QUANTA TECHNOLOGY

REPORT

Load Forecasting for Alberhill System Project

PREPARED FOR

Southern California Edison (SCE)

DATE

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(Version 1)

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1.0	12/20/2019	Final report

EXECUTIVE SUMMARY

In support of the Alberhill System Project, this report presents the methodology and results of two independent load forecasts developed for Southern California Edison (SCE). The area of study is the Valley South and Valley North region, which are relevant for capacity and reliability studies in evaluation of the Alberhill System project.

The first forecast uses trending of historic data with S-Curve fitting that accounts for predicted future load growth by extrapolating current and recent historical trends in load growth in a way that accounts for the fact that eventually land in an area "will fill up" with development, so that further growth is less likely to occur. Three load-growth trends were developed in this study, namely current trend, reduced trend, and low trend forecasts. In this methodology, the future expectations of distributed energy resources (DERs) are accounted assuming the intrinsic trend is embedded in the recent history of load data.

The second forecast also uses S-curve curve fitting but is done from a spatial perspective, incorporating current and future land use according to city and county development plans. The spatial forecast considers the forecast of DERs presented in the 2018 Integrated Energy Policy Report (IEPR) from the California Energy Commission (CEC). The 2018 IEPR forecasts for DERs in SCE's System were disaggregated by SCE for the Valley South and Valley North territory.

Results for both forecasting methods show some differences in forecasted load at particular years. The method based solely on trending resulted in a linear-like forecast curve, and the spatial forecast method delivered a load growth curve with higher initial growth rate, and a reduced growth rate for years farther in the future. Regardless of that, both forecasts estimate year 2022 as the year when the total transformation capability of the Valley South region could be compromised due to load growth.

The conclusions and the opinions presented herein are based on the work performed as described in this report and information provided by the client for this study. Quanta Technology reserves the right to revise these conclusions and opinions if and when additional information becomes available.

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1 INTRODUCTION

This report presents two independent load forecasts developed for Southern California Edison (SCE), which apply two different approaches for load forecast: Trending-based forecast, and Spatial load forecast. Both approaches are consolidated methods widely used in the electrical utility power systems industry. The decision of using one or the other usually depends on the amount and quality of source information available, and on time constraints. In this case the main reason to pursue both methods is verification, being the load forecast is an essential piece of subsequent capacity and reliability studies for the Alberhill System Project.

The Valley South and Valley North regions are considered the subjects of study in this load forecasting task. Even though the Alberhill System Project is directly linked to the Valley South region, the Valley North region is also included to provide for analysis of power transfer scenarios to be considered in reliability studies across various system alternatives. The forecasts encompass the 10-year period from 2019 until 2028. The methodology and results for the two forecasting approaches are presented in the following way.

Chapter 2 presents fundamental aspects that are common to both forecast approaches. This includes S-Curve fitting, weather normalization of historic load data, and the definition of the horizon year. Chapter 3 covers the Trending-based forecast with its data requirements, methodology, and results. Similarly, Chapter 4 describes the spatial load forecast, data, methodology and results. Chapter 5 presents a summary of comments and conclusions.

2 COMMON CONCEPTS AND DATA

2.1 Historic Load Data

SCE provided historic recorded peak load information for the Valley South and Valley North regions (Table 2-1). These values are not weather-normalized, but are adjusted to remove data capture errors and abnormal system conditions, and to correct for non-dependable generation. A similar set of data was received for all substations in the study area. This information was used for both forecast as discussed in chapters 3 and 4.

Table 2-1. Recorded historic peak load in MVA.

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Valley South	787	829	894	924	928	897	925	881	943	947	995
Valley North	671	602	698	692	750	703	727	681	761	782	777

2.2 Weather Normalization

Weather normalization of load forecasts as well as the historical load data used in load studies is a recommended practice. It increases the likelihood that trends and patterns in load growth due to weather are identified as such, and that trends and patterns due to other causes (customer growth, changes in usage habits) are correctly tied to those causes. In turn, this leads to a better understanding of load growth causes, and that makes for more accurate and useful forecasts (Willis, Power Distribution Planning Reference Book, Second Edition, 2004).

The initial step for the load forecasting of the Valley South and Valley North regions consisted of normalizing the historic load data provided by SCE. The purpose of weather normalization is to generate a set of historic load data, which is independent of any temperature level that was present at times of peak-demand occurrence. This puts all historic load information at the same reference temperature level and allows comparisons between different data points.

