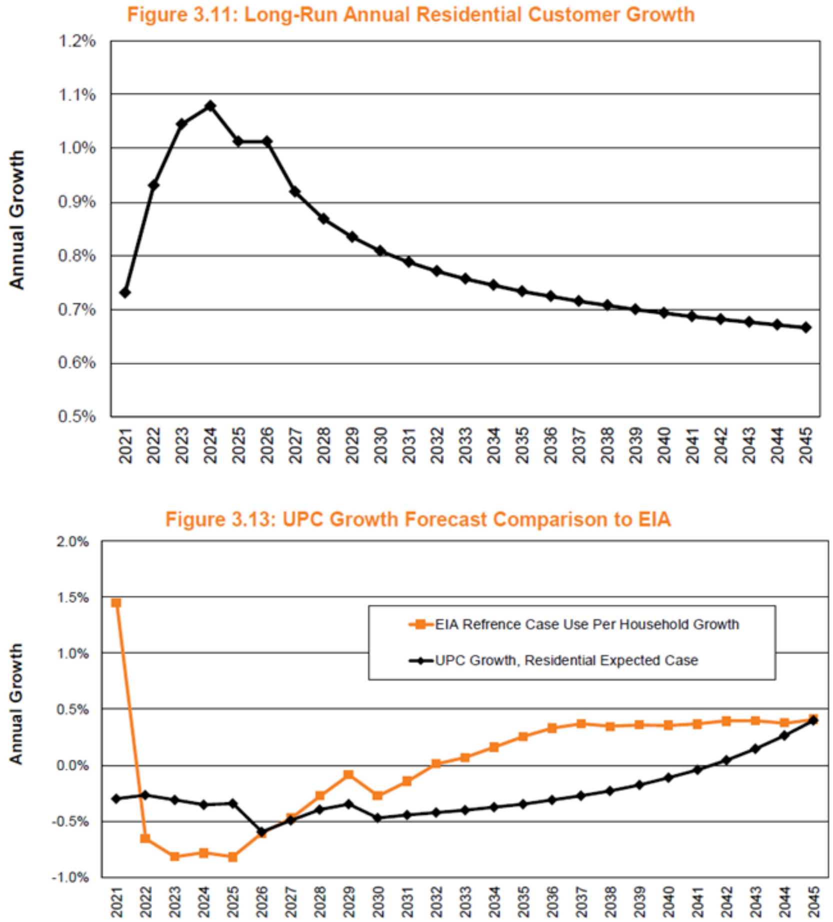
[28] National Grid, *Proceeding on Motion of the Commission as to the Rates, Charges, Rules and Regulations of Niagara Mohawk Power Corporation for Electric and Gas Service*, Testimony and Exhibits of Joseph F. Gredder and Theodore E. Poe Jr., Book 4, Case 17-E-__, April 2017

[29] Pacific Gas and Electric Company, *Prepared Testimony – 2020 Energy Resource Recovery Account and Generation Non-Bypassable Charges Forecast and Greenhouse Gas Forecast Revenue Return and Reconciliation – Public Version – Section 2: Sales and Peak Demand Forecast*, June 2018

[30] Portland General Electric Company, *Before the Public Utility Commission of the State of Oregon – UE 394 Load Forecast – Direct Testimony of Amber Riter*, July 2021

[31] Avista, *Electric Integrated Resource Plan*, 17th Edition, Final Date April 1, 2021

Figure 9. Example Customer Count Growth and UPC Growth from Avista



Source: Avista

This approach is recommended to better allow the forecast to accommodate structural changes in the composition of LUMA's customers that affect forecast energy and demand. Consider for example, the adoption of EVs, or an increase in the number of customers taking service under some (as yet non-existent) Time-Of-Use (TOU) rate.

Projecting a different UPC profile forecast for each major *type* (e.g., segment) of residential or commercial customer means that the overall aggregate forecast can more easily be adjusted for anticipated changes in the composition of the customer types, e.g., more TOU customers and more EV customers and fewer "standard" residential customers.

As residential and commercial customers are segmented to better identify differing characteristics (particularly ownership or use of load modifying equipment), the UPC forecast should also evolve into an hourly projection of energy consumption. This is important for capturing the intra-daily shifts in demand patterns as result of load modifiers, shifts which may affect class-level peak demand.

Guidehouse believes it is unlikely that that the class-level hourly data available within the horizon anticipated by this report will be sufficient to allow for the estimation of class-level peak demand directly, though approaches (more robust than the current approach) for leveraging other existing data may be used to project class-level peak demand. In a sub-section below, Guidehouse has recommended using hourly generation data as the basis for a forecast of system peak demand, a forecast which could be used, in combination with class-level hourly data, to calibrate a more precise forecast of class-level peak demand.

Additional support for this recommended future method, and examples of other utilities that have use it, may be found in Section A.1.1 of Appendix .

Projecting Industrial, Public Lighting, and Other Sector Demand and Energy

A UPC-based approach may not be suitable for customer segments like Public Lighting, or very large industrial or government facility customers. Large industrial forecast consumption should be projected based on observed meter data of the individual customers, enhanced with insights provided by LUMA Key Account managers, or the customers themselves. For very large customers (e.g., sub-transmission or contract customers) most North American distribution utilities project demand on the basis of historic trends, substantially adjusted based on the opinion of experts: Key Account managers and customers.

FortisBC[32] differs from most comparable utilities in this respect. This utility forecasts large industrial energy use (in both its electricity and natural gas forecasts) using an innovative survey strategy, which presents industrial customers (both very large and more moderately sized) with historical patterns of use and asks the customers to project any adjustments. The most recent IRP indicates receiving responses from customers representing 92% of this class's load.

For other customer groups (e.g., public lighting, agriculture) the application of historic trends, consistent with the existing approach where aggregate class consumption (rather than UPC * customers), may remain a suitable approach for forecasting sector consumption.

Estimation of System Peak Demand Using Hourly Generation Data.

At present, system peak demand is estimated through the application of historical load factors to projected class-level consumption (scaled up to account for losses through an efficiency factor). In the much longer term (beyond 10 years), as LUMA develops a substantial volume of hourly or sub-hourly customer meter data, the LFR team should consider developing the system peak demand forecast from the same hourly models that will be used to deliver its energy consumption forecast.

Guidehouse has recommended (see Section 4.2.2.2) that LUMA select a representative load research sample following its determination of data needs in Phase 3 of its improvement plan and deploy interval metering to this sample as soon as possible following the determination of the data needs. It is unlikely, however, that these data will – over the period of development considered in this report – be sufficient to support the development of a robust projection of class-specific system peak demand. There simply won't be a long enough history available until several years after the load research sample is deployed.

[32] PDF page 34 of 87 from:
FortisBC, *FortisBC Inc. Resource Planning Advisory Group (RPAG) Meeting*, 2020-06-25
https://www.cdn.fortisbc.com/libraries/docs/default-source/about-us-documents/lterp-rpag-combined-deck-june-25-2020.pdf?sfvrsn=4adf6d1d_2

Moreover, many utilities have found that using hourly generation data – along with using hourly weather and coarser economic growth drivers – has worked well in delivering accurate long-term peak demand forecasts.[33] The reason why is very straightforward: the development of peak demand forecasts *directly* from hourly generation data should yield superior results to the historical method of using *indirect* estimation from class/segment coincident peak demand factors applied to forecast consumption values.[34]

Thus, the use of hourly system load data represents a good intermediate option[35] to improve the peak demand forecast while LUMA awaits having long enough time series from load research to support load forecasting.

To summarize the LFR team should develop a forecast of system peak demand using the available hourly generation data. Individual class (or sub-class segment) coincident peak demands may then be projected on the basis of this system-level forecast of peak demand and the class-level hourly data that becomes available as a result of the deployment of metering to the load research sample. Ultimately, both the system and class/segment hourly modeling will need to be combined to develop long-term load forecasts.

Forecast peak demand derived in this fashion should make use of the probabilistic techniques described below for capturing the distribution of possible projected peak demands, and to better quantify forecast peak demands under "normal" (e.g., 50th percentile) or "extreme" (e.g., 90th percentile) weather.

Geographic Granularity

The output granularity of the Annual Forecast will be determined by the constraints of the available data and the needs of downstream internal LUMA stakeholders for the forecast. There are two levels of geographic granularity to be considered: (1) the granularity for load modeling, and (2) the granularity of outputs.

Currently, most utilities model long-term system-level[36] load growth very coarsely, either for their entire service territory or by distinct geographic regions within that territory (where they exist). Hawaiian Electric Company (HECO)[37], for example, forecasts long-term energy consumption separately for each of the largest islands: Hawai'i ("Big Island"), O'ahu, Maui, and Lana'I and PacifiCorp and Avista forecast consumption separately by state (their service territories include six and two states, respectively).

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[33] See, for example, *Integrated Resource Plan*, Oklahoma Gas & Electric, Prepared 2021, particularly Appendix A. https://ogeenergy.gcs-web.com/static-files/6fd094d7-f7d6-4dae-8ec9-7482d0071a34

[34] As noted previously it would be preferable to estimate customer class coincident peak demand using hourly customer meter data as the dependent variable, as generation values include losses, and may understate demand when load shed is required due to demand exceeding available capacity. In the absence of a robust set of hourly customer data, however, hourly generation data can provide a reasonable proxy for forecasting demand until such customer meter data as are required for such a forecast are available. In addition to using hourly generation data, LUMA forecasting personnel may wish to experiment with other data sources to project peak demand. Ultimately the most appropriate approach will depend on the findings of LUMA's ongoing data quality review.

[35] This is conditional on the quality and accuracy of the system-level generation data. LUMA continues to review the quality of available data and will continue to evolve its approaches in response to the findings of this ongoing review.

[36] Distribution planning forecasts, of course, are necessarily more granular, though typically don't extend as far out as the regulatory long-term forecast and may use that long-term forecast as a calibrating input.

[37] Hawaiian Electric, *2021 Integrated Grid Planning Inputs and Assumptions*, August 2021 Update

This coarseness in modeling is often a function of the granularity of available exogenous inputs (e.g., GDP, employment, etc.) and the needs served by that forecast (revenue planning, power procurement). This is in contrast to the more granular distribution asset forecasting techniques which often are more medium-term (e.g., extending approximately five years) and make use of extant connection requests (e.g., Toronto Hydro[38]), non-structural time-series approaches (e.g., Central Hudson[39]), as well as weather, trend and economic regression analysis driven approaches (e.g., PG&E[40]).

The LUMA LFR team should expect in the longer-term to produce a more geographically granular forecast than at present. This will be important for substantially improving the accuracy of the overall class-level energy (sales) and class-level peak demand forecast. These improvements in accuracy are delivered by accounting for the geographic disparity in the adoption of load modifiers such as EVs, DG, storage, and other DERs. The availability of geospatial projections of DER adoption and increasingly granular customer (as opposed to asset) demand data from improved metering should be used to develop more geographically granular projections of customer energy consumption and demand.

Such increased granularity will enable greater alignment between the LFR team's functions and those of distribution planning, ensuring greater consistency of assumptions[41] and modeling mechanics. This in turn will allow for more accurate customer system cost attribution, important for the purposes of rate-setting, particularly for customers with DERs and participating in any net metering initiatives.

With the present state of customer metering in Puerto Rico, it is difficult to identify what may be possible in the next seven to ten years in terms of geographic customer-level forecast granularity. Guidehouse would recommend that the LFR team continue to work with other teams represented on the GC to identify the most suitable geographic boundaries for any future geographically disaggregated modeling. The drivers for the selection of the regions to be used for modeling could include: significant anticipated differentials in the adoption of EVs and DERs in the future, the availability of reliable aggregate load data (e.g., from distribution and transmission assets serving the region) to allow for data reconciliation, and the availability of region-specific data that can be used in modeling (e.g., distribution of customer classes, population and load modifier forecasts, etc.)

The anticipated *modeling* granularity that LUMA's LFR team should consider will be determined based on the availability of data and the differences in model drivers that is observed across different regions. That is, using traditional econometric methods, a separate regression may be used to model each customer type's UPC profile in geographic areas. Or LUMA may find that the UPC profiles are similar across these areas, but the customer count forecast by segment needs to be different for different regions. The ability of the LFR team to model different

[38] Toronto Hydro, *Distribution System Plan 2020 – 2024*, Case Number: EB-2018-0165, Exhibit 28, Section A1

[39] Demand Side Analytics prepared for Central Hudson, *2018 Central Hudson Location Specific Transmission and Distribution Avoided Costs Using Probabilistic Forecasting and Planning Methods*, July 2018

[40] PG&E compares its regression-based asset-level forecast with a geo-spatial allocation of an input forecast provided by the California Energy Commission (CEC) and will select one of these, or blend them for its ultimate forecast. The CEC forecast provided for distribution planning takes as an input the coarser long-term energy and peak demand forecast also developed by PG&E.

[41] Where appropriate: distribution planning may require materially different weather assumptions (e.g., design criteria or 95th percentile weather) than forecast sales.

geographic regions separately may be constrained by the quality of the data available and the anticipated differences in growth rates, weather sensitivity, etc. by region. As LUMA continues to collect data and review its quality, the level of geographic granularity that is prudent to apply will continue to evolve.

Guidehouse understands that LUMA intends to continue to explore various ways to enhance forecasting input data and approaches and that LUMA may assess the practicality and benefits of forecasting customer class-level energy and load by region as opposed to developing it for the island as a whole and then allocating the forecast to regions.

Load Forecast Uncertainty

We begin the discussion of long-term load forecast uncertainty with the observation that all point estimates containing long-term forecasts of the economy, electricity loads, retail sales, housing starts and virtually any other item are wrong. In causal modeling, errors can result from forecast drivers themselves being different than what was forecasted, e.g., economic growth variances, weather not being “normal” (50th percentile or historical average), unexpected fuel price shocks being passed onto customers, and the quantifiable casual relationships evolving over time. Given these facts, best load forecasting practices call for:

6. Developing a *range of load forecasts* through scenario analysis, and/or probabilistic or stochastic analysis.

7. Performance testing the range of load forecasts by *backcasting* how well the load forecasting models would have performed given now known values of the independent variables: economy, price, weather and other variables in the causal models (See the section below on Performance Monitoring for more information on how this is done.)

8. Through (1) and (2) load forecasting professionals are able to cut through the fog of apparent forecast errors and explain *why*, for example, the forecast of loads over the last year differed from the midpoint of the load forecast range, and differentiate between model performance (over which the LFR team has control) and the performance of the input variable forecasts (over which the LFR team may not have control).

