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Load Forecasting in Electric Utility Integrated Resource Planning

Juan Pablo Carvallo, Peter H. Larsen, Alan H. Sanstad, Charles A. Goldman.

Energy Analysis and Environmental Impacts Division

October 2016

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FINAL VERSION

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Disclaimer

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Acknowledgements

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Abstract

Integrated resource planning (IRP) is a process used by many vertically-integrated U.S. electric utilities to determine least-cost/risk supply and demand-side resources that meet government policy objectives and future obligations to customers and, in many cases, shareholders. Forecasts of energy and peak demand are a critical component of the IRP process. There have been few, if any, quantitative studies of IRP long-run (planning horizons of two decades) load forecast performance and its relationship to resource planning and actual procurement decisions. In this paper, we evaluate load forecasting methods, assumptions, and outcomes for 12 Western U.S. utilities by examining and comparing plans filed in the early 2000s against recent plans, up to year 2014. We find a convergence in the methods and data sources used. We also find that forecasts in more recent IRPs generally took account of new information, but that there continued to be a systematic over-estimation of load growth rates during the period studied. We compare planned and procured resource expansion against customer load and year-to-year load growth rates, but do not find a direct relationship. Load sensitivities performed in resource plans do not appear to be related to later procurement strategies even in the presence of large forecast errors. These findings suggest that resource procurement decisions may be driven by other factors than customer load growth. Our results have important implications for the integrated resource planning process, namely that load forecast accuracy may not be as important for resource procurement as is generally believed, that load forecast sensitivities could be used to improve the procurement process, and that greater emphasis should be placed on strategies to manage uncertainties in load forecasts.

Keywords: resource planning, forecast error, load, retrospective analysis, resource expansion, electric utility.

Executive Summary

Integrated resource planning (IRP) is a process used by many vertically-integrated U.S. electric utilities to determine least-cost and risk-managed portfolios of supply and demand-side resources that meet future electricity needs of customers, comply with regulatory requirements and government policy objectives and, in many cases, fulfill obligations to shareholders. Integrated Resource Planning evolved in the late 1980s and 1990s from least-cost planning (LCP), which was developed to ensure that demand-side measures to reduce electricity consumption—especially end-use energy efficiency—were considered by utilities in addition to supply-side (generation) resources. Forecasts of energy and peak demand are a critical component of the IRP process. There have been few, if any, quantitative studies of IRP load forecast performance and its relationship to resource planning and actual procurement decisions.

In this study, we conduct a retrospective analysis of energy and peak demand forecasts for a set of integrated resource plans published by electric utilities operating in the Western United States. We analyze energy and peak demand forecasts from utility IRP plans filed in the early- and mid-2000s and compare these forecasts to subsequent actual observed loads. We also examine load forecasting techniques and sensitivity analyses; performance over time; the relationships among load forecasting, resource planning, and procurement; and strategies that utilities used to manage uncertainties in future load forecasts.

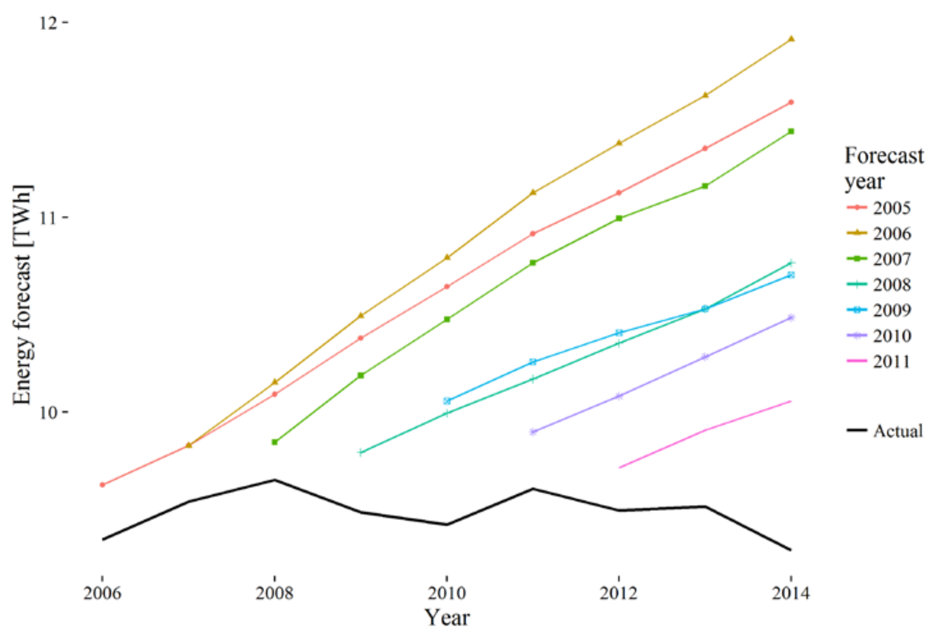

Figure ES-1 Load forecasts from seven subsequent IRPs and actual load for a Western U.S. utility.

A comparison of load forecasts to actual energy use and peak demand reveals that energy consumption growth was overestimated by all but one utility over planning periods beginning in the mid-2000s and ending in 2014. Moreover, peak demand growth was also overestimated in eight of the eleven cases we examined (those utilities that reported their peak forecasts). Utilities that projected the highest growth rates in energy and peak demand also experienced the lowest actual growth, especially for observed energy consumption.

Furthermore, examination of forecasts from more recent IRPs indicates a persistent overestimation of demand growth over planning periods up to year 2014, even in the presence of much slower-than-anticipated actual growth (see Figure ES-1 for an example from one utility). A number of the utilities highlighted the effects of the national recession that began in 2008-2009 to explain this phenomenon. Over time, the utilities did adjust their forecasts of projected load growth downward in response to lower-than-expected demand, but continued to overestimate future loads. Most of the utilities indicated that they expected national and regional economies would follow a historical pattern of relatively quick recovery from the recession, which influenced their load forecasts in more recent plans. Accordingly, the slower-than-expected economic recovery contributed to over-estimates of future load in more recent IRPs.

We find some correlation between forecasting methods—and their relative complexity—and forecast accuracy. In addition, utilities that had the most accurate peak demand forecasts were also among the most conservative in terms of their expected peak demand growth. Utilities with relatively more complex models had less forecast error than those that employed simpler models. There are structural reasons that may also explain the relative accuracy of load forecasts. For example, we find that utilities with a larger share of industrial load in their mix generally had larger forecast error. We believe that this may be caused by the highly elastic and “lumpy” nature of industrial customer load as well as the difficulty in predicting entry and exit of industrial customers from a utility service territory. These results suggest that, among the utilities we studied, there may be small marginal benefits to the planning process of greater model complexity.

Load forecast sensitivity analysis is an important component of risk assessment and management within IRP process. In the context of our study, sensitivity analyses are especially important because strategies derived from load forecast sensitivity analysis may allow the resource plans to adjust as new information comes in. Over time, we find that utilities have improved the breadth and sophistication of their load forecast sensitivity analyses. However, we find that both older and more recent IRPs generally lack an adaptive component that details how utilities would respond in practice were subsequent actual values of critical input variables—like load — to correspond to those studied in these sensitivity analyses rather than to those assumed in "base cases." We also find that load variation from the base case produces differences in projected revenue requirements for utilities that are much larger than the differences in revenue requirements from the resource portfolios that are designed and compared to select the “preferred” one.

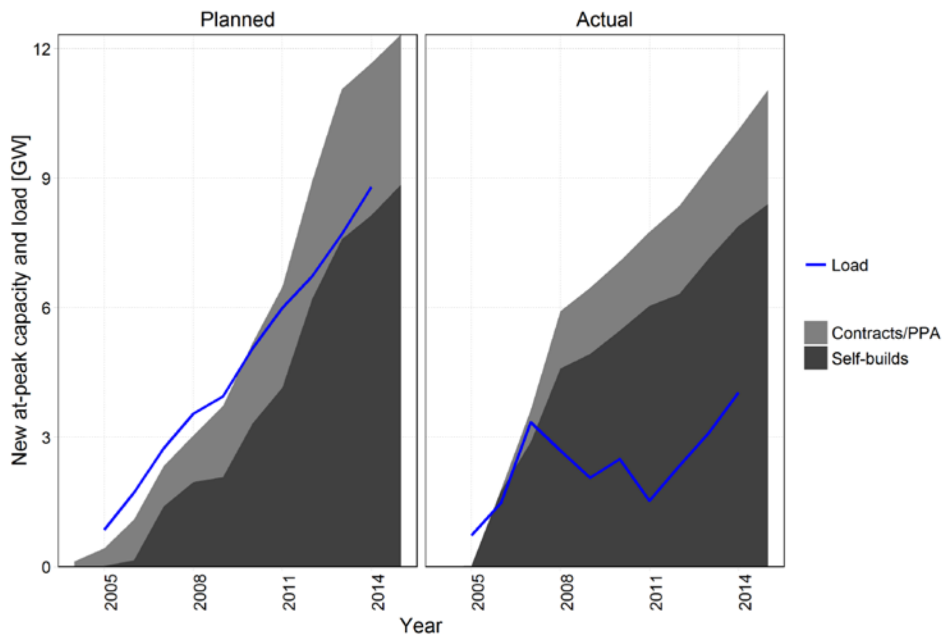

Figure ES-2 Planned and actual (procured) at-peak capacity with forecasted and observed peak demand.

For this sample of utilities, we find that aggregate planned and actual capacity expansion levels were generally consistent over the time period of our study. However, in aggregate, actual resource procurement decisions were not closely aligned with observed changes in load (see Figure ES-2). Actual incremental capacity additions were partially attributable to retirements of existing plants, which accounted for about 2.5 GW among our sample of utilities.

We find that load forecast methodologies have not changed significantly in the past 15 years, although there is evidence in more recent plans of the inclusion of potential structural change drivers such as distributed energy resources and electric vehicles. We did find that utilities which fundamentally changed their forecasting techniques had relatively larger forecast errors in earlier periods. This suggests an active effort to by the utilities to react to forecast error, although we do not have evidence that these changes led to reduced forecast error in subsequent periods. In general, we believe that our findings of load forecast performance and their relationship to procurement are applicable to current resource planning and procurement processes.

Our findings suggest that (1) load forecast accuracy may not be as important for resource procurement as previously believed, (2) load forecast sensitivities could be used to improve the procurement process, and (3) comprehensively addressing load uncertainty should be prioritized over developing more complex forecasting techniques. To the best of our knowledge, this is the first comparative and retrospective study of long-range energy and peak demand forecasts for electric utilities. We identify several key topics for further research to better understand the results and inform industry stakeholders about the role that load forecasts play in electricity sector infrastructure investments.

1. Introduction

From the origins of the U. S. electricity industry in the 19th century with Thomas Edison's first power-generation plant in New York City, electric utility planning and operations have become highly complex, multi-faceted processes. Electric utility integrated resource planning (IRP) is the key mechanism through which many vertically integrated U. S. utilities or load-serving entities (LSEs) [1] operating in states with a regulated electricity sector determine how to provide electricity services to customers while complying with applicable energy and environmental regulations and policies, and respecting the economic objectives of both the utility and customers. IRP entails the use of a range of quantitative analytical methods, including computational modeling and statistical analysis. The IRP applications of these methods include forecasting variables including load - electricity consumption and peak demand, analyzing possible "portfolios" - combinations of types and amounts of generation, assessing energy efficiency and other means of influencing demand and ensuring that supply and demand are balanced over a specified planning horizon. By design, the IRP process involves multiple stakeholders beyond utilities themselves, including regulators, ratepayer advocacy groups, other entities within the power industry, and non-profit organizations.

Electric utility integrated resource planning has its origins in "least-cost planning," a methodology developed in the 1970s to incorporate "demand-side resources" – measures to promote energy efficiency and conservation – along with the supply-side resources, i.e., generated electric power, that had traditionally been the sole focus of utility planning. Over the past several decades, the technical tools and methods used in IRP have become more complex and the requirements placed upon IRP – with regard to goals and objectives as well as process guidelines – have increased. Concurrently, there has been increasing interest among researchers, regulators, and other stakeholders in understanding the details of how IRP is conducted and how its outcomes relate to its goals, and in ways to enhance and improve IRP both technically and from a process perspective.

Among their other provisions, state regulatory requirements for IRP generally stipulate openness with respect to information, involvement of non-utility and other stakeholders besides regulators, and similar process elements. They do not in general, however, require actual evaluation or validation of models or methods.[2] While not an evaluation or validation analysis as such, the work described in this paper builds upon previous reviews and assessments of IRP, including

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[1] "Load-serving entity" is a more precise term than "utility" to refer to firms that sell electric power to end-use customers. However, in this paper these terms will be used interchangeably.

[2] Although for reasons discussed later in the paper we do not include IRPs by large California investor-owned utilities in our analysis, California is an exception in that its state public utilities code explicitly stipulates that models used in electricity planning and operations be validated. It is also interesting to note that the U. S. Energy Policy Act of 1992, which requires utilities to conduct integrated resource planning, also stipulates that approval of utility-submitted IRPs by regulators of the Western Area Power Administration is contingent upon the fulfillment of several criteria including that the utility "[provide] methods of validating predicted performance in order to determine whether objectives in the plan are being met."

load forecasting and dating back to the 1980s, by outside researchers, with recent examples being Aspen and E3 (2008) and Wilkerson et al. (2014). It is aimed at contributing to the understanding of IRP and focuses on the methods, results, and planning applications of utility load forecasting.

Estimates of load over time horizons up to two decades are a cornerstone of the integrated planning process: notwithstanding the multiple purposes and aspects of IRP, the LSEs' core objective and obligation is to ensure reliable and affordable electricity supplies for their customers. Load forecasting is thus of *prima facie* interest in analyzing and assessing IRP.

In addition, as noted above the treatment of demand-side resources has been a central motivation for IRP dating back to the 1970s, and utilities' incorporation of energy efficiency and related measures is fundamentally based upon their analyses and forecasts of load and the factors affecting it. This element of IRP has only increased in importance in recent years, as increasing energy efficiency and demand response has become a goal of a growing number of U. S. states and utilities. From both analytical and regulatory-policy perspectives, understanding how efficiency is analyzed within and implemented through IRP requires first understanding LSEs' basic load forecasting techniques, methods, and results.[3]

Despite these considerations, there has been little analysis of load forecast *performance* – i.e., accuracy - in the context of IRP, nor of how it is related to utilities' procurement decisions. These decisions include building or acquiring of power generation plants, purchasing power from other sources, implementing demand-side management programs, and other means of securing electricity supplies and services for their customers. This paper aims to help fill this gap, and reports the results of an analysis of load forecasting conducted in the mid-2000s by twelve utilities in the western United States. We complement our analysis by examining, in addition, recent plans for each of these utilities. It is the first of a two-part study of the relationship between planning and procurement in utility IRP. It explores the role of load forecasting in planning and how its accuracy relates to potential differences between planning and procurement. The second paper will analyze in greater depth and detail the regulatory process that connects the planning process with procurement decisions.

The paper is organized as follows. We begin with an overview of previous research on various elements and aspects of IRP in Section 2 to situate our work. We then describe the sources of data used for our analysis, followed by a discussion of the LSEs' forecasting methods and inputs in Section 3. Next, the metrics used to compare forecasts to actual energy and peak demand are defined in Section 4, followed by our quantitative findings on forecast performance in Section 5. We then turn to a discussion of the economic-demographic projections used in the forecasts and their relationship to forecast accuracy, and present a quantitative review of the LSEs' projected growth rates and retrospectively-revealed forecast errors in successive IRPs in Section 6. Next, in Section 7 an analysis of load sensitivity methodologies and performance is conducted along

[3] Experience in California has demonstrated that understanding the role of efficiency and efficiency policies and programs in load and demand forecasting can be very challenging (REF DAWG).

with a discussion of changes to LSEs' load forecasting methods and inputs over time in Section 8. We present a summary of results comparing the load forecasts to planned and actual procurement in Section 9. The study concludes with a summary and suggestions for further research.

2. Background

Descriptive as well as critical reviews of least-cost planning and IRP began to appear in the 1980s, as these processes were adopted across the U. S. In keeping with the origins of this type of planning, some of this literature included discussions of IRP's treatment of energy efficiency and conservation, and the potential for "demand-side management (DSM)" programs to reduce load growth. More generally, it included analyses of factors within (i.e., endogenous)—and beyond (i.e., exogenous)— the control of LSEs that impact the performance of forecasts including (1) forecasting methods employed by planning departments; (2) company and technological characteristics; and (3) the broader economic and regulatory environment (Goldman et al., 1993).

Hirst (1989) reported findings from a case study of, and drew lessons from, a specific planning exercise by a utility in the Pacific Northwest. Hirst (1990) and Hirst et al. (1991b) reviewed more than 30 resource plans from electric utilities, focusing on "technical competence" - including load forecasting — and made recommendations for improvements; in the case of load forecasting, however, these recommendations were not based on a quantitative analysis but rather emphasized methodological issues, especially the treatment of DSM. Hirst (1994) also critically reviewed key elements of IRP as practiced by utilities at the time, including load forecasting, and identified best practice. Schweitzer et al. (1991) reviewed plans from more than 20 load-serving entities with an emphasis on demand-side management activities. Hirst et al. (1991a) surveyed the regulatory, institutional and technical status of IRP at that time – including the treatment of DSM in load forecasting – and made recommendations for improvement in each category. Sioshansi (1992) explored the effect of incorporating technologies—including demand-side management and energy efficiency—on electric utility resource processes, plans, and outcomes. Mitchell (1992) surveyed the status of IRP with respects to its adoption and implementation across U. S. states. Aspen and E3 (2008) reviewed IRP planning processes and methods across U. S. states, and compared critical assumptions, timeframes, models, and procurement processes used by nearly 20 LSEs across the Western U.S., including inputs to and methods for load forecasting. Wilson and Biewald (2013) identified IRP "best practices," including examples of load forecasting by specific utilities and recommendations for load forecasting improvements, while a study conducted for U. S. state energy policy-makers examined how utilities' load forecasting is taking account of the emergence of electric vehicles (NASEO 2013). Wilkerson et al. (2014) reviewed nearly 40 long-term electric utility plans representing ~90% of generation within the Western United States and Canadian provinces, and identified assumptions about future growth of electricity demand and supply, the types of risk utilities consider in their long-term resource planning, and the consistency in which utilities report resource planning-related data.

In addition to these studies dealing at least in part with technical matters, a number of studies have addressed institutional and contextual aspects of IRP. For example, English et al. (1995) analyzed the role and impacts of energy efficiency advocacy groups in planning processes, while Hirst (1988) discussed state public utility commissions' roles in and responsibilities for IRP, and Hadley and Hirst (1995) discussed utility IRP from the electric utility shareholder perspective. More recently, Wilson and Peterson (2011) surveyed the rules and regulations governing IRP across U. S. states.

Complementing this work on IRP *per se* has been research on computational modeling in electricity planning. Eto (1990) and Foley et al. (2010) discussed models and software used in electricity planning. Kahn (1995) analyzed the advent of "production cost (optimization) modeling" by utilities in regulatory processes, including those involving IRP. Rosekrans et al. (1999) reviewed and compared several electricity planning models, many of which are used in IRP.

Despite reviews and discussions of load forecasting among other technical aspects of IRP, the work summarized above has not quantitatively studied load forecast nor analyzed its accuracy. By contrast, several papers from the 1980s did so. Willis and Northcote-Green (1984) compared methods and accuracy of 14 distribution system load forecasts. Nelson and Peck (1985) analyzed "summary" load forecasts from the 1970s prepared by the National Electricity Reliability Corporation (NERC), which combine individual utility service territory- and regional-level forecasts into a national-level forecast. They found systematic over-projection of demand. Mitchell et al. (1986) retrospectively evaluated the accuracy of long-term load – both energy and peak – forecasts by utilities, government agencies, and academic researchers. However, none of these studies analyze the impacts of forecast error and the feedback between forecast performance, planning and procurement.

While short-term electric load forecasting has been and continues to be the focus of considerable research, these older studies of long-term forecast performance have not been followed up by more recent work nor have they been expanded to understand the implications of forecast performance in the planning and procurement process. In the following sections we present the results of our analysis, which addresses this topic.

3. Data sources and methods

Our quantitative analysis of forecast performance relies largely on two types of data: forecasts and actual[4] values. In this section, we describe the methodology to obtain this information, the original sources of the data, and how this information is used throughout the analysis. The same sources are used for the qualitative descriptions of load forecast and load growth sensitivity methodologies.

We collect forecasts from integrated resource plans that were made roughly a decade ago – from 2003 to 2007 – by twelve load-serving entities (LSEs) across the Western Electricity Coordinating Council (WECC). The analysis focuses on WECC because this territory includes the largest U. S. LSEs that were required to file resource plans during this period (Wilkerson et al., 2014)[5]. However, we exclude three large California investor-owned utilities (IOUs), because the California planning framework – the so-called "Long Term Procurement Planning" process – is qualitatively different from the other resource planning mandates in WECC (Aspen and E3, 2008). Outside of the California IOUs, the LSEs selected for this study are the twelve largest in WECC representing 34% and 32% of customers and retail sales in 2014, respectively.