Naturally, the determination of the reference temperature is essential, and this was performed by utilizing 18 years of historic daily-maximum temperatures obtained from the average historic temperatures provided by the Elsinore and Temecula weather stations for the Valley South substations, and by the March Air Base weather station for the Valley North substations.

Figure 2-1 and Figure 2-2 show the number of occurrences of a certain temperature or higher during the last 18 years. From these figures, and using interpolation, it can be observed that a temperature T = 109.6°F happens, on average, once every 2 years, and the temperature T = 110.5°F occurs, on average, once every 5 years. The first value (T = 109.6°F) has been used as the reference temperature representative of a normal weather peak temperature, and it is applied to non-coincident, historic substations load. The second value (T = 110.5 °F) has been used as the reference temperature representative of heat storms that occur once every 5 years, and it is applied to coincident Valley North System and Valley South System historic load.

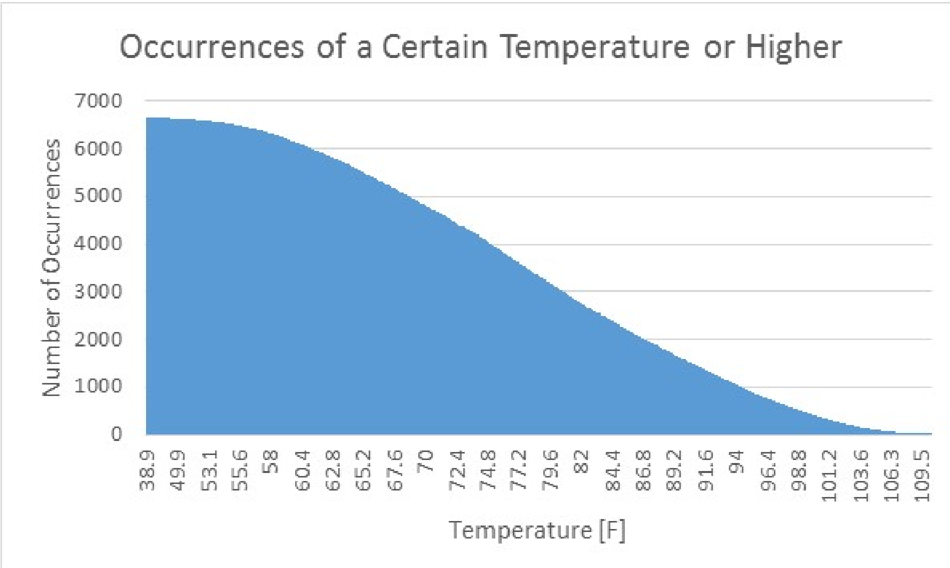

Figure 2-1. Number of occurrences of a certain temperature or higher during the last 18 years.

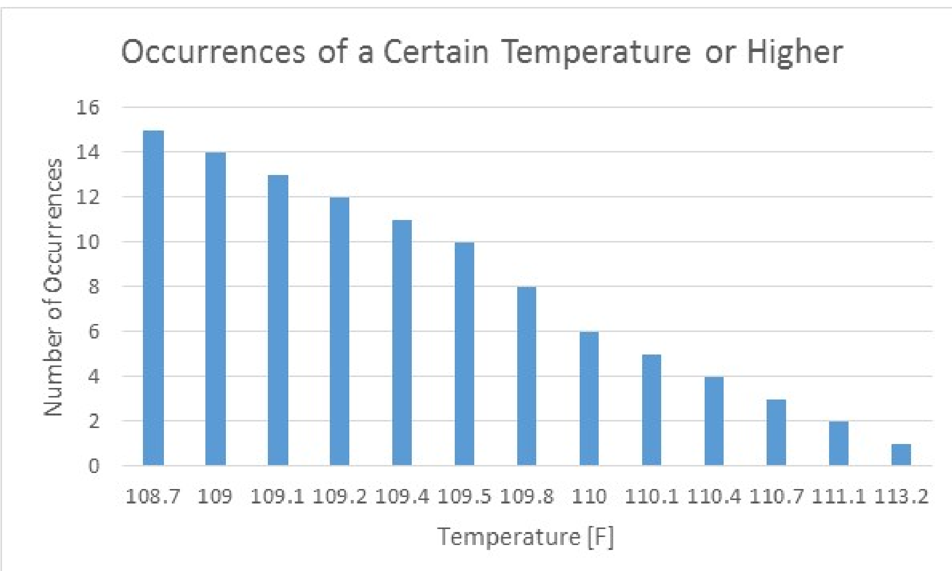

Figure 2-2. Detail of a section of Figure 2-1.

