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Best Practices in Electricity Load Modeling and Forecasting for Long-Term Power System Planning

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# BEST PRACTICES IN ELECTRICITY LOAD MODELING AND FORECASTING FOR LONG-TERM POWER SYSTEM PLANNING



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Advanced Energy Partnership for Asia

# BEST PRACTICES IN ELECTRICITY LOAD MODELING AND FORECASTING FOR LONG-TERM POWER SYSTEM PLANNING

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## List of Acronyms

|        |  |
|--------|--|
| ADOPT  | Automotive Deployment Options Projection Tool      |
| BUENAS | Bottom-Up Energy Analysis System                   |
| DER    | Distributed Energy Resource                        |
| DPV    | Distributed Photovoltaic                           |
| EE     | Energy Efficiency                                  |
| EV     | Electric Vehicle                                   |
| GDP    | Gross Domestic Product                             |
| IDEA   | International Database of Efficient Appliances     |
| LBNL   | Lawrence Berkeley National Laboratory              |
| LEAP   | Low Emissions Analysis Platform                    |
| LOADM  | LOAD curve model                                   |
| MEPS   | minimum energy performance standard                |
| NREL   | National Renewable Energy Laboratory               |
| PDOE   | Philippines Department of Energy (PDOE)            |
| PV     | photovoltaic                                       |
| RDMA   | Regional Development Mission for Asia              |
| RE     | renewable energy                                   |
| SAM    | System Advisor Model                               |
| TWh    | terawatt-hour                                      |
| USAID  | United States Agency for International Development |
| ZPAC   | Zero-emission vehicle Planning and Charging        |

# Table of Contents

|  |           |
|--|-----------|
| Executive Summary.....   | viii      |
| <b>1 Introduction .....</b>  | <b>1</b>  |
| <b>2 Stakeholder Engagement .....</b>  | <b>3</b>  |
| <b>3 Data Acquisition and Management.....</b>  | <b>5</b>  |
| Case Study 1. Using Proxy or Simulated Data When Country-Specific Data Are Unavailable:<br>Modeling Distributed Generation With Insufficient Data in Mexico..... | 7         |
| Case Study 2. Using Surveys to Obtain Data: Collecting Data on Building Energy Use in India.....   | 8         |
| Case Study 3. Using Web Crawling to Obtain Data: Collecting Data on the Existing Energy<br>Efficiency Market in Indonesia .....                                  | 9         |
| Case Study 4. Using Proxy Data or Telematics During Data Acquisition for Transportation Sector:<br>Lessons from Jamaica and the United States .....              | 9         |
| <b>4 Model Selection and Validation.....</b>   | <b>12</b> |
| Buildings Sector Load Modeling.....  | 12        |
| Case Study 5. Modeling Residential Electricity Demand: Developing Load Baselines in Indonesia..  | 14        |
| Transportation Sector Load Modeling: Modeling Vehicle Electrification at a Macro Scale .....   | 15        |
| <b>5 Scenario Development and Analysis .....</b>   | <b>17</b> |
| Case Study 6. Scenario Development to Support Load Modeling and Forecasting for Long-Term<br>Power Sector Planning in the Philippines .....                      | 17        |
| Case Study 7. Analysis to Support Buildings Sector Load Modeling: Energy Efficiency Opportunities<br>in South Africa’s Residential Sector .....                  | 18        |
| <b>6 Results Dissemination .....</b>   | <b>20</b> |
| <b>7 Broader Crosscutting Considerations.....</b>  | <b>21</b> |
| <b>8 Conclusions and Main Takeaways .....</b>  | <b>22</b> |
| References .....   | 23        |



## List of Figures

|   |    |
|---|----|
| Figure 1. General steps in a long-term load forecasting and modeling process.....   | 2  |
| Figure 2. Urban ownership of key household appliances in China (1990–2019).....   | 6  |
| Figure 3. Load curve for end-use categorization during summer (left) and winter (right) in Gujarat .....<br>(Source: Garg, Maheshwari, and Upadhyay 2010).....              | 9  |
| Figure 4. Flowchart of BUENAS calculation (Source: McNeil et al. 2013) .....  | 13 |
| Figure 5. Development of Indonesia’s average daily load curve in the business-as-usual scenario between<br>2010 and 2030 (Source: McNeil, Karali, and Letschert 2019) ..... | 15 |
| Figure 6. Energy efficiency opportunities in residential South Africa (USAID and EE4D 2021b) .....  | 19 |

## List of Tables

|   |    |
|---|----|
| Table 1. Concerns about Modeled Battery EV (BEV) Range .....                | 11 |
| Table 2. Key Trends Informing Scenario Development in the Philippines ..... | 18 |

## Executive Summary

The Philippines’ energy sector is rapidly evolving with increased deployment of variable renewable energy and distributed energy resources (DERs), potential electrification of transportation, and with increased electricity use for end uses such as cooling. As part of a multiyear collaboration, the U.S. Agency for International Development (USAID) Regional Development Mission for Asia, the National Renewable Energy Laboratory (NREL), and Lawrence Berkeley National Laboratory (LBNL), through the Advanced Energy Partnership for Asia, have supported the Government of the Philippines and the Philippines Department of Energy (PDOE) to enhance clean energy planning at the national level. Part of this support has focused on growing PDOE’s capabilities for enhanced load and modeling forecasting for long-term power system planning.

Long-term load (or demand) forecasting is the basis for power system planning and investment. The terms load modeling and load forecasting are sometimes used interchangeably, but they are different. Load modeling could include modeling of current or historical load to understand their characteristics. Load forecasting focuses on producing insights on the electricity needed to meet future electricity demand. Load forecasting can be classified as short-term (intraday and day-ahead), medium-term (one week to several months ahead), or long-term (one or more years).

This report highlights best practices (summarized in Table ES 1) for enhanced load modeling and forecasting for long-term power sector planning. The best practices touch on stakeholder engagement, data acquisition and management, modeling and validation, and scenario development. Case studies are provided to highlight crosscutting lessons that could inform enhanced load modeling and forecasting across different country settings. Though this work presents best practices resulting from support to the PDOE, the list is by no means exhaustive—nor is it meant to be prescriptive.

**Table ES-1. Summary of Load Modeling and Forecasting Best Practices**

| Step                            | Best Practices and Principles to Consider  |
|---------------------------------|--|
| Stakeholder engagement          | <ul style="list-style-type: none"> <li>• Identify a diverse and representative list of potential stakeholders.</li> <li>• Identify a champion in key power sector planning departments.</li> <li>• Clearly outline the goals of the overall load modeling and forecasting activities and the role of stakeholders in the process.</li> </ul>   |
| Data acquisition and management | <ul style="list-style-type: none"> <li>• Create a data inventory and identify data acquisition needs.</li> <li>• Establish data standards, survey methods, and data submission templates.</li> <li>• Set up a regular data acquisition or submission schedule for each sector or data type.</li> <li>• Maintain transparency in the acquisition process and data management.</li> <li>• Protect the security of sensitive data.</li> <li>• Keep a record of historical data for reference and use during subsequent load modeling and planning efforts.</li> <li>• Prioritize subsectors of importance for improvements in load modeling and forecasting efforts.</li> </ul> |

| Step                              | Best Practices and Principles to Consider   |
|-----------------------------------|---|
|                                   | <ul style="list-style-type: none"> <li>• Use proxy or simulated data when country-specific data are unavailable.</li> <li>• Use broader set of data collection methods such as surveys, web crawling, and telematics when historical load data are unavailable.</li> </ul>  |
| Model selection and validation    | <ul style="list-style-type: none"> <li>• Establish objectives of the modeling work with stakeholders at the onset of modeling process.</li> <li>• Be transparent about the benefits and tradeoffs of each model option, explain all model assumptions, limitations, and uncertainties, and discuss how the modeling results can be interpreted.</li> </ul>  |
| Scenario development and analysis | <ul style="list-style-type: none"> <li>• Develop a clear narrative that is shaped by the short- and long-term policy goals and key socioeconomic and technology trends.</li> <li>• Clearly outline a baseline scenario and its assumptions.</li> <li>• Develop alternative scenarios to compare the potential impact of policies and key trends on load forecasts.</li> <li>• Reduce overall uncertainty in analysis results by conducting regular stakeholder engagement workshops and conducting sensitivity analysis.</li> </ul> |
| Results dissemination             | <ul style="list-style-type: none"> <li>• Publish and disseminate model documentation.</li> <li>• Publish and disseminate an analytical report of the modeling results.</li> <li>• Where possible, provide access to some of the non-sensitive inputs and results.</li> </ul>  |

This report was developed in consultation and partnership with the PDOE. The primary audiences for this report are:

- *Energy system modelers and planners* in the PDOE tasked with modeling electricity load and forecasting future demand, especially given the ongoing energy transitions in the power, transportation, and building sectors.
- *Energy sector decision makers within energy ministries and utilities in the Philippines* looking to understand the value of enhanced load modeling and forecasting and develop frameworks to incorporate findings from load modeling and forecasting in their planning and decision-making activities.