The years for the IRPs are selected in order to enable comparison with realized observations – i.e., observed values of energy and peak demand — through 2014, the most recent year for which these values are currently available (see Table 1). Depending on the LSE, between seven and eleven years of observed energy and peak demand can be compared to the original forecast.

The choice of years also satisfies several other criteria. First, we need plans that were created sufficiently long ago that their forecasts can be compared to observed values over periods lengthy enough to allow substantive analysis[6]. Second, plans that are older than those selected tended to have several shortcomings: the information included in them was scarce, both in terms of data and descriptions; the techniques for forecasting may have changed significantly; and the electricity deregulation movement in the late 1990s may have had an important effect on their assumptions. Because the earliest plan (2003) followed the California electricity crisis of 2000-2001, we presume that the effects of deregulation would have already been absorbed in the planning processes. We believe that using plans from 2003 and later enables reasonable conclusions about trends and the implications of policies. Finally, we also reviewed one recent plan (produced between 2011 and 2015) for each LSE to understand if and how the methodologies and techniques used to produce forecasts had changed in time.

[4] We refer to these also as "realized" or "observed" through the paper.
[5] ERCOT and the Eastern Interconnection utilities filed no or very few resource plans in the early 2000s, largely due to the deregulation process.
[6] In the case of PNM and PGE we selected the oldest plans we were able to find that included the required data. PNM filed its first resource plan in 2005 but it did not include most of the quantitative data required for the analysis.

Table 1 **Load serving entities (LSEs) and integrated resource plans analyzed in this study.**

LSE short name	LSE name	First Plan Year	Recent Plan Year	Reference
Avista	Avista Corporation	2005	2013	(Avista, 2013, 2005)
COPSC*	Public Service Company of Colorado (Xcel Energy)	2003	2011	(COPSC, 2011, 2004)
Idaho	Idaho Power Company	2006	2013	(Idaho, 2013, 2006)
LADWP	Los Angeles Department of Water and Power	2006	2012	(LADWP, 2012, 2006)
NVPower	Nevada Power Company	2006	2012	(NVPower, 2012, 2006)
NW	NorthWestern Corp. dba NorthWestern Energy	2004	2013	(NW, 2013, 2004)
PacifiCorp	PacifiCorp	2004	2015	(PacifiCorp, 2015, 2005)
PGE	Portland General Electric Company	2007	2013	(PGE, 2014, 2007)
PNM	Public Service Company of New Mexico	2007	2011	(PNM, 2011, 2007)
PugetSound*	Puget Sound Energy, Inc.	2005	2013	(PugetSound, 2013, 2005)
Seattle*	Seattle City Light	2006	2012	(Seattle, 2012, 2006)
SierraPacific*	Sierra Pacific Power Company	2004	2013	(SierraPacific, 2013, 2004)

* These LSEs are also known as PSCo (COPSC), PSE (PugetSound), SCL (Seattle), and SPP (SierraPacific). We use our own short names through this paper.

The analysis period includes the 2008 economic recession, which *prima facie* could be expected to have a substantial effect on the accuracy of load forecasts made prior to its onset. For several reasons, however, we see this as increasing the interest and usefulness of our analysis. First, it is a truism that all forecasts - including those of electricity use - are subject to error due to unforeseen circumstances. The documentation indicates that the LSEs view economic and demographic variables as the primary drivers of demand, and the inevitability but always uncertain timing of events such as recessions means that such events are essentially guaranteed to affect long-term load forecasts in not-fully-predictable ways, regardless of the forecast interval. Thus, an analysis period including the downturn that began in 2008 - which was unusually severe - can if anything allow greater insight into the nature of load forecast accuracy and how forecast errors are addressed in the IRP process than might be available from studying a period without such an event. Put differently, the 2008 recession provides an interesting "stress test" of LSE load forecasting procedures in the context of IRP. Second, because the recession affected all regions of the U. S. to some extent, including the service territories of the LSEs in our sample, it does not undermine our comparative analysis and indeed, to the extent that the effects of the recession varied across these territories, adds useful variation to our sample. Finally, the procurement activities following the IRP load forecasts necessarily also reflected the recessions' effects, and thus the latter do not interfere with our goal of studying the relationships between load forecasting and procurement.

3.1 Forecast information from plans

Our analysis considers specific information from resource plans including utility forecasting techniques, company characteristics, and the regulatory environment. Three basic types of forecast data are collected from each IRP:

1. Peak load
2. Energy demand
3. Demand side resources (energy efficiency and demand response)

We record the base- or reference- case load forecast in each resource plan (all the LSEs produced these cases for energy, and all but one for peak). We also record high and low load forecasts when available. Utilities that file resource plans do not always have the same definition of their "position," i.e., the difference between existing resources and forecasted demand. For example, LSEs deal differently with energy efficiency and demand response measures. Some subtract projected savings from these resources into their load forecasts, and some report them separately. For the forecasts that had not already done so, we subtract these savings from the raw energy and peak demand forecasts in order to calculate net load[7]. The use of net forecasts is appropriate for comparison with actual energy and peak demand, since the latter have embedded within them the effects of demand-side programs and other acquired energy efficiency over the periods considered in the analysis.

3.2 Information on actual energy use and peak demand

Data on actual energy consumption and peak demand were obtained primarily from the Velocity Suite system supplied by ABB-Ventyx—an online database system that compiles publicly-available data and also contains proprietary values for variables that are not always publicly-available, including retail fuel prices and marginal costs (ABB-Ventyx, 2016).

The Velocity Suite system contains load data (retail sales), which are typically reported through the Energy Information Administration (EIA) Form 861. As defined by the EIA, "The Form EIA-861 and Form EIA-861S (Short Form) data files include information such as peak load, generation, electric purchases, sales, revenues, customer counts and demand-side management programs, green pricing and net metering programs, and distributed generation capacity." (EIA,

[7] By doing this, we implicitly include in our assessment the performance of energy efficiency and demand response forecasts. We recognize that the actual demand side resources may differ from these forecasts, but we lack the data to test this.

2016) In order to conduct forecast-to-actual comparisons, it is necessary to identify the types of sales that utilities themselves considered as part of the "position" for the resource planning process. We determine that all IRPs account for retail sales to ultimate consumers when creating their forecasts, and that all except LADWP and COPSC include transmission and distribution losses to reflect demand at the generation level. Therefore, we incorporate losses into the retail sales information reported via form EIA-861.

In addition, we inspect the IRP narratives and quantitative information to determine which LSEs account explicitly for selected wholesale sales for which they had firm contracts at the time of the forecasts. For example, short-term transactions that are used as hedging or as a market opportunity would typically not be included in the resource plan. However, sales to smaller municipalities and electric cooperatives under certain contracting arrangements would be included. We find that all LSEs, with the exception of NW, counted "requirements service[8]" wholesale sales in their resource plans. We use data from EIA Form 412 and FERC Form 1 to identify and include appropriate wholesale sales as part of actual outcomes for each LSE. Finally, we use historical information presented in the most recent plans of the several LSEs that reported it to check our estimates for actual values.

4. Description of forecasting methodologies

We characterize the methods employed by LSEs to forecast energy, peak demand, and hourly profiles using the following categories:

1. General forecasting framework—e.g., the mix of customer classes evaluated, makeup of forecast scenarios.

2. Key variables and analytical methods—e.g., time-series regression, statistically-adjusted end-use models, cooling degree-days, number of customers.

3. Sources of forecast assumptions—e.g., IHS Global Insight, Inc., EPRI, Moody's Analytics, Inc.

We provide an overview of the LSEs' load forecasting; further details are given in Appendix B. In addition to the base case or "expected" forecasts, most of the LSEs also produce low and high load forecasts using differing assumptions. We summarize and analyze these alternative forecasts in section 7 and Appendix D.

LSEs typically split their residential and commercial forecasts into numbers of customers and use-per-customer, using different methods to forecast both separately. Industrial consumption forecasts are usually based on direct feedback from the largest customers, complemented with

[8] According to EIA-861, "Requirements service is service which the supplier plans to provide on an ongoing basis. The reliability of requirement service must be the same as, or second only to, the supplier's service to its own consumers."

regional or sectoral market research reports. Only a few of the LSEs evaluated in this paper reported load forecast results by customer class.

We find that roughly three quarters of the LSEs in our sample relied on externally-developed demographic and economic forecasts. These external forecasts came from a mix of public and private sources, including universities, state/federal agencies, and consulting firms. We also find that most of these sources are proprietary, which prevents scrutiny from stakeholders and further analysis from regulators.

Another key component of a number of the load forecasting frameworks is the potential for customers to respond to changes in electricity prices (i.e., price elasticities) through a combination of electric consumption reduction and fuel switching. For example, as the price of electricity increases or the price of natural gas decreases, it is expected that electric load will decrease and natural gas consumption increase as a rational response to these price signals. About half of the LSEs in our sample reported specific information about price elasticities—with all falling within the -0.10 to -0.20 range (NVPower, PugetSound, Avista, and PacifiCorp)[9]. Avista is the only LSE that reports cross-price elasticities with natural gas, although Idaho also points that "changes in relative fuel prices can have significant impacts on the future demand for electricity" (Idaho, 2006, p. 4 Appendix B). In contrast, NW and SierraPacific report that they find no empirical evidence for statistically significant price elasticities for electricity or for natural gas.

We evaluate these and other variables in order to understand the similarities and differences among the LSEs' forecasting procedures (see Figure 1). We find economic-demographic projections, historical sales data, and weather variables to be the most commonly-used variables to produce load forecasts. For each LSE, we also qualitatively assess the complexity of the load forecast by comparing the number of variables used to forecast residential and commercial/industrial demand and the analytical methods employed (see Table 2). For example, utilities including PNM, NW and SierraPacific use simpler models compared to the models employed by COPSC, LADWP, and PugetSound. This complexity is a function of the number of variables, the types of variables, and the modeling technique and its implementation.

Four types of modeling approaches, of varying degrees of complexity, were used by the various LSEs to create energy, peak demand, and hourly load forecasts: Time-series regression, cross-sectional regression, engineering or "bottom-up", and statistically adjusted end-use (SAE). Time series and cross-sectional regressions consistently use historical sales and weather variables as determinants of electricity demand. SAE models have a hybrid structure combining engineering end-use technology models with econometric equations. This type of data intensive model represents demand in terms of a saturation component (for appliance ownership), an engineering component (for appliance energy intensity), and a behavioral component (Hirst et al., 1977; Hirst

[9] Unfortunately, no LSEs indicate whether they report short or long term price elasticity values.

and Carney, 1978; Sanstad et al., 2014). SAE models were employed by three of the twelve LSEs in our sample, while the two "pure" regression models are used by the majority of the LSEs. We identify what method is used for both residential and commercial customer classes. In a few cases, however, methods are not customer class-specific. For example, PacifiCorp uses a moving average method for short-term forecasting and an SAE for long term projections. Similarly, SierraPacific uses an ARIMA (auto-regression, integrative, moving average) method for the number of customers and a regression method for the use per customer.

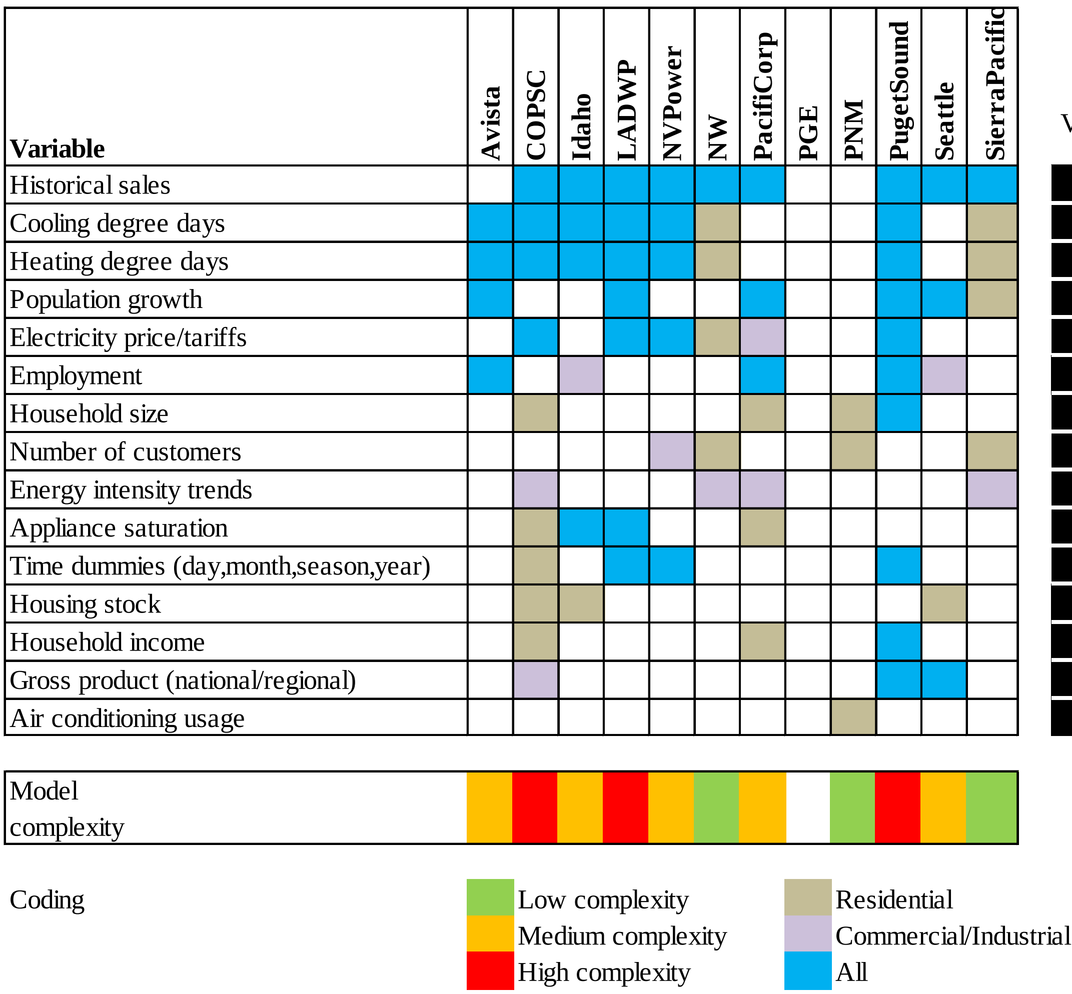

Figure 1 **Variables used for residential and commercial/industrial load forecasts, and model complexity[10].**

Finally, the breadth and depth of technical documentation on load forecasting varied quite widely among the LSEs in the older IRPs. In some cases, detailed information – including input types and values, mathematical formulae, and parameter estimates - were provided; in others, there was only narrative description. In no case, however, was there sufficient information to actually

[10] There is no information available for PGE in their 2007 plan. Blank spaces means that the variable is not documented or formally employed in the forecast.

replicate the individual LSE forecasts or to test their sensitivity to the error in the input parameters. This general inability to replicate individual LSE forecasts prevents stakeholders from critically examining the assumptions, techniques, and results of the load forecast.

Table 2 **Modeling approaches for residential and commercial load forecasting[11].**

	Time series regression (AR*, MA**)	Cross-section regression	Engineering model	SAE
Avista		RC		
COPSC				RC
Idaho				RC
LADWP		RC		
NVPower	RC	RC		
NW	C	R		
PacifiCorp				
PGE				
PNM			RC	
PugetSound		RC		
Seattle		RC		
SierraPacific				

*AR: Auto-regressive; **MA: Moving Average
R: Residential; C: Commercial

5. Quantitative analysis of forecast error

We are interested in assessing the impacts of forecast errors in the electric planning and procurement process. In this section we numerically compare the energy and peak demand forecasts reported by LSEs in their IRPs to actual outcomes over the corresponding period.

5.1 Comparison methods

We employ two different metrics to compare forecasts to actual results - i.e., to estimate forecast errors (Hyndman, 2006):

- *Sum of errors*: Annual forecast errors for each LSE were calculated as the differences between that LSE's forecasted value and the actual value for each year of the forecast. We divide the sum of these errors by the corresponding sum of total load that was actually realized by the LSE during the forecast period. This serves to normalize the metric in order to compare forecast performance across LSEs of varying sizes. This technique averages out positive and negative deviations, which is useful for identifying systematic error that is expected given the variability of loads.

[11] There is no information available for PGE in their 2007 plan.

- *Annual average growth rate (AAGR):* We compare the first and last year forecast and actual values to estimate an average annual growth rate for each. The AAGR represents the rate at which the first year forecast or actual value would need to grow to match the final year assuming a compound growth rate. This relationship is captured in equation (1) and (2) below:

$$Y_{t+n} = Y_t \times (1 + AAGR)^n \tag{1}$$

where Y_t is a forecast variable of interest (in our case energy and peak demand). Rearranging terms we have:

$$AAGR = \left(\frac{Y_{t+n}}{Y_t}\right)^{\frac{1}{n}} - 1 \tag{2}$$

The sum of errors is a relative metric, so a larger % difference implies larger forecast error over the time period of analysis. The AAGR captures, on average, the implied growth rate for a given variable. The difference between a forecast and an observed growth rate is, in this case, a measure of forecast error. We characterize the error in load forecasting (i) to understand how it may be correlated with specific methods, variables, or sources and (ii) to compare how these load forecast results relate to resource acquisition (see section 9).

5.2 Energy

Figure 2 shows normalized energy consumption forecasts and observed and equivalent for each LSE. This normalization yields growth rates for both forecasted and observed values. The analysis time frame corresponds to the range of years between the first year in the forecast and 2014 (the most recent year for which we have observed values). In some cases, sales seem relatively inelastic to the 2008 economic crisis and actual energy sales are close to the base forecast. However, sales for most LSEs stalled during and after the recession.

We compare the sum of errors in each LSE's analysis period with the sum of actual energy consumed in that period (Table 3). The immediate conclusion from this table is that proportional forecast error varies importantly across the LSEs in our sample, ranging from close to zero to almost 20%. The usual affirmation that "all forecasts are wrong" may be valid, but our empirical analysis suggests that, whether by chance or for other reasons such as methodological differences, forecast error in the analysis period is significantly smaller for some utilities than others[12].

[12] With this metric, forecasts from earlier plans have greater chance of having larger proportional error. However, we do not find a correlation between age of plans and error in our analysis, probably because the plans are at most 3 years apart.

Table 3 **Sum of errors as a proportion of total load for forecast horizon of 2014.**

LSE	Sum of errors (1) [TWh]	Sum of actual load (2) [TWh]	Proportional Error (1)/(2)
PGE	29.12	151.31	19%
Avista	14.73	85.36	17%
NVPower	26	199.01	13%
SierraPacific	10.57	89.37	12%
Idaho	13.47	138.43	10%
PNM	5.64	85.17	7%
COPSC	21.41	365.05	6%
LADWP	13.04	236.45	6%
PacifiCorp	33.43	580.63	6%
Seattle	5.15	100.48	5%
PugetSound	2.09	206.15	1%
NW	-1.29	68.5	-2%

In the analysis from Figure 2, the growth rate reflects the ratio between a given year's forecasted value and the first year forecast (and similarly for observed values). Growth rates are relevant because they convey expectations for potential resource needs that are independent of consumption levels and of existing resources. We see more clearly that some LSEs were more resilient or insensitive than others to the recession and that several have not shown signs of recovery in energy sales growth rates by 2014. In some cases (e.g. LADWP, COPSC, and PacifiCorp) we see that energy forecasts before the economic crisis seemed underestimated compared to actual load growth in that period. This may have been due to higher than anticipated economic activity during the "bubble" that preceded the economic downturn.

We calculate the Average Annual Growth Rate (AAGR) to facilitate comparison of growth estimates (Table 4). The AAGR condenses the medium-term accuracy of the forecast when compared to observed values as it is calculated by taking 2014 as the end year for all samples.

Utilities in our sample expected between 0.6% and 2.6% average growth rates for energy net of demand side resources. Observed growth rates for energy were much smaller, averaging close to zero across our sample of LSEs. About half of our sample shows negative observed AAGR and the ones that show positive AAGR are just above zero. The two exceptions are PacifiCorp, which grew at roughly two thirds of its expected rate, and NW, whose observed growth doubled its forecast growth for energy consumption. By comparing results in tables 3 and 4 we find that generally LSEs with smaller proportional errors will also show more accurate forecast AAGR.