To proceed with normalization by temperature, and utilizing the historic load data, a load-temperature sensitivity was determined. To do so using the most closely correlated load-temperature data, Auld Substation load data and the Temecula Weather Station temperature data have been used for the Valley South area. Figure 2-3 shows the load-temperature relation for the complete range of load and temperature pairs. Here it can be observed that temperature dependence of load can be approximated by a quadratic equation in the global range. When attention is paid mostly to the range between 90°F and 110 °F, and a new curve fitting is done only for that range of data, the resulting quadratic fitting curve becomes approximately linear in the limited range of temperatures being observed, as shown in Figure 2-4.

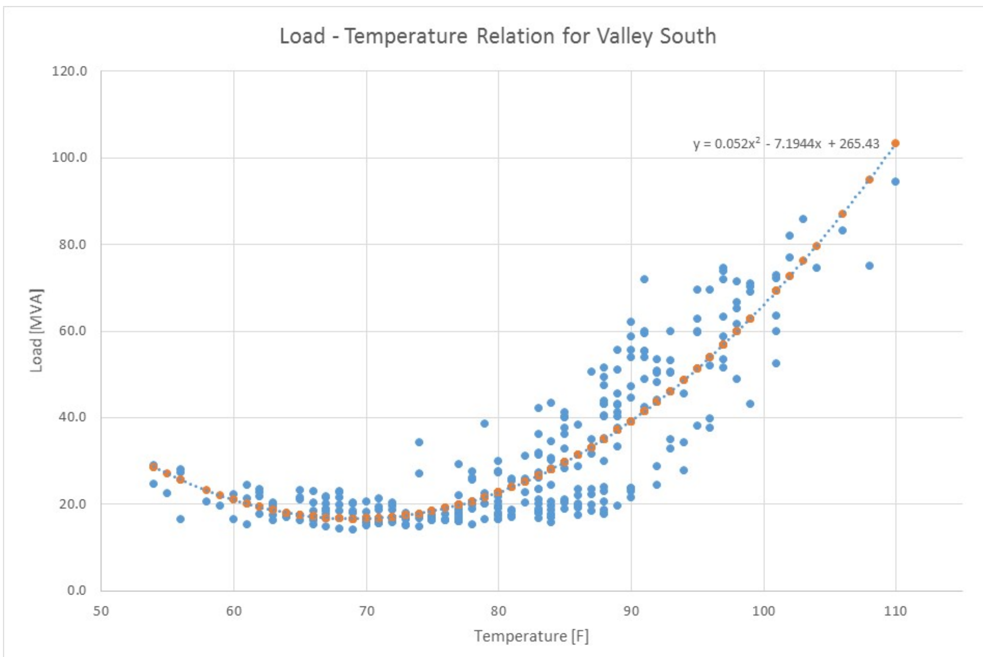

Figure 2-3. Load/temperature relationship for the Valley South region, full temperature range.