The best practices presented here also have broader applicability to other countries looking to develop enhanced load modeling and forecasting approaches for long-term power sector planning.

# 1 Introduction

Long-term load (or demand) forecasting is the basis for power system planning and investment. In this report, the term load refers to the amount of electricity demand at any given time in terms of megawatts (MW). With increasing adoption of distributed energy resources (DERs), electrification of various end uses, changing customer profiles, and emerging technologies that enable end users to participate actively in the power system, conducting enhanced long-term load modeling (through the combination of top-down, more econometric approaches to bottom-up and sector-specific approaches) has become more important and more complex than ever before.

*This report presents a set of best practices for enhanced long-term load modeling and forecasting.<sup>1</sup> Recognizing that each country has unique economic and sociopolitical contexts that impact how load forecasting is conducted, the report also highlights experiences from other countries that may provide useful lessons for the Philippines Department of Energy (PDOE).*

Load forecasting and modeling can be conducted by utilities, energy planning and regulatory authorities, consulting firms, and various research organizations. An important consideration before embarking on a load modeling effort is to determine the objectives and intended use of the model. Some objectives and intended uses to consider include:

- Informing long-term power sector planning or economic policy
- Informing transmission planning
- Evaluating the resource adequacy (i.e., the ability of supply to meet customer demand at every moment) of the power system
- Coordinating the maintenance of generation and transmission assets.

Identifying the objectives and the intended use of load forecasts helps determine the most appropriate load forecasting methods to use. Based on input from PDOE, this report focuses on enhanced load modeling and forecasting methods to inform long-term power sector planning. A modeling team could be based in PDOE's power system planning department, or it could be a cross-department team made up of staff from the energy, transportation, buildings, and industrial offices, or it could be based on an external research institution supporting PDOE's planning efforts.

Long-term load forecasting and modeling can be organized into four general interlinked steps that are underpinned by continual stakeholder engagement (Figure 2). Stakeholder engagement is weaved into every step of the load modeling and forecasting processes from identifying objectives and defining priorities to inform scenario development and modeling, to deciding on the channels and methods for disseminating results. It is important to coordinate across these steps and plan based on the overarching objectives rather than conducting each step separately. For example, each load model has different data requirements, so data acquisition should be conducted with consideration of the type of model the data will support. As the data acquisition progresses, the modeling team may discover that some data are

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<sup>1</sup> Even though the two terms—load modeling and load forecasting—are sometimes used interchangeably, they are different. Load modeling could include modeling of current or historical load to understand their characteristics. It focuses on the mathematical representation of the relationship between the power and voltage in a load bus (Anmar Arif et al. 2017). Load forecasting focuses on producing insights on the electricity needed to meet *future* electricity demand. Load forecasting can be classified into short (intraday and day-ahead), medium (one week to several months ahead), and long term (one or more years).

unavailable and may need to modify the model or the modeling approach, especially if the model is being developed or used for first time.



**Figure 1. General steps in a long-term load forecasting and modeling process**

The following sections discuss each of the steps in Figure 1 in detail, and case studies are included where appropriate.

## 2 Stakeholder Engagement

### Key Takeaways

- Identify a diverse and representative list of potential stakeholders.
- Identify a champion in key power sector planning departments.
- Clearly outline the goals of the overall load modeling and forecasting activity and the role of stakeholders in the process.
- Develop a clear and consistent schedule and communications approach for sharing initial findings, obtaining and incorporating stakeholder feedback, and publishing the final results.

It is important to engage with a diverse group of stakeholders—throughout the load modeling and forecasting processes—with a particular emphasis on geographic and end-user diversity, gender equity, and the inclusion of underrepresented groups. Working with and obtaining input from different stakeholder groups, especially those that may not typically be included in these stakeholder engagement processes, creates an opportunity to hear their needs and understand how the outcomes of load modeling and forecasting practices could impact their customer experiences. Stakeholder engagement could take the form of a steering committee composed of representatives from policymakers, regulatory agencies, utilities, industry representatives, ratepayer advocacy groups, researchers, and other entities in the power sector and the end-use sectors. The committee can serve to guide the overall development of load forecasts and to propose new topics that can be considered during scenario development, such as energy storage adoption and electrification of transportation.

Typically, several rounds of stakeholder meetings are needed throughout the load modeling and forecasting processes. The meetings can help establish the objectives and priorities of the modeling work and support one or all the steps of the long-term load forecasting and modeling processes outlined in Figure 1:

- **Data Acquisition and Management (Section 3):** Coordinating across different entities to obtain data access; reviewing data acquisition method and management practices
- **Model Selection and Development (Section 4):** Reviewing the inputs, assumptions, techniques, and limitations of the model; guiding the selection, development, and calibration of the model
- **Scenario Development and Analysis (Section 5):** Informing the range of scenarios for analysis and reviewing preliminary load forecasting results
- **Results Dissemination (Section 6):** Informing the dissemination and outreach strategy

The steering committee could be supplemented by working groups focused on specific subsector and end-use topics, such as energy efficiency, electrification, distributed generation, or transportation.

Some best practices to consider while developing a stakeholder engagement approach include:

- *Identifying a list of potential stakeholders* that is informed by the goals of the load modeling and forecasting activity and broader long-term power system planning efforts. During this step, intentional efforts can be made to include stakeholders beyond those regularly included in this process. These could include ratepayer advocacy groups focused on consumer concerns such as air pollution from fossil fuel generation and long-term affordability of energy tariffs, groups representing consumers in rural and more isolated parts of a country and those lacking electricity access, as well

as groups representing consumers most vulnerable to climate disaster and displacement. Such stakeholders could provide important input during the load modeling activity, especially during the scenario development step.

- *Identifying a champion* in each key department (e.g., power system planning and transportation departments) that will serve as the main point of contact during the load modeling and forecasting processes.
- *Clearly outlining the goals* of the overall load modeling and forecasting activity and the role of stakeholders in the process.
- *Developing a clear and consistent schedule and communications approach* for sharing initial findings, obtaining stakeholder (including public) feedback, incorporating stakeholder feedback into the next iterations of load forecasting, and publishing the final results. Intentional efforts can be made to present and share the findings across multiple mediums to ensure the results of the work are accessible to as many stakeholders and consumers as possible.

### 3 Data Acquisition and Management

#### Key Takeaways

- Create a data inventory and identify data acquisition needs.
- Establish data standards, survey methods, and data submission templates.
- Set up a regular data acquisition or submission schedule for each sector or data type.
- Maintain transparency in the acquisition process and data management.
- Protect the security of sensitive data.
- Keep a record of historical data for reference and use during subsequent load modeling and planning efforts.
- Improve load modeling and forecasting efforts by starting with subsectors that are of particular importance.
- Use proxy or simulated data when country-specific data are unavailable.
- Use innovative data collection methods such as surveys, web crawling, and telematics when historical load data are unavailable.