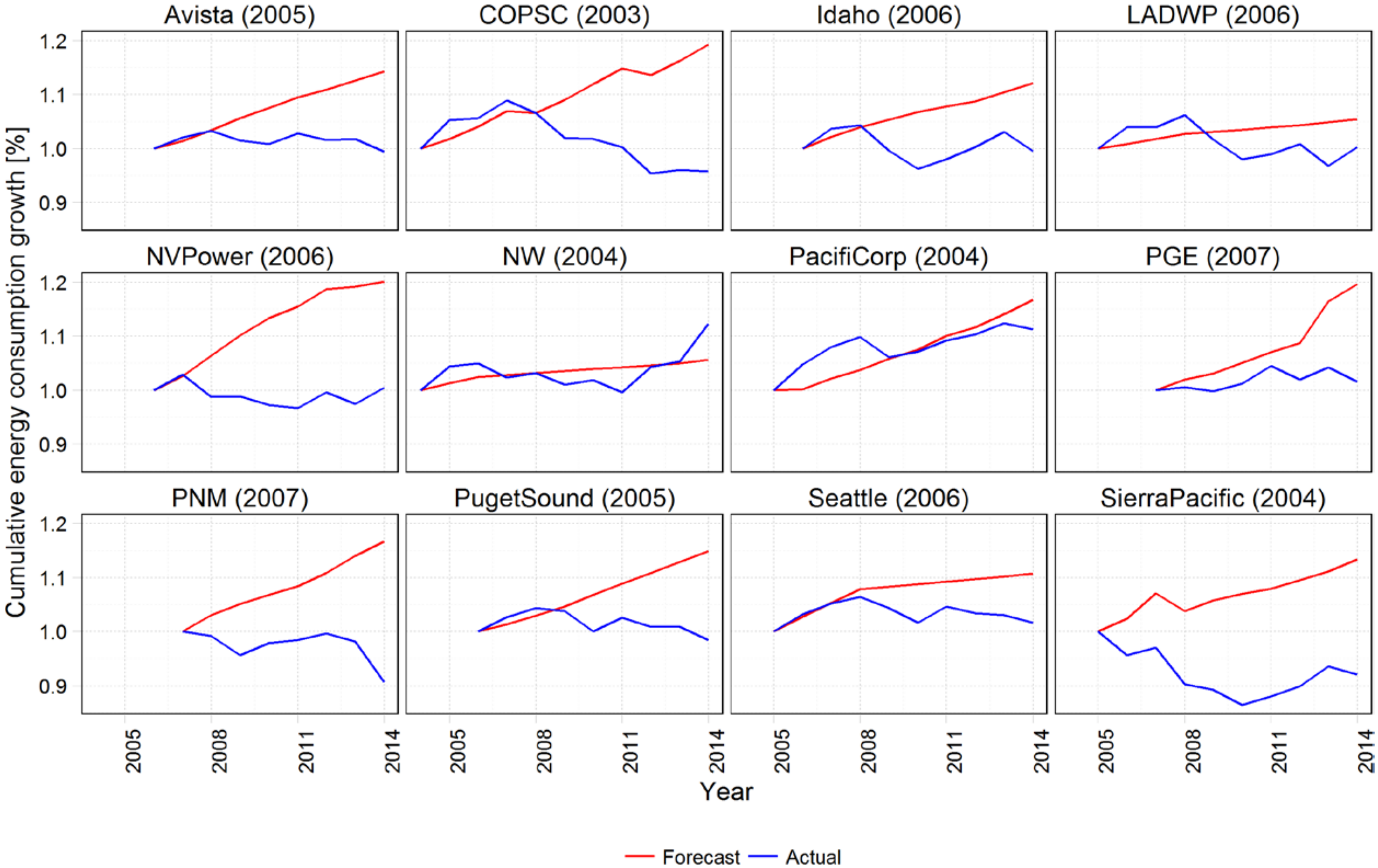

Figure 2 **Forecasted and actual energy consumption growth.**

Table 4 **Average annual growth rate for actual and forecast load**

	Energy AAGR		
LSE	**Base Forecast**	**Actual**	**Difference**
PNM	2.2%	-1.4%	3.6%
PGE	2.6%	0.2%	2.4%
SierraPacific	1.4%	-0.9%	2.3%
COPSC	1.8%	-0.4%	2.2%
NVPower	2.3%	0.1%	2.2%
PugetSound	1.7%	-0.2%	1.9%
Avista	1.7%	-0.1%	1.8%
Idaho	1.4%	-0.1%	1.5%
Seattle	1.1%	0.2%	0.9%
LADWP	0.6%	0.0%	0.6%
PacifiCorp	1.9%	1.3%	0.6%
NW	0.6%	1.2%	-0.6%

5.3 Peak demand

Peak demand forecasts are qualitatively different from energy consumption forecasts, particularly due to their greater sensitivity to weather variation. We find that the accuracy of energy consumption forecasting for a given utility did not necessarily correlate with the accuracy of its peak demand forecasts. In addition, several utilities reported that they were witnessing reduced load factors in their residential load. This means that historical hourly profiles and load factor assumptions may be less informative for peak demand forecast and make the latter more difficult to assess.

We find that several LSEs (COPSC, PGE, and NVPower) see mixed forecasting results — for some years underestimating and for others over-estimating. Other LSEs (Avista, Idaho, SierraPacific, NVPower, and Seattle) consistently over-estimate in the period after the financial crisis, which is symptomatic of a slower-than-expected recovery. Finally, some LSEs (PacifiCorp, LADWP, and PNM) seem to have small systematic under or over-estimation of energy and peak load, but reasonably accurate average growth rate forecasts. This situation occurs with forecasts that underestimate and overestimate actual values in different periods. The average over longer periods of time yields reasonably accurate growth rates, but still shows errors in energy and/or peak load forecast.

As with energy consumption, we extract the implicit growth rates in both forecasted and observed peak demand values and compare them (see Figure 3). We also calculate the Average Annual Growth Rate (AAGR) to facilitate comparison (Table 5). Peak demand growth rates generally show a slowdown after the economic crisis, but not for all LSEs. Seattle, Avista, PGE, and PugetSound – all in the Pacific Northwest – show a lagged halt in growth compared to other utilities (e.g. COPSC, NVPower, and PNM) whose growth rates reflect an immediate impact. PacifiCorp, LADWP and NW were relatively less affected by the crisis. Peak demand growth rates are more resilient when compared to energy consumption growth rates, which is consistent with the LSEs reporting reduced load factors after the economic crisis.

Table 5 **Peak demand average annual growth rates for forecasted and actual values.**

	Demand AAGR		
LSE	**Base Forecast**	**Actual**	**Difference**
PNM	1.9%	-0.8%	2.7%
COPSC	2.1%	-0.5%	2.6%
NVPower	2.4%	-0.1%	2.5%
Avista	1.8%	0.4%	1.4%
PGE	1.9%	0.8%	1.1%
Idaho	1.4%	0.4%	1.0%
Seattle	1.7%	1.2%	0.5%
PugetSound	1.1%	0.8%	0.3%
PacifiCorp	1.3%	1.3%	0.0%
LADWP	0.3%	1.8%	-1.5%
SierraPacific	1.7%	3.4%	-1.7%
NW	NA	4.1%	NA

Utilities in our sample expected growth rates between 0.3% and 2.4% for peak demand net of demand side resources. Growth rates for peak demand are much higher than for energy. In addition, several utilities reported higher peak demand growth than forecasted, even in the presence of the 2008/2009 crisis. This is consistent with statements in recent IRPs that report worsening[13] (i.e., a reduction) of load factors in residential and commercial customers. We also compare energy and peak demand observed values and find that peak demand forecast error shows much larger variance across utilities. This supports the notion that it is more difficult to forecast long term peak demand than energy consumption.

A comprehensive and exhaustive assessment of load forecast error would require weather normalization of actual values. Unfortunately, we neither have access to the data nor the resources to perform this level of analysis. It is important to note, however, that weather normalization typically has more of an effect on short-term forecast performance. Normalizing

[13] Utilities typically use a negative connotation to refer to load factor reductions, because it means they sell less energy using the same infrastructure putting upward pressure on rates and/or reducing their profits.

weather has less of an impact on long-term forecasts like those analyzed in this paper[14]. Having said that, we examine the historical record for cooling and heating degree-days (CDD and HDD) for the Pacific U.S. region to characterize the weather in the period analyzed. We find that there were warmer-than-average years in 2014 and 2015, but all other years in our period of analysis were considered “normal”. For this reason, we believe that our findings would be largely unchanged if we included weather normalization for each observed value and for every LSE. Interestingly, LSEs do not report weather as a primary source of long-term forecast error, which also supports the aforementioned point.

[14] Climate change will impact CDD and HDD in the very long term. However, changes in CDD and HDD will not be large enough in the 10 to 20 year periods used for resource planning to be a relevant source of forecast error.

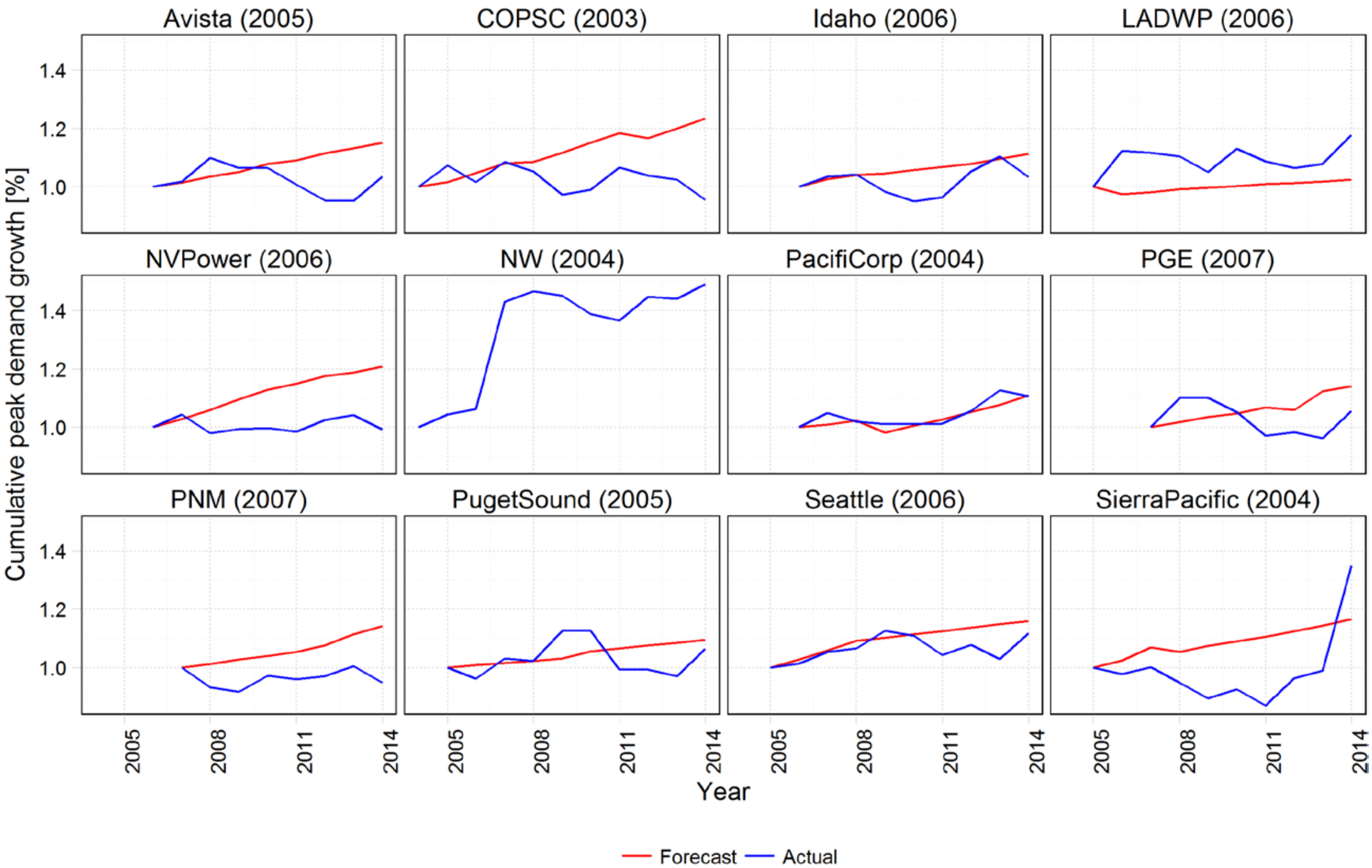

Figure 3 **Forecasted and actual peak demand growth.**

Notwithstanding the general pattern of forecast inaccuracy, we find that forecasts for some LSEs performed significantly better than others, even in the presence of the economic recession. Our preliminary analysis suggests that best performance is not correlated to the size of the utility or to its geographical location. However, given the relative ranking in Table 3, we find that larger utilities have intermediate forecast error. This is perhaps a consequence of having a diverse and large pool of customers that smooths economic impacts on forecast. We also find that LSEs with lower forecast error tend to have fewer sales to industrial customers in proportion to their total sales. This makes intuitive sense: industrial customers are probably the most elastic customer class in relation to economic growth. Their load is hard to forecast and its lumpy nature has a significant impact on forecast results. As some LSEs report in their plans, industrial customers commonly communicate their intention to move in to their service area or to increase load, but they rarely report an impending termination of operations or downsize. This very preliminary assessment suggests that load composition may have an impact on the planning strategy and load sensitivity analyses.

With a few exceptions, we find consistent over-estimation of future energy consumption and peak demand by the LSEs in the resource plans from the mid-2000s. In the following section, we discuss the companies' changes to their forecasts in subsequent IRPs, including the extent to which forecast errors were reduced over the planning periods ending in 2014. In Section 7 we assess into what extent load forecast sensitivities were able to reflect an extreme event like the 2008 recession.

6. Economic forecasts and revisions to load growth forecasts

6.1 Economic forecasts

Long-term energy modeling is unavoidably subject to considerable uncertainty. The forecast errors discussed in this paper might reasonably be considered an example of this fact. At the same time, it would be expected that the continual revision and updating within the IRP process serves to progressively lower these errors, reducing or minimizing their potential consequences for capacity expansion.

Perhaps the most important issue for the present analysis is the U. S. national recession that began in 2008. Although the macroeconomic business cycle is an established phenomenon, predicting the timing and magnitudes of economic downturns remains an inexact process, and moreover the magnitude and duration of the recession that began in 2008-2009 are widely (though perhaps not universally) recognized to have been unusually severe. Thus, despite the *ex-ante* unpredictability of the exact macroeconomic details, ongoing IRP processes would be expected to have, in subsequent years, accounted for dramatically reduced economic activity and its effects on electricity use (along with other influences on load growth subsequent to the year the original forecasts were created).

We examine IRPs and load forecasts for certain years following those in which the above-discussed forecasts were made for a number of the LSEs. We call these IRPs "intermediate" in the context of this analysis since they were produced between the "older" and "recent" ones employed throughout this study (see Table 1). These intermediate IRPs reveal that, while forecasts are of course revised and updated, the LSEs themselves devote varying levels of attention to retrospective examination, evaluation, and correction of their own load forecasts and forecast errors. In some cases, there is not only considerable analysis of this type, but also improvements in forecasting methods in order to obtain greater accuracy. In others, while forecasts are updated, there is little or no retrospective discussion in the documents we examined.

In those cases in which forecast errors are discussed *ex post*, the LSEs as expected highlight reduced economic activity as the key factor for previous overestimation of load growth over the time period in question. In some cases, the effects of demand-side management programs to promote energy efficiency are also cited – that is, as reducing growth more than had been anticipated. As we noted previously, the available documentation is not sufficient to replicate the load forecasts and fully determine the quantitative importance of different inputs. However, in the plans that cite these demand-side effects, they appear to be clearly secondary to (considerably smaller than) those of reduced economic growth.

For example, Avista's planning process demonstrates sustained attention to evaluating and improving load forecasts, and reveals the company's emphasis on the importance of economic growth projections for forecasting electricity use, and on the effects of the recession during the planning period we are examining. In its 2005 IRP, the company states that "employment and population forecasts provide the basis for electric customer projections," which are in turn the basis for its load forecasts. At that time, Avista projected 1.8% average annual customer growth, and 2.1% average annual electricity sales growth, over the twenty –year (2005-2025) forecast period. Similarly, in its 2007 IRP, Avista continued to project average customer growth of 1.8%, and sales growth of 2.0%, over twenty years.

Avista's 2009 IRP noted the slowdown in national and regional economic growth that had begun by that time, but stated that "…the current recession is expected to end by 2011," and projected twenty-year 1.7% average annual growth in both customers and sales. The company's 2011 IRP discusses the continuing effect of slower economic growth on sales, while continuing to assume that the recession would end in 2011. It was not until the 2015 IRP that the company reported that population and employment growth in its service territory had begun to recover.

Similarly, in its 2011 IRP, COPSC discusses the effects of the slowdown that had begun in 2008, including employment declines in Colorado, by way of explaining the slower-than-predicted load growth over the previous several years, while predicting strong economic, population, and employment growth, and hence "recovery" in load growth, going forward through 2018.

Idaho's 2006 IRP contains extensive documentation of the company's methods and models for demographic and economic analysis, including detailed forecast tables of population, employment, etc. in Idaho. By contrast, the 2009 and subsequent Idaho IRPs contain significantly less documentation of this type. They do, however, address the effects of the recession – both the 2009 and 2011 plans state that load growth had been slower than predicted in the previous plan because of the national and service area economic slowdown. The LSE highlights the growth rate in the number of households in its service territory as a key basis for load forecasting. In its 2006 IRP, it projected that the average annual growth rate in this quantity would be 1.7% over twenty years; in 2009, the forecast was 1.3%, and in 2011 1.2%.

In these examples and several others, the pattern appears to be that economic factors contributed significantly to the lower-than-forecast load growth we have discussed above, but that the LSEs continued, over successive IRPs, to predict economy recovery to at least some degree, and therefore a recovery in load growth rates from those in the aftermath of the recession. For most if not all of the LSEs, however, significant economic recovery, and therefore return to higher load growth rates, were not forthcoming for a number of years. Given the LSE's reliance on macroeconomic forecasting services such as Global Insight, this may reflect the fact that economists in general, including forecasters, did not anticipate the very slow and partial recovery, by historical standards, from the recession that began in 2008-2009. Given the considerable apparent impact of economic factors on load growth over the period we are studying, these facts highlight the importance of economic and demographic forecasting in the IRP process, including the *relative* impact of these factors compared to others that influence load growth and are analyzed in the IRP processes.

6.2 Revisions of load growth rates in subsequent forecasts

We can also draw upon the successive IRP updates to examine changes to the load forecasts themselves. For the ultimate purpose of the present analysis – relating load forecasts to capacity expansion – what is of particular interest is the extent to which forecast errors are reduced during the planning periods in which capacity expansion decisions are made. As discussed above, we are focusing on the years up to and including 2014 since that is the most recent year for which estimates of actual load are available from the EIA. Thus, consider a load forecast made in 2005 that extends to 2014 or beyond. Although the forecast may, in retrospect, embody non-negligible errors over the 2005-2014 horizon, updated forecasts made after 2005, but before 2014, might have reduced these errors and thus mitigated their potential impact on capacity expansion.

Examining successive forecasts in this manner shows that, although in some cases errors do decline, for most LSEs they remain non-negligible. Indeed, in most cases we see a sustained over-estimation of load growth-to-2014 even as the year in which the forecast was conducted approaches 2014. Specifically, actual load growth to-year-2014 was in most cases small or even negative as the years-of-forecast approached 2014, but the forecasts themselves continue to project positive growth at rates that have turned out to be higher than actual rates and in some cases of the opposite sign (negative rather than positive).

This pattern is shown for several LSEs in the following tables. The first is for Avista, and illustrates the format of the information (Table 6). The earlier Avista IRP discussed in this paper is from 2005 (with 2006 being the first forecast year). Avista also produced IRPs in 2007, 2009, and 2011 (with first forecast years corresponding to the IRP years), with its 2011 IRP including a comparative table of these load forecasts. The second column of the table gives the corresponding average annual growth rates of load (energy) from each, calculated from the forecasts' base years *through 2014*. The third column gives the actual growth rates for each period. Thus, for example, the original (2005) IRP projected an average energy load growth rate of 2.35% through 2014; the actual rate turned out to be -0.07%. The most recent (2011) forecast projected a three-year growth rate of 1.62 %, with the actual being -1.11%. This information is displayed graphically in Figure 6.

Table 6 **Avista – Forecasted and actual energy consumption growth rates to 2014**

Period	**LSE-Projected AAGR**	**Actual AAGR**
2006-2014	2.35%	-0.07%
2007-2014	2.60%	-0.38%
2009-2014	1.78%	-0.41%
2011-2014	1.62%	-1.11%

Figure 6 shows the systematic decline in forecasted growth rates in successive revisions as well as actual energy use by the LSE's customers. There is a very consistent relationship between the growth rate two years before the forecast and the average forecast growth rate.

Table 7 gives similar information for COPSC. In this case, the only LSE forecasts available to us were from 2003 (with 2004 being the forecast base year) and 2011 (with 2012 the base year). Both the projected load growth rate and the forecast error decline from 2003 to the 2011 IRP, but there is again an over-estimate of future loads.

Table 7 **COPSC – Forecasted and actual energy consumption growth rates to 2014.**

Period	**LSE-Projected AAGR**	**Actual AAGR**
2004-2014	1.78%	-0.43%
2012-2014	0.81%	0.18%

For Idaho Power (Table 8), forecasts were available from IRPs or plan updates in 2006, 2008, 2009, and 2011. While the error is lower for the 2008 forecast than for the others, there is again a consistent over-projection of load growth.