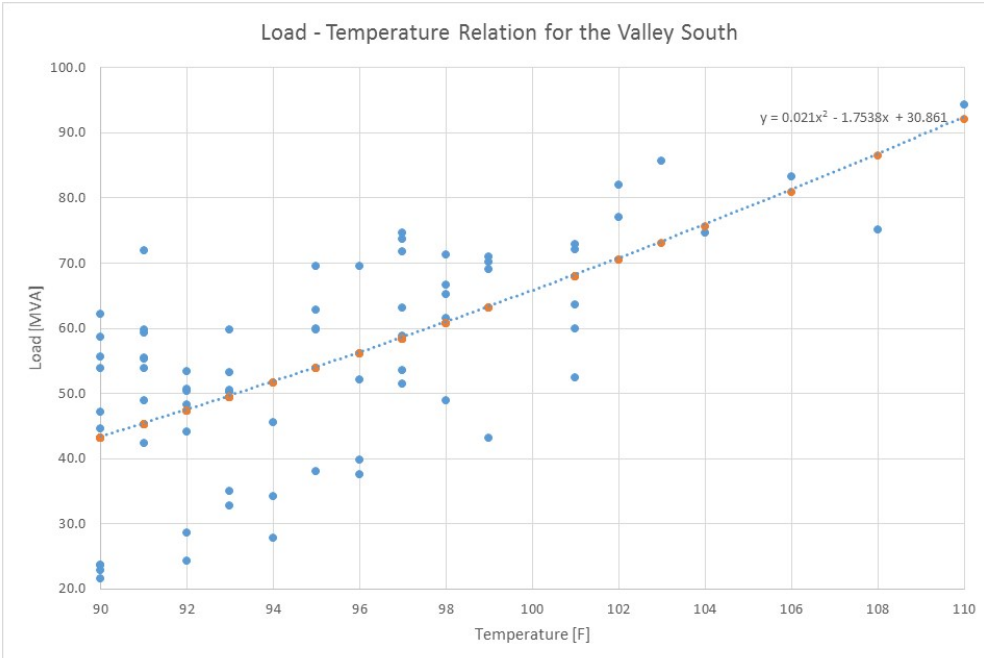

Figure 2-4. Load/temperature relationship for the Valley South region, 100±10 °F temperature range.

For the Valley North region, the March Air Base temperature data has been used to obtain Valley North load-temperature sensitivity. The results are plotted in Figure 2-5 and Figure 2-6. As in the case for the Valley South, one curve fitting was done for the wide range of temperatures, and another curve fitting was done for the reduced range of temperatures.

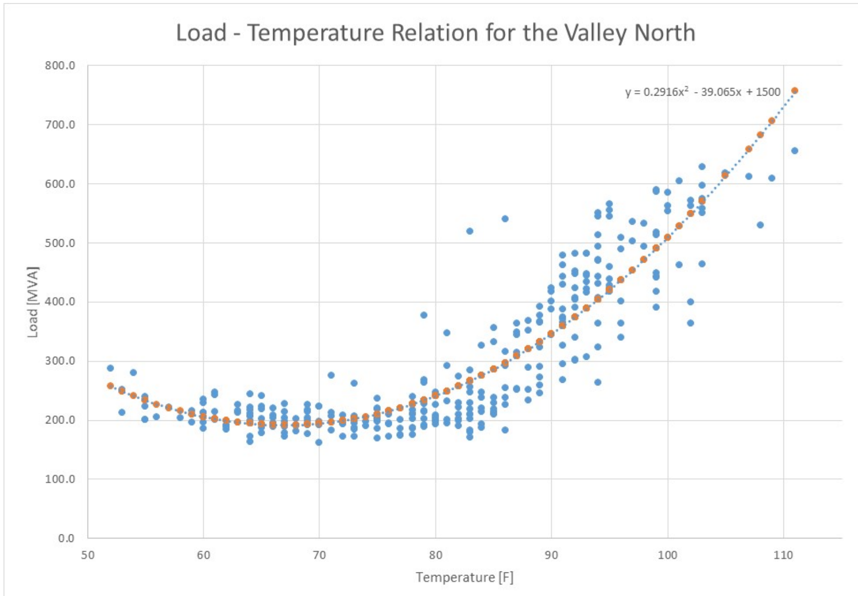

Figure 2-5. Load/temperature relationship for the Valley North Region, full temperature range.

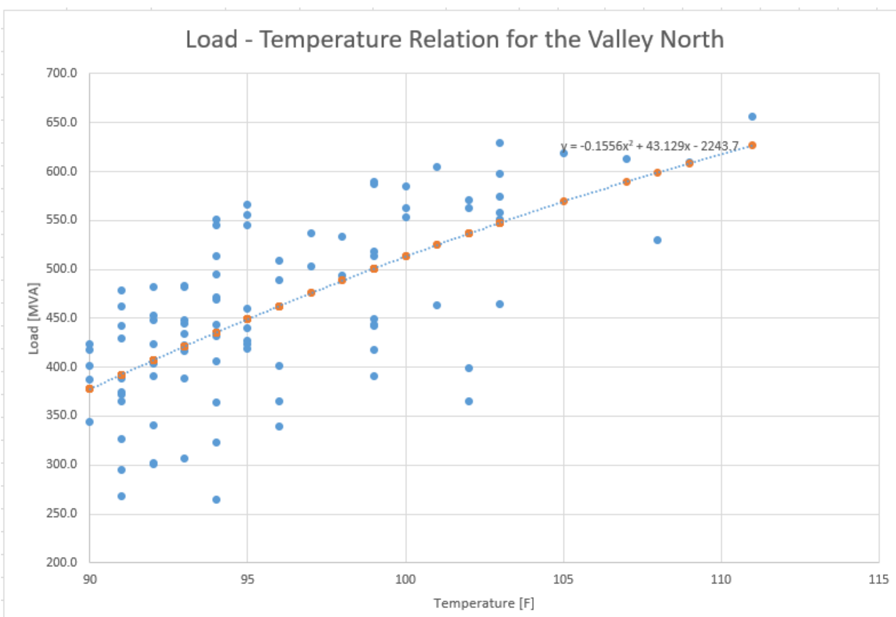

Figure 2-6. Load/temperature relationship for the Valley North Region, 100±10 °F temperature range.