Load modeling and forecasting may involve a variety of input data, including socioeconomic data (e.g., population, gross domestic product (GDP), gross national income, equipment, and appliance ownership data), environmental data (e.g., temperature, solar irradiation), sector-specific data (e.g., building sizes and dwelling types), and historical electricity demand data (e.g., historical peak load). The robustness of load modeling and forecasting is highly dependent on the quality and quantity of the input data. As a best practice, countries can develop a data acquisition plan that includes the following:

- *Create a data inventory and identify data acquisition needs*, including what types of aggregated and socioeconomic data (e.g., population, GDP, gross national income, equipment and appliance ownership data), historical load shapes from similar regions and times, and sector-specific data (e.g., building and transportation sector load data) are needed and at what geographical and temporal resolution. Having a regularly updated data inventory can provide the modeling team and the stakeholder committee with a clear picture of existing data and gaps in data availability so that they can identify critical data acquisition needs. Identifying data acquisition needs can inform a data acquisition strategy to support more robust load modeling and forecasting.
- *Establish data standards, survey methods, and data submission templates*. Doing this helps ensure each utility, local government, survey agency, or other data-submitting entity provides the necessary data containing standardized information and in a consistent format. This can help streamline the acquisition of data cross many different entities and at high temporal and geographical resolution (e.g., hourly or county-level data) and reduce errors due to, for example, inconsistent terminology or units.
- *Set up a regular data acquisition or submission schedule* for each sector or data type. Doing so can help create a structured approach for collecting data for initial modeling as well as for future updates to load forecasting. Having a predetermined schedule will allow data-submitting entities to incorporate the schedule into their planning so that they are prepared for the next round of data submission.

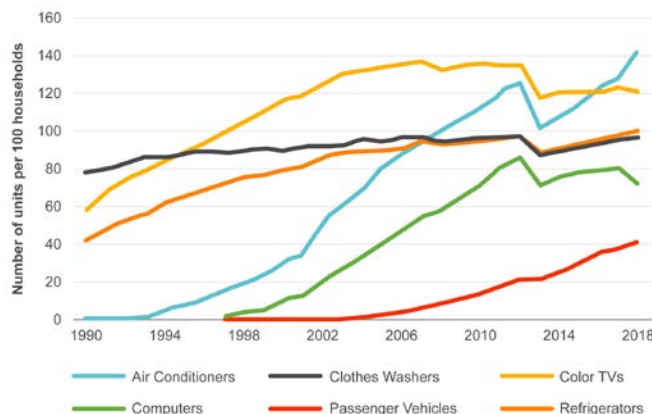


- *Maintain transparency in the acquisition process and data management.* During the data acquisition process, the entities conducting surveys or gathering data ideally are transparent about which data are being gathered, the purpose for gathering them, how long they will be stored, and other key information (e.g., with whom the data could be shared). At the end of the data acquisition process, making some nonsensitive, aggregated data (e.g., historical electricity usage by sector or by end use) publicly available could be highly valuable to relevant industries and research communities.
- *Protect the security of sensitive data.* It is important to protect the data collected against potential cybersecurity threats and data leakage, especially those data that may contain personal identifiable information gathered through surveys.
- *Keep a record of historical data.* As a country starts regular data acquisition, it is important to maintain a database of historical data, as these historical data may provide insights on the evolution of the electricity and end-use sectors.

These data acquisition and management best practices could facilitate the acquisition and management of large amounts of data from varied sources; however, acquisition can still be an administratively and technically complex activity, especially in countries where historical and current load data are generally unavailable or are difficult to access. This complexity deepens if there is also an identified need for an enhanced load modeling and forecasting approach for the various subsectors, as more data are needed to support detailed sector modeling and data needs can vary substantially by subsector, which could necessitate tailored data acquisition strategies. Additionally, data availability and data access (which may not be readily available to the

### Box 1. Subsector Trends Can Influence Peak Loads and Load Shapes

Globally, and in Southeast Asia in particular, space cooling is the fastest-growing use of energy in buildings due to increasing urbanization and rising income levels, and to climate-change induced increases in average daily temperature (Pavanello et al. 2021; IEA 2019; Khosla et al. 2021). China has seen a rapid increase in the ownership of cooling equipment and appliances over the past decade as household income has increased (Figure 2). As a result, space cooling has accounted for more than 10% of total electricity demand growth in China since 2010, and it accounted for around 16% of peak electricity load in 2017 (China Statistics Press n.d.). That share can reach as much as 50% of peak electricity demand on extremely hot days, as seen in recent summers. Assessing changes in peak load and load shape due to changes in this subsector can help planning agencies anticipate a significant portion of future load requirements, which can in turn inform generation procurement decisions.



**Figure 2. Urban ownership of key household appliances in China (1990–2019)**

Long-term load modeling and forecasting approaches in the Philippines have historically been top-down, using historical load data normalized by population, gross domestic product (GDP), and weather to model load and scaling the load using historical load shapes from similar places and times or based on expected changes in population, GDP, and weather. However, given the above-mentioned trends (e.g., changing cooling load, which has also been observed in the Philippines), more enhanced approaches to long-term load modeling and forecasting are needed to support power system planning efforts. These enhanced approaches must align with the priorities and capabilities of each country. For example, in a country with limited data availability, approaches developed could focus on subsectors that are of particular importance (e.g., cooling load or electrification of transportation).

designated power sector planning working group) can pose another challenge if data are considered proprietary or business sensitive.

However, there are approaches to mitigate some of these challenges, which are highlighted in the following case studies. A first approach is to prioritize and focus on specific subsectors that are of particular importance to the country such as residential demand (specifically the cooling demand) and to simplify the representation of other subsectors to limit potential data requirements (See Box 1). For example, in discussions with the PDOE, understanding load forecasts and trends in the residential buildings and transportation sectors were identified as key priorities in long-term power sector planning. A second approach is to use proxy data or simulated data when country-specific data are unavailable (See Case Study 1). A third approach is to use a broader set of data collection techniques such as surveys, web crawling, telematics, and other techniques (See Case Studies 2, 3, and 4).

## Case Study 1. Using Proxy or Simulated Data When Country-Specific Data Are Unavailable: Modeling Distributed Generation With Insufficient Data in Mexico

Several countries are exploring the potential role of DERs, especially distributed solar photovoltaics (DPV), in future power systems. Significant deployment of DERs can impact the magnitude and shape of net load, especially peak load. Modeling and forecasting adoption of DERs and how it could impact future load has become increasingly important, but the data needed to support DERs modeling and analysis may sometimes be unavailable. In this situation, countries may choose to use proxy or simulated data, as demonstrated by Mexico's DER analysis.

In 2018, the National Renewable Energy Laboratory (NREL) partnered with various power sector entities in Mexico through a U.S. Agency for International Development (USAID)-funded program to inform Mexico's DPV policy (A. Y. Aznar, Zinaman, and McCall 2018). The analysis was conducted using NREL's System Advisor Model (SAM), open-source software for simulating the performance and economics of DERs, including DPV, battery storage, and biomass.

Conducting the DPV analysis requires a range of data; however, some key data were difficult to obtain in Mexico and assumptions or simplifications were needed. For example:

- **Technological Data:** The team used standard technical assumptions for DPV systems from SAM instead of country-specific system data, which could result in a less accurate representation of DPV systems available in Mexico. However, DPV components are highly commercialized and globally traded, thus the technical specifications of, for instance, a DPV panel are not very different from one country to another. Therefore, the use of the proxy data will not significantly impact the results.
- **System Costs Data:** The team estimated DPV system costs by interviewing solar developers and other industry stakeholders in Mexico because reliable cost data were not available. The system cost data could have a significant impact on the modeling result. To make up for the lack of a robust, comprehensive database, the team interviewed a wide and diverse range of solar developers and other industry stakeholders. System costs could vary due to geographical, sectoral, or installer differences, so it is important to consider such variances during such data collection interviews.
- **Household Load Data:** The team calculated load profiles based on local weather data and typical Mexican household characteristics because hourly customer consumption data were not available. This is a common approach for household load estimation. It leads to less variation in load profiles of different customers, and the impact on the results could be mixed (i.e., higher or lower estimates of DPV deployment depending on the customer's electricity rates and other factors), but the impacts are relatively small.