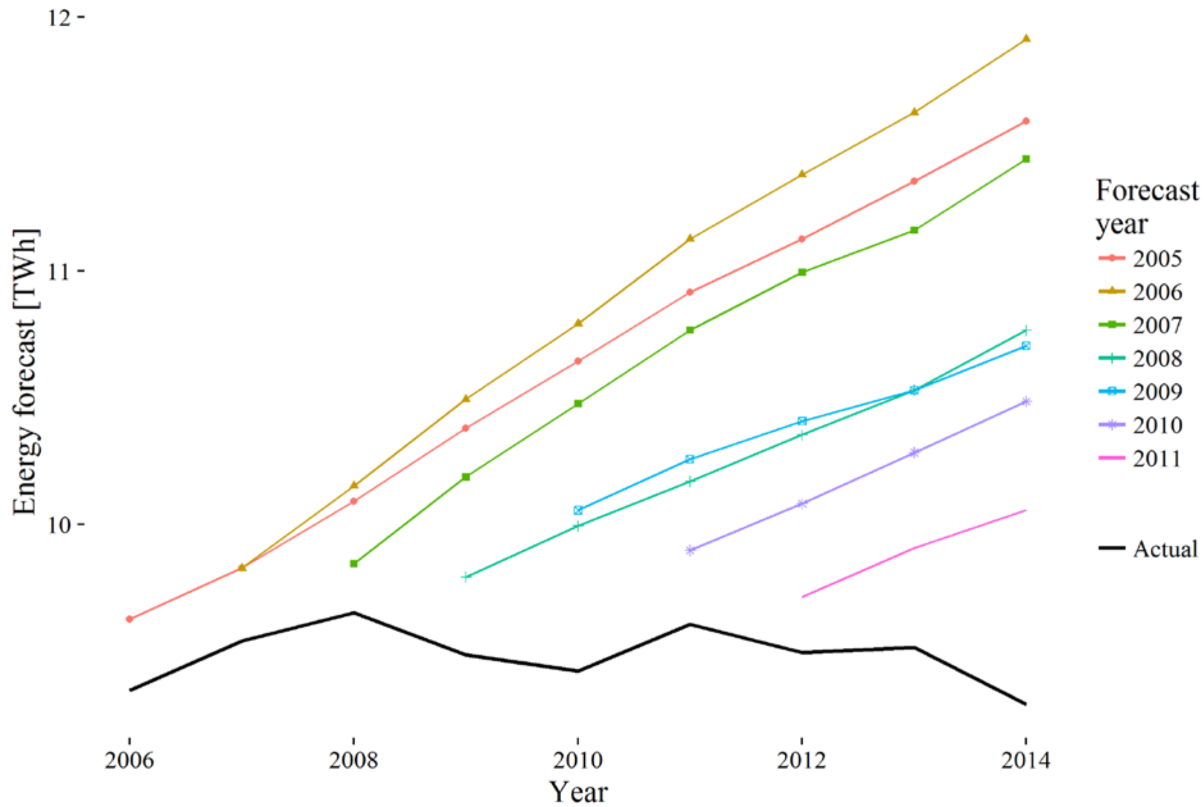

Figure 4 **Intermediate energy consumption forecasts for Avista 2005-2011.**

Table 8 **Idaho – Forecasted and actual energy consumption growth rates to 2014**

Period	LSE-Projected AAGR	Actual AAGR
2006-2014	1.79%	-0.06%
2008-2014	1.57%	-0.77%
2010-2014	2.00%	0.86%
2012-2014	2.12%	-0.35%

In the case of LADWP (Table 9), in addition to its 2006 IRP, short-term growth rates were projected in a 2010 IRP. The table shows the same pattern of reduced but not eliminated over-estimation of growth, which is also present in the case of Nevada Power (Table 10), comparing 2006 and 2009 forecasts (with first forecast years 2007 and 2010).

Table 9 **LADWP – Forecasted and actual energy consumption growth rates to 2014.**

Period	LSE-Projected AAGR	Actual AAGR
2006-2014	1.22%	-0.45%
2010-2014	0.84%	0.56%

Table 10 **Nevada Power – Forecasted and actual energy consumption growth rates to 2014.**

Period	LSE-Projected AAGR	Actual AAGR
2007-2014	2.29%	-0.51%
2010-2014	1.23%	0.28%

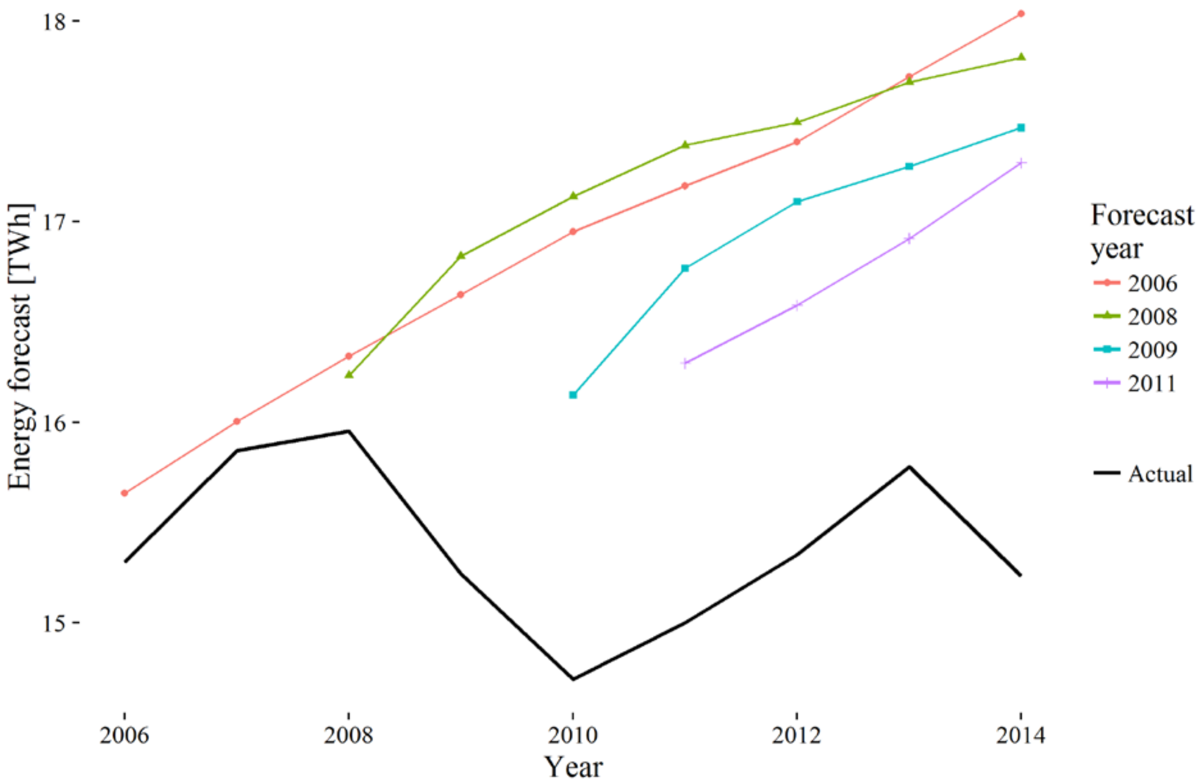

Figure 5 **Intermediate energy consumption forecasts for Idaho 2006-2011.**

Only the previously-discussed 2004 IRP forecast was available for Northwestern Energy (Table 11). In retrospect, the Northwestern Energy forecast under-estimated load growth to 2014. Similarly, as shown in Table 12, PacifiCorp's 2004 IRP forecast (with first forecast year 2006) turned out to be an underestimate. However, the company's forecasts in subsequent IRPs over-estimated growth to 2014.

Table 11 **Northwestern Energy**

Period	LSE-Projected AAGR	Actual AAGR
2005-2014	0.47%	0.74%

Table 12 **PacifiCorp**

Period	LSE-Projected AAGR	Actual AAGR
2006-2014	1.12%	1.47%
2007-2014	2.56%	1.01%
2009-2014	2.40%	0.47%
2011-2014	2.52%	1.63%

Tables 13 through 17 present analogous comparisons for the remaining LSEs in our sample, and show a similar over-estimation of load growth in IRPs over time. With the exception of Sierra Pacific, the forecast errors are increasing from older to newer forecasts.

Table 13 **PGE**

Period	LSE-Projected AAGR	Actual AAGR
2007-2014	1.78%	0.23%
2009-2014	2.10%	0.09%
2012-2014	2.30%	-0.18%

Table 14 **PNM**

Period	LSE-Projected AAGR	Actual AAGR
2007-2014	2.22%	-1.39%
2012-2014	1.72%	-4.62%

Table 15 **Puget Sound**

Period	LSE-Projected AAGR	Actual AAGR
2006-2014	1.75%	-0.19%
2012-2014	1.90%	-1.19%

Table 16 **Seattle**

Period	LSE-Projected AAGR	Actual AAGR
2006-2014	1.52%	-0.19%
2012-2014	1.93%	-0.84%

Table 17 **Sierra Pacific**

Period	LSE-Projected AAGR	Actual AAGR
2005-2014	1.40%	-0.53%
2008-2014	1.44%	0.33%

Overall, while the LSEs continually "course correct" (i.e., update and revise) their load forecasts, there appears to be a general pattern of persistent over-estimation of load growth.

Ongoing forecast adjustment is important and worthwhile, but our analysis reveals there is still systematic error patterns due to the methods employed in load forecasting. In the following section, we explore load growth sensitivities reported in older plans to understand the methods and strategies they developed and planned for to deal with this inevitable uncertainty.

7. Load forecast sensitivities in resource planning

We have shown that LSEs that developed IRPs in the early to mid-2000s observed economic conditions that generally contributed to optimistic load forecasts. While a few utilities have relatively smaller forecast errors—in both energy and peak demand—the majority of utilities evaluated in this study tended to over-estimate these values within their IRPs. The IRP process has evolved to consider the risks due to uncertainty of certain key variables, including future customer load. Accordingly, many LSEs use analytical techniques to measure how robust resource portfolios are to exogenous changes to these key variables. These analysis techniques are classified as scenario-based (i.e., sensitivity) and probabilistic (i.e., stochastic) risk assessments (see e.g. Wilkerson et al. (2014)).

In earlier sections, it was shown that actual load was generally lower than expected load. It follows that there is a risk of excessive capacity being built if expansion plans were not revised after the initial IRP was filed. This risk of acquiring more resources than needed – either by overbuilding capacity or through power purchase agreements – may translate to higher costs to consumers than necessary depending on whether these investments or contracts were actually made and included in the rate base. For this reason, we analyze the low and high load sensitivities from older IRPs to understand whether utilities were required to respond to potential deviations from their base case load forecast and how.

7.1 Review of load forecast sensitivity methods

In this section, we evaluate (i) the method used to create alternative load forecasts; (ii) the results of the load sensitivity analysis, (iii) the strategies developed by LSEs to respond to these alternative forecasts; and (iv) how LSE's methods have evolved from older to more recent plans. Detailed descriptions of load sensitivity methodology and results for each LSE are included in Appendix D and a summary in Table 18 below.

Evaluating the methods used to produce alternative load forecasts is an important step, because these methods reflect utility (and/or regulatory) motivation for considering a wider range of future conditions including alternative population growth, regional economic, and customer consumption scenarios. In the earlier plans, we find that most LSEs use percentiles or deviations from the base forecast as their alternative. In contrast, in more recent IRPs most 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, among others. These scenarios usually analyze joint variation in quantitative variables such as natural gas and electricity market prices as an improved alternative to one-on-one variable sensitivity analysis. While the design of future scenarios remains a challenge, these new approaches should provide a better basis for robust planning processes.

We find three possible methodological approaches for sensitivity analysis of load forecast in older plans[15]. The first is LSEs that simply did not perform any sensitivity analysis, even when estimating alternative load forecasts. The second is LSEs that perform the analysis, but that do not produce an alternative portfolio. The last is LSEs that adjust their preferred portfolio to the new load conditions. The difference between the last two approaches is that the second holds investments as fixed and therefore test the impact of load deviation on operational costs/savings in their portfolios to verify that their preferred portfolio remained as the least-cost solution. In contrast, the third outcome produces an adapted portfolio that can be the basis of an adjustment strategy to alternative load conditions. We find that about half of the LSEs in our sample of older plans either were not required to perform sensitivities or were not required changing their preferred portfolios in light of new load conditions. In more recent IRPs, we find that most of the LSEs that perform sensitivity or stochastic risk assessments also develop new portfolios that are different than their original and preferred base case.

In most cases, reassessment of preferred resource portfolios in response to load forecast sensitivity analysis resulted in drastically different timing and size of resources. We inspect the sensitivity results in older and recent IRP to confirm that inter-scenario utility revenue requirement differences were usually much larger than inter-portfolio revenue requirement differences[16]. In some cases, the inter-portfolio valuation difference was small enough that it could be statistically insignificant. In contrast, several LSEs reported adjustments up to ±20%-40% of capacity under low or high load conditions. Load growth is generally the most important assumption in sensitivity analyses conducted by the utilities in terms of its quantitative effect. It follows that the development of methods to deal with variation in high-impact, uncertain variables—especially load growth—may be more relevant for utilities than the choice of a "preferred" portfolio under a given base case scenario.

[15] It is important to consider that LSEs develop their resource plans subject to the conditions, restrictions, and obligations imposed by the frameworks that regulate them. The reader should not interpret that the presence or absence of certain analyses or method is necessarily a choice of the LSE, but a requirement of the planning rules.
[16] In this context, inter-portfolio refers to the creation and evaluation of several different resource portfolios to find the least cost and lowest risk (i.e., "preferred") portfolio. Inter-scenario refers to the corresponding revenue requirement effects from varying assumptions of key variables including load growth, natural gas prices, capital costs, etc., usually performed as part of the sensitivity analysis.

Table 18 **Summary of load sensitivity methods in older IRPs.**

LSE	Source of alternative forecast	Assessment method	Horizon	Results	Strategy	Change from older to recent IRP
Avista	Economic model; Statistical (Distribution)	Scenarios; Stochastic	Long term for energy, short term for peak demand	Capacity adjustment; timing and resource mix not changed.	React to new information	Quantitative instead of qualitative scenario analysis; improved load model.
COPSC	Statistical (Percentile)	No information	Long term for energy, short term for peak demand	No information	No information	None
Idaho	Statistical (Percentile)	Scenarios	Short term for peak demand	Capacity and timing adjustment	Procure small, flexible resources	Stochastic instead of scenario analysis
LADWP	Statistical (Percentile)	No information	Short term for peak demand	No information	No information	None
NV Power	No information	No information	No information	No information	No information	No information
NW	Market prices elasticity	Scenarios	Short term for peak demand	Operational cost reassessment	No information	Stochastic instead of qualitative scenario analysis
Pacificorp	Statistical (Distribution)	Stochastic	Long term for energy, short term for peak demand	Operational cost reassessment	No information	Add scenario analysis.
PGE	Statistical (Percentile)	Scenarios; Stochastic	Long term for energy, short term for peak demand	Capacity and timing adjustment	Use market purchases/sales as buffer	None
PNM	Statistical (Percentile)	Scenarios	Short term for peak demand	No information	No information	Improved load model
PugetSound	Economic model	Scenarios	Long term for energy.	Capacity adjustment; timing and resource mix not changed.	No information	Only additional scenarios
Seattle	Economic model	Scenarios; Stochastic	Long term for energy	No information	No information	Improved load model
SierraPacific	Economic model	Scenarios	Long term for peak demand	Capacity and timing adjustment	No information	None

The adoption and intensive use of stochastic risk analysis in several recent IRPs is a good step in aligning inter-scenario and inter-portfolio decisions. However, there is still a general absence of methods to produce and follow-up with clear strategies that respond to higher or lower realized load. In one of the few examples of regulatory implementation of adjustment strategies, the Utah Commission requires Pacificorp to produce "resource acquisition paths." These paths transparently lay out responses to specific potential outcomes of relevant variables in the planning process and act as an "extension" of the typical action plan included in most IRPs.

In older or more recent IRPs, most LSEs did not report any type of analysis on the effects that alternative load growth scenarios would have on their planning outcomes. For those plans that did report these analyses, we identify two approaches to deal with this uncertainty: (1) resource flexibility and (2) market transactions. Flexibility refers to the procurement of smaller and quick deployment supply or demand-side technologies to adjust rapidly to new conditions (e.g. Idaho and Avista). LSEs report that they would expedite or defer deployment of these smaller and modular resources in response to higher and lower load conditions than expected, respectively Market transactions pertain to purchases/sales using non-firm transactions as a "buffer" for long-term, structural adjustment due to higher or lower than expected customer load (e.g. PGE)[17]. LSEs report that they would sell their output to the market if load conditions were lower than anticipated and purchase if load was higher.

Both of these strategies have limitations. The focus on flexible resources restricts the types of technologies that would be deployed and reduces opportunities for larger capital intensive projects. The use of market transactions, as suggested by some LSEs, assumes that market purchases are always on the margin, which is not necessarily accurate in all cases. Also, national or global economic performance will jointly affect electricity market conditions as well as load growth. Economic downturn may create surplus on electricity markets due to load contraction and therefore make market purchases more attractive. The use of market purchases or sales as buffers may not recognize this strategy. Finally, relying on market purchases as a strategy for long term adjustment implies coupling electricity price uncertainty with load growth uncertainty. This makes the entire strategy formulation much more complex.

[17] Other LSEs did mention in their IRPs market purchases as a hedging tool for short term supply-demand mismatches, but these market purchases are not discussed within the context of a load sensitivity analysis.

7.2 Quantitative analysis of load sensitivities

In this section, we study the base forecast, the range covered by the high and low load growth forecast estimates, and the actual load[18].

We observe that two LSEs, Northwestern and Sierra Pacific, developed very large "envelopes" around their base forecast that encompassed their actual retail energy sales and obligations (Figures 6 and 7). All other LSEs, including those LSEs with a relatively smaller forecast error, did not produce alternative forecasts that encompassed actual outcomes for energy sales. Most of the LSEs developed symmetrical and narrow forecast envelopes with a low average annual growth rate (AAGR) forecast boundary that was significantly higher than the observed average annual growth rate for energy (see Tables 19 and 20). The preceding is an example of the challenges of producing alternative forecasts that can span a wider range of possible future outcomes. It also reflects the tradeoff between the span of alternative forecasts and the complexity of the strategies to address them: a larger span requires a more sophisticated sensitivity analysis and strategy development.

Table 19 **Average annual growth rate for actual and forecast load, with sensitivities.**

	Energy AAGR			
LSE	**Low Forecast**	**Base Forecast**	**High Forecast**	**Observed**
Avista	0.3%	1.7%	2.9%	-0.1%
COPSC	1.6%	1.8%	2.0%	-0.4%
Idaho	1.5%	1.7%	2.3%	-0.1%
LADWP	-	0.6%	-	0.0%
NV Power	-	2.3%	-	0.1%
NW	-1.7%	0.6%	1.9%	1.2%
PGE	1.2%	2.6%	3.1%	0.2%
PNM	-	2.2%	-	-1.4%
PacifiCorp	1.1%	1.9%	2.1%	1.3%
Puget Sound	1.2%	1.7%	2.3%	-0.2%
Seattle	0.3%	1.1%	1.9%	0.2%
Sierra Pacific	-0.2%	1.4%	2.5%	-0.9%

We also evaluate the performance of alternative peak demand forecasts. The results for the peak demand forecasts are different than the results for the energy forecasts. Observed energy consumption growth was generally less than anticipated, but peak demand growth exhibits mixed

[18] In the case of Pacificorp, which does not provide point estimates for its alternative load growth forecast but a distribution of values, we use the 10th and 90th percentiles as the low and high values, respectively. No alternative energy forecast information was reported for LADWP, NVPower, and PNM, and no alternative peak demand forecast were available for NVPower, NW, PacifiCorp, and Seattle.

results with both over and underestimation of actual peak demand. In addition, in most cases the spread of the forecast envelope is wider for peak demand than for energy (e.g., COPSC, PGE, Puget Sound, and Seattle). This wider spread may reflect the simultaneous consideration of short term (e.g. weather) and long term (e.g. growth) uncertainty in the sensitivity analysis (energy sensitivity only considers long term). Sierra Pacific was the only utility whose forecast envelope consistently encompassed the observed load over time, but it was also the sensitivity with the largest spread (see Figure 6). While a larger spread can effectively encompass many different future scenarios, it also requires a more flexible procurement strategy to alternate between these scenarios.