Historic peak loads per substation were adjusted for temperature using the normal 109.6°F reference temperature and the respective interpolation equations as shown in Figure 2-4 (for Valley South region) and Figure 2-6 (for Valley North region). The results obtained for the Alessandro 115/12 kV substation are shown in Table 2-2, and for Auld 115/12 kV in Table 2-3; the temperature-adjustment results for all the other substations, and for the total Valley South and Valley North regions, can be found in the **SCE Load Forecast...xlsx** file, in the "**Valley Historic**" and "**All Substations (I)**" sheets.

Table 2-2. Weather Adjustment for Alessandro 115/12 kV Substation

Year	Max. Temp. North [F] (March Air Base)	Alessandro Load 115/12 kV [MVA]	Alessandro Load 115/12 kV [MVA] (Adjusted 1-in-2 Weather)
2008	108	95.8	98.2
2009	107	88.5	92.2
2010	109	98.8	99.6
2011	108	94.6	96.9
2012	107	93.1	96.9
2013	109	105.3	106.2
2014	106	103.5	109.7
2015	105	96.5	104.1
2016	111	100.7	98.8
2017	109	104.9	105.8

Table 2-3. Weather Adjustment for Auld 115/12 kV Substation

Year	Max. Temp. South [F] (Temecula)	Auld Load 115/12 kV [MVA]	Auld Load 115/12 kV (Adjusted 1-in-2 Weather) [MVA]
2008	108	102.8	107.6
2009	108	101.2	106.9
2010	111	105.8	102.2
2011	107	114.6	123.9
2012	106	126.9	143.4
2013	108	103.1	109.2
2014	106	106.0	121.1
2015	108	102.0	107.6
2016	110	110.0	107.4
2017	109	117.8	119.2

Additional considerations of the number of cooling degree days, and number of customers were used to normalize historic load for the spatial load forecast. The resulting number of normalized cooling degree days[1] for 1-in-5-year heat storm is 27.8. The results of weather-normalization for the Valley South area are shown in Figure 2-7, and for the Valley North are shown in Figure 2-8.