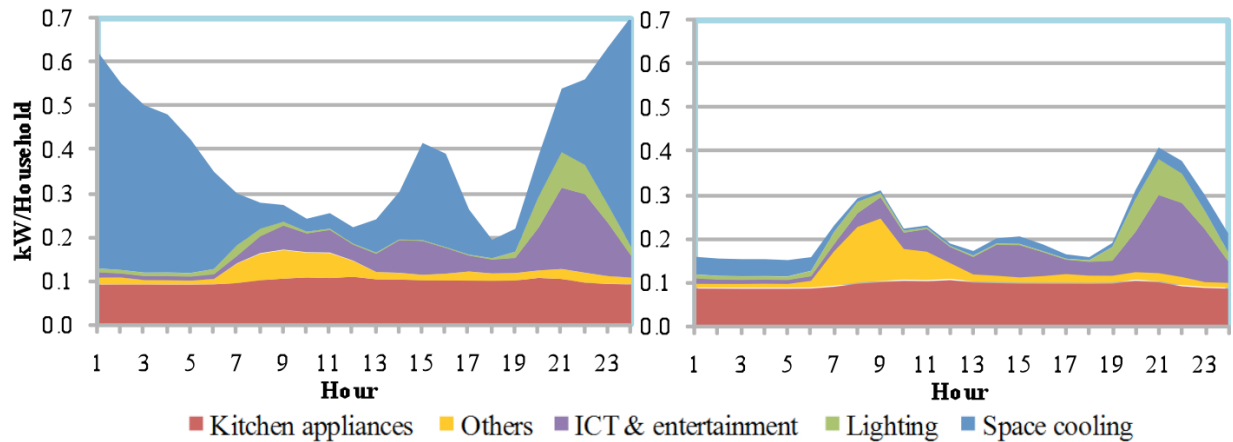
Despite the lack of some data, the proxy or simulated data the team used made it possible to generate reasonable estimates of Mexico's DPV potential, annual customer bill savings, DPV payback periods, environmental impacts of DPV adoption, and other insights that could support estimating how DPV adoption could impact future load and power sector plans. The Philippines is currently recording significant adoption of DPV by households and businesses. Adopting a similar approach to address data gaps could provide the Philippines with a reasonable understanding of potential DPV adoption trends and impacts on peak load, which could in turn inform long-term power sector planning efforts (especially in places with high load and DPV adoption such as Manila).

## Case Study 2. Using Surveys to Obtain Data: Collecting Data on Building Energy Use in India

Through its 2011 Household Energy Consumption Survey, the PDOE has a survey mechanism to collect end-use data, and there is interest in adapting its approach to be more robust, in terms of (1) including survey questions that could more directly inform load modeling and forecasting, and (2) incorporating sampling strategies that ensure data collection captures emerging energy end-user trends in households. This case study presents an example of collecting data on building energy use in India, which could be adapted to the Philippines context. The example also further illustrates the value of using surveys to collect end-use data. Surveys can be a critical data collection tool during enhanced load modeling and forecasting processes as they provide end-use data that can support more bottom-up load modeling efforts to complement more top-down, econometric-based load models and forecasts. In this example, Lawrence Berkeley National Laboratory (LBNL) worked with the state of Gujarat in India to design and implement load research surveys targeting 400 residential and 200 commercial establishments (Amit Garg, Jyoti Maheshwari, and Jigeesha Upadhyay 2010). The steps included:

- **Developing Survey Questionnaires, Instrument Designs, and Sampling Strategies:** Survey questions need to be carefully developed to collect meaningful data that can be used to address energy consumption research questions. Regional sampling size can be determined based on electricity sales and population size in different jurisdictions.
- **Testing the Questionnaires and Incorporating Pilot Test Corrections in Final Survey Instruments:** The pilot testing is to ensure the survey designs are understood clearly by the target actor groups.
- **Implementing the Survey and Analyzing and Reporting Survey Results:** Developing an effective implementation strategy would incentivize and improve response rates.

In this case, the sample size was distributed evenly among utilities, geography, sectors, and population income levels. Sampling strategies can be adjusted based on local conditions. For example, some small towns had less than one sample allocated for commercial establishments; therefore, at least 10 samples per small town were allocated in the Gujarat case. When designing survey instruments, the scope of end-use categories ideally would include cooking, information and communications technology, entertainment, lighting, appliances (e.g., air conditioning, electric water heating, washing machine, ceiling fan, and refrigerators), and other uses. In this example, the end-use consumer profile provided a solid foundation for assessing growth in peak demand as seen in Figure 3, which shows the load curve for Gujarat.



**Figure 3. Load curve for end-use categorization during summer (left) and winter (right) in Gujarat (Source: Garg, Maheshwari, and Upadhyay 2010)**

ICT is information and communications technology.

### Case Study 3. Using Web Crawling to Obtain Data: Collecting Data on the Existing Energy Efficiency Market in Indonesia

Web crawling is another innovative approach that can be used when data are unavailable. It can be used to collect data on the current and historical equipment markets (i.e., sales). For example, the data required to estimate the baseline of equipment energy consumption can be gathered from retailers' websites. Given this, LBNL developed the International Database of Efficient Appliances (IDEA), which automatically gathers data from online retail sites and compiles it into a repository (USAID and EE4D 2021a). It includes information on the efficiency, price, and features of different appliances and devices in markets. In Indonesia, IDEA was deployed to evaluate the baseline energy consumption for air conditioners and inform policy recommendations. This was complemented by a collection of data using crowdsourcing (Letschert et al. 2017). The resulting data set gave a detailed and robust picture of Indonesia's air conditioner market, including product characteristics, efficiency ratings, and retail prices. The analysis revealed that most of the market already exceeded the most stringent ratings, indicating existing regulations for air conditioners needed to be revised to spur energy efficiency in the market. This is an example of how IDEA may be applicable to, and deployed in, the Philippines context.

Though equipment sales data are helpful, using only equipment sales data is insufficient for load forecasting. Load forecasting requires a total stock of equipment especially for devices with long lifetimes like vehicles. Therefore, the following transport case study provides some best practices on how to estimate stock with limited data.

### Case Study 4. Using Proxy Data or Telematics During Data Acquisition for Transportation Sector: Lessons from Jamaica and the United States

Transportation load in several countries is expected to significantly grow and evolve due to increased electric vehicle (EV) deployment and the electrification of private and public modes of transport. Therefore, there is an increased need to account for how disruptions and changes in the transport sector could impact future electricity demand. Developing an accurate inventory of the current transportation stock across various transportation modes is key to transportation forecasting. At a minimum, a transportation data inventory should include vehicle stock, transportation fuel use, and vehicle-kilometers

traveled. To forecast EV penetration and public charging needs, it is useful to have data on mode of travel, percentage of access to home charging, gasoline prices, drive cycle profiles, and geospatial data from telematics; see A. Aznar et al. (2021) for a general explanation of how these data are used. However, many countries may not have data on the transportation sector (e.g., the total vehicle stock or vehicle adoption trends) that is needed to support detailed load modeling and forecasting for the transportation sector.

Using proxy data or telematics is a proven approach for collecting transportation sector data for use in load modeling and forecasting activities. Using proxies for missing data can provide some useful insights to support load modeling efforts. For example, when Johnson et al. (2019) developed the Jamaica Transportation Greenhouse Gas Reduction Plan, vehicle stock data had not been captured by the Jamaican government in recent years. However, vehicle imports by date and vehicle age were captured by Jamaica's Island Traffic Authority. Additionally, the World Bank had published data on the number of vehicles per thousand people. The authors used these data sets to develop the following metrics:

- Estimated vehicle stock by multiplying the number of vehicles per capita times the Jamaican population
- Average lifetime of imported vehicles by dividing the vehicle stock estimate by the annual vehicle imports and adding in the average age of vehicles at import.