This part of Section 4.2.1.2 begins with an overview of some of the different approaches for modeling uncertainty (scenario analysis and different types of probabilistic approaches), and is followed by a discussion of scenario analysis and development, and a discussion of probabilistic techniques. Table 6 provides a summary of some the key characteristics of three of the most commonly used[42] approaches for modeling electricity load forecast uncertainty, as well as Guidehouse’s recommendations for their incorporation into the future methods.

[42] This table is not intended to be comprehensive and omits – for example – the use of Monte Carlo simulation techniques for modeling load directly using pure time series methods (i.e., without causal inputs). This example is omitted because it violates Principle 1, although a more detailed example of this type of approach’s implementation is provided in Appendix A.

Table 6. Summary Table of Uncertainty Approaches

	Scenario Analysis	Probabilistic – Historical Distribution	Probabilistic – Monte Carlo Simulation
Description	Apply alternative (sensitivity) input forecast assumptions, either to model parameters (macroeconomic variables, electricity prices) or load modifiers (DERS, EVs, etc.)	Apply observed historical values (or combinations of values) of key inputs with stochastic qualities (e.g., weather) to model parameters to identify distribution of outcomes. Select as inputs the combination of values delivering the desired probability (e.g., 90th percentile, 50th percentile, etc.)	Model the historical series (e.g., weather) and its data generating process (i.e., the stochastic shocks and their persistence in the time series). Simulate large set of projected series by repeatedly taking random draws from the assumed density function (distribution) of random shocks and applying these to model parameters.
Use-Cases	Modeling different visions of the future driven by factors not embedded in the historical record e.g., changes to forecast DER or EV uptake (due to policy or other exogenous effects).	Modeling distribution of forecast outcomes from different combinations of historically observed weather to estimated percentile probability of weather-driven load.	Modeling distribution of forecast outcomes from a simulated distribution of a given weather or price variable.
Key Benefits	Understand the sensitivity of forecast consumption and peak demand to different combinations of changes, e.g., very high electricity prices slow EV adoption but increase DG adoption.	Use of observed weather provides transparency: 90th percentile weather is some combination of temperature, humidity, etc. with some precedent. Does not require structural assumptions about data generating process (aside from assumption that historical probability is a guide for future).	Large number of simulations provides a smooth distribution (e.g., hundreds) of potential input values, can allow for very fine-grained analysis (e.g., what's the difference between 95th and 99th percentile outcome).
Short-Comings	Can be highly speculative, can result in significant stakeholder time commitment when defining scenarios (always another "what if?")	Probabilities are tied to historical distributions. May understate probabilities of extreme future weather events and the effects of accelerating trends in average weather values.	Requires strong structural assumptions about the distribution of random data. Can deliver simulated outcome variables in tails of distribution disconnected from observable history. Challenging to model multiple processes simultaneously (e.g., cloud cover and temperature) as doing so requires assumptions about joint probability density functions. Can be seen by stakeholders as opaque and "black box".
Recommendation	**Implement for highest uncertainty load modifiers.**	**Implement for modeling weather-based uncertainty.**	Not recommended for modeling weather uncertainty for Annual Load Forecast, though may be appropriate in other applications.

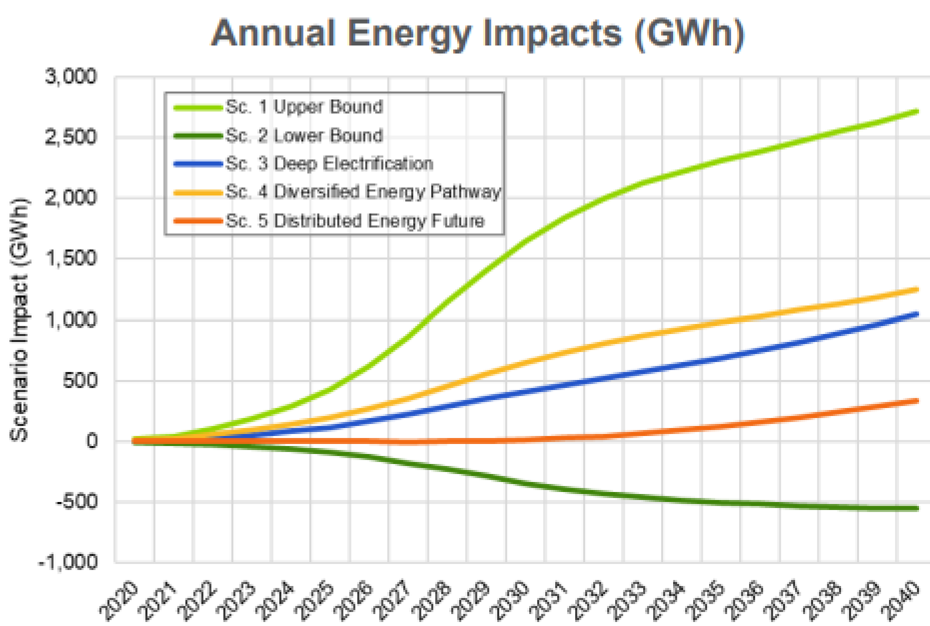
Most utilities now develop multiple load forecasting scenarios to understand the consequences of different future outcomes and the pathways forward they suggest. As noted in a 2016 Lawrence Berkeley National Laboratory (LBNL) paper[43]: "… *in more recent IRPs most Load-*

[43] Carvallo, Juan Pablo; Larsen, Peter H.; Sanstad, Alan H.; Goldman, Charles A.; Ernest Orlando Lawrence Berkeley National Laboratory, *Load Forecasting in Electric Utility Integrated Resource Planning*, October 2016

Servicing Entities (LSEs) are developing comprehensive future settings that reflect the interactions of several different fundamental variables such as economic and population growth and alternative technology adoption…"

FortisBC, for example, in its last two Long-Term Electricity Resource Plans (LTERPs), considered five alternative scenarios[44], each exploring the impacts on its reference forecast of substantial changes in structural load drivers, including adoption of light to heavy-duty EVs, residential and commercial PV (with and without storage support), and growth in novel loads (e.g., cannabis production, data centers). Scenarios and load drivers considered were selected in consultation with external and internal stakeholders. In addition to two "envelope" scenarios to test the extremes, stakeholder input was essential to developing the narratives for the scenarios of most interest: "Deep Electrification", "Diversified Energy Pathway", and "Distributed Energy Future".[45] An example output is presented in Figure 10 below.

Figure 10. FortisBC LTERP Load Scenarios



Source: FortisBC[46]

Guidehouse anticipates that scenario development would be, along with the use of hourly UPC modeling, geographic specificity, and probabilistic modeling, a core component of the LUMA LFR team's future forecast methods. Additional benefits of such scenario analysis include motivating thinking about longer-term contingencies and what policy choices might mitigate against such futures. For example, rapid adoption of rooftop solar combined with expanded Air

[44] In both cases quantitative outputs for these scenarios were developed by Guidehouse on FortisBC's behalf.

[45] A key element of these outputs was the development of a simplified web-based output tool that allows stakeholders to approximately identify the effect when alternative values are adopted for the most crucial inputs defining the scenario outcomes. That is, stakeholders were provided with a tool to help them understand the potential implications of scenarios of individual interest that were not adopted as part of the consensus of the advisory group that drove this process.

[46] PDF page 34 of 87 from: FortisBC, *FortisBC Inc. Resource Planning Advisory Group (RPAG) Meeting*, 2020-06-25 https://www.cdn.fortisbc.com/libraries/docs/default-source/about-us-documents/lterp-rpag-combined-deck-june-25-2020.pdf?sfvrsn=4adf6d1d_2

Conditioning (A/C) penetration might further erode system load factors, putting future upward pressure on rates, a situation potentially mitigated by the adoption of time-varied pricing and a policy of encouraging EV adoption.

Such scenarios also provide planners with a venue to be responsive to stakeholder concerns and demonstrate the flexibility to consider stakeholder input on future developments, even where it may not align with the consensus of expert opinion within LUMA. This may be particularly useful when modeling the impacts of aspirational legislative polices on customer loads.

In addition to scenarios, many utilities employ probabilistic techniques to address uncertainty. In load forecasting, probabilistic and stochastic methods are often simulation-based approaches applied to forecast the *distribution* of the output time-series dependent variable, rather than simply a point-estimate. This can be a very helpful output when the use-case for the forecast has an asymmetric loss function – that is if the cost of under-forecasting (for example) load is much higher than the cost of over-forecasting.

Probabilistic techniques are principally used to model the effects of exogeneous data that significantly impact loads, and for which there is a sufficiently robust history of observable values to motivate simulation. Temperature and temperature-related variables are a prime candidate for such uncertainty analyses (e.g., as used by Ontario's Independent Electricity System Operator[47] (IESO) - for its Reliability Outlook or Electric Reliability Council of Texas (ERCOT)[48] for developing its forecast scenarios). PacifiCorp uses stochastic techniques to model DG production and its impact on the net load forecast.[49]

In load forecasting, probabilistic methods are often simulation-based approaches applied to forecast the *distribution* of the output time-series dependent variable, rather than simply a point-estimate. This can be a very helpful output when the use-case for the forecast has an asymmetric loss function – that is if the cost of under-forecasting (for example) load is much higher than the cost of over-forecasting.

For modeling the uncertainty associated with weather, Guidehouse recommends that in the longer term the LUMA LFR team adopt a simulation approach based on observed historical weather. This style of approach to probabilistic weather projection has the great advantage (among others) of being able to capture the non-linear effects of accumulated thermal build-up more accurately. This style of approach (applied by ERCOT and the IESO, among others) involves the application of historically observed combinations of weather variables to forecast regression model parameters to better assess the range of energy or demand values associated with these observed weather combinations.

The resulting output distribution can then be used for delivering a probabilistic forecast: the median peak day weather is applied in the forecast period for 50th percentile forecast, and similar percentiles of the distribution (e.g., 90 or 95th) to reflect uncertainty and the GC's desired

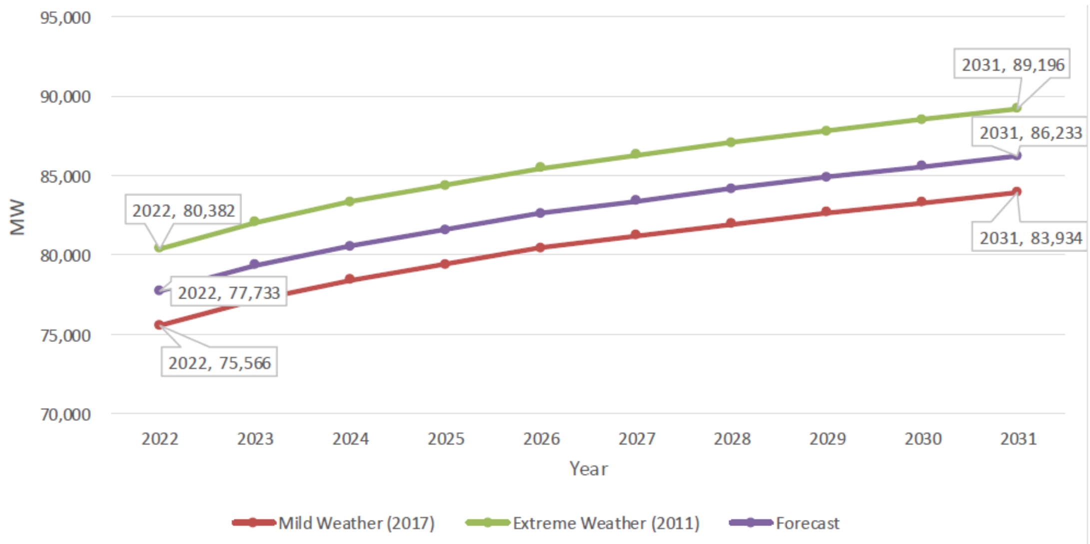
[47] Independent Electricity System Operator, *Methodology to Perform the Reliability Outlook*, March 2021

[48] Electric Reliability Council of Texas, Inc. *200 ERCOT System Planning: Long-Term Hourly Peak Demand and Energy Forecast*, January 18 2022

[49] Stochastic techniques are also used to model random variation in pricing that may affect power procurement (in interconnected markets). This is not addressed in this section as it is not directly relevant to load modeling in LUMA's service territory. In the unlikely event that LUMA were to anticipate a significant amount of flexible load to become subject to some form of real-time pricing, inclusion of probabilistic modeling of the real-time price (and its concomitant effect on demand) would be recommended.

confidence interval containing extreme weather forecasts. Figure 11 shows the outcome of this approach as applied by ERCOT on forecasted peak demand. Extreme weather is derived from the 90th percentile weather values, and the reference forecast from the 50th percentile values.

Figure 11. Outcome of ERCOT Probabilistic Weather Projection



Source: ERCOT

As noted in the table above, a great advantage of this approach is that no structural assumptions regarding random shocks (or the joint probability of shocks to different weather types) need be imposed. The weather applied to deliver a forecast value can be directly tied to a historical value. This offers much greater transparency than a Monte Carlo approach.

Considerable additional discussion of load forecasting uncertainty analysis, and accompanying examples, may be found in Appendix .

<u>Intra-Annual Forecast Updates</u>

In the current state, the LFR team develops Quarterly Updates three times per fiscal year to support the updates of the FCA and PPCA rate-riders. The current approach to these updates is to apply an entirely different analytic framework to develop the near-term (i.e., remaining fiscal year) projection of energy and demand through the use of generation data.

We recommend that the LFR team continue to update forecast values at this frequency but do so in a fashion consistent with the overall framework of the Annual Forecast approach. Specifically, Quarterly Updates should be driven principally by the application of updated input forecasts to the model estimated parameters.[50] This will ensure that the Quarterly Updates will capture the effects of any major macro shocks (e.g., the emergence of a global pandemic, or

[50] It is our expectation and recommendation that the model parameters – the estimated relationships to which the forecast input variables are applied – will be re-estimated once per year (reflecting updates to observed consumption and demand) to support the development of the Annual Forecast. For the Quarterly Updates, however, the expectation is that only the input exogenous forecast variables are updated, and no re-estimation is required.

major recession or financial crisis) that result in substantial revisions to forecast economic variables.