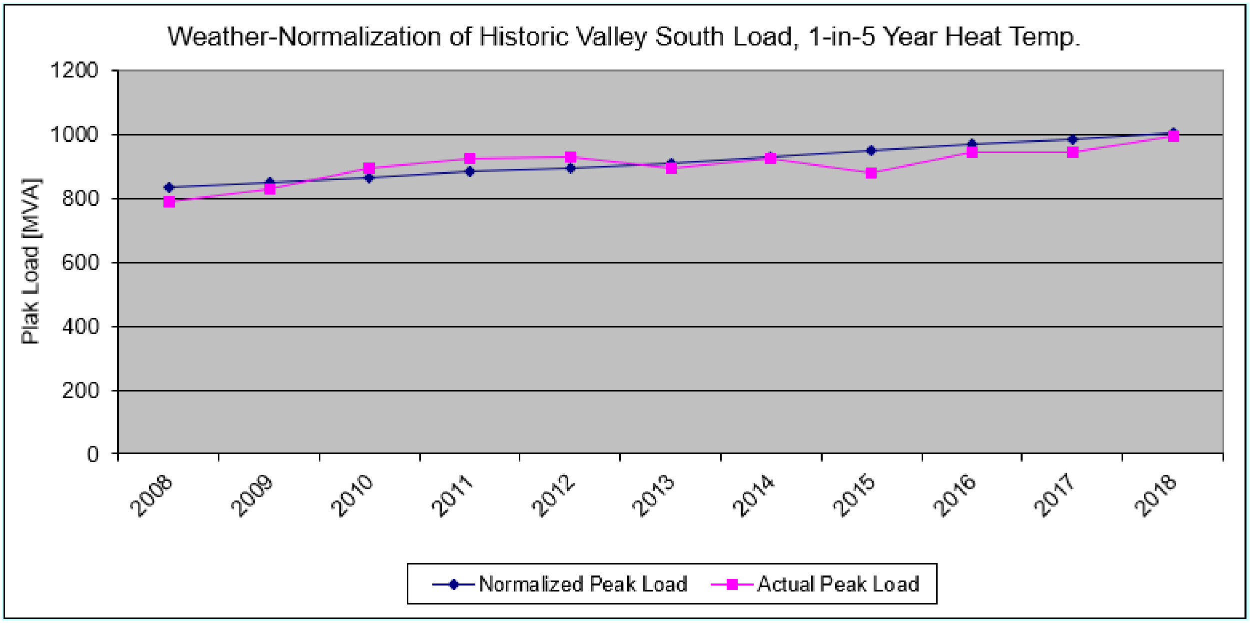

Figure 2-7. Registered and normalized peak load for Valley South

[1] The number of cooling degree days are computed as the difference between the average daily temperature (computed using the daily maximum and minimum temperatures), and the reference 65°F. INSITE uses the cooling degree days as one of the three driving variables to correlate weather information with electrical load, being the other two, the maximum temperature and the number of customers.

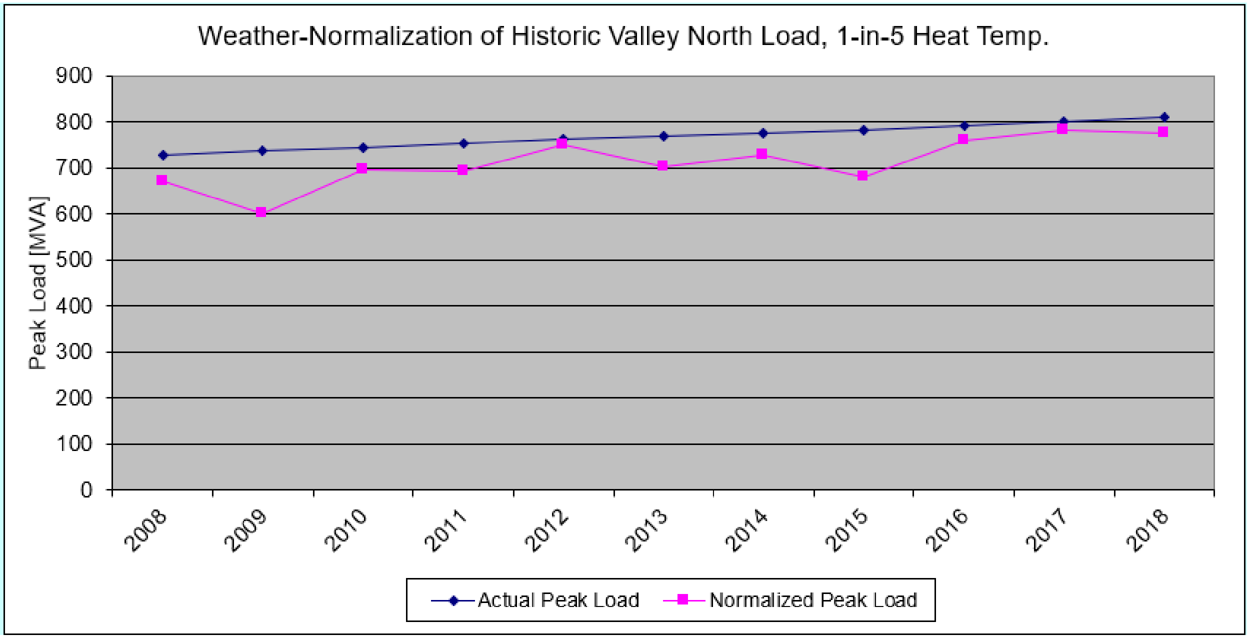

Figure 2-8. Registered and normalized peak load for Valley North

2.3 S-Curve Trending

The approach for load forecasting of the Valley South and Valley North regions relies on sigmoid functions, or S-Curves to represent the typical behavior of load growth in defined areas. Figure 2-9 presents the characteristic S-Curve which responds to a family of curves defined by:

$$f(t) = \frac{K_1}{1 + e^{K_2(t-K_3)}} + K_4$$

where K_1, K_2, K_3, and K_4 are constants.

The family of curves is characterized by three periods, starting with a slow growth rate to represent the early developments in a certain area. This initial period is followed by a fast-paced growth period, resembling the apogee of development, to finally reach a period of mature development represented with a saturated slope.