These estimates were then used to develop a serviceable estimate for a transportation greenhouse gas reduction plan.

Telematics is another technique for collecting transportation data required for power and transportation sector modeling and planning.<sup>2</sup> Telematics with GPS location, speed, and daily kilometers traveled can help analysts understand where vehicles park and how much electricity they require to complete daily routes. These data can be used to inform decision-making such as assessing individual vehicles for EV replacement. Unfortunately, telematics data are not always available for every vehicle. In this case, it is useful to compare vehicles without data to similar vehicles with this information. For example, NREL developed the Zero-emission vehicle Planning and Charging (ZPAC) tool for the U.S. federal government to identify good candidates for electrification based on (1) how many days per year an EV would need to charge publicly to complete its mission and (2) the amount of greenhouse gas emissions they could avert by driving on electricity instead of gasoline.<sup>3</sup> Though this tool is developed for the U.S. context, it serves as a reference point for the type of tool that could be custom-developed based on local issues and circumstances.

The ZPAC calculations were simple for vehicles with telematics data. However, many vehicles in the U.S. federal fleet did not have telematics data. However, NREL had gasoline fueling transaction data for these vehicles by date, quantity, and geolocation. NREL was able to develop a machine-learning model to estimate how frequently the vehicle candidates would need to rely on public charging (Table 1). This informed decision-making for federal fleet managers as they ascertained which vehicles were best suited for electrification.

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<sup>2</sup> Telematics use data from vehicle sensors, speed, and location to display information about vehicle operation, such as idling, energy consumption, and travel patterns.

<sup>3</sup> For more information this fleet electrification planning process and tutorials on how to use the ZPAC tool, visit [FY22 Federal Fleet Electrification Planning Training](#).

**Table 1. Concerns about Modeled Battery EV (BEV) Range**

| <b>Reported BEV Range Concerns</b>       |   |
|--|---|
| 1 = Minimal Public Charging Likely       | Vehicle requires midday charging fewer than 5 times in a year |
| 2 = Some Public Charging Likely          | Vehicle requires midday charging 6–10 times in a year         |
| 3 = Unknown                              | Insufficient data   |
| 4 = Frequent Public Charging Likely      | Vehicle requires midday charging 11–15 times in a year        |
| 5 = Very Frequent Public Charging Likely | Vehicle requires midday charging more than 16 times in a year |

These four case studies—for Mexico, India, Indonesia, and the United States—present innovative ways to collect data and address data gaps to support enhanced load modeling and forecasting efforts. Overall, these examples highlight the complexity of the data acquisition process and the need for unique and creative approaches to collecting data depending on data needs, available data, country context, and load modeling and forecasting objectives.

Once the data acquisition step is complete, the focus shifts to selecting and developing the model to be used in the actual load modeling and forecasting exercises.

## 4 Model Selection and Validation

### Key Takeaways

- Begin modeling process by engaging with stakeholders to discuss the objectives of the modeling work.
- Be transparent about the benefits and tradeoffs of each model option, explain all model assumptions, limitations, and uncertainties, and discuss how the modeling results can be interpreted.

Model selection and development requires engagement between the load modeling team and the stakeholders to ensure the models are fit for the purpose and can capture the main priorities of stakeholders. The modeling team needs to:

1. Discuss with stakeholders the objectives of the modeling work.
2. Prioritize these objectives.
3. Be transparent about the benefits and tradeoffs of each model option.
4. Explain all model assumptions, limitations, and uncertainties.
5. Discuss how the modeling results can be interpreted.

Models are only useful when they are used to answer specific questions. Though modeling can provide useful insights on how the future load may evolve and which factors can impact that evolution, no model can predict the future and a single model or scenario is generally limited in terms of the type of insights it can provide (Mai et al. 2013). For example, if the goal of the activity is to understand the potential impact on rooftop solar growth assuming a certain amount of subsidy is provided for DPV, the modeling team can use a DER adoption model with cost curves and compare a scenario with subsidies to one without subsidies to provide insights.

This section provides two modeling approaches—one from the buildings sector and one from the transportation sector—as examples of what models may be applicable for the Philippines context.

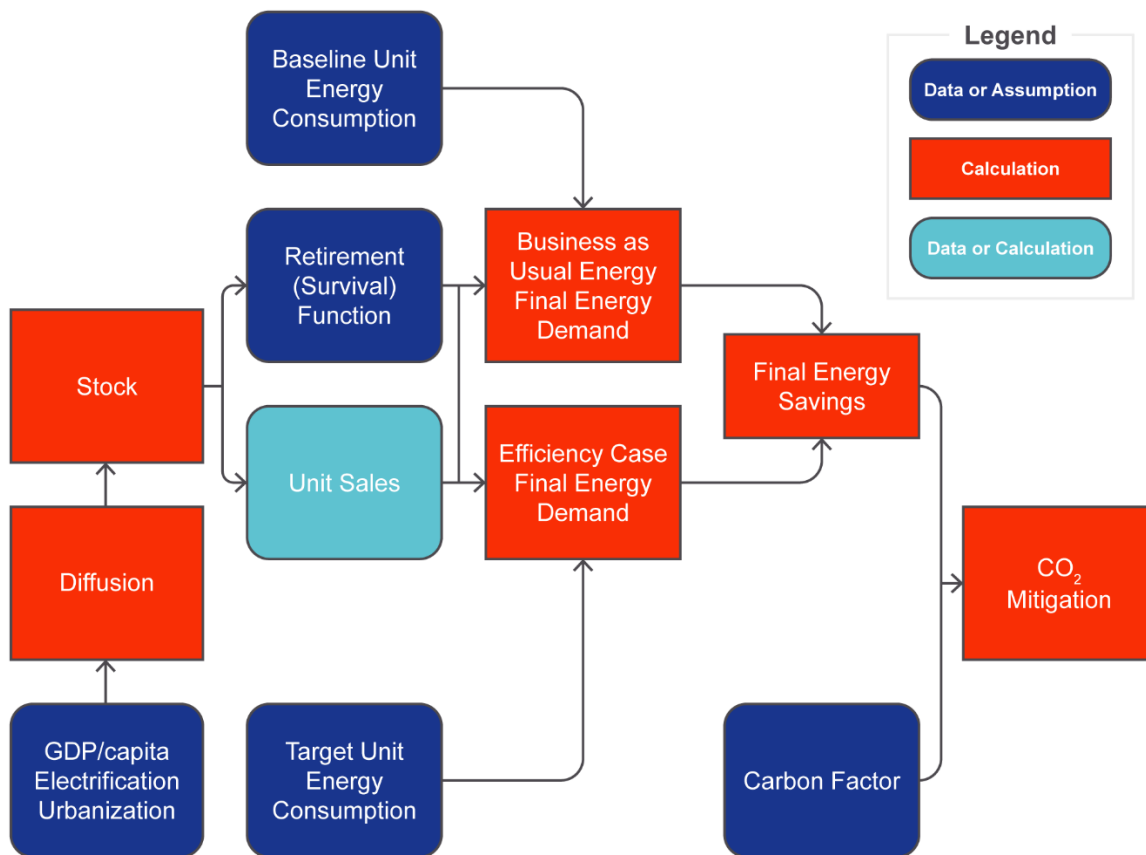
### Buildings Sector Load Modeling

Growth in energy demand is primarily driven by increased use of electric equipment in the residential, commercial, and industrial sectors due to increased income, population growth, urbanization, building construction, and industrial production. The total stock of equipment and their electric consumption can be modeled either according to an econometric diffusion model or according to unit sales projections if forecasts are available. Data collected as described in Section 3 can be used to determine a baseline of energy consumption in scenario-based software.