Table 20 **Peak demand average annual growth rates for forecasted and observed values, including sensitivities.**

	Peak Demand AAGR			
LSE	**Low Forecast**	**Base Forecast**	**High Forecast**	**Observed**
Avista	0.3%	1.8%	2.9%	0.4%
COPSC	1.9%	2.1%	2.5%	-0.5%
Idaho	1.5%	1.7%	2.3%	0.4%
LADWP	-	0.3%	1.1%	1.8%
NVPower	-	2.4%	-	-0.1%
NW	-	NA	-	4.1%
PGE	1.3%	1.9%	2.9%	0.8%
PNM	-	1.9%	2.4%	-0.8%
PacifiCorp	-	1.3%	-	1.3%
PugetSound	0.9%	1.1%	1.8%	0.8%
Seattle	-	1.7%	-	1.2%
SierraPacific	-0.8%	1.7%	2.8%	3.4%

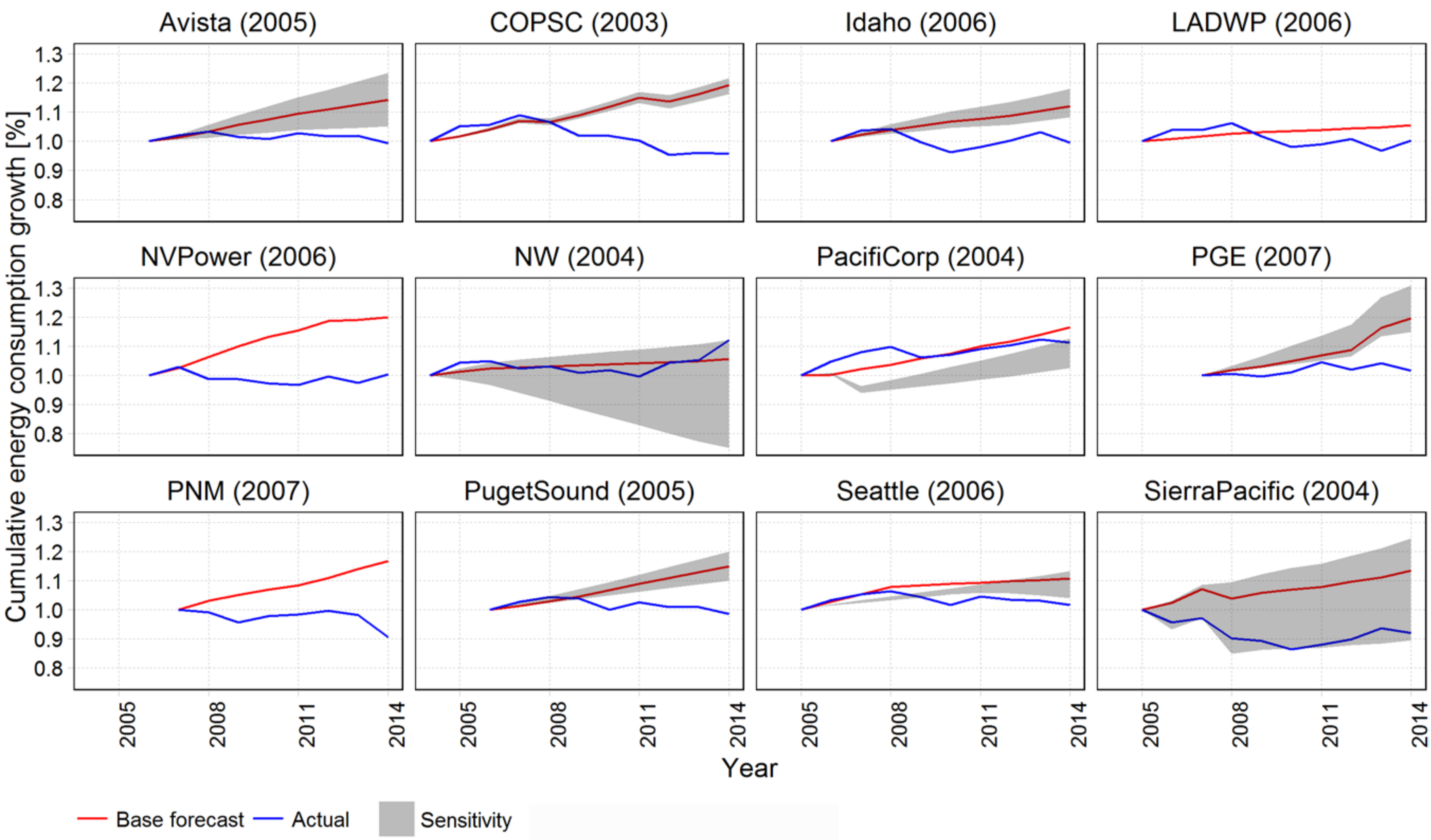

Figure 6 **Forecasted and actual energy consumption growth, with alternative load growth forecasts.**

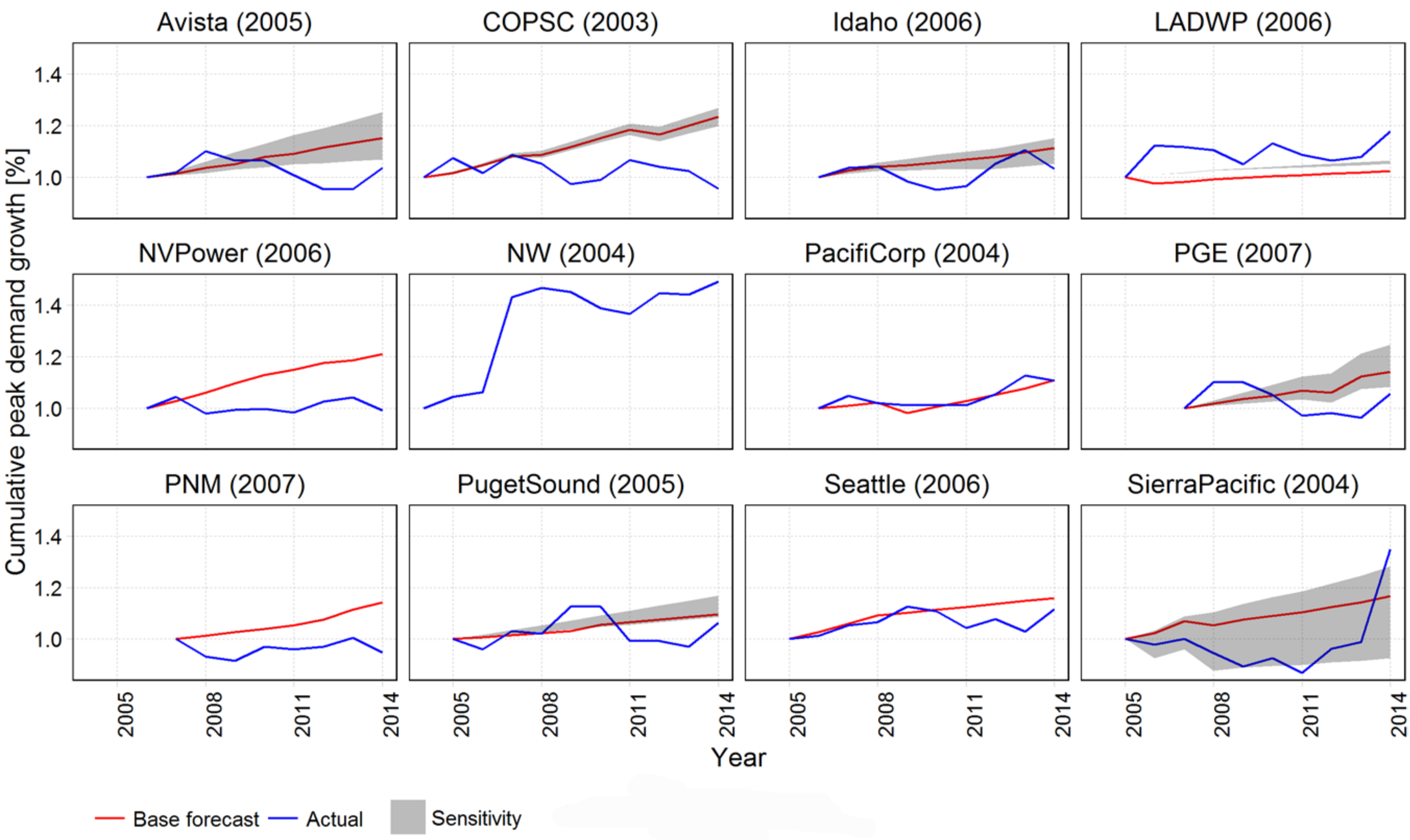

Figure 7 **Forecasted and actual peak demand growth, with alternative load growth forecasts.**

8. Comparison between older and recent plan load forecast methodologies

We compare load forecast methodologies from older and recent plans for two reasons. First, we want to understand whether there is a qualitative relationship between forecast error and adjustments to forecast methodology as a response. Second, analyzing any changes in forecast methodologies helps to ascertain the applicability of our findings to present day planning processes.

Between IRP filing dates, electric LSEs often make adjustments to their load forecasting analysis framework (e.g., mix of customer classes evaluated, makeup of forecast scenarios); choice of variables and analytical techniques (e.g., time-series regression, statistically-adjusted end-use models); and sources of key economic and demographic assumptions (e.g., IHS Global Insight, Inc., EPRI, Moody’s Analytics, Inc.). These changes are made in an effort to ultimately improve forecast accuracy in light of (1) evolving market and regulatory conditions; (2) perceived improvements to analytical techniques; and (3) access to more accurate forecast assumptions.

LSEs that implemented procurement decisions based on load forecasts that had larger errors may have had the most incentive to make changes to their forecasting inputs, methods, or both between filing dates. If so, then older and newer IRP forecasting methods can be compared to determine the degree of change between filing dates as a possible response to forecast errors. Figure 8 summarizes the extent of changes made for each of the LSEs considered in this study and the three categories related to forecast methodology described in section 4.

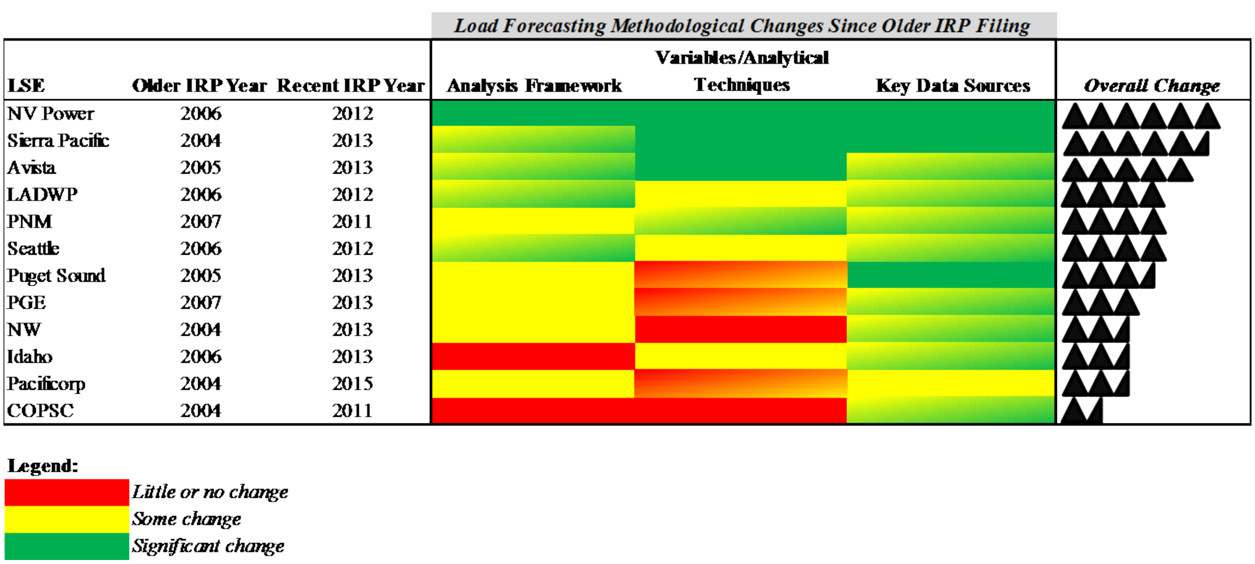

Figure 8 **Load forecasting methodological changes since earlier IRP filing.**

Overall, nearly all of the LSEs considered in this study found new data sources for key modeling assumptions (e.g., population, regional economic activity). Half of the LSEs made changes to all three components of their load forecasting methodology (analysis framework, technique, and source of data). Some LSEs made significant changes to load forecasting-related variables and analytical techniques, but a larger share of LSEs made very small or no changes within this specific category. Most LSEs did not make significant changes to the analysis framework between filings. NV Power, Sierra Pacific, and Avista made the most significant methodological changes between plan filings. Colorado Public Service Corporation, PacifiCorp, and Idaho Power made the least number of changes.

8.1 Changes to analysis framework

Changes to load forecasting frameworks typically involved incorporating additional sets of load forecasts based on a wider range of growth scenarios (NV Power, PGE, LADWP, PacifiCorp, Seattle City Light) or changing the mix (or number) of customer classes considered in the analysis (Seattle City Light, LADWP, Avista, Puget Sound, NV Power). In some cases, LSEs assumed that future load growth was lower than the low growth rate reported in the earlier plan. Sierra Pacific and Puget Sound Energy are two examples of LSEs which made changes to customer classes to reflect the importance of new types of customers including transportation (i.e., electric vehicles).

8.2 Changes to variables and analytical techniques

Many changes to load forecast variables and analytical techniques involved migrating from one modeling technique to another. For example, Sierra Pacific switched from an econometric/time-series based modeling approach to a statistically adjusted end-use (SAE) modeling approach. Conversely, Avista indicated that their load forecasting methodology is "undergoing significant restructuring [and] involves using an Auto Regressive Integrated Moving Average (ARIMA) technique" (i.e., time-series based econometric modeling). Other LSEs simply incorporated new variables including those used to capture adoption of electric vehicles (Idaho Power, LADWP, PNM, Seattle City Light, Avista, NV Power) or saturation of energy efficiency initiatives (PGE, NV Power, Idaho).

8.3 Changes to sources of key externally-produced assumptions

Perhaps most interestingly, there was a significant consolidation in the source of external data used in the production of LSE load forecasts. A number of LSEs began using IHS Global Insight, Inc. in their earlier plans, specifically, for demographic and regional economic growth estimates, and the majority of the LSEs now do so (COPSC, Sierra Pacific, PGE, NV Power, Avista, PacifiCorp, and Seattle). A smaller number of LSEs rely on Moody's Analytics, Inc., local/state/federal government agencies, or post-secondary educational institutions for regional demographic and economic assumptions. It is not immediately evident why this consolidation took place. The Electric Power Research Institute (EPRI) and Itron, Inc. were consistent sources of assumptions about customer responses to prices and end-use saturation and efficiency projections.

One utility planner, who wished to remain anonymous, indicated the following about third-party forecast performance and how commissions may view these vendors:

> "[Third-party forecast provider redacted] county-level forecasts consistently over-stated the speed and strength of the economic recovery in our service area. I believe this was a significant factor in the observed over-forecasting. The heavy reliance on [redacted third-party forecast provider] by [redacted] and other utilities may be connected [with] the increasing usage of [redacted third-party forecast provider] by state governments for the purpose of forecasting state revenues. That is, the adoption of [redacted third-party forecast provider] by state governments may have been viewed as a "seal of approval" by the utilities regulated by the same states. From the utilities' perspective, if [redacted third-party forecast provider] was good enough for the states' revenue models, then it may have been easier to argue that [redacted third-party forecast provider] was also good enough for their load models. In addition, I have noticed that many commission staff members often "signal" that they trust third party forecasts more than the utilities' in-house forecasts. If this preference is strongly signaled, then utilities may be inclined to adopt third party forecasts to deflect any future criticism."

The overall reliance on a few number of third-party forecast providers may be one reason that forecasts were consistently over-estimated by other LSEs as well. This finding implies that planners should consider supplementing third-party forecasts or conducting alternative economic forecasting to minimize forecasting error that can be attributed to outside parties.

8.4 Evolution of forecasting methodologies and variables

This comparison established that there have been few if any changes in forecasting methodologies over the past decade or so that would limit the applicability of our analysis of older plans to understanding present-day practices by the LSEs. The types of variables used in the load forecasting process have essentially not changed and, while some LSEs have changed their analysis techniques, they have switched to techniques that were already in use in earlier plans and have not, apparently, adopted or developed new techniques. We are confident that our findings and suggestions are very much applicable to current and future resource planning processes.

There is a general convergence across utilities in the forecast modeling technique and the sources of economic data. In relation to the former, we find that both time series and cross sectional regressions have become the typical analytical framework to produce base case forecasts for energy and peak demand. LSEs incorporate many variables in their models, but they also acknowledge that population and economic growth are the main drivers in their load forecasts. These regression methods inevitably rely on historic information that may tend to reproduce past economic, social, and regulatory trends.

Regarding the sources of data, we observe a convergence of sources for the basic economic and social-demographic forecasts, which can have an important implication. Regulators have increasingly been using benchmarking approaches to compare regulated utilities for purposes that range from rate setting to informational (Jamasb and Pollitt, 2000; Lowry and Getachew, 2009). Similarly, regional planning entities typically compile forecasts from utilities under their purview to determine aggregate load growth and expansion scenarios. Utilities report that forecasts are very sensitive to a small set of variables, namely economic and population growth. When LSEs use the same source for economic variables, their forecast errors become jointly determined and correlated. The benefit of benchmarking and aggregation that may average out errors in forecast is diluted with this convergence of sources. In addition, the use of proprietary forecasts adds an undesirable layer of obscurity to a process that was designed to encourage transparency and involvement from the public. When utilities use proprietary data, they are typically not allowed to make public the underlying values used in their load forecasting models, which may preclude scrutiny and evaluation of their results.

In the following section we assess the potential performance of load sensitivity methodologies and strategies by comparing forecast and actual load against planned and procured resources.

9. Comparing load forecasts and resource planning & procurement

We have established a general trend of load over-estimation and varied methods to analyze and formulate strategies to deal with load growth uncertainty. In this section we verify whether resource procurement was adjusted to actual lower load growth levels and how load sensitivity analysis described before may have informed this adjustment. It would be expected that supply-side capacity expansion would be greater than peak demand growth, particularly because supply-side resources that are not dispatchable (e.g., wind and solar) may not contribute to meet peak demand or may contribute a limited amount to resource adequacy. Hence, we perform two analyses: one comparing load to nameplate resource capacity and the other comparing load to available-at-peak resource capacity. We report the available-at-peak analysis in this section and the nameplate capacity in Appendix E.

We de-rate the nameplate capacities for both planned and actual supply-side resources based on average "capacity available at peak" ratios from the resource plans we study. In this case, de-rating means we estimate capacity available at peak as a fraction of nominal nameplate capacities, which are usually larger. We assume that coal and combined cycle natural gas plants have a firm equivalent capacity of 85%; geothermal, peaking natural gas units, and nuclear have 100% equivalent capacity; PV, generic renewables, and wind resources have a 10%[19] equivalent capacity and unknown resources[20] a 40% equivalent capacity. We check that these assumptions

[19] A recent paper estimates that utilities in the West assign a larger capacity credit for solar of 30%-50% (Mills et al., 2016). We use a 10% because it was a common reported value for most utilities in the early 2000s. In any case, there was little solar PV planned and procured for our sample of utilities, so its capacity credit has a minor effect in the results.

[20] In many cases LSEs that rely on market purchases in their resource plans do not know a priori what type of technology will produce the capacity they expect to purchase. These are labeled "unknown resources" for our purposes and apply only to planned resources. The 40% figure is roughly the ratio of firm to non-firm products purchased by utilities.

are reasonable by comparing the planned expansion to the forecast peak demand. Aggregate peak demand forecast of ~9 GW by 2014 was quite consistent with a planned expansion of roughly ~12 GW in the same period (Figure 9, right panel). This is a result we expect: meeting peak demand growth is a fundamental constraint of IRP. With these assumptions we then estimate that "at-peak" procurement was ~11 GW, a fifth of those in PPAs and the remainder in self-builds (Figure 9, left panel). Over the narrower 2007-2014 period, the at-peak capacity acquired was over 8 GW. This value should be compared against less than 1 GW aggregate growth in peak demand in the same period.

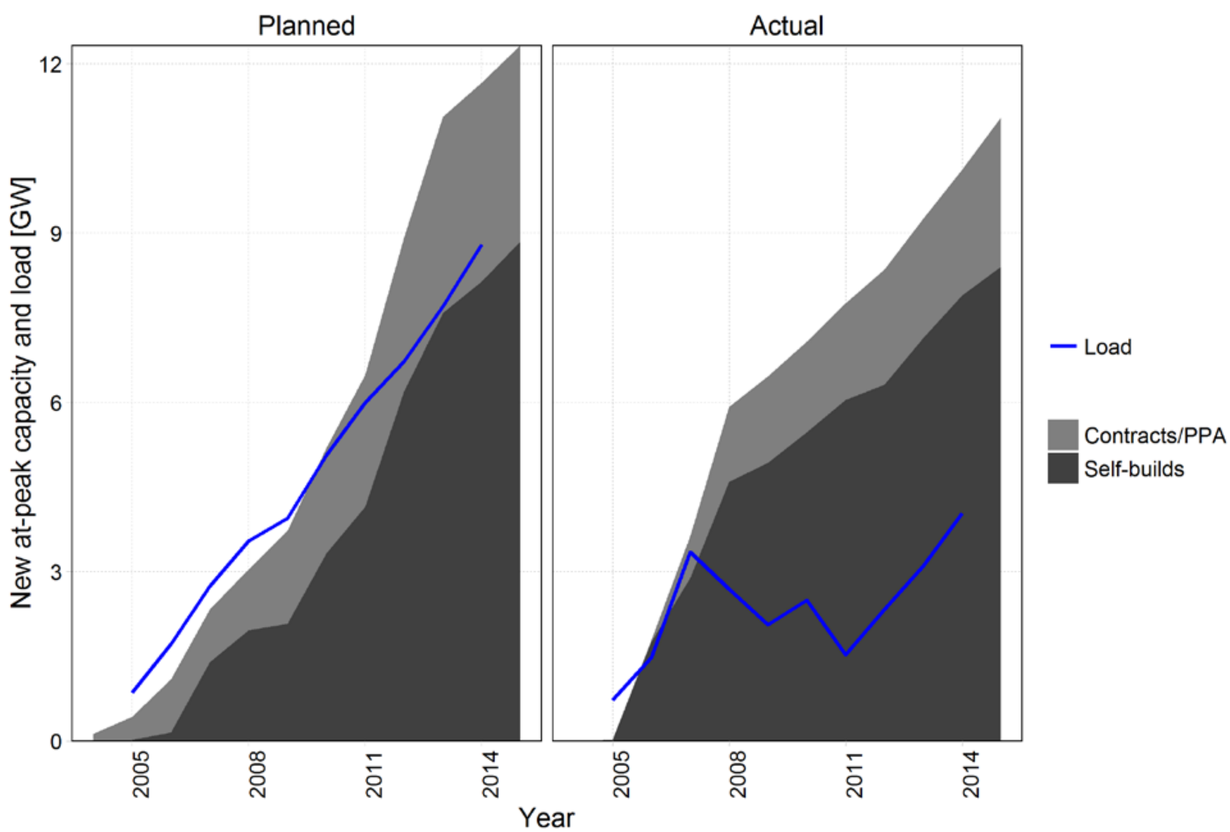

Figure 9 **Planned and actual (procured) at-peak capacity with forecasted and observed peak demand.**

Retirement of plants may explain in part the excess procured capacity. For our sample of utilities, we find that generation units totaling approximately 2.5 GW of at-peak capacity were retired in the 2005-2014 period. We also find that over 80% of the retirements accrue to three specific LSEs (LADWP, Nevada Power, and COPSC). An analysis of individual LSE load-procurement balance is out of the scope of this study, but is included in our follow-up paper.