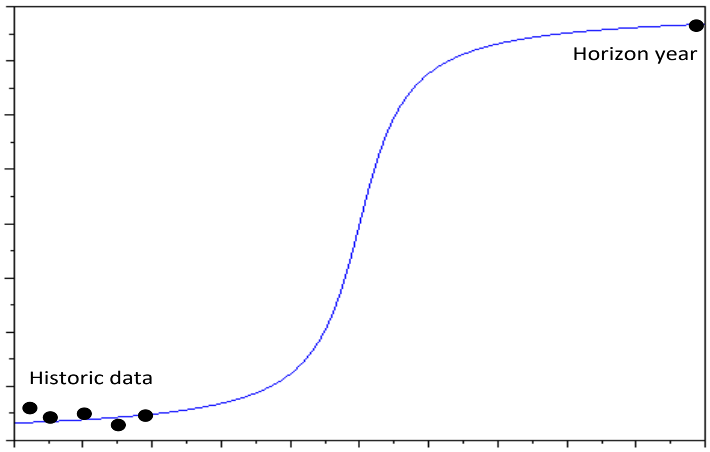

Figure 2-9. Characteristic S-Curve.

Historic load information and horizon-year load may lie on any of the three regions of the curve. In this project, the horizon year has been defined as year 2048. A horizon of 30 years in the future is a common industry practice for long-term forecasts, as discussed in Section 2.4.

This particular forecast method, commonly called "S" curve or Gompertz curve trending, was identified as particularly suited to forecasting in distribution planning in the late 1970s, in one of the industry's first multi-utility, cross-industry studies of load forecasting methods (Shula, 1979)[2]. It has a long history of successful application by many utilities (Menge, 1979), (Willis, Spatial Electric Load Forecasting, 2002), (IEEE Power Engineering Society. Power Education Committee, 1992). Quanta Technology's senior consultants have worked with it for over forty years, and considers it the most useful and accurate form of historical load trending at the distribution level. Quanta has never seen a situation where it was applied as recommended in (Willis, Spatial Electric Load Forecasting, 2002) and (IEEE Power Engineering Society. Power Education Committee, 1992) in which this method did not provide satisfactory results. It was developed in the 1980s and is technically known as the "S-Curve fit regression with horizon-year load"[3] method. Commercial versions of it have been marketed or used as part of their technical tool offerings by several software companies, or developed in-house at some utilities, and has been used for decades by utilities like Commonwealth Edison of Chicago, Florida Power (now Duke Florida), PacifiCorp, Centerpoint, and many other utilities.

In addition to its longstanding track record in the industry, Quanta Technology's distribution planning teams consider this method as having the best combination of user-friendliness, manageable data needs, quick setup, and forecast accuracy for distribution planning. Quanta Technology has developed an improved version of "S-Curve trending" called INSITE®, which its planning and engineering teams use for

[2] An EPRI report on the work, "Research into Load Forecasting and Distribution Planning," Project RP-570, report # EL1198, 1979, can be obtained by EPRI members. The report is lengthy and focuses mostly on other forecast methods tested and why they did *not* work as well. A succinct summary of that project and its positive findings is given in "Long-Range Distribution Planning – A Unified Approach," by three of the principles in the project research team, available from IEEE.

[3] S-Curve and Gompertz Curve are both common names for the same method.

distribution planning studies. Some large co-ops, many medium-sized municipal utilities (e.g., Madison Electric, Lincoln Electric, and Fortis BC), and larger utilities (e.g., PG&E, Duke Energy, Pepco, and Dominion) have used Quanta Technology's INSITE in studies of substation growth for planning studies filed with regulators. The algorithm is also used as the short-term trending solution in the LoadSEER forecast program for distribution and DER planning, sold and supported by Integral Analytics (IA). IA's website says this forecasting tool is licensed by utilities comprising 30% of the power industry.

The method's distinction from simple polynomial regression is that it fits S-Curves, or "Gompertz curves", to load histories (see Figure 2-10). A basic fact long known in the industry is that load growth at the distribution (i.e., the substation and feeder) level is invariably not a straight line trend over the long term but, instead, an S-Curve with a very identifiable period of more intense growth/redevelopment that occurs locally in different small areas at different times as each "fills up" with growth or redevelopment. For example, load growth within a city continues because those brief "spurts" of growth eventually "move on" to other neighborhoods and other areas of the city. Moreover, there are definite statistical properties and behaviors that have been shown to occur among the S-Curves of growth in power systems – interrelationships and correlations that can be used to improve load forecasts. Statistical analysis of area size, load characteristics, and other factors can be used to determine characteristics of the expected S-Curve's steepest ramp rate and period in a way that provides more forecasting accuracy than simple polynomial regression will provide. (Again, for more detail and explanation, see (Willis, Spatial Electric Load Forecasting, 2002) and (IEEE Power Engineering Society. Power Education Committee, 1992)).