4.2.1.3 Performance Monitoring & Output Data Warehousing

Performance monitoring refers to internal workflow QC undertaken by members of the LFR team and to a commitment to continuous improvement through retrospective examinations of previous forecasts. External (to the LFR team, not LUMA) quality review and approvals by the GC and its delegates are addressed in Section 4.2.3.

Internal Workflow QC

The codebase or modeling architecture developed by the LFR team for the Annual Forest (and Quarterly Update updates) should reflect a philosophy of "defensive" development. That is, while effort must be made to ensure that the codebase and inputs do not include errors, *it must be assumed that errors will occur.* The LFR team must adopt a formal process or set of procedures to ensure that when errors *do* occur – for example due to an unexpected interaction when a novel scenario is deployed – that they can be detected, and corrected.

A key component for such a process is the output of interim values and tables as the input data roll through the scripts that manage the model estimation and forecast outputs. These may include binary checks (e.g., "sum checks", "max checks", etc.) or more complex tables of output values or relationships. Prior to up-chain submission of forecast outputs within the organization all such outputs should be checked, and – where relevant – commented on by members of the LFR team.

Such checks should be performed both by the lead analyst responsible for the given process, but also by a colleague (either a manager or in an adjacent role) to provide a "fresh eyes" examination. The socializing of such checks internally within the team (including with more junior team members) is vital, not simply to catch errors, or identify unexpected outputs (which can often provide important interpretative insight) but for educational purposes.

Formal checks of interim outputs provide opportunities for more senior team members to train their teams in the interpretive elements of forecasting. Code development, econometrics and other techniques of the data sciences can all be learned through formal education and training, but interpretative analysis, the ability to examine an output and understand its implications – what it *means* – requires hands-on experience.

A formal, collaborative, and well-documented internal QC process not only minimizes the likelihood of any errors propagating before they can be caught, but is essential for developing skills and abilities, maintaining institutional memory and expertise, and ensuring the longevity of the (sometimes hard) lessons learned by more experienced analysts.

Retrospective Forecast Review and Continuous Improvement

Whenever a forecast (whether a reference forecast or scenario) is finalized and approved, all input sets, and model objects[51] *must* be preserved in some accessible archived format. As data volumes and model complexity grows, storage may present challenges and solutions will need to be developed to avoid any unnecessary duplication of archival materials, but the preservation of such materials is critical for the continuous improvement of forecast accuracy. All results and outputs require their own data warehouse, analogous to the exogenous input data warehouse (described in Section 4.2.1.2) and the demand and energy input data warehouse (described in Section 4.2.2.2).

It is an axiom of predictive analysis that all forecasts are wrong. Understanding *why* previously made forecasts do not match observed outcomes is essential for continuously improving the quality of forecasting. Formal comparisons of past forecasts with observed values is also important for maintaining accountability and building institutional trust.

In the long term, the LUMA LFR team should, as part of its annual forecasting outputs, include a written assessment of, at a minimum, the previous year's forecast.

The forecast-to-observed comparison should proceed in two steps. The first is a simple comparison of the forecast and observed variables. Though important for transparency, this comparison is in the less useful of the two comparisons that should be performed. For one thing, since observed weather will likely not match the normal or (depending on the type of forecast), extreme weather used to project load material discrepancies between the two series will be inevitable.

Far more important (from the perspective of continuous improvement) is the comparison of a "back cast" or *ex post* forecast with observed values. An *ex post* forecast is what is output when the observed values of input variables *from the period covered by the original forecast* are applied to the estimated model relationships. Put another way, this series is what is obtained when instead of applying the forecast input variables to the estimated relationships, the actual, or observed, inputs are applied to those relationships.

Comparing this *ex post* forecast of load to actually-observed load then helps to reveal the quality of the model. If, for example there is a significant deviation between the original forecast and observed values, but very little deviation between the *ex post* forecast and the observed values, this would indicate that the model is performing very well, and the issue is with the forecast input variables.

In such a case as this the problematic inputs (and their impact on forecast outputs) could then be isolated through iterative replacement of forecast inputs with observed inputs. The outcome might be a reconsideration of the source of (for example) forecast macroeconomic variables, or the identification for improvements in certain internally generated input forecasts.

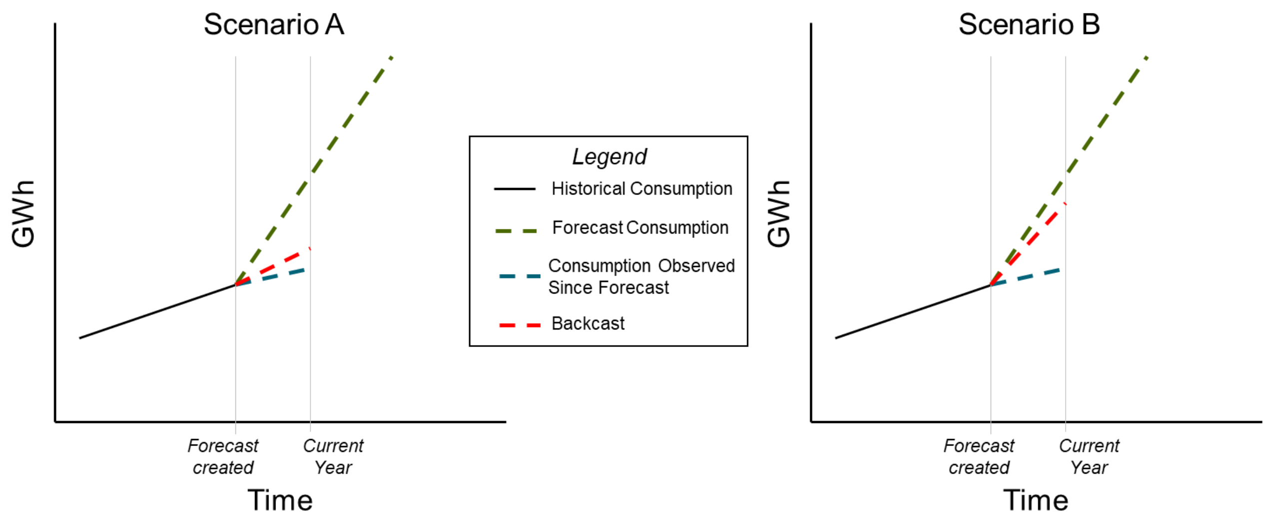
Consider the example shown in Figure 12. One year after it was developed, the forecast (green dashed line) is compared to observed actuals (blue dashed line). It appears to have significantly

[51] "Object" in this case refers to the bundle outputs typically output when econometric or other models of dependent/exogenous variable relationships are estimated. In the case of a regression this might include parameter values, summary statistics, in-sample predictions and residuals, the covariance matrix, diagnostic inferential statistics, etc.

over-estimated future consumption. After performing a backcast (red dashed line), the LFR team better understands the issue.

- In Scenario A, the backcast (red dashed line) is very similar to observed values. In this case the driver of the forecast error is an input forecast. More accurate input forecasts are required. Where the LFR team is constrained or required to use an input forecast identified as problematic, sensitivity scenarios should be developed with alternative inputs to provide additional context to the reference forecast that is a function of the problematic input forecast.
- In Scenario B, the backcast is similar to the original forecast and considerably overstates observed consumption. In this case the driver of the forecast error is one or more of the regression-estimated model parameters. It's likely that a different model should be used, or at least explored.

Figure 12. Backcast Comparison Example



Source: Guidehouse

Such *ex post* forecast review and be used to supplement out-of-sample model testing when determining in each cycle what updates may be appropriate to any model specifications.

As noted above, such an assessment should be performed (when the capabilities are in place and the resource capacity has been developed to do so) on an annual basis, with the previous year's forecast examined. The shortcoming of this is that comparing only the most recent year may reveal deviations that are minor over a 12-month period but that could propagate and result in more serious systematic forecast biases over the longer term.

To address this issue, older forecast model objects should periodically be revisited, and *ex post* forecasts output to identify to just how much some of the estimated relationships have changed over time. Such examinations will only be useful when the current forecast's structure is approximately similar to that of the older forecast (e.g., more or less the same variables being used, etc.) Key triggers for this kind of deeper historical review could include: consistent patterns of bias in *ex post* forecasts, significant suspected changes in the relationships between load drivers and load (for example due to economic shocks), or the introductions of disruptive technologies or programs (e.g., highly subscribed new tariffs, substantially increased sales of enabling technologies, etc.)

Finally, all formal reviews of prior year forecasts should identify key lessons learned that can be applied to subsequent forecasts, even when the lesson may simply be that the existing model is performing to expectations and should continue to be used.

4.2.2 Technology

The "Process" component detailed above is the core of the future methods; it is the techniques and approaches described above for this component that will define the character and quality of the LFR team's forecasts. These processes, however, are impossible to implement as intended without the tools – the Technology – appropriate to enable it. This section provides a description of the analytics and data management tools that the LFR team will, in the longer term, require at its disposal to deliver on the methods discussed above. It is *not* intended to provide a detailed breakdown of the strengths and weaknesses of any specific platforms, software, or metering technologies, but instead is a general discussion of what capabilities are required of such tools to serve the needs of the LFR team and LUMA.

The two subsections immediately below outline the most crucial groups of technology needed to support the next-generation processes described in the section above. They are:

- **Analytics Technology.** The LFR team should, in the longer-term completely transition to a code-based development environment to allow for the flexibility required for the processes described above. The selected development environment should allow for direct integration with large databases of customer meter data, generation data, and (as relevant or required) distribution asset data.

  As data volumes and the complexity of operations increase, processing requirements will exceed the capabilities of desktop machines and operations should be executed on dedicated LUMA or secure cloud-based servers or clusters. Third-party "software-as-a-service"-type analytics may be considered for adoption.

- **Data Collection and Storage Technology.** UPC customer profile development requires high-frequency customer meter data. A robust load research sample of meters will fill this gap until comprehensive AMI deployment becomes feasible. As with the input data warehouse discussed above, all processed profiles and cleaned metering data will need to be stored such that it can be accessed interactively by LFR and other team analysts interactively from the selected development environment.

4.2.2.1 Analytics Technology

At present, the LFR team relies principally on Microsoft Excel (and, to a lesser extent Access and EViews[52]). In the longer term, such tools will be insufficient for the LFR team's needs. Importantly, to develop the type of resilient workflow that enables agile team response to

[52] http://www.eviews.com/home.html

requests for scenario development and analysis, some form of code-based development environment will be required. This environment must allow users to query the key data warehouses (i.e., the input data warehouse discussed above, and a data warehouse of customer and asset load data) directly, and should, ideally, be sufficiently flexible to support a variety of load and load research analytics, not just forecast development.

There exist a variety of different types of platforms and programs that may be selected to support analytics and forecasting, both open-source and proprietary. Given some of the data challenges that LUMA faces, and the unique geographic and demographic circumstances of its service territory, Guidehouse recommends that the LUMA LFR team consider adopting an open-source development environment, such as R software or Python.

The selection of the development program (whether open-source, as recommended, or proprietary) must be made in consultation with other analytics groups (particularly those involved in load forecasting) at LUMA. The institutional benefits of a common platform across departments and groups are considerable, reducing costs of transitioning personnel from one area to another, and permitting collaborative innovation across teams.

Recent surveys of data scientists[53] indicate that open-source platforms continue to be the most popular platforms amongst practitioners (doubtless due to their use in the academic community). Python and R software[54] are both suitable tools for the type of workflows discussed above. Open-source tools provide many cost and work-flow advantages – in particular very active and engaged online communities with accessible code examples.[55] The adoption of open-source tools will likely, however, require the enhancement of IT personnel to ensure the appropriate architecture is in place to support server- or cloud-based deployment of such solutions.

Considerable development of processes and workflows will be required (and are discussed in Section 5) with the adoption of a new development environment, as would hiring and training additional personnel along with new training for the existing team. A systematic and measured internal approach to workflow and modeling development, however, will mean greater “ownership” of the process by the LFR team, which in turn will mean greater accountability and, in the long-term, greater stability and accuracy. The flexibility of such systems makes them suitable for wider adoption within the organization for more generalized analytics, which in turn can yield benefits from integration and cross-pollination with other groups, as well as skills redundancy to mitigate the effects of team attrition.

The open-source platforms above are noteworthy in that they provide a sufficiently powerful and flexible development environment to be used for all the required pre-processing and analytics required by the LFR team and others, as well as being equipped with modeling routines sufficient to directly support estimation and extrapolation needs. For example, Guidehouse uses

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[53] Such as this one by Kaggle (a subsidiary of Google, and host of an online community for data scientists). Kaggle, *2020 Kaggle Data Science & Machine Learning Survey* https://www.kaggle.com/code/paultimothymooney/2020-kaggle-data-science-machine-learning-survey/notebook accessed May, 2022

[54] R is the primary data science tool used by Guidehouse’s Analytics group.

[55] Guidehouse migrated from a SAS to R development environment beginning in 2013, to great success. Guidehouse’s experience has been that doing so has considerably lowered the barrier to entry to junior staff, who often join with existing experience in R or Python, and that this has in turn motivated much greater cross-team collaboration and innovation.

R to connect directly with NOAA's API and with server or cloud-based data warehouses. It can also be used for geo-spatial modeling, data preparation as well as estimating econometric error correction models and implementing machine learning algorithms.

Whatever solution is eventually selected by the LUMA LFR team (in consultation with its internal stakeholders and the GC), it must be one capable of meeting the modeling requirements described in the Process section above. As the data sets available grow in size, this will inevitably mean that the solution must be hosted either on internal servers or as some part of cloud-based service. This fact should be considered as the merits of competing systems are debated internally.

Although Guidehouse strongly recommends the adoption of an open-source development environment, many utilities do use proprietary environments (such as Statistical Analysis Sysytem (SAS) or MATLAB) software and some supplement these with industry-specific pre-packaged tools. The largest issue around using such tools relates to People as discussed in Section 4.2.3. The specialized training required to be a load forecaster *and* a programmer using these proprietary languages is incompatible with team attrition and the movement of personnel within the modern service industry.

For example, Guidehouse has seen several utilities suffer from being unable to replace workers in whom they have invested considerable time training in specialized software. This issue can be mitigated through the use of open-source platforms with much larger existing user-bases. Utilities with an existing code base may be reluctant to undertake the cost of refactoring their existing processes from a proprietary to an open-source platform, but the LFR is in a superior position relative to these entities: LUMA is moving from old non-code-based load forecasting approaches to new code-based ones and is therefore less affected by that kind of history or institutional inertia. Finally, although Guidehouse does not recommend proprietary load forecasting software packages for LUMA, in the interest of providing a representative perspective, these are discussed in section A.2 of Appendix .