To understand the total projected energy consumption within the buildings sector, the Philippines could consider using tools developed by LBNL—the Bottom-Up Energy Analysis System (BUENAS) and the LOAD curve model (LOADM)—to predict the equipment stock in buildings and the unit energy consumption of the equipment. LBNL developed BUENAS to project equipment sales based on economic growth and to assess the potential for energy savings and greenhouse gas emission reduction due to efficiency policies for lighting, heating, ventilation, air conditioning, appliances, and industrial equipment. BUENAS is built within the Low Emissions Analysis Platform (LEAP), a tool that is widely used globally for energy and climate mitigation planning (UNFCCC 2021) as it enables detailed

consideration of technological developments, including equipment efficiency, residential appliance use, power sector efficiency, and lighting and cooling use.<sup>4</sup>

BUENAS is a bottom-up stock accounting model that predicts energy consumption for each type of equipment according to engineering-based estimates of annual unit energy consumption, scaled by projections of equipment stock. Figure 4 shows how the stock turnover model works. BUENAS calculates final energy demand according to unit energy consumption of equipment sold in previous years. When possible, the appliance stock in the residential sector is modeled by a stock turnover analysis using historical sales data combined with appliance lifetime estimates. Diffusion (ownership) levels for these years are then calculated by dividing the stock by the number of households in the country. Diffusion and stock can be extrapolated to future years using BUENAS macroeconomic modeling, which uses GDP, electrification, urbanization, climate parameters, and population as drivers. For more information about BUENAS, see (2013).



**Figure 4. Flowchart of BUENAS calculation (Source: McNeil et al. 2013)**

Once energy consumption is projected with BUENAS, the load profile can be determined based on the variety of equipment that composes the energy consumption projected. LBNL developed an add-on to BUENAS called LOADM that uses regionally standardized hourly load profiles specific to different end uses. LOADM uses appliance and sector-specific daily load profiles obtained from the literature in the absence of country-specific data (Karali, McNeil, and Letschert 2015). End-use load profiles are typically sourced from countries with available data and similar climates to the modeled region or area, such as Malaysia, Japan, countries in Europe, and some cities in India. LOADM can distinguish seasonal and day-of-week variants on daily load profiles. The resulting end-use hourly load profiles can then be

<sup>4</sup> Visit the LEAP website (<https://leap.sei.org/>) for more information.



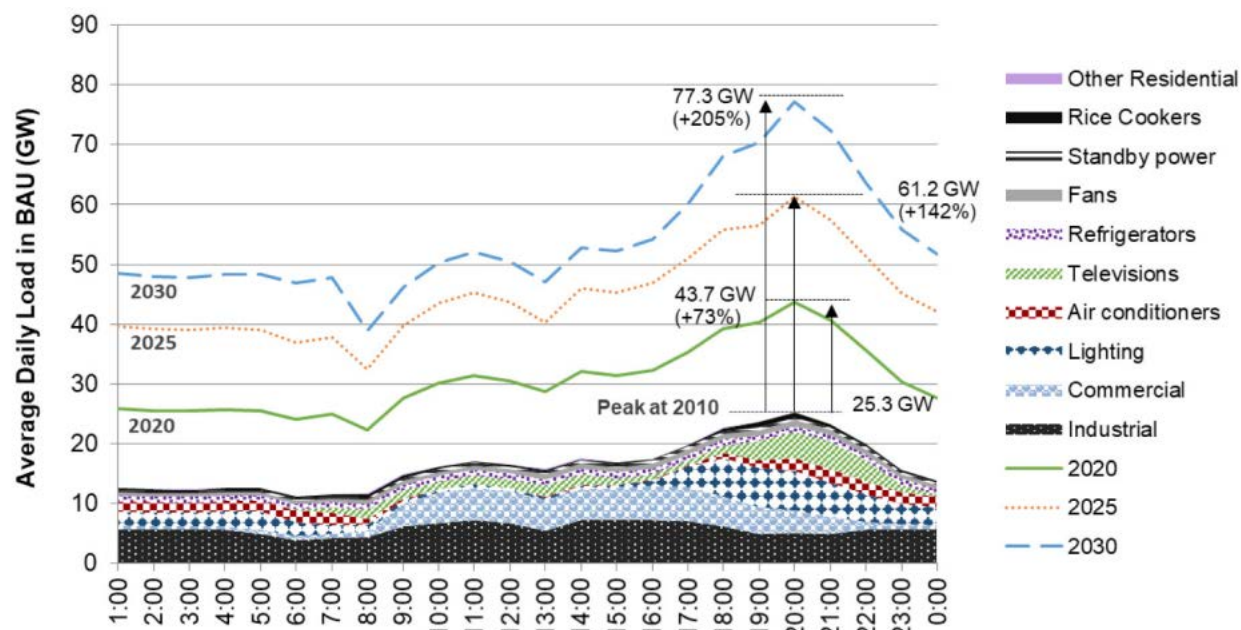
aggregated to yield a forecast of national electricity load curves, including the time of day and magnitude of peak system load. These load forecasts can then be used in power sector planning efforts to understand how different end-use profiles will evolve over time.

In summary, the Philippines could consider the BUENAS model and LOADM for forecasting the energy demand of common types of household appliances, lighting, and heating and cooling equipment in both the residential sector and in nonresidential buildings. The primary driver of energy use of these end uses are increases in population, income, household appliance ownership rates, floor space in the commercial sector, and overall industrial and economic growth. LOADM considers historical demand and projects the peak demand and evolution of daily load curves at the national level from 2010 to 2030, based on the annual demand projections provided by BUENAS. LOADM is also potentially helpful in instances where data are unavailable as it can use load profiles from countries with similar climates and circumstances as the Philippines.

## **Case Study 5. Modeling Residential Electricity Demand: Developing Load Baselines in Indonesia**

To model electricity demand, the combined BUENAS and LOADM approach was applied to Indonesia's power system (McNeil, Karali, and Letschert 2019). This approach provided insights into how various demand end uses could evolve over time in Indonesia. Rapidly growing sales of equipment (driven by GDP and population) yields a rapid increase of load requirement from the different end uses, especially for large appliances like air conditioners and refrigerators. Specifically, air conditioner and refrigerator ownership is projected to increase more than ninefold and threefold from 2010 to 2030 respectively. As a result, this business-as-usual projection of end-use demand concludes that electricity generation capacity may need to increase by roughly threefold between 2010 to 2030 to meet this demand. For Indonesia, this translates to the need to build an estimated 95 new 500-MW power plants, confirming concerns about infrastructure constraints, the threat of continued shortages, a massive burden on available capital, and environmental concerns.

Figure 5 shows the daily load demand for 2010 as a stack of the demand from different end uses. The figure also shows projected load up to 2030 in the business-as-usual scenario. In this scenario, Indonesia's average peak demand is projected to increase by 142% (reaching 61.2 gigawatts [GW]) in 2025, and by 205% (reaching 77.3 GW) in 2030, compared with 25.3 GW in 2010. Meeting this growing demand requires adding electricity generation capacity of 36 and 52 GW in 2025 and 2030 respectively. In 2030, the electricity demand at the peak is mostly distributed among residential air conditioners (21 GW), the commercial and industrial sectors (13.3 GW and 14.8 GW), and residential lighting, refrigerators, and televisions (13 GW, 4.5 GW, and 3.5 GW respectively). Note that the share from residential air conditioners, lighting, and refrigerators (50%) is larger than the share from the commercial and industrial sectors (36%) at the peak in 2030. And the contribution of air conditioners to peak load grows roughly tenfold between 2010 and 2030, representing the most significant peak load demand increase.



**Figure 5. Development of Indonesia's average daily load curve in the business-as-usual scenario between 2010 and 2030 (Source: McNeil, Karali, and Letschert 2019)**

Overall, this example highlights the power of modeling tools in providing insights into future electricity load, highlighting specific subsectors and end uses of concern.