Then, retirements can account for about a third of the excess procured capacity compared to actual load[21].

The actual response of LSEs to lower-than-expected load conditions stands in contrast to their reported results and strategies from the load sensitivity exercises described in section 7. Many LSEs found important changes in resource acquisition timing and capacity when applying alternative load forecasts in their IRP modeling exercise. We do not see this reflected in practice, as most procurement capacity and timing decisions are consistent with base case expansion even under actual low load outcomes. The fact that procurement is persistently aligned with load forecasts is in line with the findings in section 6, with LSEs systematically forecasting positive and higher growth rates than informed by very recent observed values. Our cursory review does not support that load sensitivities had an important role to inform procurement decisions because we do not see adjustment strategies reflected in quantities procured. Acquired resources seem to generally follow the original planning, regardless of the short and medium term performance of load forecasts and of actual energy sales and peak demand.

10. Summary and conclusion

We have quantitatively and qualitatively analyzed the methods for and performance of load forecasts for a set of electric integrated resource plans created by utilities in the Western U.S., and examined load sensitivities and the relationships among load forecasting, planning, and resource procurement. A comparison of forecasts to actual energy use and peak demand reveals that all but one of the LSEs overestimated energy consumption growth over planning periods beginning in the mid-2000s and ending in 2014, and that eight of the eleven LSEs that forecast peak demand also over-estimated this quantity. In addition, we find that most of the LSEs that had the highest expected growth rates also experienced the lowest actual – in some cases negative - demand growth.

Furthermore, examination of forecasts from more recent IRPs indicates a persistent overestimation of demand growth over planning periods up to year 2014, even in the presence of much slowed actual growth, for most of the LSEs in our sample. A number of the utilities highlighted the effects of the national recession that began in 2008-2009 to explain this phenomenon. Over time, the utilities did adjust their forecasts of projected load growth downward in response to lower-than-expected demand, but continued to overestimate. The IRP documentation suggests that for most of the LSEs, to a significant extent this apparently reflected an expectation that the national and regional economies would follow a historical pattern of relatively quick recovery from the recession. Thus, most utilities expected that load growth

[21] We recognize there are other concomitant factors that could influence resource procurement that we do not analyze here. For example, changes in renewable portfolio standards (RPS) targets may force larger adoption of renewable resources, or unanticipated earlier retirement of plants or termination of contracts may require larger capacity additions.

would recover as well. The actual, slower-than-expected economic recovery thus contributed to over-estimates of future load in more recent IRPs.

We find some correlation between forecast methods and complexity, and the accuracy of forecasts. In addition, the LSEs that had the most accurate peak demand forecasts were also among the most conservative in terms of their expected peak demand growth. LSEs with relatively more complex models had less forecast error than those that employed simpler models. Among the more complex techniques, Statistically-Adjusted End-use (SAE) models did not perform much better than other load forecasting methods and models. These results suggest that, among the LSEs we studied, there may be small marginal benefits to greater model complexity. There are structural reasons that may also explain the relative accuracy of load forecasts. For example, we find that utilities with a larger share of industrial load in their mix generally had larger forecast error. We believe that this may be caused by the highly elastic and lumpy nature of industrial customer load as well as the difficulty in predicting entry and exit of industrial customers from a LSE service area. This suggests that industrial loads should be modeled and risk assessed separately from the remaining loads to understand utility-level impacts of large adjustments.

Load sensitivity analysis is an important component of risk assessment and management in IRP. In the context of our study, it is especially important because strategies derived from load sensitivity analysis may adjust and impact resource plans as new information comes in. Over time, we find that LSEs have improved the breadth and sophistication of their sensitivity analysis of load forecasts. However, we find that both older and more recent IRPs generally lack an adaptive component that details how utilities would respond in practice were subsequent actual values of critical input variables—like load — to correspond to those studied in these sensitivity analyses rather than to those assumed in "base cases." More importantly, we find that load variation from the base case produces differences on revenue requirement for an LSE that are much larger than the differences in revenue requirement from the resource portfolios that are designed and compared to select the “preferred” one.

For our overall sample of utilities, we find that aggregate (pooled across utilities) planned and actual capacity expansion levels were generally consistent over the time period of our study. However, in aggregate, actual resource procurement were not closely aligned with observed changes in load. Actual capacity additions were partially attributable to retirements of existing plants, which accounted for about 2.5 GW for several utilities. It is possible that this apparent over-procurement reflects LSEs seeking to avoid resource adequacy problems by hedging against rapid rebounds in load that may exceed their ability to procure unforeseen required firm capacity. The volatility in observed peak demand growth rates and the quick recovery of some LSEs’ peak demand provide evidence in favor of this.

We find that load forecast methodologies have not changed significantly in the past fifteen years, although there is evidence in recent plans of inclusion of potential structural change drivers such as distributed energy resources and electric vehicles. We did find that LSEs with more changes in their forecasting methodologies had previously had relatively greater forecast errors. This suggests an active effort to at least react to forecast error, although we do not have evidence that these changes lead to improvements in accuracy. In general, we believe that our findings of load forecast performance and relationship to procurement over our analysis period are applicable to current planning and procurement processes even if we studied decade-old plans.

To our knowledge, this is the first quantitative and comparative retrospective study of energy and peak demand forecasts by LSEs. This paper has been primarily descriptive and exploratory and as such our findings indicate several key topics for further research to better understand and to explain our results.

First, was over-optimism regarding resumption of economic growth following the severe recession of 2008-2009 the fundamental reason for the persistent over-estimation of load growth during the study period? If so, what does this imply about the role of economic growth assumptions in overall IRP processes and the strategies that may be derived from load sensitivity analyses? In addition, how much of this over-estimation may be due to under estimation of energy efficiency gains?

Second, what were the reasons for the divergence between load forecasts, on the one hand, and procurement, on the other? What were the differences in resource mix, timing, and market transactions between planning and procurement, and what the potential impact of these differences is?

Third, what is the balance between a better forecast to select the right portfolio and a better strategy to switch between portfolios and adjust to changing environments under a budget constrained planning process? What shape should these strategies take and what improvements would they have on the planning and procurement processes?

These questions, particularly the second, will be the topic of our second paper, in which we will investigate the connections between IRP and procurement processes in depth. We hope that both this paper and its sequel will contribute to the goal stated in the Introduction, of furthering the understanding of IRP among a diverse group of stakeholders, and contributing to the further evolution and improvement of planning methods and outcomes.

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12. Appendix A – Adjustments to data

We adjust the monetary values from both plans and actual data to express them in real 2014 dollars and allow meaningful comparisons. We use the Gross Domestic Product implicit price deflator based on data from the Bureau of Economic Analysis (Table 21)

Year	GDP Deflator Index	% Change from 2014
2000	81.89	27%
2001	83.75	25%
2002	85.04	24%
2003	86.74	22%
2004	89.12	20%
2005	91.99	17%
2006	94.81	14%
2007	97.34	11%
2008	99.25	9%
2009	100.00	9%
2010	101.22	7%
2011	103.31	5%
2012	105.21	3%
2013	106.93	2%
2014	108.69	0%

Table 21 **GDP deflator used to adjust monetary costs to real 2014 dollars.**

13. Appendix B – Demand forecast methodologies

The following table provides details on demand forecast methodologies for the older resource plans. We identify the framework or general rules required for forecasting, the variables and methods used, and the sources for the data.

LSE	Year	Framework	Variables and methods	Sources for data
COPSC	2004	• They project native load and firm wholesale requirements. They are required by law (LCP rule 3060(b)) to estimate high, base, and low forecasts. • Classes include residential, commercial, industrial, large industrial, public authority, street lights, interdepartamental, and wholesale/resale customers. • Energy and demand are forecasted similarly, with an added variable in demand to capture specific weather-driven peak events. • High and low estimates are created by modifying economic growth and weather variables. They essentially use the third quartile instead of the median for high and the first quartile for low.	• Statistically-Adjusted End-Use (SAE) model. • Residential Customer number (CN) comes from housing stock forecasts. Use-per-customer (UPC) composed from saturation (unknown source) and utilization for cooling, heating, and base use. The latter are simulated from electricity price, household income/size, and CDD/HDD/LightHours respectively using exogenous elasticities. UPC is regressed based on these estimates and monthly company data, using monthly fixed-effects. Implementation is methodologically unclear. • Commercial/Industrial CN methodology is not provided. UPC similar to residential. Saturation based on annual energy intensity (kWh/sqf) trends. Utilization simulated from electricity price, GSP, and CDD/HDD/LightHours. • Large industrial customer sales are forecast based on historical data, market trends, and customer input.	• Demographic and economic: Center for Business and Economic Forecasting, Inc. • Cooling, heating, and base use: internal using data from 1991. • Elasticities for residential utilization: EPRI's REEPS model. • Saturation trends: EPRI's COMMEND model.
NW	2004	• Not clear what load they project, but they do create high, base, and low forecasts. • Classes include small (<50 kW) and large (two tiers, <5MW and >5MW) customers.	• Their approach is econometric, but does not show an end-use approach. They rely on weather and customer number as main explanatory and forecasting variables. • Small customer: they regress consumption to average annual customer count, HDD,	• MT population forecast provided by NPA Data Services, Inc. and made available through MT Census and Economic Information Center. • U.S. economic growth, income

LSE	Year	Framework	Variables and methods	Sources for data
		• Their forecast methodology seems to point to energy forecasting rather than load. They actually do not provide the latter. • They use recent (<5 year old) data to model monthly and hourly consumption patterns. • Low load estimate created by assuming large customers switch to other provider. High load assumes that users with choice (under deregulation) return to NW because default supply price is lower than retail.	CDD, and tariff rates for the past 23 years (1980-2002) to establish historic coefficients. Weather variables and average customer count are independent variables that exhibit a consistent relationship to usage. • <u>Large customer:</u> <5MW is estimated based on rolling five year average of usage plus adjustments for any expected changes based on customer communication; >5MW receives more detailed analysis and communication to determine future levels. • "There is little evidence in the 23 years of data gathered which shows that electricity price changes have an impact on total electric consumption"…."implies that price elasticity of demand for electricity is zero." (p.57). They provide several explanations for this. • They adjust results by DSM.	projections, etc. came from U.S. Economic Projections (U.S. Dept of Commerce). GDP, population, and income projections assumed are included on pages 15-25 of the "Book 2 document"
Sierra Pacific	2004	• Sierra Pacific forecasted peak load and energy out to 2024. They are required by law (NAC Chapter 704) to estimate high, base, and low forecasts. • They predict sales for each of their customer classes and state combinations (CA and NV). Larger customers (GS-3, GS-4 classes) are forecast individually. • Low load case anticipates a "slight downturn in the economy", less population growth (95% base case	• <u>Customer number</u> forecasting by tariff type using an ARIMA model with 1st/12th order autoregressive terms and dummy variables for certain years. • <u>Rates:</u> future rates are forecasted to assess price-elasticity effects. • <u>Cross-price elasticity</u>: they estimate non-statistically significant or negative natural gas/electricity cross-price elasticity. • <u>Use per customer</u>: for non-individual analysis they regress UPC in terms of twenty-year average monthly HDD/CDD, wind speed (if significant), population growth, and historical sales. For large	• CPI from Global Insight's US Economic Outlook. • Population forecast was internal, but a 2001 regulatory decision forced Sierra to use the Nevada State Demographer's. (p.8-9). Sierra thinks this forecast is too low and it seems they created a hybrid. • Hourly loads from EPRI's HELM model.

LSE	Year	Framework	Variables and methods	Sources for data
		confidence interval), and fewer customers. 0.07%/0.24% growth for the summer/winter peak. • High load case assumes more customers, greater population growth (95% base case confidence interval), and a stronger economy. Summer and winter peak growth of 2.85%/2.88%, respectively. • They expect "no major technological changes, such as electric automobiles" (p.9) to affect end-uses of electricity. • They acknowledge recent changes in their seasonal peak due to larger NV growth compared to CA. • Very similar to process used in 2001 IRP.	customers they perform one-on-one estimations for 5-year growth and replicate this result for the next 15 years. • They find population growth is the primary driver of load growth. • Base summer and winter peak loads are expected grow ~1.81-1.83%. Base case energy is expected to grow 1.55%. Manufacturing (3.27%) and residential (2.69%) are expected to grow the most and mining (-1.38%) and industrial the least (-0.19%) (Volume 1, p. 5). • Hourly peak load forecasts were estimated using HELM model (designed by EPRI), which allows utilities to estimate hourly load projections given individual load shapes for each sector. HELM produces loads without losses so losses are incorporated later. • They do not adjust results by DSM, arguing its effect were "of minimal impact upon the system" (33)	
PGE	2007	• Forecast reference, high, and low scenarios with normal weather conditions. High and low are based on base case growth plus/minus 1 standard deviation. This translates into 1% increase/decrease in growth from the base case. • They report median peak load values. • PGE expects to turn from winter to summer peaking in the next 15-20 years.	• Fundamental factors: economy, immigration, life expectancy, and business environment, particularly high tech sector. • Expect higher commercial load, lower residential load, and uncertainty in industrial customers. • They face opt-in/opt-out customers under retail competition. Their strategy is to acquire resources for 1/3 of existing eligible opt-out customers and find the rest on the short- term market. There is no formal forecast for returning/leaving customers.	• No information on sources of data.

LSE	Year	Framework	Variables and methods	Sources for data
		• "Overall demand has always rebounded to grow over time based on macroeconomic and fundamental drivers." (p.40)	• No information on their forecasting models.	
NV Power	2006	• Produce only an expected or base case forecast. • They apply weather normalization their winter and summer historical peak data.	• Econometric models (not SAE) separate for each customer class. Forecast sales, customers, and residential retail rates. • Explanatory variables include CDD/HDD, real retail rates (residential only), monthly/seasonal fixed effects, total residential customers (non-residential only). • Residential: Sales per customer from 1979-2005. -10% elasticity for retail rates as result. Use dummies for year > 2001 (reduction in usage), and 1st/12th order autoregressive terms. • Number of customers: Regress number of residential customers by population from Clark County and a 1st order autoregressive term. CN for other classes are regressed from this residential customer number estimate. • Large general service: Only use CDD/HDD to explain ~90% variation. • Retail rates: They expect 24% increase in real retail rates from 2004 to 2006 and then remain flat. Their forecast is internal and no details are provided.	• Weather data for CDD/HDD for Las Vegas from NOAA. • Population forecasting is very important for them. They retained Univ. Las Vegas, who used a general equilibrium economic and demographic model developed by Regional Economic Models, Inc (REMI) specifically for Clark County for 2005-2035. See p.34 of App2-1 for population predictions. A quick review shows they were off by ~20% on a total population basis or they expected 3 times more growth than actually happened by 2013.
Puget Sound	2005	• Forecast an expected, high, and low scenario. Main difference is GDP growth at 3%, 3.6%, and 2.6% respectively, in addition to lower inflation/higher productivity for high scenario	• They forecast billed energy sales, customer number, system peak load for electricity and gas, and hourly load profiles. • Sales = UPC * CN; the later are estimated through regressions based on historical data from 1990 to 2003. They manually	• They do not mention most sources of data besides their internal sales and load information. • Economic and retail rates forecast from "May 2003 US Forecasts"

LSE	Year	Framework	Variables and methods	Sources for data
		(inverse for lower). • Customer classes include residential, commercial, industrial, street lights, and resale. • Minor methodological changes from 2003 LCP, including higher weather resolution data and spatial load growth estimates. • They create very complex functional forms that rely heavily on lagged operators. I believe there is an important risk of inaccuracies from propagating errors through the functional form. • They generally expect lower growth than historical results.	adjust these estimates (see below). They mention several end-uses, but they don't use them as explanatory variables. • <u>UPC</u>: Regression by class and month in terms of retail rates (includes lags), HDD/CDD, demographic variables (income, household size, population, employment, growth, building permits), monthly dummies. • <u>CN</u>: Regression by class and month based on same demographic variables and monthly dummies. Population and employment are primarily used. • <u>Residential</u>: semi-log functional form, with long lags in rates and demographic variables. They estimate -0.19 price elasticity. Manual adjustments include expected conservation, fuel switching, and tariff switching. • <u>Other sectors</u>: Double log form, also use lags in explanatory variables. Estimate -0.16/-0.19 price elasticity for Comm/Ind respectively. Manual adjustments include expected conservation, fuel switching, and tariff switching. • Peak load is estimated based on regressing hourly peak MW on monthly sales for residential and commercial, and also interacting weather sensitive portions of load with temperature measurements and monthly dummies. Very complex regression. • Hourly demand profile was based on HELM for 2002, but replaced now with a regression of hourly load (1994-2004) on	prepared by Global Insight. Expect growth between 2.9% and 3.6%. • Hourly temperature comes from NOAA observed data at Seattle airport. • They also use a set of account-specific assumptions about certain customers starting or closing their service.

LSE	Year	Framework	Variables and methods	Sources for data
			hourly temperature (1950-2003). They use lags on loads and linear/squared temperature variables, plus an autoregressive term and holiday dummies.	
Avista	2005	• Prepared medium, high, and low forecasts, under the suggestion of the Technical Advising Committee. Main determinant is population growth changes, roughly double growth for "high" and no growth for "low". • They generally refer to residential and commercial classes, although they sporadically mention specific customers (Boeing, Fairchild Airforce Base).	• "Key driver of the electricity customer market is population growth" (p.1-4). • 1998-2004 retail sales grew 1.2%, but they forecast 2.1% for 2005-2025. • Price elasticity estimates: residential -0.15, commercial -0.10. Cross price (NG) elasticity at 0.10 for all classes, and income elasticity at 0.75. These come from own estimates. They don't expect an impact on forecast. • Their language suggests they use regression analysis, but there is no evidence of the functional form or method in the plan itself or the formal appendices. • Slides from stakeholder meetings reveal they do include also weather through CDD/HDD using "96% of Normal" in base forecast (2 s.d.). Electric price forecasts are simply assumed to grow at certain %, although these may be results of the Aurora model runs.	• National/County employment and population forecasts from Global Insight, from March and June 2004 respectively.
Idaho	2006	• Create six load forecasts. The low has 90% probability of being exceeded, while the high 10%. The medium case is the median. All these are estimated under normal weather. They further develop their median forecast by considering normal, 70th, and 90th percentile weather impacts. The growth forecasts bound the	• They use regressions for UPC, with different variables. It seems they use a SAE for peak load only, but they do not use the term and their explanation is very qualitative. They extensively use different percentiles throughout their analysis. • "Weather conditions are the primary factor affecting the load forecast on the hourly, daily, weekly, monthly, and seasonal time horizon. Economic and demographic	• Economic 2006 forecast developed by Idaho Economics, based on a national and regional economic activity forecast by Global Insight. • Electricity price increases (they explicitly say that) are modeled internally, while gas prices are from Global Insight.