4.2.2.2 Data Collection and Storage Technology

In addition to having an analytics platform capable of (and suitable for) developing the overall forecast workflow and model estimation and projection, the availability of sufficient data is crucial to the successful execution of the future methods described in the Process section (4.2.1). This section addresses questions of how data to support customer consumption and demand forecasting may be collected, and then the appropriate manner in which such data should be warehoused and made accessible to the LFR team.

As in the discussion of the analytics technology platforms, the perspective reflected here is that of the load forecasting practitioners; detailed discussions of different types of metering, or of the qualities of different large-scale data management programs are beyond the scope of this report. Rather, this section outlines what capabilities could reasonably be expected to be in place in the next seven to ten years to serve the needs of the future methods' processes.

Data Collection

In the very long term, Guidehouse assumes that LUMA will adopt some form of AMI metering that will make hourly or sub-hourly meter data for most customers available to the LUMA LFR team. It seems improbable, however, that such metering will be comprehensively in place within seven to ten years.

The future methods specified in the Process will require high frequency load data with sufficient history (e.g., 2 – 3 years at minimum) to allow for the effective estimation of UPC profile relationships. Such input data could be provided from a load research sample, carefully selected and strategically expanded, year by year. In deploying metering to a load research sample, LUMA should carefully consider the marginal costs of applying some metering to end-uses of particular interest (e.g., Heating Ventilation and Air Conditioning (HVAC), EV charging, etc.) in addition to whole-building metering.

By the time the future methods outlined in the Process have been mostly developed (e.g., in approximately seven to ten years) the data from a mature load research sample must be in hand to support them. As is addressed in the road map in Section 5, LUMA, the selection of an initial set of meters to make up the first group of load research meters should be expedited to ensure the availability of the required historical data when such data are required.

It should be noted that the planning and execution of this data collection must be informed by the determinations made in Phase 3 of LUMA's plan (see the introduction to this report), the identification of data needs.

Section A.2.2 of Appendix   provides some additional recommendations and discussion of how other data collection activities may supplement this sample metering.

Data Warehousing

As with the exogenous inputs, some central repository for prepared (i.e., "clean", analysis-ready) demand data will be required. In its early years (when the LFR team is still relying on load research sample interval data) size is unlikely to be an issue, but the LFR team and others should ensure that whatever solution is selected for demand data storage, it is scalable over time. Once AMI metering data begin to become available the rapid accretion of data may be challenging to manage.

The data warehouse under discussion here is not intended to act as a Meter Data Management System (MDM/S) – though of course such a system will be necessary to accommodate AMI data and any kind of time-varied pricing – but rather as an analytic resource to the LFR team and other teams as necessary. Like the exogenous inputs data warehouse, data tables within the demand data warehouse should be updated on a regular basis, and a clear line of responsibility for delivering (and advertising) those updates established.

It should be possible for the LFR team (and others) to query interactively from the database using the selected analytics development environment to minimize the introduction of error during transfers, and to allow for processes to be automated. As with the input data warehouse, redundancy should exist in the personnel responsible for administering and managing the data warehouse to ensure the continuity of available expertise and avoid any interruptions of data updates.

4.2.3 People

The "Processes" section above outlined some of the future analytic methods and processes that should be adopted by the LFR team in the longer term. The "Technology" section discussed some of the tools that would be required to enable those methods. This section, "People" describes some of the characteristics that would be required of the load forecasting personnel that are part of the LFR team, and some of the management structures and organizational incentives that would need to be in place to maximize the value that the team offers.

4.2.3.1 Team

The LFR team will require a diversity of skills to implement the methods and use the tools described above. The interdisciplinary team will likely need to include:

- Econometricians, with formal training in causal / structural modeling as well as time series analysis and approaches for diagnosing (and correcting) violations of the classical regression analysis assumptions (e.g., serial correlation).
- Data scientists, with training in the application of machine learning techniques, for example to (potentially) identify and attribute major changes in usage patterns to new end-uses (e.g., EVs, DERs)
- Data engineers, with training in database management, design, and maintenance.
- Engineers, with training in electricity generation, transmission, and distribution systems, and an in-depth understanding of the physical realities being analyzed by the data scientists and econometricians.

New hires with econometric, data science, or data engineering backgrounds should have accomplished some graduate studies (i.e., have either a relevant Master's degree or a graduate diploma from a highly targeted technical program). *Guidehouse estimates the LFR team will require, to support the updated processes discussed above, approximately six full-time personnel, however this may change depending on the skills and backgrounds of the individuals within the team*.

Some personnel may not be full-time members of the team or may be shared across other teams. For example, UPC profile modeling should include the input and review of an engineer well acquainted with the physical realities being modeled – such an engineer could be seconded to the LFR team on a part-time basis for just this purpose. Likewise, a data engineer may not be required as a full-time member of the team but might be shared with other teams within LUMA with deep data requirements.

Regardless of the formal departmental assignment of the members, the mix of skills above is crucial, as is the need to ensure some overlap in expertise. The econometricians, for example, should be able to execute queries from the data warehouse, and the engineers should be able to interpret the signs and values of parameters estimated using regressions. This overlap of skills ensures a certain amount of embedded redundancy essential to maintaining team resiliency. *The successful completion of annual updates to the forecasts or scenarios should never hinge on the availability of a single person.*

Within the team, personnel should be encouraged to provide each other with mentorship and to build the resiliency of the team with an informal or quasi-formal apprenticeship model. Section 4.2.1.3 ("*Internal Workflow QC*") noted the educational importance of QC activities. Model, forecast, and workflow updates (i.e., annual maintenance and changes) share this characteristic and provide an opportunity for more experienced personnel to tutor those with less experience in reviewing inputs, updating workflows, and interpreting the outputs.

Ultimately the goal of such internal team development via apprenticeship and informal mentoring is to perpetuate an institutional memory of lessons learned and to help accelerate the development in junior team members of analytic intuition[56], even in fields in which they may have little or no formal training.

4.2.3.2 Management & Organization

The "Team" sub-section above focused primarily on goals and expectations for intra-team development – informal ways of working that should be encouraged by management. This section focuses on the role of management in enabling such intra-team development, collaboration and integration with other teams and workflows, and of establishing a formal accountability and review structure that culminates in the approval of a final official version of the Annual Forecast by the GC.

This section begins with a discussion of team structure – covering some of the same material above but focused on management's responsibilities for developing it. It continues with a discussion of strategies to encourage collaboration and the adoption of a common work culture with other load forecasting teams (e.g., distribution planning and system operations), and concludes with a sub-section outlining what a formal approvals process used for finalizing the Annual Forecast might eventually resemble.

<u>Team Structure, Collaboration, and Culture</u>

At present, the LFR team is small (three Full Time Employees (FTEs)), and with very little in-built redundancy. Much of the analytic work is performed by the team lead, and it is unclear whether to what degree the team could continue with its work if the team lead were unable perform their duties, for whatever reason.

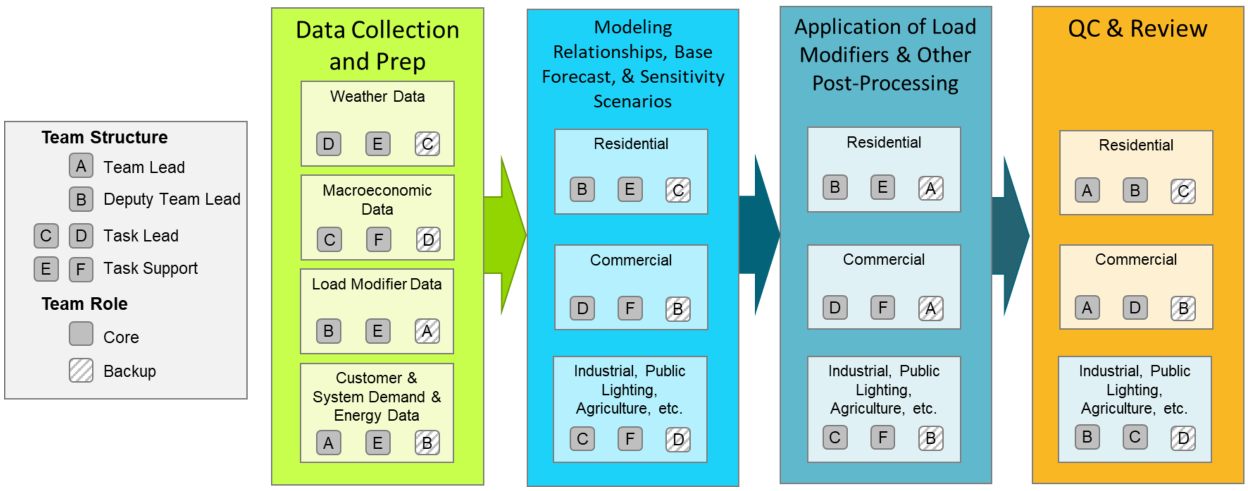
Subsection 4.2.3.1Team above noted the diversity of skills required for the team, the importance in overlap of skills and abilities (to ensure against team attrition), and the potential

[56] "Analytic intuition" here refers to the ability of experienced analysts and forecasters to intuit – *to feel out* - the narrative reality driving the observed data, and to validate, adjust, or reject that intuition on the basis of evidence derived from the data at hand. This ability to understand and articulate the underlying narrative driving the modeling choices and the forecast outcomes is an essential component of load forecasting teams. The importance of this skill will only grow as the disruptive load modifiers without historical precedent (e.g., DERs, EVs, etc.) proliferate.

for personnel to be shared with other departments or teams (particularly those undertaking forecasts or forward-looking projection).

Team management should formally track the responsibilities of all team members in a manner consistent with the forecast development and update steps laid out in any QC (see Section 4.2.1.3) or procedural (see Section 4.2.3.2) documents. That is, for each discrete task or set of tasks there should be identified (at minimum) two people: a task lead and a task support team member. Ideally there should additionally be for each task a backup team member, though for some tasks, depending on the experience of the support team member, they may be able to take on this role. Figure 13 presents a stylized example of what this structure could look like (assuming a backup person for each task), across different tasks. This is intended for illustrative purposes only.

Figure 13. Team and Task Structure – Illustrative Example



Day-to-day updates and minor changes are planned by the lead and may be executed by the support resource or by the support resource in collaboration with the lead. The backup person (if one is assigned and the complexity of the task requires it) is available to replace *either* the lead or the support person if necessary. The expectation would be that support personnel would rotate through a variety of tasks as support resource, allowing them to act as backups to multiple leads, replacing them temporarily or – if necessary due to attrition – permanently.

From time to time the team may be augmented using external consultants to accomplish specific tasks over defined periods of time. The focus of such augmentation should be on enabling the LFR team improvements – supporting self-sustaining changes, rather than outsourcing LFR team functions.

Additional recommendations for supporting team development and encouraging collaboration and the development of a common work culture across teams (outside of the LFR team may be found in Appendix)

Accountability and Review

The set of forecast and data management processes outlined above entail many complexities, and a potentially extended chain of custody (e.g., the preparation of many different sets of input data, some from different teams, the estimation of models for different customer sectors by VoC specialized groups, etc.) Even with the best internal QC procedures errors or unexpected output values will inevitably appear.

The long-term Annual Load Forecast process needs to be situated within a governance structure with formal sign-off requirements to ensure not just the quality of the output, but its consistency with the needs and assumptions of other business processes. In parallel to a governance structure that identifies sign-offs by analysis leads or qualified managers in departments providing inputs, transparent and clear documentation of processes must be maintained and updated on a regular basis. Finally, management may consider periodically benchmarking the LUMA LFR team's documented approaches against those of peer utilities through a combination of literature review and interviews.

Depending on the degree to which the LUMA LFR team integrates with other departments' load forecasting or analytics teams, the ultimate sign-off that identifies the most recent version of the Annual Load Forecast as the final official version in the current cycle may below either to the Vice President (VP) of Regulatory, or to an executive group (no more than 2-3 individuals) to which this responsibility is delegated by the GC.

The party or parties responsible for the ultimate sign-off should be provided with a document compiling summaries of up-stream QC and input validation sign-offs by the leads or managers responsible. For example, the input forecast of EV adoption might be addressed by a section summarizing:

- The updated forecast values and any material changes in trends or output values.
- Any methodological or input changes applied since the last iteration produced, with a concise justification for their adoption.
- A comparison of the updated projected values against both actuals and the previously provided forecast accompanied by any supporting narrative (as needed)
- Formal confirmation that a set of pre-determined QC checks were performed (and what those checks were)

All such content (with perhaps the exception of a formal acknowledgement of QC checks confirmed) would be expected to be developed and documented anyway as a reporting supplement to the output forecast and so should not therefore represent a significant incremental level of effort on the part of the leads responsible. The approval document rather would act as a targeted "check-list" and summary compilation of the most crucial information required to ensure that the final responsible party is sufficiently confident in the integrity of the workflow (and the quality of its output) to provide the final sign-off.

Note that such an approval document act as a supplement to, not a replacement for, any standard reporting documents required to accompany forecast submission. It would be intended to allow the party or parties responsible for final sign-off to confirm the review and sign-off of all upstream analysis leads and managers and to identify any major changes from previous versions that might require additional discussion with the GC.

Documentation and Review of Approaches

As noted above the summary accountability report would be a supplement to a formal load forecasting report presenting outputs and providing such analysis as is required to contextualize the projected outputs from both the reference forecast and any scenarios developed.

Guidehouse would anticipate that this formal internal report would be accompanied by data sheet appendices providing appropriately aggregated forecast outputs and inputs.

The specific contents of such a report will be determined by internal reporting requirements and the scope of the forecast and its outputs, but Guidehouse would anticipate that detailed discussions of methodology and approach would not be included, unless as an appendix.

Rather, the LFR team should develop a separate detailed presentation of the modeling approach. This document would not necessarily require the level of detail of a procedural document, but should include an identification of key modeling choices, inputs used, etc. Guidehouse would anticipate that this detailed methodology would only need (depending on the velocity of the evolution of the LRF team's forecasting approach) to be updated every 2 – 4 years, though an annual technical update highlighting material changes to the core approach should be produced on an annual basis.

Additional discussion of recommended documentation and internal publication processes may be found in Appendix .