## Transportation Sector Load Modeling: Modeling Vehicle Electrification at a Macro Scale

Model selection and development for transportation load modeling and forecasting is informed by factors including transportation trends, data availability, and potential EV adoption and infrastructure policies. The Philippines has announced various transportation policies and targets, including EVs accounting for 10% of new vehicle sales by 2030, electrification of jeepneys, and increased adoption of alternative fuels. So, PDOE is interested in understanding the potential impact of these policies on future electricity load.

Available approaches and tools to model EV adoption (Muratori et al. 2020; Amara-Ouali et al. 2021), include:

1. *Economy-wide energy scenario models* that assess the impacts of policies and technology development (e.g., the impact of Philippines' EV adoption policies)
2. *Vehicle choice models* that project adoption rates for specific vehicle models based various attributes (e.g., adoption rates for jeepneys in the Philippines)
3. *Exploratory accounting models* that generate estimates based on historical EV adoption rates and patterns (e.g., future hybrid EV adoption rates in the Philippines based on historical adoption rates)
4. *Techno-economic feasibility models* for fleets or other vehicle operators to determine EV needs (e.g., battery and motor size)
5. *Refueling infrastructure models* to assess charging infrastructure needs to support EV adoption goals (e.g., infrastructure needs to support Philippines' 2030 EV vehicle sales goals).

Depending on transportation sector priorities and policies of interest, PDOE could focus on developing or adapting one of the five types of models above. Vehicle choice and exploratory accounting models are widely used to support transportation load modeling and forecasting. For example, NREL's Automotive Deployment Options Projection Tool (ADOPT), a vehicle choice model, can provide a very detailed forecast of the vehicle market in the United States, including endogenously creating new EV models. However, such models require very comprehensive details to develop a baseline that includes, for example., price, interior space, acceleration, fuel economy, and annual sales for every vehicle on the automotive market (Brooker et al. 2015). That data can then be used to generate and calibrate a model that predicts which existing vehicles will sell well and which new vehicles will be brought to market. The data can be quite useful for manufacturers and policymakers, but developing this sort of model is very time-intensive.

If the detailed data required for vehicle choice modeling are unavailable but PDOE still has interest in estimating future EV adoption rates, exploratory account models could be used. These models can generate higher level projections of EV adoption with far fewer inputs. For example, the International Energy Agency's Mobility Model is an Excel-based accounting model that can be used to identify how to reach specific future targets at the national and global levels. It contains data on several countries and world regions and is updated consistently.<sup>5</sup> The Mobility Model works at a higher level than ADOPT, patterning results from vehicle registrations, retirement ages, stock by vehicle type, and urbanization. The outputs include EV adoption rates, rolling stock, charging infrastructure, and costs. The Mobility Model is the foundation of the forecasts used in the Global Electric Vehicle Outlook publications (IEA, Electric Vehicles Initiative, and Clean Energy Ministerial 2021). Using this type of exploratory account model can often be a good starting point for obtaining reasonable EV adoption estimates that can be fed into a broader load modeling and forecasting effort. Modeling efforts can then be scaled as needs evolve and data availability and acquisition processes become more robust.

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<sup>5</sup> For more information, visit the [IEA Mobility Model](#).

## 5 Scenario Development and Analysis

### Key Takeaways

- Develop a clear narrative that is shaped by the short- and long-term policy goals and key socioeconomic and technology trends.
- Clearly outline a baseline scenario and its assumptions.
- Develop alternative scenarios to compare the potential impact of policies and key trends on load forecasts.
- Mitigate the risk of uncertainties in analysis results by conducting regular stakeholder engagement workshops and conducting sensitivity analysis.

Scenario development allows planners to explore a wide range of topics that may impact potential future energy system evolutions rather than assuming a single potential future energy system evolution in modeling. Scenarios could explore variations in population growth, GDP, fuel and technology prices, technology advancement, trade, and specific energy policy interventions (e.g., demand side management and energy efficiency (EE) programs) (USAID and EE4D 2021b). Generally, scenarios are developed according to two sets of possible futures: a baseline scenario and an alternative scenario.

A baseline scenario, also called reference scenario or business-as-usual scenario, is the state against which change is measured. This scenario generally refers to projections that assume no energy related policies or measures will be implemented beyond those already in force or being implemented. They represent expected energy consumption in the absence of new policy development and are typically compared with alternative scenarios that integrate effects of new policies. Alternative or policy scenarios are constructed to assess the impacts of specific technological trends and policies, generally in terms of energy savings, load reduction, greenhouse gas emissions reduction, or other criteria. The construction of baseline and alternative scenarios requires a set of clearly described assumptions. Some of these assumptions (typically socioeconomic drivers such as population and GDP growth) will remain constant as they are not directly affected by policy decisions, whereas other assumptions such as efficiency improvements, fuel switching, or adoption of EVs can change due to policy decisions.

### Case Study 6. Scenario Development to Support Load Modeling and Forecasting for Long-Term Power Sector Planning in the Philippines

Development of a clear narrative is key to scenario development, and it is largely shaped by short- and long-term policy goals and by key socioeconomic and technology trends. Over several months, NREL and LBNL held several calls with various departments in PDOE and transportation departments to identify key policy goals and frame the scenarios of interest for load modeling and forecasting activities.

The goals of this effort were contextualized within the Philippines' overall goal for its load modeling and forecasting activities, which is to better represent (1) changing trends in existing loads due to rising income levels and increase adoption of DERs and (2) potential changes in future load due to policies and technological trends such as EV adoption to inform generation procurement decisions and overall long-term power sector planning efforts. Through several stakeholder discussions with PDOE, several scenarios of interest were identified. These are summarized in Table 2.

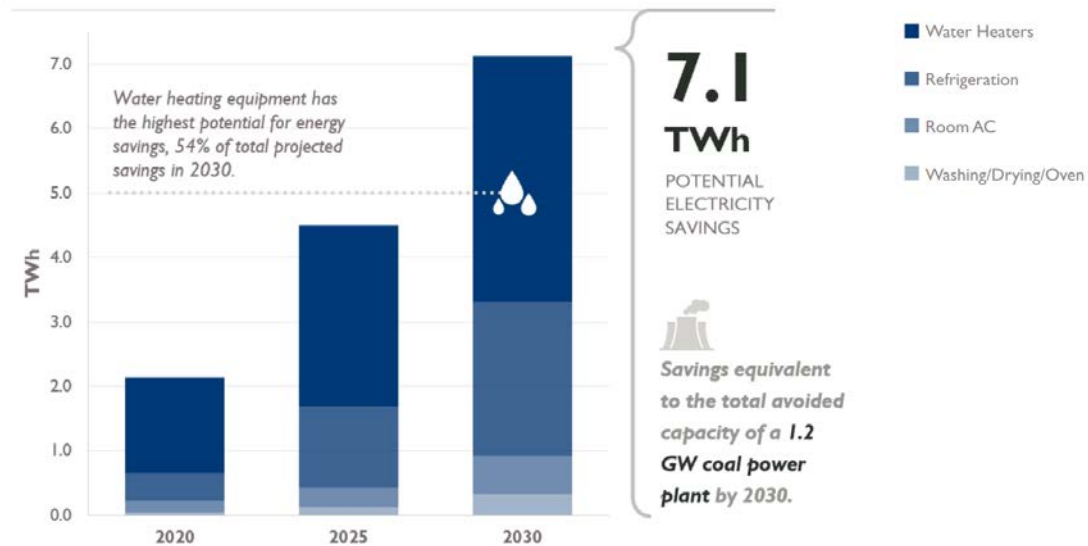
**Table 2. Key Trends Informing Scenario Development in the Philippines**

| Sector                       | Trends to Inform Scenario Development  |
|------------------------------|--|
| Residential buildings sector | <ul style="list-style-type: none"> <li>• Increased teleworking and reduction in transportation use due to the coronavirus pandemic</li> <li>• Increased adoption of air conditioning</li> <li>• Increased adoption of energy efficient appliances due to minimum energy performance standards</li> </ul> |
| Commercial buildings sector  | <ul style="list-style-type: none"> <li>• Reduced commercial building load due to the coronavirus pandemic</li> <li>• Adoption of building codes</li> <li>• Switch from diesel generators to solar PV and battery energy storage</li> </ul>   |
| Industrial sector            | <ul style="list-style-type: none"> <li>• Changes in share of energy-intensive industries</li> <li>• Increased energy efficiency in select industries</li> </ul>  |
| Transportation sector        | <ul style="list-style-type: none"> <li>• Varied EV adoption rates due to existing and planned EV policies and changes in adoption trends due to the coronavirus pandemic</li> </ul>  |
| Supply-side considerations   | <ul style="list-style-type: none"> <li>• Impacts of increased adoption of rooftop PV on the overall load that needs to be met by large-scale generation</li> </ul>   |