LSE	Year	Framework	Variables and methods	Sources for data
		others. Base forecast grows 1.9%/yr, low at 1.5% and high 2.4%. • Base forecast is median growth with 70th percentile weather impact. Their monthly hourly forecast for peak load uses 95th percentile weather. • They analyze residential, commercial, irrigation, and industrial classes. They individually analyze three large customers and their firm sales contracts, making assumptions about their continuity. • They include losses in their estimates.	conditions affect the load forecast over the long-term horizon." (p.29) • <u>Peak loads</u> are regressed from temperature (HDD/CDD/GrowingDD), space heating saturation, A/C saturation, historical average load and precipitation, For large customers, peak load is based only on historical load. • Mention that "changes in relative fuel prices can have significant impacts on the future demand for electricity" (App.A-p.4). However, they don't estimate or show elasticities. • <u>Residential</u>:CN directly forecast from expected household growth. UPC expected to decline, regressed from HDD (winter), CDD (summer), "trends", and rates. Sales = UPC * CN. No information on functional forms or what "trends" are. • <u>Commercial</u>: CN estimated from residential CN. UPC identical to residential, as well as sales. • <u>Irrigation</u>: Expect increase in CN, but reduction in UPC, for zero growth. Only qualitative arguments given. • <u>Industry</u>: Develop 16 regression models, one for each economic activity group. They regress historical sales from historical employment for each group, and forecast using the employment projections. For larger customers the procedure is similar, with additional one-by-one adjustments. • Adjust sale forecasts by expected DSM levels from prior year plans.	
LADWP	2006	• Forecasts for six classes:	• They use employment and personal income	• LADWP purchases a

LSE	Year	Framework	Variables and methods	Sources for data
		residential, commercial, industrial, intradepartmental, streetlight and Owens Valley. • They sensitivize their forecast for different temperatures. They use different temperature percentiles to model alternative peak load forecasts. • Include historical losses.	data as proxies for local GDP. • <u>Res, comm, and ind sales</u> are forecasted using GLS. They regress historical sales against demographic, economic, weather and electric price variables, with additional dummies for specific events. • <u>Net energy load</u> is projected from sales regression using historical monthly allocations and historical losses. • <u>Peak demand</u> is based on a regression of historical hourly demand against temperature bins and apply this elasticity to a forty-year mean peak day temperature. They project peak demand using the same growth rate as sales. • Monthly allocations are based on historical monthly load factors applied over the sales forecast. “To forecast load for each hour of the year, we use the Loadfarm algorithm developed by Global Energy.” (p.B-3) • They do not discount DSM because they treat it as a resource, but acknowledge that some of this growth will not be realized.	demographic and economic forecast of Los Angeles County from the Los Angeles Modeling Group of the UCLA Anderson Forecast Project. • The Los Angeles County Forecast provides time series data for various demographic and economic statistics beginning with year 1991 and continuing through the forecast horizon. • LADWP also reviews the State of California Department of Finance demographic forecast for population data. • LADWP purchases a construction forecast from McGraw-Hill Construction service. • Weather data is collected from three NOAA stations. • Internal information includes historical sales, billing cycles, budget, and rates.
PacifiCorp	2004	• “The load forecast that is used in the IRP is updated every two years and is a 20-year hourly forecast of expected loads.” (43). Prepared in March 2004. They include historical/future DSM in their projections. • They project a single forecast for their four classes. • They also add losses, separately by each retail class.	• “Near term forecasts rely on statistical time series and regression methodologies while longer term forecasts are dependent on end-use and econometric modeling techniques.” (App I p.127) • <u>Near term</u> (at most 3 years): They forecast UPC and CN per state and class: res, com, street lights, and irrigation. CN “relies on weighted exponential smoothing statistical techniques formulated on a twelve-month moving average of the historical number of	• County and state-level economic and demographic forecasts provided by Global Insight, in addition to state office of planning and budgeting sources. • No reported sources for their engineering estimates on appliance usage or for the weather data.

LSE	Year	Framework	Variables and methods	Sources for data
			customers." (I-127). More weight is given to recent observations. • They use a very simple "time-trend" analysis for short term UPC, regressing consumption in time. Industrial customers are forecasted on a case-by-case basis; they don't provide the methods. • Long term: statistical model with several explanatory variables: price elasticity (elec and fuels), economy, conservation, appliance/building replacement. They also forecast employment, population, and income for Pacificorp's states. "Employment serves as the major determinant of future trends among the economic and demographic variables used to "drive" the long-term sales forecasting equations" (I-129). These variables are obtained from Global Insights consultants. • They find electricity price elasticity of 0.10 (absolute value) in internal econometric study. • <u>Residential</u> demand forecast models several structural variables (inhabitants, fuel price, income, structure type) and includes 14 energy end-uses (appliances and space/water heating) with their saturation expectation. They use a CDA or engineering estimates for the use per appliance, and multiply by estimates of saturation and housing stock to estimate consumption. They run separate analysis for new/old homes and single/multi/mobile families. • <u>Commercial</u> is similar to residential, with 7	

LSE	Year	Framework	Variables and methods	Sources for data
			end-uses and 12 commercial activities, but use sqf instead of housing stock. • Industrial they regress "industrial production indexes for the specific industry [on] the relative prices of electricity and natural gas." They break this class in 9 industry categories. • Hourly forecast are created from regressions of historical behavior against weather variables, temporal variables (day/week/season)	
PNM	2007	• Forecast retail loads, existing firm wholesale customers, and transmission/distribution losses (~11%). Special stipulation (Case 3137) requires that only wholesale contracts before 2002 to be included. • There are high/low forecasts in the Appendix that are mentioned in the Sensitivity analysis. They adjust energy and peak load by ±1.5% to create alternative scenarios.	• There is almost no information about the methods they use, what variables they incorporate, and how they derive their estimates. • Key drivers in peak load forecast are CN, higher AC use on homes, and construction/house size (due to low interest rates). They also forecast energy and CN. • Residential: CN * UPC. Expect 2.3% growth on CN and 1.2% on UPC. • Commercial: CN * UPC. Expect 1.7% growth on CN and 2.2% on UPC. • Firm wholesale: City of Gallup use a "statistical" method and City of Navopache a historical projection. Other firm customers use specific methods.	• No source information.
Seattle	2006	• Forecasts do not include any programmatic conservation, a statement of their consideration of DSR as supply resources. They actually make an effort to remove underlying conservation from their load forecast. • Forecast for 9 customer sectors:	• The only variable information is that "The load forecast is based on forecasts of several key economic and demographic variables, primarily employment and the number of households in the service area" (p.13). • Create correlations between historical load for each customer sector and "selected	• "Dick Conway and Associates produces the economic and demographic series for SCL's service area" (App p.48) • Besides internal sales and consumption data, there are no other external information requirements.

LSE	Year	Framework	Variables and methods	Sources for data
		residential, commercial, government, food, metal, stone, aerospace, ship building, and other manufacturing • Develop low, base, and high forecasts with 0.3%, 1.2%, and 1.9% growth, respectively. • As other hydro-based LSEs, they compute joint load-hydro probabilities to understand the chances of drought with high demand concurrently occurring.	economic and demographic variables" (App p.48). Main drivers are number of households and of employees for several customer categories. Mention that "equations are estimated for each sector" without further detail of technique/method. • As many others, qualitatively describe their service territory and trends. • For peak load they analyze distributions of historical peak load, not clear what for. • Do not expect increase in UPC for residential sector (App p.50). They do expect commercial load to drive growth.	

14. Appendix C – Changes in load forecast methodologies from resource plans.

The following table includes details on changes in demand forecast methodologies from the older to the recent resource plans (see Table 1). We identify the framework or general rules required for forecasting, the variables and methods used, and the sources for the data.

			Methodological changes since older IRP		
LSE	**Older IRP year**	**Recent IRP year**	**Framework**	**Variables and analytical techniques**	**Data sources (population, economic activity, weather, other)**
COPSC	2004	2011	• Framework has not significantly changed since earlier plan (see table above for details about framework)	• Variables and methods have not significantly changed since earlier plan (see table above for details about variables and methods). • Elasticities for sales forecasts continue to be inferred from ERPI's residential end-use model (REEP) and EPRI's COMMEND model: -0.2 price and income for residential; 0.6 GSP and -0.2 price for commercial/industrial.	• Demographic and economic growth estimates now come from IHS Global Insight, Inc. (earlier source was Center for Business and Economic Forecasting, Inc.)
NW	2004	2013	• Newer plan provides both energy and load forecasts (earlier plan did not provide peak load forecasts) • Framework does not appear to have significantly changed since earlier plan (see table above for details about framework).	• Variables and methods have not significantly changed since earlier plan (see table above for details about variables and methods). • Both plans note that the price elasticity of demand is assumed to be zero. However, the newer plan notes that a Smart Grid Demonstration Project will help the company monitor	• County-level population forecasts are a product of Regional Economic Models, Inc. (REMI) via the Montana Census & Economic Information Center (CEIC) (earlier source for population projections came from NDA Data Services, Inc. via the MT CEIC) • Future economic conditions are not included in newer IRP

			Methodological changes since older IRP		
LSE	**Older IRP year**	**Recent IRP year**	**Framework**	**Variables and analytical techniques**	**Data sources (population, economic activity, weather, other)**
			• Base peak load forecast is median probability of occurrence; assumed that low and high loads are determined using similar process as noted in earlier plan.	price elasticities in the future.	forecast (earlier source noted that economic growth, income, etc. came from U.S. Department of Commerce)
Sierra Pacific	2004	2013	• Adjusted load to account for impact of EV/PV adoption, DR, DSM, and system losses (earlier plan indicated "no major technological changes, such as electric automobiles" to affect end-uses of electricity; results were also not adjusted for DSM because these effects were—"of minimal impact upon the system")	• Began using Statistically Adjusted End-Use Model in 2009 (earlier plan used in ARIMA model to forecast number of customers with $1^{st}/12^{th}$ order autoregressive terms and dummy variables for certain years). • Not clear how different new SAE method is from old method, because older method did involve predicting end-use per customer based on weather, population growth, sales, etc. • Newer plan forecast database includes: "historical billed sales, number of customers, population and economic data, prices, weather conditions and historical end-use saturation and efficiency trends" • Implicit reference to use of elasticities in both plans:	• Regional demographic and economic growth estimates now come from IHS Global Insight, Inc., but the State of Nevada's State Demographer high population forecast was also used in some way (earlier source used a hybrid of an internal population forecast and the State Demographer). • Itron, Inc. data was used to determine end-use saturation and efficiency projections. Sierra Pacific also conducted residential appliance saturation surveys to supplement information provided by Itron, Inc.

			Methodological changes since older IRP		
LSE	**Older IRP year**	**Recent IRP year**	**Framework**	**Variables and analytical techniques**	**Data sources (population, economic activity, weather, other)**
				newer plan indicates that "Real household income impacts residential average usage per customer; older plan indicates that there are non-statistically significant or negative natural gas/electricity cross-price elasticities • Weather forecasts in both plans based on average over last 20 years	
PGE	2007	2013	• Added another set of high and low demand forecasts based on much higher (lower) growth scenarios—plus and minus two standard deviations (earlier plan had base and +/- 1 standard deviation high/low growth scenarios) • In addition to high/low scenarios, weather-driven load changes are stochastically-modeled per 2007 requirement from OPUC Order 07-	• Weather forecasts in both plans based on average over last 15 years • Both plans have little or no information about the regression model used to forecast demand. • Fundamental assumptions impacting load forecasts: weather (temperature); economic outlook; population forecast; industrial customer trends (earlier plan fundamental factors include: economy,	• Little or no information was included about data sources in 2007. In 2013, PGE uses local economic/demographic data from Oregon Office of Economic Analysis, national data from IHS Global Insight, Inc. and California employment forecasts from the California Employment Development Department • Weather is the most important driver of load forecasts, but no information about where weather data came from.

LSE	Older IRP year	Recent IRP year	Methodological changes since older IRP Framework	Variables and analytical techniques	Data sources (population, economic activity, weather, other)
			002 (IRP guidelines).	immigration, life expectancy, and business environment, particularly high tech sector) • Continue to expect higher commercial load, lower residential load, and uncertainty in industrial customers, but also indicated that there would no load growth in street lighting due to conversion to LED-based lamps. • Ran 100 iterations to capture the random variations in hourly weather-driven load • No mention of elasticities except that customer price elasticities were used in determining DR potential	
NV Power	2006	2012	• Newer plan includes low, base, and high case energy and peak demand forecasts (earlier plan only contained a base case forecast) • Newer plan contains	• Newer plan explicitly accounts for end-use saturation and efficiency projections in the residential and commercial sales forecast models (earlier plan does not appear to incorporate end-	• Demographic growth estimates now come from combination of IHS Global Insight, Inc., Center for Business and Economic Research (CBER-UNLV), and Las Vegas Convention and Visitors Authority. Other economic

			Methodological changes since older IRP		
LSE	**Older IRP year**	**Recent IRP year**	**Framework**	**Variables and analytical techniques**	**Data sources (population, economic activity, weather, other)**
			reorganization/consolidation of the types of customer classes modeled: residential, small C&I; large C&I; public street and highway lighting; and public authority (earlier plan modeled residential; general service; large general service, which includes six subclasses; large general service-1; public authority; and street lighting).	use or efficiency projections in the load forecast methodology) • Newer plan accounts for "residual DSM savings (not embedded in the sales models), small net metering (solar PV and wind), DR reductions, and plug-in electric vehicle, plus any other significant changes in expected demand not captured by the estimate forecast models" (earlier plan did not explicitly indicate that any of these factors were accounted for in the forecast). • Newer plan forecasts using statistically-adjusted end-use models (SAE) (earlier plan was based on time-series econometric modeling); weather-normalization technique also appears to have changed due to switchover to SAE • Elasticities used in modeling are -0.15 (price), 0.2 (income), 0.2 (households) (earlier plan	information—historical and future—comes from IHS Global Insight, Inc. (earlier source of all data was CBER-UNLV and Regional Economic Models, Inc.) • Elasticities came from EPRI's Residential End-Use Energy Planning System model (REEPS) • NV Power now utilizes Itron, Inc. by incorporating their end-use saturation and efficiency projections in their load forecasts.

			Methodological changes since older IRP		
LSE	**Older IRP year**	**Recent IRP year**	**Framework**	**Variables and analytical techniques**	**Data sources (population, economic activity, weather, other)**
				used -0.10 for price elasticity)	
Puget Sound	2005	2013	• Modeling framework and number of load forecast scenarios does not appear to have significantly changed since earlier plan (see table above for details about framework). • One change is the inclusion of a new class of customers: transportation (earlier plan customer classes include residential, commercial, industrial, street lights, and resale). • Continue to use very (most) complex functional forms that rely heavily on lagged operators, quadratic terms, and a mix of data transformations (log-log, semi-log, etc.).	• Variables and methods have not significantly changed since earlier plan (see table above for details about variables and methods). • Not surprisingly, time-series data used to develop load profile and other components includes data up through 2011 (earlier plan, for example, was based on temperature and load data through 2003 and 2004, respectively) • Puget Sound acknowledges that customers are adopt electric vehicles, but that the "initial adoption of EVs and plug-in hybrids would not have significant effects on PSE's energy needs or distribution system" • Not clear how transportation class of customers is modeled differently from other customer classes described in the earlier plan. • No specific mention of elasticities (earlier plan had extensive information about	• Use wider variety of national/state/local sources to develop demographic and economic growth estimates including: (1) Moody's (for U.S. econ./demographic forecast); (2) Washington State Employment Security Department, Bureau of Economic Analysis, Bureau of Labor Statistics, Office of Financial Management (state of Washington); (3) Puget Sound Economic Forecaster; and (4) Washington State Economic and Revenue Forecast Council (earlier source for U.S. data was IHS Global Insights, Inc. and little information provided about other data sources)

LSE	Older IRP year	Recent IRP year	Methodological changes since older IRP Framework	Variables and analytical techniques	Data sources (population, economic activity, weather, other)
				elasticities assumed in load forecasting)	
Avista	2005	2013	• Avista prepares low (0.5% employment growth average), medium, and high (2.5% employment growth average) load forecasts (earlier plan assumed 0% growth for low and double medium growth for high) • Customer classes specifically include: residential, commercial, industrial, and street lights (earlier plan referred to residential and commercial)	• "Avista's load forecasting methodology is undergoing significant restructuring. The restructuring involves using an Auto Regressive Integrated Moving Average (ARIMA) technique. ARIMA improves the modeling of economic drivers involving population, industrial production, income levels and energy prices to predict long-term energy demand. This new methodology will improve forecasts in 2015 IRP" (earlier plan did not provide detailed information on method, but regression analysis was suggested) • New plan contains significant detail on equations used to project population, HDD/CDD, etc. • Avista notes that estimating elasticity is "problematic and that they "lack sufficient data to estimate elasticity values for its service area" (earlier plan had detailed price	• Wider variety of sources used to project demographic and economic growth including: (1) IHS Global Insight, Inc.; (2) U.S. Federal Reserve; (3) Bloomberg; (4) U.S. DOE-EIA; and (5) internal forecasts (earlier source listed was IHS Global Insight, Inc.) • "The load forecast uses 30-year monthly temperature averages recorded at the Spokane International Airport weather station through 2012."

LSE	Older IRP year	Recent IRP year	Methodological changes since older IRP: Framework	Variables and analytical techniques	Data sources (population, economic activity, weather, other)
				elasticity estimates). • Considered use per customer with and without EV adoption (earlier plan did not explicitly indicate how EV adoption would impact load forecasts).	
Idaho	2006	2013	• Similar framework to earlier plan where load forecast scenarios are based on alternative probabilities of occurrence weather and economic activity will be different than the median assumptions • Newer plan average load growth rate is assumed to be 1.1% annually with peak load growing 1.4% under all three scenarios (earlier plan had higher growth rates)	• Newer plan considers impact of increased adoption of EV • All other variables and methods appear to be similar or the same as what was reported in the earlier plan • Newer plan appears to contain even less information (when compared to older plan) describing forecasting methods, models, and techniques • Newer plan contains implicit reference to price elasticity, but no explicit information on what that elasticity value is ("Longer term, the effect of economic recovery is tempered in the forecast by higher retail electricity price assumptions that incorporate estimates of assumed carbon legislation, which decreases the average load forecast") • EE impact is included in	• The economic forecast is now based on a forecast of national and regional economic activity developed by Moody's Analytics, Inc. The national, state, metropolitan statistical area (MSA) and county economic projections are tailored to Idaho Power's service area using an in-house economic database (earlier source of economic data came from Idaho Economics based on national/regional economic activity forecasted by IHS Global Insight, Inc.).

			Methodological changes since older IRP		
LSE	**Older IRP year**	**Recent IRP year**	**Framework**	**Variables and analytical techniques**	**Data sources (population, economic activity, weather, other)**
				sales forecast, but DR is excluded and treated as an resource option	
LADWP	2006	2012	• Newer plan presents alternative 1-in-10 peak load and energy forecasts by the date the forecast was made (earlier plan has base case peak demand; hot weather peak demand forecasts; and single energy forecast) • Newer plan contains a seventh customer class: plug-in electric vehicles (earlier plan includes forecasts for six customer classes: residential, commercial, industrial, street lighting, Owens Valley, and Intra-departmental)	• Variables and methods (e.g., generalized/ordinary least squares regressions)—with exception of plug-in electric vehicle forecasts from third-party—appear to be similar or the same as what was reported in the earlier plan	• Similar sources for population/economic forecasts (e.g., California Department of Finance, McGraw-Hill Construction forecast, State of California Economic Development Division L.A. County Forecast), but expanded use of (1) electric vehicle penetration forecasts from California EV coalition; (2) Los Angeles Port Authority electrification forecasts; and (3) housing forecasts from the city of Los Angeles. Weather information continues to be provided by NWS/NOAA, but another weather data source was added in the new IRP (Los Angeles Pierce College)
Pacificorp	2004	2015	• Newer plan includes three different load forecast sensitivities: low (low economic growth from IHS Global Insight and low industrial growth in Utah/Wyoming); base; and high (high	• Newer plan specifically refers to using statistically-adjusted end-use model for residential class customers—ITRON provided a spreadsheet model to predict future changes in energy efficiency; industrial forecasts are provided	• Company now uses both ITRON load forecasting software systems and state-by-state population and economic information provided by IHS Global Insight, Inc. (earlier source listed was state-level information from IHS Global Insight, Inc.)

			Methodological changes since older IRP		
LSE	**Older IRP year**	**Recent IRP year**	**Framework**	**Variables and analytical techniques**	**Data sources (population, economic activity, weather, other)**
			economic growth from IHS Global Insight and high industrial growth in Utah/Wyoming) (earlier plan includes single load forecast)	directly by customers; commercial forecasts are made by using regression analysis techniques forecasting sales using historical sales, non-manufacturing employment, and weather (earlier plan refers to process similar to SAE for residential, commercial, and other customers but technique is not explicitly called SAE; industrial customers are forecasted in close consultation with actual customers) • Newer plan does not directly mention price elasticities (earlier plan indicates that price elasticities of demand are 0.10)	
PNM	2007	2011	• Newer plan projects load under three scenarios: (1) low; (2) base/mid; and (3) high. Difference between older and newer plan is that newer plan uses low and high trajectories based on information provided by	• Newer plan considers impact of increased adoption of EV—including conducting sensitivities around the assumed uptake • Both plans have little or no information about the regression models and techniques used to forecast demand (newer plan:	• Little or no information was included about data sources in 2007. In 2011, PNM identified the University of New Mexico Bureau of Business and Economic Research as the source of population forecasts. Information about electric vehicle penetration was

			Methodological changes since older IRP		
LSE	**Older IRP year**	**Recent IRP year**	**Framework**	**Variables and analytical techniques**	**Data sources (population, economic activity, weather, other)**
			the University of New Mexico and IRP Working Group (earlier plan simply assumed that low was 1.5% lower than mid and high was 1.5% higher than mid forecast)	"PNM uses a statistical-based time series modeling to prepare its load forecasts…includes three parts: a forecast of retail loads, a forecast of existing firm wholesale customers, and a forecast of distribution and transmission losses". • Newer plan contains implicit reference to price elasticity, but no explicit information on what that elasticity value is was included in the plan ("the usage equation captures season differences within a year, responses to weather, and changes in usage patterns over time that result from life-style changes, price, and other factors") • Newer plan acknowledges that weather impacts load forecasts (earlier plan does not mention the word "weather"—or anything related to weather)	collected from KEMA, EPRI, and NRDC studies—and New Mexico population estimates for future came from the U.S. Census Bureau. No known source for weather information.