5. Future Methods: Transition Plan Road Map

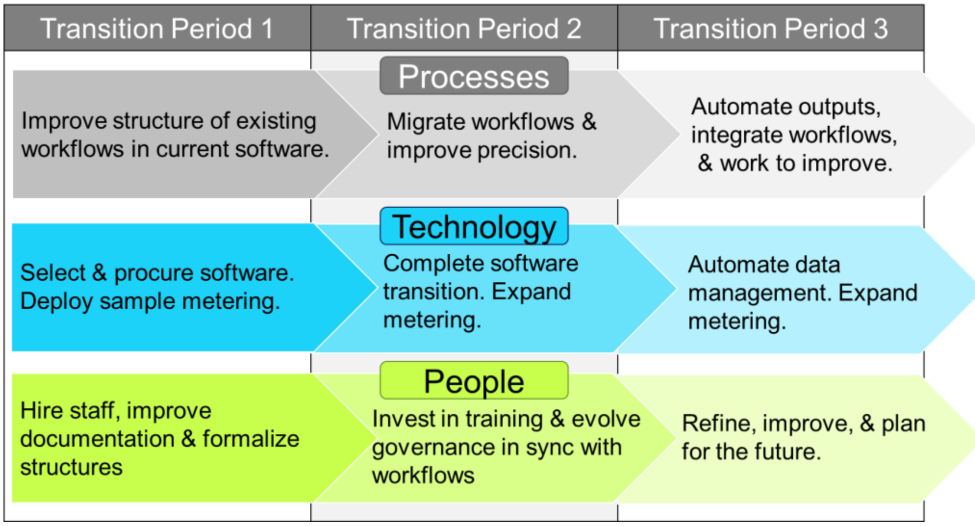
The previous section of this report provided a high-level description of the future methods LUMA's LFR team should adopt in the longer term. These methods cannot be adopted overnight – to ensure its success, the changes laid out above must be developed deliberately and carefully.

Measured and systematic evolution of LUMA's load forecasting techniques is important to:

- **Foster development** of the LFR team and other LUMA teams that undertake forward-looking analyses of demand and energy. The long-term success of the LFR team – and the quality of its outputs – will depend on its ability to drive its own evolution. Steady incremental change will allow the team and its management to "own" its future methods.
- **Retain and expand institutional memory**. Load forecasting requires interpretive analysis, driven by a systematic review of inputs and outputs filtered through expert opinion and intuition. These require experience to develop. The LUMA LFR team's lead provides a strong foundation of institutional knowledge upon which to build, but as the team expands, time will be needed to transfer and expand that knowledge.
- **Avoid disruptions to outputs**. The LFR team's outputs are critical inputs to a number of business and regulatory processes at LUMA. Changes to methods must not disrupt these outputs. To safely avoid such disruption systems or workflows must be transitioned systematically with care. In some cases, it may be prudent to run both workflows (the old and the new) in parallel for one forecast cycle to identify the impact of updates on output.

Informed by an understanding that change must be deliberate and carefully executed, this section provides a high-level road map to assist LUMA's LFR team in negotiating the transition from its current state to the future methods outlined in the previous section. Figure 14 provides a stylized summary of the transition process.

Figure 14. High-Level Transition Roadmap[57]



This section provides a summary transitional road map for the workstreams identified in Section 4 in each of the sections that follow.

The Guidehouse team notes that the volume of recommendations is substantial, and that the practical constraints and changing realities faced by the LFR team may require them to implement these recommendations selectively and may require adjustments to the relative timelines plotted out below.

Guidehouse believes that it is possible for all of the transitions outlined in this section may be completed in the 10-year time-frame time span anticipated by this report, *subject to the availability and provision of the funds and resources (human and material) to enable them*. Implementing these transitions will, however, be a significant undertaking with many interdependencies.

As LUMA continues to assess the quality of the data available and collect new data, the 10-year planning horizon identified in this report should be periodically re-examined in the context of other on-going changes to the environment in which LUMA operates and revised if required.

Finally, though the Processes, Technology, and People workstreams are all presented separately below, they are not independent of one another, and completion of some transitions in one workstream may require the completion of transitions in another workstream. The three most important dependencies here are:

1. **The LFR Team Needs a Technical Lead.** The LFR team has considerable experience in forecasting long-term load growth at LUMA, understands the local context and institutional needs very well, and has shown flexibility in adapting to the challenges that it has faced so far.

   To proceed with the transition as mapped out below, however, the team requires a *technical* lead to provide assistance to the team lead. The technical lead should be

[57] Note that references to metering here are not meant to indicate the assumption of full AMI deployment, but rather of the deployment of a relatively small number of meters to a carefully chosen load research sample.

someone with a load forecasting background, experience with open-source development platforms and at least 10 years of experience working in the utility industry.

2. **The LFR Team Will Need a Code-Based Development Environment.** Most of the processes in Transition Period 2 and 3 will require the availability of a code-driven development environment in which the more advanced workflows can be developed. The timing of the selection and stable implementation of a development environment will play a vital role in determining the pace of transition. Likewise, once the new development environment is in place, the pace of the transition will depend on the growth of the LFR team's fluency in that environment's language.

3. **Customer Metering Should be Prioritized.** Later periods in the transition roadmap include significant development of hourly customer modeling. To enable this, historical hourly customer data will be required. LUMA should prioritize beginning the deployment of metering (e.g., load research) to a representative sample of customer meters as soon as Phase 3 of LUMA's plan (the complete assessment of data needs) is complete and a sample plan developed.

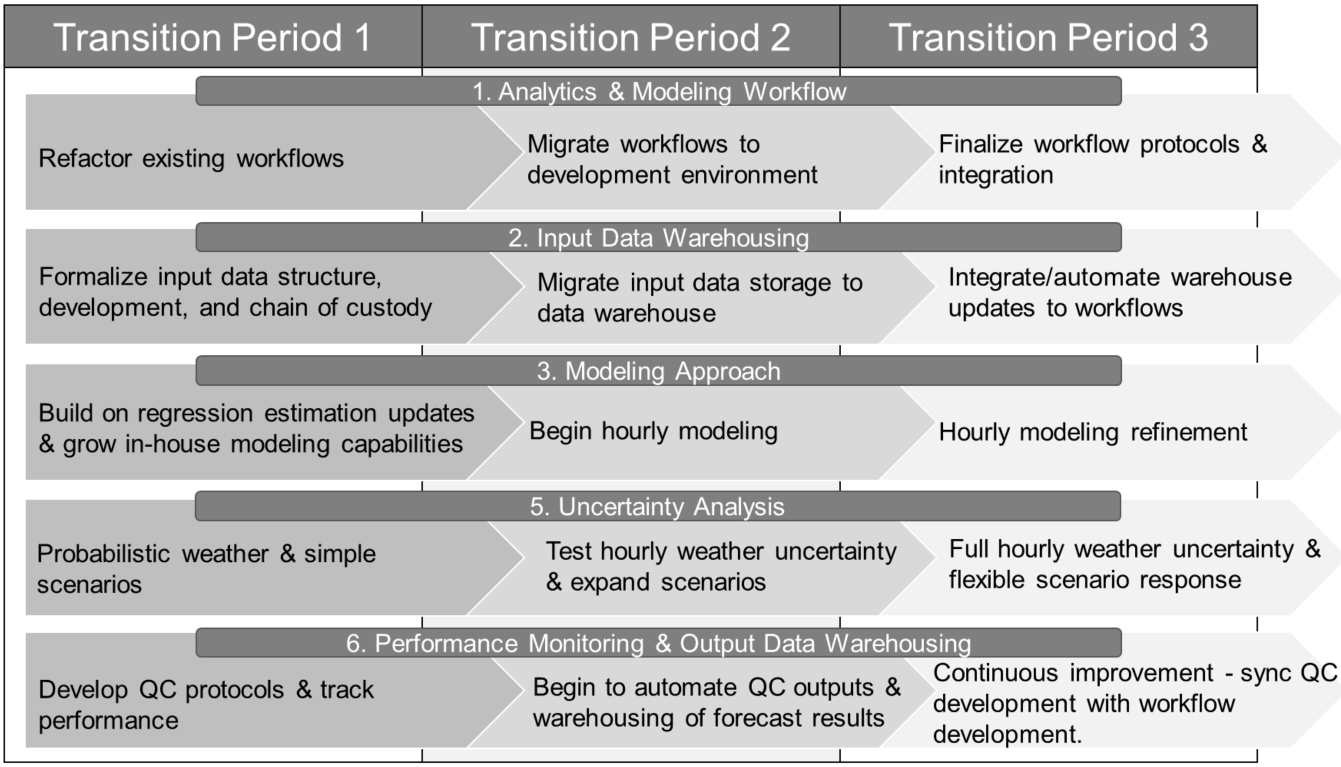
The remainder of this section is divided into three sections, each one providing additional detail regarding the recommended transitions for Processes, Technology, and People.

5.1 Processes

Figure 15, below, provides a more detailed map of the transition workstreams for the Processes. These all follow the same general structure laid out above:

- Improve structure of existing workflows in current software.
- Migrate workflows & improve precision.
- Automate outputs, integrate workflows, & work to improve.

Figure 15. Processes Transition Roadmap



5.1.1 Analytics & Modeling Workflow

The analytics and modeling workflow refers to the larger process within which each of the more specific procedures (demand modeling, uncertainty analysis, etc.) exists. The three key stages for this workflow, by Transition Period (TP) (TP1, TP2, TP3), are to:

1. **TP1: Refactor existing workflows.** The existing Excel workbooks that together combine to deliver the Annual Forecast outputs (and Quarterly Updates) are reflective of an organic evolution. The logic across them is challenging to follow, and far too many manual interventions are required (increasing the potential for error). The LFR team should adopt a consistent set of Excel development leading practices and apply these to a reorganized set of workbooks. As existing workflows are refactored existing procedures and documentation should be updated to reflect any changes applied and the new file structure.

2. **TP2: Migrate workflows to development environment.** Adopting a new environment for workflows, especially one that requires a transition from mostly point-and-click (Excel) to the writing of code (R or Python) can be challenging. To help develop the team's skill with the new platform, the first task should be to transfer over the existing workflows to the new environment and test the outputs against those from the old environment to ensure alignment. Following replication, the team can begin to expand the sophistication of its approach by taking advantage of the more flexible capabilities of the new development environment.

3. **TP3: Finalize workflow protocols & integration.** In the final Transition Period, the LFR team should have sufficient experience in the development environment to complete the adoption of all modeling or data management requirements noted in the other workstreams. In this Transition Period, the LFR team shifts from a core focus on development to one of maintenance and continuous improvement. Once processes and workflows stabilize, and focus begins to shift to maintenance, a concerted effort must be made to document these to ensure transparency and resiliency to personnel changes.

5.1.2 Input Data Warehousing

The input data referred to here are the exogenous inputs used to model customer consumption and demand (weather, economic factors, load modifiers, etc.). The discussion of the transition related to the warehousing of dependent variable data (demand, consumption, etc.) may be found in Section 5.2.3 and the discussion of the transition related to the warehousing of output data (results, model objects, etc.) may be found in Section 5.1.5.

The three key stages to the development of the input data warehousing are:

1. **TP1: Formalize input data structure, development, and chain of custody.** Assign the collection and processing of inputs to sub-teams with the LFR team, and create a central, logical, and transparent file structure with separate but adjacent directories for original data inputs (untouched), workbooks that process and prepare the data, final outputs required as inputs to the estimation and forecasting process.

2. **TP2: Migrate input data storage to data warehouse.** Migrate input data management from the structured file management structure to a data warehouse (i.e., a relational database) that can be accessed interactively from the new data environment.

3. **TP3: Integrate/Automate warehouse updates to workflows.** Where possible, automate input data collection (e.g., web-scraping historic macroeconomic variables) and processing tasks to minimize the introduction of errors through user inputs.

5.1.3 Modeling Approach

The modeling approach here refers to the estimation of historical relationships to which forecast input variables are applied to deliver the base forecast, and the application to this of load modifiers, as required or relevant. The three key stages to the development of the modeling approach are:

1. **TP1: Build on regression estimation updates & grow in-house modeling capabilities.** Obtain external assistance to re-estimate the core forecast regression models and then learn to use and to update any code developed by the external team for monthly consumption estimation. Build on this codebase to develop a customer count forecast and transition to a monthly UPC time customer count approach. Test for violations of classical Ordinary Least Squares (OLS)[58] assumptions and implement error correction models Error Connection Models (ECMs) if required. Begin experimenting with modeling system peak demand using hourly generation data.

[58] Ordinary least squares (OLS) is the standard approach for the estimation of unknown parameters in a linear regression model.

2. **TP2: Begin hourly modeling.** Develop robust hourly model for projecting peak demand based on hourly generation data. Use research sample hourly metering data to begin developing hourly models of customer class consumption.

3. **TP3: Hourly modeling refinement.** Transition to hourly UPC of residential and commercial customers on the basis of research sample load data. Expand number of segments used for residential and commercial sectors to accommodate structural changes in customer types (e.g., standard residential customers, EV owners, etc.)

5.1.4 Uncertainty Analysis

The uncertainty analysis transition focuses on expanding the capabilities of the LFR team beyond a single-point projection of customer class consumption and system peak demand, to a workflow that incorporates probabilistic projection and scenario analysis. The three key stages to the development of the uncertainty analysis are:

1. **TP1: Probabilistic weather & simple scenarios.** Enhance the existing forecast approach by applying probabilistic weather and develop 2 – 3 simple alternative future scenarios to account for different growth pathways in key load modifiers. Plan out application of probabilistic weather techniques to hourly generation data modeling.

2. **TP2: Test hourly weather uncertainty & expand scenarios.** Implement hourly probabilistic projected weather for modeling hourly system demand based on generation data. Expand scope of long-term scenarios, considering alternative interactions of drivers (e.g., growth in rooftop solar PV with little EV adoption).

3. **TP3: Full hourly weather uncertainty & flexible scenario response.** Finalize hourly weather probabilistic projection for application to hourly UPC modeling. Put in place input forms and code mechanics such that new scenarios can be specified, run, and outputs shared on a very short turn-around time to provide greater analytic flexibility to LUMA management.