Typically, once stakeholder groups have agreed on scenarios, technical staff will work with the modeling team to translate the scenarios into modeling and forecasting scenarios. Scenarios can then be developed based on this information and modeled and analyzed to assess how specific policies and technology trends could impact future load.

### **Case Study 7. Analysis to Support Buildings Sector Load Modeling: Energy Efficiency Opportunities in South Africa’s Residential Sector**

The next step after scenario development is using the selected model to conduct load modeling (and/or forecasting) and consider the implications of the findings. In South Africa, LBNL conducted load modeling and scenario analysis to help inform the energy policy authority’s review of minimum energy performance standard (MEPS) levels. The analysis assessed the program’s potential impact in terms of energy savings (load reduction), emissions reduction, air pollutant reduction, and other benefits. The results estimated an annual 7.1 terawatt-hours (TWh) of potential electricity savings in 2030, shown in Figure 6. These energy savings were equivalent to avoiding the need to potentially construct a 1.2-GW coal power plant by 2030. Water heating equipment had the highest potential for energy savings: 54% of total project savings in 2030. Electricity savings also constituted direct cost savings for consumers. On average, household utility bills could be \$47 lower annually by 2030 if the assessed standards and labeling program was implemented (Stephane de la Rue du Can et al. 2020). This analysis used scenario development focused on EE to explore impacts on building sector demand and by extension, procurement of electricity generation. The scenarios were developed based on existing and expected policies, and international best practices. The business-as-usual scenario was based on existing policy in 2016, and the two MEPS scenarios were based on an upcoming policy at the time, which was subsequently implemented in 2021, as well as a more stringent standard based on international best practices.



**Figure 6. Energy efficiency opportunities in residential South Africa (USAID and EE4D 2021b)**

Scenario development and analysis can be a powerful decision-making tool; however, it is important to account for or mitigate the risk of uncertainties of analysis results. First, as highlighted earlier, conducting stakeholder engagement workshops can help shape the scenarios considered as well as validate or revise key assumptions as stakeholders may have access to some key input data. Another strategy consists in conducting sensitivity analysis. For parameters with high levels of uncertainty, models can be run with different assumptions for the same parameter to evaluate the parameter’s impact on overall load analysis findings.

## 6 Results Dissemination

### Key Takeaways

- Publish and disseminate a model documentation.
- Publish and disseminate an analytical report of the modeling results.
- Where possible, provide access to some of the non-sensitive inputs and results.

Convey modeling results accurately to stakeholders and the public is crucial. One best practice is to publish and disseminate a model documentation, including the modeling methodology, scope, inputs (and/or sources of inputs), assumptions, and limitations. Doing so can lend transparency to analysis and help other researchers understand the modeling results and lend credibility to the modeling effort. Another best practice is to publish and disseminate an analytical report of modeling results. Such analytical report would explain the objectives of the modeling work, briefly describe the methodology, present the scenarios considered, and guide readers through the major trends observed in, or conclusions derived from, the results. The report would also clearly explain the limitations of the work and uncertainties in the results and conclusions. One good example is Palchak et al. (2017), a published renewable integration study that contains detailed information about the input data sources, the modeling method, study limitations, analytical results, along with easy-to-understand infographics and animated videos for dissemination.

As mentioned in the section on data acquisition and management (Section 3, page 5), providing access to some of the non-sensitive inputs and results would also be useful for the industry, the research community, and the public. Openly sharing input data and results is not only a good practice in lending transparency and credibility to the results, but doing so also leads to greater reproducibility—allowing other researchers or modelers to build on existing modeling work instead of having to repeat it. Such data can be provided in aggregate at the provincial or municipal level.

## 7 Broader Crosscutting Considerations

It may also be useful during load modeling and forecasting activities to consider how broader societal crises, events, and trends have impacted and may continue to impact load. For example, in the Philippines, residential and transportation load changed substantially during the coronavirus pandemic due to restrictions such as the enhanced community quarantine. As these restrictions limited movement, people were more likely to stay at home, increasing residential load. However, the increase in load did not replace the decrease in load from the decline of commercial activities (Lowder, Lee, and Leisch 2020). For example, despite restrictions to population movement, the demand in the Luzon and Visayas interconnected grids decreased by 30% in 2020 (Rivera 2020). Therefore, during the stakeholder engagement, and in the scenario development and analysis stages, it is helpful to consider how the modeled scenarios can be designed to ensure prior, ongoing, and future impacts due to the pandemic are incorporated in the analysis. Additionally, in the data acquisition and management and stakeholder engagement processes, there may be a need to consider a range of data collection methods that minimize human contact as much as possible, such as virtual data collection methods, such as web crawling techniques, among others (see Case Study 3). More generally, lessons from the pandemic indicate it may be prudent to proactively account for the potential impact of large-scale health and environmental crises in load modeling and forecasting practices. This could be done by including public health and environmental experts during the stakeholder engagement and scenario development process.

Another consideration is the increased high heat days the Philippines will experience due to climate change. Major cities like Manila and the surrounding metro area are already experiencing high heat hazard (Estoque et al. 2020). As the country institutes adaptation measures in the coming years and decades, those measures will come as the number of air-conditioning units increases, further increasing the end-use load. Also, there is a renewed focus on how activities incorporate and support ongoing efforts to provide reliable and affordable electricity access to the people of the Philippines. Load modeling and forecasting efforts feed into long-term power sector planning efforts that ensure reliable, secure, and affordable energy in the Philippines. Beyond that, there may be opportunities to consider who is included and consulted during the load modeling and forecasting processes.



## 8 Conclusions and Main Takeaways

This report provides some load modeling and forecasting best practices and case studies that focus on stakeholder engagement, data acquisition and management, model selection and development, scenario development and analysis, and results dissemination. Each country has unique socioeconomic and political contexts that make certain approaches more effective than others, yet we highlighted some common principles and methods that can help achieve better results. Some best practices to consider when enhancing load modeling and forecasting approaches include:

- Enhanced load modeling and forecasting are evolving processes that require periodic assessment and, as needed, modifying the key research question, updating inputs and assumptions, and addressing emerging technological or societal trends.
- To improve the long-term load forecasting and modeling at the PDOE, it is important to assemble a diverse stakeholder committee to guide these efforts. Working with and obtaining input from different stakeholder groups, especially those that may not typically be included in these stakeholder engagement processes, creates an opportunity to hear their needs and understand how the outcomes of load modeling and forecasting practices could impact their customer experience.
- The robustness of load modeling and forecasting is highly dependent on the quality and quantity of the input data. Developing a comprehensive data acquisition and management plan that is tailored to the specific country context will allow for more useful load modeling and forecasting results. Countries can consider prioritizing and focusing on specific subsectors, simplifying representation of other subsectors, using proxy data or simulated data if country-specific data are unavailable, and considering a broader set of data collection techniques.
- Models are only useful when they are used to answer specific questions. It is important to ensure the model(s) selected can answer the load and planning questions of most interest to PDOE.

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