			Methodological changes since older IRP		
LSE	**Older IRP year**	**Recent IRP year**	**Framework**	**Variables and analytical techniques**	**Data sources (population, economic activity, weather, other)**
Seattle	2006	2012	• Load forecast is only reported by mix of three types of customers: commercial, residential, and industrial (earlier plan reported loads for nine sectors: residential, commercial, government, food, metal, stone, aerospace, ship building, and other manufacturing) • Load is expected to grow about 1.4% annually over planning period without new programmatic conservation efforts; programmatic conservation efforts will decrease annual load growth to 0.8% average (earlier plan reported low of 0.3%, medium of 1.2%, and high of 1.9%) • Newer plan does not report low, medium, or high scenarios—only with and without programmatic conservation impact	• The newer plan contains no information on how load forecasts were produced, but it did indicate that system load is forecasted annually (earlier plan indicated that correlations were made between historical load for each customer sector and "selected economic and demographic variables") • Noted that each IRP cycle since 2008 has led Seattle to increase and then decrease the assumed adoption of EV in the load forecast (2008 IRP=67aMW; 2010 IRP=107-170aMW; 2012 IRP=8-36 aMW) • Use Monte Carlo simulation based on normal distribution of yearly data from 1981-2011—within Aurora XMP platform—to evaluate range of possible loads (earlier plan noted that SCL analyzed distributions of peak load, but it was not clear how these were used at the time).	• Seattle City Light now uses IHS Global Insight, Inc. for national economic/demographic forecast data and the Puget Sound Regional Forecaster for regional forecasts (earlier data source for economic and demographic forecasts was Dick Conway and Associates)

			Methodological changes since older IRP		
LSE	**Older IRP year**	**Recent IRP year**	**Framework**	**Variables and analytical techniques**	**Data sources (population, economic activity, weather, other)**
			• "Extreme weather conditions, very high or low temperatures, significantly affect the expected pattern of the usage of the electricity of City Light's customers when monthly studies are done, but it is not as significant as economic upturns or downturns when a yearly study is performed."		

15. Appendix D – Description of load sensitivity analysis in older and recent IRPs.

Colorado Public Service Company/Xcel Energy (COPSC)

COPSC's older plan includes both low and high forecasts due to a regulatory requirement imposed on the utility. These alternative forecasts are created by using first and third quartiles, instead of medians, for the underlying economic and weather variables that govern load growth. We could not find information indicating that the low (high) forecasts were used in the selection of the preferred portfolio.

However, in the more recent IRP, COPSC documented a more refined approach to include alternative load forecasts in the selection of the preferred portfolio. High and low sales estimates correspond to the 15% and 85% percentiles of an historic sales distribution. COPSC conducted sensitivity analyses by producing new portfolios for each high/low load forecasts, acknowledging that different load conditions require estimating alternative capacities—and combinations of technologies—necessary to meet load and policy mandates. In this example, the lower load forecast caused the capacity expansion model to suggest a portfolio that avoided building 0.7-1 GW of new NGCTs and NGCCs. Conversely, the higher forecast required an additional 0.9 -1 GW of the preceding technology types. It is important to note that these load-driven swings in capacity represent a significant portion of the total expected capacity (approximately 50%-75%) for this utility over the planning horizon. However, we found no evidence of an acquisition strategy that explicitly takes into account the potential for unplanned deviations in customer load.

Northwestern Energy (NW)

Regulations put forth by the Montana Public Service Commission require risk evaluation, management, and mitigation for both price and load (quantity) uncertainty (Mont. Admin. R. 38.5.8213 (1)(f)). According to these regulations, load uncertainty comes from variation in several underlying variables including fuel prices, environmental regulations, and weather—among other factors. Consequently, NW's older plan includes both high and low load forecasts. The utility expects lower load if market prices are lower than default supply prices. This leads larger customers to switch from the default rate to a retail rate and therefore reduces the load that the LSE has to procure for. Higher load forecast comes from the opposite effect. NW performs a qualitative sensitivity analysis by discussing the management and mitigation strategies under different risks. NW's qualitative sensitivity analysis is focused on short-term, operational cost risk rather than the potential for over or under-investment in infrastructure (capital risk). We find no direct connection between the alternative load forecasts and the qualitative discussion of management and mitigation strategies.

In a more recent IRP, however, NW develops and applies a stochastic risk assessment framework that employs statistical likelihoods (probability distributions) of future: fuel and electricity prices; CO_2 abatement costs; temperature; and monthly/seasonal/hourly loads. The NW stochastic-based model repeatedly draws from each probability distribution to evaluate the expected value and variance of short-term, operational costs under three portfolios. However, there appears to be no direct connection between longer-term load variation and investment levels in resource capacity, as capital investment levels for each portfolio are treated as a sunk cost. One justification for this approach may be that NW intends to rely on market transactions to balance its hourly and monthly positions. A large volume of market purchases would have to take place under higher-than-expected load, while a lower-than-expected load outcome could lead to the company selling their surplus capacity into the open market (NW, 2013, fig. 6-39).

Sierra Pacific Power (Sierra Pacific)

Sierra Pacific produced low and high load forecasts in their older IRP as required by Nevada regulation (Nev. Admin. Code § 704.9475). The low load forecast assumes a weaker-than-expected economy and exit of two large customers. Alternatively, the high forecast assumes a stronger economy and no loss of customers. The alternative load forecasts imply a ± 500 MW capacity position difference—or a ~40-50% of the 1GW of capacity planned by the final year of the planning horizon under the base forecast. Sierra Pacific identified 12 candidate portfolios with different installation years and plant capacity values to meet their base case load need. Low and high load forecast sensitivities resulted in contracted and expanded portfolios, respectively. The capacity contracted (expanded) in these alternative portfolios is consistent with the ± 500 MW position difference from the alternative load scenarios.

Sierra followed a very similar approach in a more recent IRP. Low and high load forecasts are built by modifying economic, mining activity, and DSM/DR/Net Metering penetration assumptions. As was the case earlier, sensitivity results for low and high load forecast conditions result in contracting or expanding the capacity of each portfolio and/or delaying or advancing potential procurement decisions, respectively.

Portland General Electric (PGE)

PGE produces high and low load forecasts that correspond to the base forecast growth plus and minus one standard deviation from the base, respectively. PGE explicitly acknowledges that these alternative forecasts do not reflect modeling of underlying economic and demographic variables, but simply intend to produce “demand boundaries, or jaws, that are sufficiently large to incorporate a mid-term departure from the reference forecast caused by business cycle and/or macroeconomic fluctuations.” (PGE, 2007, p. 41). Load growth sensitivity analysis is required as part of Oregon IRP regulations (Guideline 4b of Order No. 07-002) and includes high/low growth scenarios and stochastic load risk analysis. Weather is the only stochastically-determined variable affecting load in the PGE planning documentation.

PGE creates twelve portfolios designed to meet peak demand five years ahead of the IRP base year (in this case, 2012). PGE uses this approach to minimize the negative effect of long-term uncertainty in the selection of the preferred portfolio. In all portfolios, a third of the capacity required is met through short- and medium-term market purchases. The deterministic impact of alternative load growth forecasts in PGE's portfolios is then reflected in reduced or increased market purchases. This methodology assumes that market purchases are always on the margin and, as with other cases, ties the load growth forecast error to the electricity market price forecast error. PGE's more recent IRP follows the same load growth sensitivity approach used in the 2007 IRP.

Puget Sound Energy (PSE)

In the 2005 IRP, Puget Sound Energy adopted a scenario-based approach for the uncertainty analysis. PSE created internally consistent low and high economic performance scenarios with corresponding impacts to load growth and natural gas prices. For example, the average annual load growth in the base case was 1.8% with low and high scenarios of 1.2% and 2.3%, respectively. PSE analyzed four supply-side portfolios as part of their resource planning process. These four supply-side portfolios are quite similar and include coal, CCCT, and renewable energy options.

Puget Sound load growth sensitivity results show changes in the quantity of planned resources, but not significant changes in the type of supply-side resource or timing. It should be note that, while capacity differences are on the order of 5% of overall capacity, the corresponding monetary value of these portfolios under the base case, low, and high load forecasts differs by 15%-20%.

In a more recent IRP, Puget Sound follows the same methodology to define load forecast scenarios. In this case, however, PSE considers a broader set of variables that define a given scenario, including emission regulations for four pollutants, alternative fuel prices, various regional transmission constraints as well as both local and regional demand scenarios. We find that the difference between the low and high load forecasts scenarios is significant and ranges from 30%-50%. Interestingly, PSE implemented a stochastic modeling approach to develop candidate portfolios finding that these portfolios generally do not differ much across the load forecast scenarios.

Avista

Avista uses a dual-risk assessment approach that involves stochastic and scenario-based simulations, which are referred to as "futures" and "scenarios" in their IRP language. Avista prepared high and low forecast scenarios with the guidance of a Technical Advisory Committee. They use population growth in their service area as the sole driver for higher and lower load growth. They emphasize that these scenarios do not represent boundary conditions for load growth. In addition, they employ a distribution of hourly loads by month and week in each one of 15 load zones in order to run a Monte Carlo analysis for Western Interconnect electricity prices. These distributions of load are mainly intended to represent short-term variation in load due to weather variation. Avista also develops and applies a stochastic analysis for natural gas prices, hydropower generation, and wind generation.

As is the case for other LSEs, Avista's stochastic analysis results do not isolate the specific effect of load growth uncertainty, because the simulation compounds all four sources of risk mentioned above. In addition, the load growth scenario analysis is limited to a qualitative assessment. Avista concludes that the frequency of the IRP process is short enough that load forecasts can be adjusted accordingly. Avista believes that "a shift in load growth will not substantially change the mix of resource types, but potentially could change the quantity." (Avista, 2005, p. 6.30)

In a more recent IRP, Avista develops its high/low forecast scenarios based on relating changes in load growth to changes in both customer number as well as electricity use per customer (UPC). Avista uses regional employment growth forecasts as drivers of the number of customers, while keeping UPC growth rates constant. In contrast to the earlier IRP, Avista conducted a quantitative-based scenario analysis. This technique involves identifying specific portfolios that meet low and high load conditions, adjusting for energy efficiency potential, and verifying that the risk profile of these new portfolios is similar to their original preferred portfolio. Through this analysis, Avista shows that timing of investments and the resource types are generally stable, but the planned capacities may increase (decrease) depending on load growth.

Idaho

The 2006 Idaho Power IRP introduces three long-term load forecasts (10^{th}, 50^{th}, and 90^{th} percentiles) and two additional short-term weather sensitivities (70^{th} and 90^{th} percentiles) based on the median value of the long-term forecast. Idaho Power then compares the performance of the preferred portfolio under two possible alternative load growth scenarios. They find that the preferred portfolio capacity would differ by ±400 MW (peak demand) under alternative scenarios, or roughly 25% of the total expansion over the 20-year analysis timeframe. Their planning strategy involves "utilizing a diverse mix of smaller, short lead-time resources… …[incorporating] the flexibility to adjust resource timing in the shorter term by either accelerating or deferring actual in-service dates to more closely match actual load growth." (Idaho, 2006, p. 85). They plan to adjust the timing and size of resource RFP for the preferred portfolio as a hedging strategy.

Idaho has continued to maintain its methodology to create short and long-term load growth scenarios, but has made recent innovations in their evaluation of the impact of these scenarios. For example, the 2013 IRP employs a stochastic approach (similar to Avista) and assesses the risk profile of their preferred portfolio against load growth and other variables with uncertainty. In addition, Idaho Power evaluates capacity margins given higher-than-expected load together with lower-than-expected hydropower concluding that hydropower offers enough hedging against a wide range of peak demand forecasts.

LADWP

LADWP's older and newer IRPs employed the same methodology to develop alternative load forecasts. LADWP estimated two alternative peak demand forecasts: a one-in-ten chance of higher temperature (and higher demand) and a one-in-forty chance of lower temperature (and lower demand). These alternative forecasts are based on short-term weather stochasticity. LADWP does not consider long-term variability in load growth. LADWP indicated that weather variability does not affect annual energy consumption. For this reason, they did not develop an alternative energy sales forecast. LADWP indicated that a load sensitivity simulation was performed, but little or no information was provided on the method used or the results from this sensitivity analysis.

Seattle City Light

Seattle City Light's older IRP developed and applied alternative forecasts for energy sales, but not peak demand. These forecasts are based on four future scenarios that include fuel price, market structure, and environmental trends. Seattle City Light employs a stochastic analysis (i.e., Monte Carlo simulation) to repeatedly draw from probability distributions for each relevant variable and then input these values into a production cost model to quantify the range of costs for several different portfolios. It is not possible for external reviewers to assess the stand-alone impact of changes in load growth, but this method does consider costs under various load scenarios.

In a more recent IRP, Seattle City Light does not estimate high and low forecasts. Instead, they create a probability distribution from a sample of ~30 years of actual peak demand and repeatedly draw from this distribution to produce alternative load values for the production cost model described earlier.

PNM

In the earlier plan, PNM produced alternative load forecasts by increasing and decreasing their base forecast growth by ±1.5%. PNM found that there were only minor impacts to their preferred portfolio under these alternative forecast conditions. In addition, PNM conducted a probabilistic analysis to test the performance of their preferred portfolio by assuming a range of alternative values for three important inputs that are statistically correlated with one other (fuel prices, electricity prices and load growth). PNM reported that the preferred portfolio continued to be least-cost, low-risk but did not release additional information about how the details of the portfolio (e.g., timing of resource acquisition) might change under these different conditions.

In a more recent IRP, PNM uses a bottom-up approach to develop alternate load growth forecasts underpinned by economic growth, building code changes, and own and cross price elasticities. PNM then performed a detailed load sensitivity analysis that identifies the timing and capacity changes of portfolios for alternative low and high forecasts. However, PNM did not develop or implement a resource acquisition strategy to specifically address these changes.

Pacificorp

In their earlier IRP, Pacificorp did not produce alternate high and low load growth forecasts. Instead, Pacificorp employed a risk assessment methodology that estimated the impact of varying loads both in the short-term (due to weather) and long-term (due to economic conditions and technological change). Pacificorp used historical sales data to determine a distribution of probable future energy sales growth. For this reason, it is impossible to isolate the effect of load on the choice of portfolio. Pacificorp did not reformulate the timing or capacities in each of its portfolios, but determines a risk and cost profile for each fixed portfolio. This finding suggests that there was no specific strategy developed by Pacificorp to respond to the potential for higher or lower levels of load growth than expected.

In a more recent IRP, Pacificorp did develop and apply three load growth forecast scenarios for coincident system peak demand and energy sales. In this plan, Pacificorp identified alternative portfolios whose timing and size reflect the two alternate load scenarios and also assesses the monetary impact of several variables—including alternative load growth. Pacificorp indicated that load growth is the most important variable affecting the future revenue requirement. Pacificorp developed strategies to address these potential outcomes through a process called the “resource acquisition path”.

NV Power

NV Power does not report information describing any type of load growth sensitivity analysis in either the 2006 or 2012 IRPs.

16. Appendix E – Nameplate capacity expansion and load growth comparison

We compile incremental capacity expansion planning data from the older IRPs for the LSEs in our sample. Information about capacity expansion is usually reflected in the loads and resources tables corresponding to a utility IRP “preferred portfolio.” The source for this and other information on long-term planning assumptions is the LBNL Resource Planning Portal (RPP[22]), an online system documenting nearly one hundred IRPs and supplemental surveys dating back to 2003.

We estimate total procured capacity additions by type of resource for each LSE starting from the same first year as indicated in the corresponding resource plan (see Table 1) through 2014—the last year for which procurement data are available. We include both owned capacity and contracts, which are the main supply side resources LSEs consider when developing their plans. We were able to attribute actual power purchase agreements (PPAs) by identifying the buyer—each one of the 12 utilities considered in this analysis—in a database of PPAs signed over the past 15 years (ABB-Ventyx, 2016).

In aggregate, the LSEs planned for ~ 20 GW of new nameplate capacity by 2015 in the IRPs reviewed in this study; roughly the same new capacity was actually realized (Figure 10). We find that actual self-builds new capacity levels were very consistent with planned self-builds capacity levels, with both reaching ~12 GW at the end of the analysis period. Realized PPAs were slightly higher than planned and grew faster than self-builds following the 2008/2009 crisis.

We compare the actual capacity growth rate to the actual peak demand growth rate and find that the actual capacity expansion of ~20 GW was almost five times higher than peak demand growth of ~4.5 GW during the same period (Figure 10, blue line). If we narrow the analysis period to 2007-2014, we find that the peak demand increased by less than 1 GW, but that there was nearly 8 GW of self-built capacity and about 7 GW of power purchase agreements signed over that period. As a benchmark, the planned incremental expansion of ~ 20 GW is only twice as high compared to the incremental forecast peak demand for the same period[23] of ~10 GW. The actual procurement to peak demand ratio was 15:1, whereas the planned resources to peak demand ratio was 2:1.

[22] See http://resourceplanning.lbl.gov

[23] In order to make a comparison over the entire time horizon, it was necessary to estimate some of the 2004-2007 values for certain plans depending on assumptions from the first year of analysis. We extrapolated using a linear regression to recreate those values – essentially using the same expected growth rates – to add the missing value for 2004-2007 for the LSEs whose plan year is 2005 or after (see Table 1 for the list of years for the older plans)

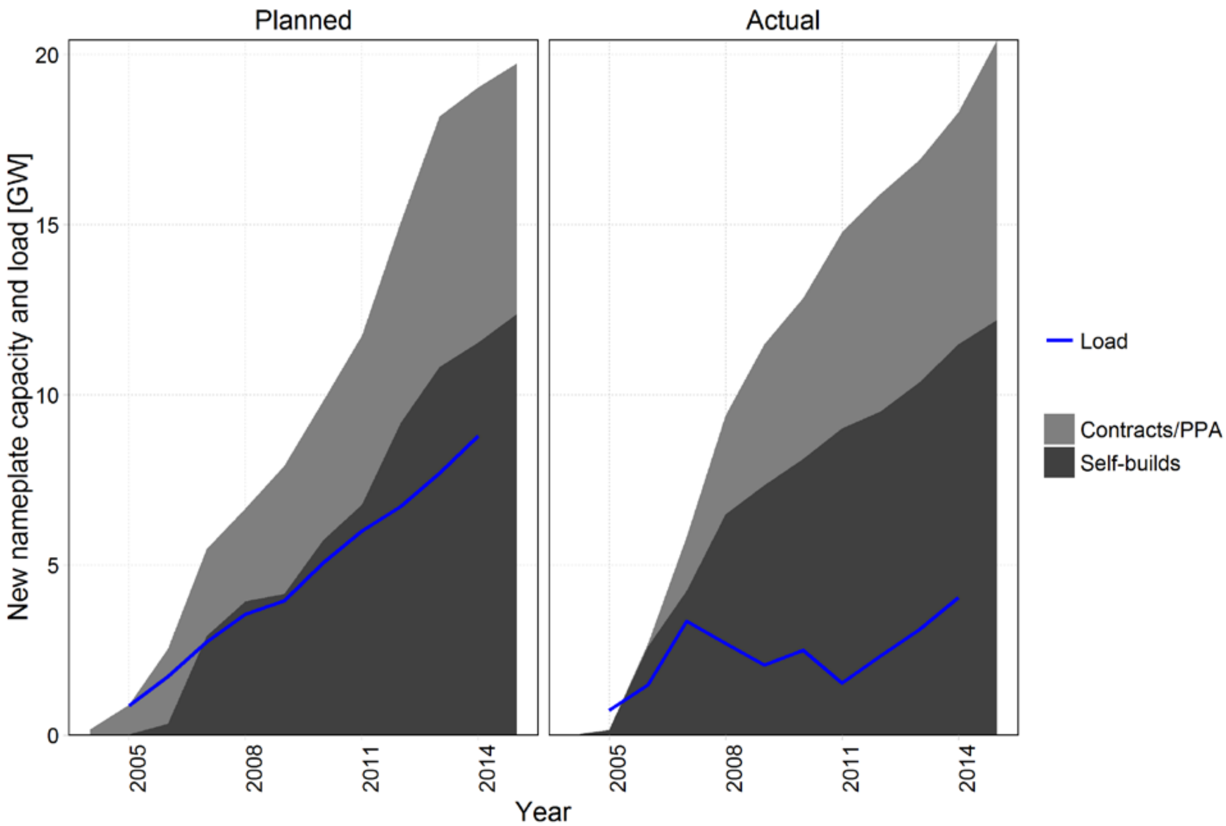

Figure 10 **Planned and actual nameplate capacity with forecasted and observed peak demand.**