5.1.5 Performance Monitoring & Output Data Warehousing

Monitoring the accuracy of historical forecasts compared to observed actuals and identifying the drivers of forecast error are essential for ongoing improvement in forecast performance. All model outputs (forecast values, estimated parameters, etc.) must be preserved and warehoused such that they continue to be available as needed. Similarly, a posture of “defensive” and ongoing QC of code and outputs will minimize preventable errors. The three key stages to the development of performance monitoring are:

1. **TP1: Develop QC protocols & track performance.** Based on the refactored workflow, create a set of QC outputs (sum checks, etc.) that can be output for each data processing step to ensure any errors are caught before they can propagate. Preserve historical forecasts and compare to observed actuals and implement semi-annual or quarterly backcasting.

2. **TP2: Begin to automate QC outputs & warehousing of output data and historical forecasts.** With the workflow migrated to the new development environment, automate the output of QC checks in the form of simple scalar checks, interim output summary

tables and plots of values. Automate storage of output forecasts to a data warehouse and the development of comparison metrics and plots (e.g., for backcast values) for performance monitoring.

3. **TP3: Continuous improvement – sync QC development with workflow development.** As workflows become more complex to accommodate hourly modeling and greater model granularity, continue to evolve QC checks, and develop an output shell of crucial QC checks and performance checks that can be shared up-chain to make forecast approvals more efficient.

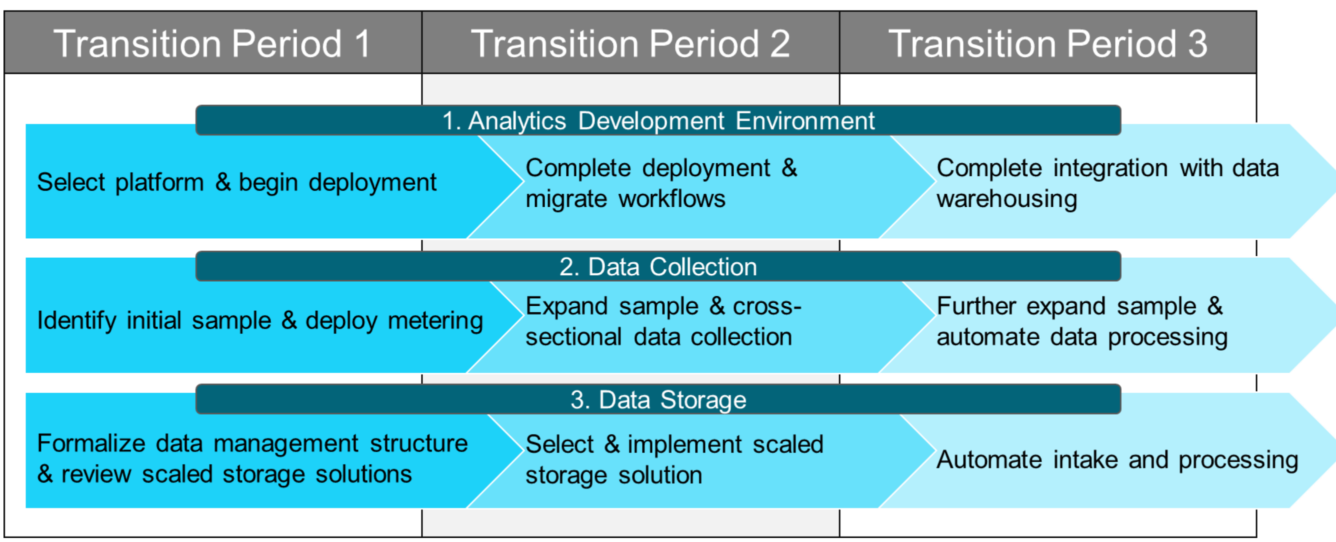
5.2 Technology

Figure 16 provides a more detailed map of the transition workstreams for the Technology element. These all follow the same general structure laid out above:

- Select & procure software. Deploy sample metering.
- Complete software transition. Expand metering.
- Automate data management. Expand metering.

As noted previously, the technology transitions are necessary conditions for the progression of the transition of the Processes in Transition Period 2 (using the new development environment) and Transition Period 3 (availability of hourly or sub-hourly customer class data from a research sample of meters).

Figure 16. Technology Transition Roadmap



5.2.1 Analytics Development Environment

The selection and implementation of the development environment is essential to allow the development of more sophisticated techniques like ECMs, hourly modeling, and flexible scenario analysis.

The three key stages to the implementation of the analytics development environment are:

1. **TP1: Select platform & begin deployment.** There are substantial collaboration and innovation benefits when analytics personnel throughout an organization use the same development platform. The LFR team should work through the GC to review the candidate platforms and select one (or more[59]). Procuring a server- or cloud-based implementation will require substantial support from IT, and team members should be encouraged to obtain local versions (i.e., laptop or desktop installs) as implementation to proceeds to help them acclimate.

2. **TP2: Complete deployment & migrate workflows.** When IT deployment is complete, the LFR team can begin to migrate workflows from Excel or locally-installed versions of the software to server- or cloud-based implementation. Version control practices and software (e.g., Git) should be implemented, and an informal mentorship and paired programming system established to build team capabilities and ensure consistent coding practices. Integration with data warehouse (i.e., accessing relational databases directly from the development environment) should begin.

3. **TP3: Complete integration with data warehousing.** Integration of the development environment with data warehousing should be in place to minimize duplicative or potentially confusing data storage. Version control should be used by all programmers, with alternative branches in place to allow for concurrent development and production versions of code.

5.2.2 Data Collection

A crucial constraint on load forecasting at LUMA (and PREPA previously) has be the dearth of robust metering data of hourly or sub-hourly customer demand. Without widespread AMI, or the prospect of any near-term full deployment of such, the establishment and gradual expansion of a load research sample of customers equipped with interval meters will be essential to supporting the development of hourly customer class-level modeling in the future.

The transition plan related to the expansion of data collection articulated below is focused on improved metering of demand, as is appropriate given the core focus of this work on the modeling (and forecasting) of customer demand and energy. The expansion of distribution, transmission, and generation asset metering is also important for the purposes of better modeling (for example) technical and non-technical losses, and the LFR team should work closely with other teams responsible for such metering to integrate such data (as it becomes available) into its modeling.

The three key stages to the implementation of the data collection transition are:

1. **TP1: Identify initial sample & deploy metering.** Develop a sample frame of residential and commercial customers that can provide a representative sample of customers. Over-sampling in some categories or segments (e.g., EV-owning residential customers) may be advisable, *provided* after-the-fact weighting can be applied to ensure sampled demands are representative of the residential and commercial customer population. Sample selection should take into account (and take advantage of) any other metering

[59] In the earlier transition periods, there are significant benefits to using only a single development platform. As capabilities develop, however, consideration may be given to adopting a second one where there are identified use-cases. For example: R is generally preferred for analytics, whereas Python is regarded by some as a more suitable platform for developing processes.

deployed by other departments (e.g., interval metering of EV TOU rate pilot participants). Meter technology selection should investigate the potential deployment of end-use monitoring for major uses such as HVAC, water heating, EVs, etc. in addition to whole-building metering.

2. **TP2: Expand sample & cross-sectional data collection.** The load research sample of meters should be expanded on an ongoing basis as resources permit to establish a robust and representative history of customer hourly data. Additional data collection of cross-sectional customer characteristics (review of property assessment data, deployment of end-use surveys) should be undertaken to enhance load data collected from the sample whole building / major end-use meters.

3. **TP3: Further expand sample & automate data processing.** Intake data processing and Validation, Editing, and Estimation (VEE) should be automated to allow near-continuous updates to the demand and energy data warehouse. Expansion of metering should continue to help develop a larger, more flexible sample for forward-looking analyses.

5.2.3 Data Storage

There exist at present multiple streams of data used by (or that may be used by) the LFR team for forecast development, including: monthly billed consumption by customer class, hourly generation data, and hourly distribution asset data. As load research metering is deployed the volume and complexity of these data will increase. To ensure the quality and replicability of the LFR team's work a data warehouse is required to house these. This will likely take the form of a relational database.

The three key stages to the implementation of the data storage transition are:

1. **TP1: Formalize data management structure & review scaled storage solutions.** A similar approach to that discussed above for analysis input data should be implemented: the establishment of logical and well-structured set of input, processing, and output directories. This will ensure a robust chain of custody of data and facilitate the delegation of data processing activities. In this phase the LFR team should also coordinate with other teams involved in the GC to review existing data storage solutions already implemented at LUMA (e.g., Oracle) and explore their applicability to this use-case. Depending on the limits and costs of any existing in-place solution, LUMA may wish to consider additional (particularly cloud-base) solutions (e.g., Snowflake).

2. **TP2: Select & implement scaled storage solution.** The scaled data warehouse solution should be implemented, and the storage of original (unprocessed) and final (processed and "cleaned") data migrated to it. Data processing (e.g., VEE) should be applied within this solution to make scaling data volumes straightforward as more meter data accrue.

3. **TP3: Automate intake and processing.** Inputs from metering or data collection to the storage solution should be automated, and VEE applied in an automatic or scheduled manner. Automated procedures should output plots and tables of summary statistics to provide up-to-date quality monitoring and assurance.

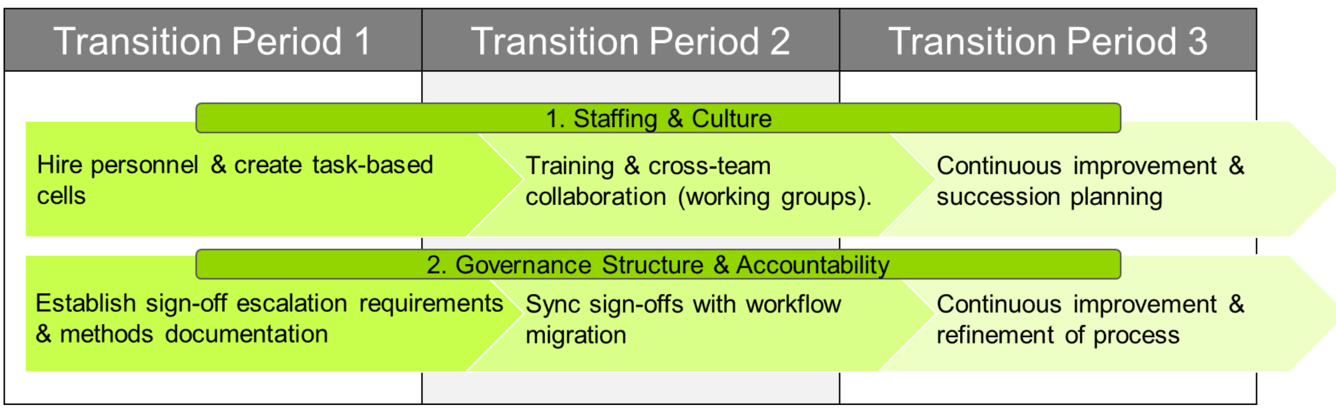
5.3 People

Figure 17, below, provides a more detailed map of the transition workstreams for the People element. These all follow the same general structure laid out above:

- Hire team members, improve documentation, & formalize structures.
- Invest in training & evolve governance in sync with workflows.
- Refine, improve, & plan for the future.

As noted in the introduction to this section, engaging an experienced person with formal training in econometrics and data science, and a history of developing long-term forecasts is a necessary condition for the longer-term development. Hiring such an individual to support the existing LFR team lead as a technical lead is essential for helping to direct the development laid out in this transition map, and to expand the capacity of the existing team (and any newer hires) to manage the new process and technologies.

Figure 17. People Transition Roadmap



5.3.1 Staffing & Culture

The LFR team requires additional members and the opportunity to train itself in the techniques and tools that will be required going forward. As the team grows, establishing lines of responsibility in a formal manner will become more important to ensuring there are no gaps in the process, and to enable the formation of cross-departmental working groups capable of collaborating on mutual problems. Such mutual assistance across teams is important for continuing to grow a shared work culture and establishing the kind of institutional memory that allows the teams to continuously build on the achievements of their predecessors.

The three key stages to the implementation of the people and culture transition are:

1. **TP1: Hire personnel & create task-based cells.** Establish a skills matrix for existing team members and identify gaps. Hire a technical lead to act as change champion within the team and assist team lead with transition activities. Hire support personnel with the appropriate skills and create cells (sub-teams) that are task-specific – related to both maintaining existing required outputs and for building capacity.

2. **TP2: Training & cross-team collaboration (working groups).** Identify tasks where substantial interactions with other departments and teams are present (e.g., distribution asset data processing, peak demand estimation, load modifier data processing) and encourage the creation of cross-team working groups to ensure consistency in data processing, providing opportunities for collaboration. Provide team members (new and existing) with self-directed training opportunities (e.g., via Datacamp) as well as more formal courseware.

3. **TP3: Continuous improvement & succession planning.** Cross-team working groups should be encouraged to continue to innovate and resources should be made available to support their development of papers and presentations for conferences to incentive development. Team and task leads should engage in succession and contingency planning to ensure the ongoing continuity of the team and its outputs.

5.3.2 Governance Structure & Accountability

As the LUMA LFR team's methods and tools evolve and change – potentially quite rapidly – a robust governance structure and methodological transparency will be vital to foster internal and external institutional trust in the team and its outputs. The application of escalating sign-offs, supported by a standard catalogue of supporting quality checks and technical documentation can help to ensure consistency of forecast outputs (and assumptions) within the organization, and faith in the mechanics driven by external stakeholders.

The three key stages to the implementation of the governance structure and accountability transition are:

1. **TP1: Establish sign-off escalation requirements & methods documentation.** The creation of formal QC check-lists and output values, tables, and plots should culminate in the development of an internal QC document submitted to the VP Regulatory along with final forecast values and other reporting. As approach development stabilizes following workflow refactoring LFR team should also develop an outward-facing methods document describing its approach. While such documentation doesn't require the mechanical detail of a Procedure, it should be sufficiently detailed to allow reviewers (assuming access to the data) to approximately replicate the LFR's approach and outputs.

2. **TP2: Sync sign-offs with workflow migration.** As the refactored workflow is migrated to the new development environment and additional analyses undertaken, the sign-off tracking document must change accordingly. On-going updates should also be made to the methods documents, including data output appendices (where relevant or appropriate) that demonstrate a link between the team's performance monitoring and the evolution of its approaches.

3. **TP3: Continuous improvement & refinement of process.** As workflows in the new development platform begin to stabilize and move toward greater refinement and granularity, sign-off support documentation should continue to evolve based on lessons learned and shifting priorities. The presentation of key elements of the sign-off document contents to the GC at periodic intervals may provide opportunities for greater integration and collaboration across teams.

Appendix A. Future Methods – Additional Detail & Examples

The purpose of this appendix is to provide additional detail and examples regarding the recommended future methods. It follows the same format as Section 4 and is divided into three sections: Processes, Technology, and People.

A.1 Processes

This section of Appendix is divided into two sub-sections, expanding on the corresponding sub-sections of Section 4:

- Load Modeling
- Uncertainty Analysis

A.1.1 Load Modeling

LUMA's LFR team should adopt an approach of modeling future consumption and demand through the use of a combined UPC and customer count forecast approach for residential customers, all but the very largest commercial customers, and all small and medium industrial customers. As noted in the transition roadmap (Section 5) this can start on the basis of monthly UPC, but in the longer term the LFR team should migrate to modeling hourly UPC.

In most contemporary applications of this approach the UPC projected is quite coarse – a monthly or annual value. LUMA's long-term development of future methods should target a much higher frequency output – an 8,760, or hourly profile of average use per customer, by year, using future interval data from AMI and/or load research samples.[60] This level of temporal granularity provides significant benefits:

- *Peak Demand and Energy Forecasting Integration.* Forecasting on an hourly basis makes it possible to use the same modeling framework for forecasting peak demand and energy consumption. Peak demand and energy forecasts may require different forecast inputs (e.g., 1-in-2/50-th percentile "normal" weather for the energy forecast, and 1-in-20/95th percentile extreme weather for the demand forecast), but can use the same estimated parameters (relationships). As noted in the main body of the report, Guidehouse believes it unlikely that hourly customer level data alone will be sufficient to deliver a robust projection of class-level peak demand, but may be so when calibrated to a forecast of system peak demand estimated on the basis of hourly generation data (for which significant history already exists).

- *Peak Migration.* Identifying the impact of load modifiers (e.g., distributed generation, energy efficiency, etc.) in the forecast can be confounded when the magnitude of their effect is sufficient to impact the timing of system peak hours. The "duck curve" effect of

[60] Given that the development of an 8,760 forecast based on meter data will require at least a few years of history from some sample of customer meters, Guidehouse anticipates that input hourly data will need to be derived from a load research sample. The ability of the LFR team to output such a forecast will therefore be dependent on the funding and deployment of a load research sample set of meters promptly following the LUMA's completion of the assessment of its data needs and the development of a robust sampling plan approved by the load forecasting Governance Committee. Depending on the progress of such data collection directly modeling 8,760 customer demand based on customer meter data may require more than the 10 year period covered by this report.

behind-the-meter solar PV may mean that the expected peak reduction value of some DSM programs may be eroded. Hourly granularity is essential for tracking intra-daily peak migrations.

- *Rate-Setting*. The ability to generate accurate hourly forecasts for specific sub-groups of customers is important for allowing rate designers to develop equitable rates that adequately recover the costs that groups of customers impose on the system, and reduce any undesirable and unintentional subsidization across tariff classes.

The specific technique to be applied by the LUMA LFR team to forecast the number of customers in each segment or group of interest, and the UPC profile will need to be determined as more data become available, and the LUMA LFR team's tools and analysis become more sophisticated. The specifics are likely to vary considerably also by customer type.

Sacramento Municipal Utility District (SMUD)[61], for example, forecasts residential customer as a function of population and commercial customer growth as a function of economic drivers such as employment and gross county product. Avista, in contrast, uses pure time-series Auto-Regressive Integrated Moving Average (ARIMA) approaches for projecting residential customer numbers, and simple smoothing or trend models for other classes

In line with Principle 1, however, Guidehouse would recommend an approach more aligned with that of the SMUD example: one in which the customer count is forecast as a function of some clearly causal input. This would likely be enhanced, or adjusted, based on (for example) the outputs of EV adoption models or projections of migrations from standard flat rates to time-varying rates prepared by other teams within LUMA.

The UPC forecast too may be derived in a variety of ways. PG&E uses econometric error correction models (linear regression enhanced via time-series modeling of residuals to correct for serial correlation), whereas PacifiCorp[62] uses a Statistically Enhanced End-use (SAE) model. FortisBC[63] simply carries forward a ten-year linear trend to forecast residential UPC.

A.1.2 Uncertainty Analysis

The expanded discussion of uncertainty analysis here is further divided into a discussion of scenario analysis, and probabilistic analysis.

Scenario Analysis

The discussion of uncertainty analysis in Section 4.2.1.2 provides one concrete example of the use of scenario analysis in utility long-term load forecasting. An additional example and discussion of this approach is provided here.

In addition to FortisBC, Salt River Project[64] offers an excellent example of the way scenarios can be used to articulate different potential future worlds, and so understand the potential

[61] SMUD, *Resource Planning Report*, April 2019

[62] PacifiCorp, *2021 Integrated Resource Plan – Volume II*, September 2021.

[63] FortisBC Inc., *2021 Long-Term Electric Resource Plan – Volume 1*, August 2021.

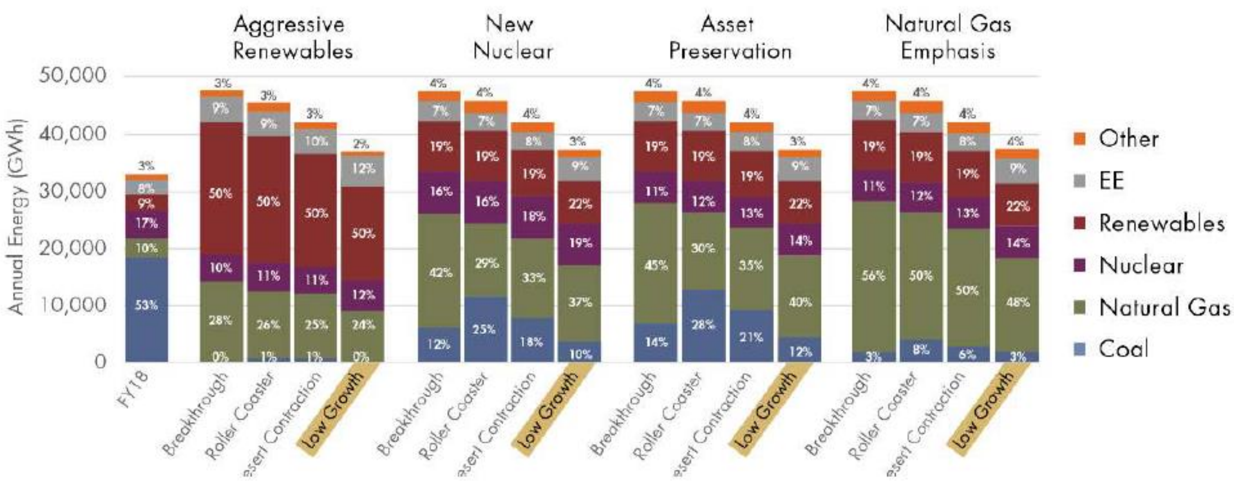
[64] Salt River Project, *Integrated Resource Plan Report 2017 – 2018*, 2018.

SRP has published annual updates to this plan since its issuance (every February) and is due to publish the next full plan in November of 2022.

consequences for forecast consumption and demand. Scenarios developed for System Remediation Plan (SRP's) 2017/2018 IRP include:

- "*Breakthrough*" which imagines continued high growth in customer numbers and consumption, price stability for input fuels, and substantially reduced costs for DERs.
- "*Roller Coaster"* which imagines increased economic volatility driving cyclic shifts in demand, historic input fuel price volatility, and no meaningful or sustained reductions in DER costs
- "*Desert Contraction"* which imagines a decaying load factor and reduced growth, primarily motivated by the acute impacts of climate change in the U.S. Southwest.

Figure 18. SRP's IRP Scenario Consumption & Corresponding Resource Mix



Source: SRP

One great advantage of incorporating scenario analysis into the overall forecast workflow – and developing that workflow such that new scenarios are straightforward and quick to run – is to provide external stakeholders with a better understanding of the materiality of any disagreements they may have about core assumptions. For example, if the reference forecast and principal scenarios assume fewer EVs than a key stakeholder believes are appropriate, flexible scenario outputs can help reassure that stakeholder by helping them understand what the impact would be of their more aggressive assumptions.

For example, a key element of FortisBC's scenario outputs was the development of a simplified web-based output tool that allows stakeholders to approximately identify the effect when alternative values are adopted for the most crucial inputs defining the scenario outcomes. Stakeholders were provided with a tool to help them understand the potential implications of scenarios of individual interest that were not adopted as part of the consensus of the advisory group that drove this process.

<u>*Probabilistic Analysis*</u>

Probabilistic approaches are important for forecasting load in high frequency (e.g., hourly) forecasts, where the use of average weather will understate weather-related swings in load due the way that averaging flattens the random day-to-day variation in temperatures. It is for this reason, for example, that Detroit Edison Gas Company (DTE's)[65] natural gas sales forecast converts monthly weather normal into a daily series that reflects intramonthly temperature volatility – in that case the intramonthly temperature volatility is critical for capturing the nonlinear impacts on gas demand when temperatures cross certain key thresholds.

The recommendation in the main body of the report is that LUMA consider the use of a probabilistic approach to weather estimation similar to that used by the IESO or ERCOT. A more detailed description of the IESO approach that maps historical weather to the regression-estimated parameters is presented below as an illustration of the approach.

- The weather for each July day over the past 31 years is applied to the corresponding regression parameters.
- This delivers 31 sets (for 31 years) of 31 (days in July) demand values.
- For each year, the weather that delivers the peak *weather-attributable* demand in that month/year combination is selected.
- This then delivers a distribution of 31 sets of peak demand-driving weather in July.

A tabular example of this process is presented in Figure 19.

Figure 19. IESO Example: Creating Monthly Normal (50th Percentile) Weather

	Year									
Rank	1985	1986	1987	1988	-----	2012	2013	2014	2015	Median
1	4,791	4,427	5,569	**4,921**	-----	5,219	4,985	5,321	4,875 →	4,921
2	4,395	4,393	5,482	4,517	-----	4,989	4,820	5,317	4,522	4,764
3	4,373	4,310	5,201	3,994	-----	4,850	4,285	4,845	4,383	4,450
4	4,272	4,057	4,912	3,971	-----	4,799	4,255	4,292	4,081	4,264
5	4,024	4,002	4,703	3,877	-----	4,630	4,126	4,291	3,847	4,084
26	2,179	2,413	2,987	2,206	-----	2,457	2,685	2,068	2,451	2,432
27	2,168	2,099	2,892	2,174	-----	2,348	2,441	1,934	2,441	2,261
28	1,807	1,954	2,821	1,840	-----	2,330	1,979	1,680	2,173	2,344
29	1,770	1,952	2,644	1,775	-----	2,180	1,756	1,366	2,125	1,963
30	1,692	1,902	2,345	1,402	-----	1,893	1,558	1,185	1,804	1,747
31	1,394	1,788	2,009	1,202	-----	1,830	**1,452**	1,111	1,692 →	1,452

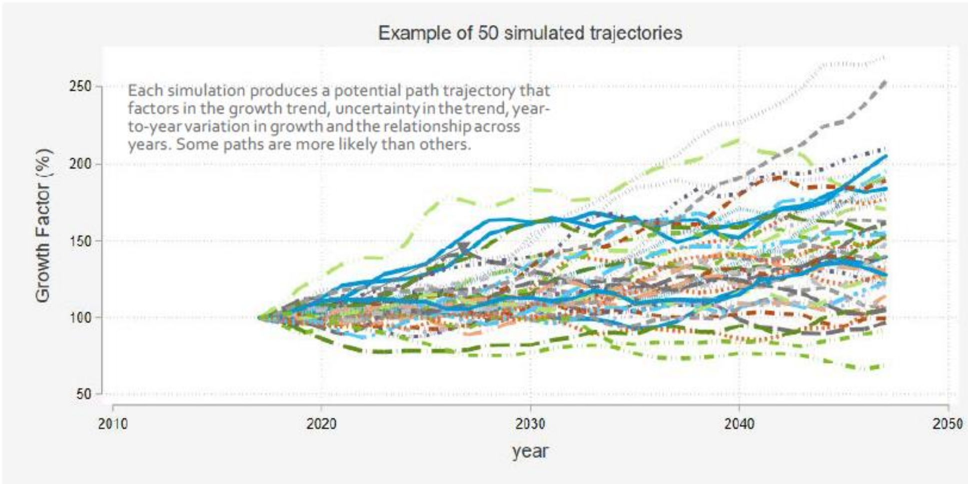
Source: IESO[66]

Probabilistic modeling of load growth using a pure time-series (without causal elements) may be used (for example by Central Hudson) to create a probabilistic forecast of demand through the application of Monte Carlo simulation. Such cause-agnostic approaches are, however, unsuitable for the long-term forecast and would violate Principle 1. Figure 20 is an example illustrating the outcome of 50 simulations undertaken for Central Hudson – as may be seen by

[65] DTE Gas Company, *Qualifications and Direct Testimony of George H. Chapel*, [rate case before the Michigan Public Service Commission],Case No. U-20642, November 2019

the random track of each simulation, these are all clearly cause-agnostic (not suitable for LUMA's long-term forecast).

Figure 20. Example of Pure Time-Series Probabilistic Load Growth



Source: Central Hudson Marginal Cost Study

Monte Carlo simulation can be used to motivate weather-driven distributions, as Guidehouse has done previously in assisting Enbridge Gas Distribution with defining its 95th percentile natural gas design day. Typically, a Monte Carlo simulation involves applying a series of random shocks to an estimated regression model, iterating through a large number of random draws to develop a distribution of outputs.

The challenge of such Monte Carlo approaches, however, is that they require strong structural assumptions regarding the error term. Some distribution (or more accurately distribution*s*) from which random shocks are drawn must be defined, and the persistence of the shock through the system accurately modeled. Monte Carlo approaches can become particularly challenging when random shocks are driven by more than one input variable as they often may be when applied to weather. For example, if substantial rooftop PV generation has been adopted, the forecast net load will be a function of both temperature and cloud cover. It seems probable that these two random variables are not wholly independent, but modeling the distribution of joint probability would likely be very challenging, both for LUMA personnel and for external reviewers.

The short-coming of probabilistic approaches based on historical weather (either the use of observed distributions, or the simulation of such via Monte Carlo techniques) is that being tied directly to historical weather values, they may fail to accurately capture future extreme weather events. The consensus from climate scientists[67] appears to be that climate change is resulting in an increase in the severity and frequency of such events. Given that such events would be (definitionally) outside the historical record, Guidehouse anticipates that the sensitivity of forecast values to such events are most appropriately addressed in scenario analysis (see below) rather than via a probabilistic approach.

[67] For example the reporting of Intergovernmental Panel on Climate Change (IPCC).

The use of historical weather as a tool for simulation and probabilistic forecasting would require adaptation to the unique features of the forecast methods and data adopted by the LUMA LFR in the long term, and the IESO example presented above should be understood to be illustrative.

Other variations[68] on this approach include using historical *hourly* weather patterns, iteratively applied to model parameters through incremental day offsets, backward and forward. This variation is another way to allow for the fact that (for example) the historical weather that might be expected to drive peak demand was observed on a weekend rather than a weekday.

Ultimately the LUMA LFR team should, in its future methods, have the ability to (at minimum) explore the distribution of potential forecast outcomes based on the expected volatility of temperature and humidity using some adaptation of one of the methods identified above.

Probabilistic techniques are best suited to understanding the scope of uncertainty related to high frequency quasi-random inputs to the forecast with historical precedent (particularly weather). Such techniques are more difficult to effectively employ when quantifying the longer-term uncertainty associated with changes in major structural drivers of load growth and patterns, particularly those without significant historical precedent and substantially affected by public policy (e.g., Distributed Energy Resources (DER), EVs, etc.)

A.2 Technology

This section of Appendix A is divided into two sub-sections, expanding on the corresponding sub-sections of Section 4:

- Analytics
- Data Collection

A.2.1 Analytics

In the main body of this report, Guidehouse recommends that LUMA (and the LFR team in particular) adopt an open-source development environment as a platform for load forecasting and other analytics. Open-source programing environments tend to be more flexible, more geared toward paired programming and other multi-user collaboration, less costly to implement, and – significantly – much easier to staff. As noted in the main body of this report, the dominance of open-source languages in academic environments means that most Master's or PhD graduates from an economics, statistics, or data science program that have used code-based analytics in their program will already have some level of competence in one of these environments.

Proprietary platforms, and purpose-built forecasting software, however, remains popular in many utility settings, typically for legacy reasons. This section of Appendix A will provide a bit of additional context on some of these options to provide LUMA with a more complete picture of what's available.

[68] Guidehouse staff have previously implemented a variation of this approach for the development of a 20-year hourly load forecast for a very large North American municipal electricity distribution utility in 2018.

This will begin with a description of generalized, highly flexible platforms (where considerable development would be required of the LFR team to develop models and workflows), identify some of the more "ready-to-wear" options available, and conclude with references to solutions offered by some newer firms that appear to amount to the outsourcing of forecast development. The point here is not to provide a comprehensive list[69] of programs but to identify the continuum along which such solutions exist.[70]

Open-source environments such as R and Python have already been recommended in the main body of the report and are not discussed here.

Proprietary environments, such as SAS or MATLAB software may be simpler than an open-source environment to get set up (e.g., require fewer LUMA IT personnel to support), though new, younger econometricians and data scientists are less likely to be conversant in these than the open-source options. SAS, although also a more general coding platform used by many different sectors appears to offer energy-sector-analytics packages.[71]

More specialized load forecasting software may also be adopted, though such software is often required in addition to (rather than instead of) the more flexible environments cited above. The most common[72] specialized software used for long- and medium-term load forecasting[73] at the system level is Itron's MetrixND and MetrixLT family of products.

The characteristic feature of these products is the use of SAE regression modeling. SAE models are very typically quite simple regression models (with only a few independent variables), but with complex "bottom-up"-style indexes as independent variables. Ameren Missouri's IRP[74] (Section 3.1.5) includes a clear algebraic and verbal description of the modeling approach. One very important consideration for the use of this kind of model is the level of detailed data required as inputs: SAE model indexes are typically functions of appliance efficiency levels and saturation as well as (in the case of the Ameren example) customer price and income

[69] A good reference list of commercial load forecasting software (though biased to distribution planning rather than system-level long-term forecasting) may be found in Section 5 of this EPRI paper:

Electric Power Research Institute; Olearczyk, M. *Load Forecasting for Modern Distribution Systems*, Technical Update, March 2013 1024377

[70] That said, it should be noted that the programs reference in the text below are the most common ones Guidehouse has observed being used by forecasting departments of utilities, through previous work in benchmarking electricity and gas forecast approaches for other clients.

[71] See, for example

SAS, *SAS Energy Forecasting*, accessed May 2022

https://www.sas.com/en_us/software/energy-forecasting.html#:~:text=SAS%20Energy%20Forecasting%20has%20been,at%20any%20level%20of%20aggregation.

[72] Guidehouse is unaware of any formal survey efforts that have documented the forecasting tools used by electricity and natural gas utilities in North America, but has extensive experience working with (or adjacent to) load forecasting teams in many distribution utilities. Guidehouse has also, additionally, undertaken several benchmarking efforts to assist clients better understand how aligned their approach is with existing industry common practice. Based on this work, Guidehouse would estimate that between 10 to 25% of the distribution utilities that generate long-term forecasts do so using the MetrixND and MetrixLT family of Itron products.

[73] This is in reference to the type of load forecasting performed by the LFR team, and not distribution planning or shorter-term projections of generation used by system operations.

[74] Ameren Missouri, *Integrated Resource Plan – Section 3: Load Analysis and Forecasting*, accessed May 2022

https://www.ameren.com/missouri/company/environment-and-sustainability/integrated-resource-plan elasticities. Obtaining input historical (and forecast) values of such variables may be challenging.

Another example worth highlighting in this discussion is that the approach used by PJM, the Regional Transmission Organization (RTO). PJM forecasts UPC with SAE models,[75] and though it contracts with Itron for input data and uses MetrixND for some modeling, it uses SAS as its broader analytics and forecasting development environment. As per a 2018 presentation by the RTO[76]: "*Some modeling is done with Itron's MetrixND software; forecast production is done with SAS software.*"

The use of open-source software provides the greatest flexibility to the LFR team in developing its forecast workflow, but also requires greater development of internal IT capabilities. Proprietary tools like SAS may be simpler to implement (i.e., can be contracted from the vendor) but will be more costly and may be more challenging to staff (given the smaller base of existing coders). More specialized software (like MetrixND or MetrixLT) can provide a nearly "ready-to-wear" solution that may be simpler to use and will reduce the amount of model testing and development required of the LFR team, but such solutions may require inputs not easily accessible, and must be implemented *in addition to* another code-based analytics platform (like SAS, R, Python, etc.)

At the far end of this continuum of possible solutions lies the possibility of complete out-sourcing. SAS and Itron offer forecasting services to accompany their products, and there appear to be an increasing number of firms offering their services for integrated load forecasting. These include professional services consulting firms (that use many of the tools identified above) and, increasingly, firms offering newly created software solutions[77] specific to load forecasting and some of its more recent challenges (e.g., DERs) and opportunities (e.g., AMI adoption).

The Guidehouse staff responsible for drafting this report is not familiar with any distribution utilities that have, to date, fully adopted such outsourcing, and Guidehouse would strongly caution LUMA against any services or software presented as "turnkey" or "pushbutton" solutions as these are unlikely to be able to provide the long-term stability and resilience of solutions developed "in-house" supplemented with outside expertise as required.

A.2.2 Data Collection

Section 4.2.2.2 in the main body of the report identifies the importance of developing a load research sample to which high frequency interval meters may be deployed in order to develop sufficient hourly customer data to begin projecting UPC at the hourly level. This section of Appendix A provides some additional recommendations and discussion of how other data collection activities may supplement this sample metering.

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[75] Resource Adequacy Department, PJM, *Load Forecasting Model Whitepaper*, April 2016
https://www.pjm.com/~/media/library/reports-notices/load-forecast/2016-load-forecast-whitepaper.ashx

[76] John Reynolds, PJM, *PJM Load Forecasting: Past Present, Future* Outage Management System (OMS) Load Forecasting Workshop, May 2018
http://www.misostates.org/images/stories/meetings/2018_Forecasting_Workshop/02c_RTO-Panel---Reynolds.pdf

[77] See for example, Recurve's "Resource Planner" offering
https://www.recurve.com/products#resource-planner

Meta-data for the load research sample meter data should include information about building occupancy obtained from billing records: that is, it is important that in the hourly or sub-hourly data collected from this sample that analysts can identify when building occupants (the customer) changes. Demand data from this metering should be supplemented by (and connected to) customer survey data.

Commercial and residential end-use surveys are instruments commonly used by jurisdictional authorities to gather important customer information that can be used for a variety of analyses, including energy efficiency potential studies, and to inform DSM program planning.[78] If similar surveys were to be deployed in Puerto Rico (e.g., for an EE or DR baseline study), there exists an opportunity to deliberately over-sample (obtaining as close to a census as possible) the load research group.

If survey data can be linked to load data for such a sample, it greatly increases the possibilities for UPC customer profile modeling and also allows the LFR team to confirm the representativeness of the sample by comparing survey responses within the load research sample, to those of the wider group of respondents (not included in the load research sample).

Finally, efforts should be made in collecting interval data from the meters of the load research sample, to take advantage of distribution asset data, any existing customer billing-to-station mapping (if it is accurate), customer billing data, and other customer survey data to try to extrapolate the UPC profiles of the load research sample. The importance of this kind of estimation or extrapolation is in establishing workflows and processes that make use of high-frequency, geographically-granular, customer data such that when AMI data *do* begin to become available, there is an analytical framework already established that makes use of such data.

Put another way: high-frequency UPC forecast profiles by customer type should be estimated with geographic specificity, even when the available data are so limited (e.g., limited load research sample data, partial distribution asset load data, customer billing data with known limitations) that the geographic precision may be spurious. So long as the limitations of the input data are well understood, then their use as place-holders will significantly improve the pace at which the LFR team (and other associated LUMA teams) can take advantage of more comprehensive hourly or sub-hourly customer metering data, as they become available.

A.3 People

<u>This section of Appendix A</u> is divided into two sub-sections, expanding on the corresponding sub-sections of Section 4:

- Team Structure, Collaboration, and Culture
- Documentation

[78] The California Energy Commission will, for example, publish the results of its Commercial End-Use Survey (CEUS) in September of 2022.
https://www.energy.ca.gov/data-reports/surveys/california-commercial-end-use-survey
The CEC has previously (in 2021) published its 2019 California Residential Appliance Saturation Study (RASS) https://www.energy.ca.gov/publications/2021/2019-california-residential-appliance-saturation-study-rass

A.3.1 Team Structure, Collaboration, and Culture

In Section 4.2.3.2, the Guidehouse team presented some recommendations for team structure and collaboration. This part of Appendix A expands on these recommendations, identifying additional management practices that help ensure team resiliency and continuity.

The rotation of the junior team members across tasks – even tasks for which they have no academic training – is vital to develop in personnel the breadth of skills necessary to ensure that team output is resilient to staffing disruptions. Part of this rotation of junior team members should include their secondment (or partial secondment) to other teams – for example distribution planning or even the IT team tasked with maintaining the servers and other IT resources used by the LFR team (data warehouses, analytic software servers, etc.)

This practice will enable junior team members to better understand the needs of other teams, help to propagate best practices, and provide them with an invaluable internal network of colleagues they can trust and work together with as they become more senior. As the team becomes more dependent on server- or cloud-based applications and data, management should push the LFR team to work closely with IT personnel so that the LFR team better understand the possibilities (and the limitations) of the resources they will share. When the analytics team and the IT team can speak the same "language", resource acquisition and maintenance will become more efficient and down-time due to server issues will be reduced.

Management may explicitly encourage and incentivize cross-team (and intra-team) collaboration and collaborative culture by establishing a regular series of inter-team workshops and encouraging (and providing resources and time) team members to develop internal presentations on findings, updates, and innovations under development. Such presentations are multi-purpose: they socialize emerging techniques across teams, encourage informal cross-team interactions and network development, and provide valuable multi-disciplinary quality review.

Participation in such efforts can be incented through a commitment from management to the development of outward facing thought leadership by the teams via conference attendance and presentations. Inter-team presentations such as those described above can provide useful testing grounds for thought leadership content that may submitted to such conferences. The prospect of attending and presenting at such conferences with funding from LUMA will incentivize personnel to innovate and (perhaps most importantly) document and share their innovations and findings, to the benefit of their team and others.

A.3.2 Documentation

In Section 4.2.3.2 the Guidehouse team made some specific recommendations for the development of output documentation for internal reporting. One of these was the recommendation that the LFR team produce and internally publish documentation providing the technical details of the overall forecast development process, including the motivation for specific modeling decisions.

Such documentation is important for two reasons: firstly, it enforces accountability and rigor. When analysts are required to explain their approaches to an internal forum like the LUMA Load Forecasting GC, it concentrates their focus and provides a powerful disincentive to "patchwork" style workarounds and adjustments. When deadlines press, and outputs are required, but counter-intuitive patterns in such outputs are present there can be the temptation for analysts to make ad hoc “patch” adjustments to correct an input they believe flawed.

Over time, such patches can accrete, complicate workflows and make them more susceptible to error and propagation of error. When an understanding exists that the analyst will need to document their change, justify it, and potentially respond to feedback (from members of the GC in this case), such changes are often applied more judiciously, and tracked more carefully going forward.

The second reason such documentation is important is that the transparency it provides help to build the confidence and trust of the LUMA LFR team’s internal stakeholders – in the quality of the work and the care and thoughtfulness with which it is produced. This can help reduce costs incurred due to duplicative .

In addition to providing a reference for internal stakeholders, documentation may be helpful as the basis for a periodic benchmarking of LUMA’s approach against industry current practice. In the longer term, once the forecasting approach has matured and is aligned with the future methods articulated above in the “Process” section, it would be prudent for LUMA to undertake (or procure from a third party) a review of the professional literature (perhaps supplemented with interviews of forecasting practitioners) output by peer utilities. Such reviews can be helpful in understanding where additional progress may be advisable, and can help contextualize the approaches used by LUMA to its stakeholders and regulator.

Finally, such documentation may provide important contextual information to third parties contracted by LUMA to perform periodic audits of load forecasting processes. Such audits are important to ensure the continued adherence to modeling practices put in place as part of any improvement activities and the alignment between the descriptions of processes and workflows provided in documentation with those processes and workflows as they are actually practiced.