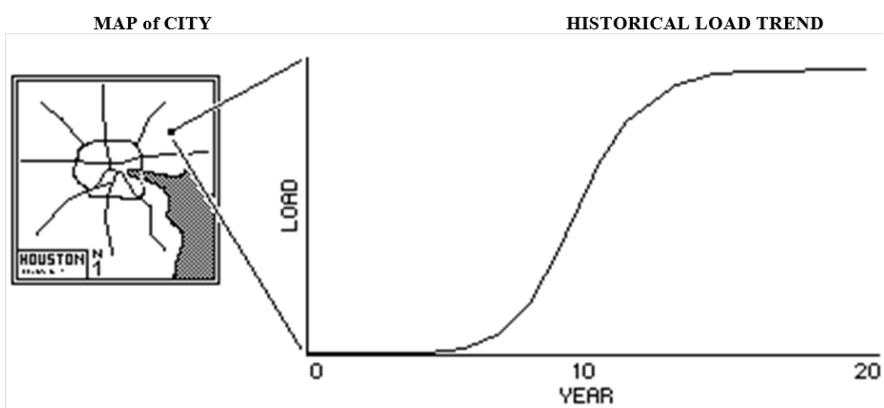

Figure 2-10. Example of the typical growth behavior of a mile-square small area within the city.

Figure 7.8 from (Willis, Spatial Electric Load Forecasting, 2002)*. Example of the typical growth behavior of a mile-square small area within the city. Once divided into "small enough" areas, growth in any region will display this characteristic. The 640 acre area experiences almost no growth for many years, then a period of rapid growth which lasts only a decade or slightly more will "fill it in."*

Quanta Technology picked this method for SCE's project because it has proven to be extremely reliable in similar projects, and because it can often be applied quickly and accurately in a short period of time (however, depending on the size of the study area and magnitude of data required can take several months just for data gathering and preparation). Growth of distributed energy resources was accounted in the forecast by considering that these resources are part of historic load data, and the considered trend was used toward future years in this study. The spatial load forecasting method discussed in Chapter 4 incorporates future DER growth using CEC IEPR forecast.

For the Trending-based forecast, the process of S-Curve fitting requires not only the historic data points, but also the determination of the horizon-year load; S-Curve fitting is done at the level of distribution substation load. On the other hand, for the spatial load forecast S-Curve fitting is done at the level of discrete smaller areas. Depending on the forecasting approach, the horizon year load has been determined in different ways, as discussed in Chapter 3 and in Chapter 4.

2.4 Horizon Year Definition

Land-use maps of General Plans were retrieved from publicly available community planning websites; the planning horizon for these maps ranged from year 2030 to year 2045. Community plans for long-term periods are usually ambitious to certain extent, and it is due to this uncertainty that it is reasonable to assume a common planning land-use horizon year which is farther in the future than that of the original plan.

Long-term planning typically looks from 25 to 30 years into the future, to a final year called the *horizon year*. While forecast periods for forecasting vary within the industry depending on the purpose of the forecast and utility, by far the most commonly used for forecasting and planning capital additions in utility's transmission and distribution systems is 25 or 30 years. There are several reasons for the selection of this time range period. A 25-year or 30-year planning horizon accommodates such things as the time required for regulatory licensing and permitting activities as well as lead times and financial budgeting for utility equipment and construction as required. Choosing a horizon of 25-30 years out is sufficient to provide a look at longer-term growth and equipment needs for several reasons.

1) Industry experience has shown that planning beyond the current lead times of equipment, to include an assessment of needs in the long term, is needed in order to do effective short and medium-range planning in the five to ten year ahead time frame (Willis & Brown, What Happens with a Lack of Long-Range T&D Infrastructure Planning, 2008).

2) This 25 to 30-year period provides a look at load growth and expected loading and use of equipment being planned for installation in the next five to ten years, over the first two decades of their service life, providing planners with a higher level of confidence that they are best matching the needs of the system in the longer term.

3) 30 years is also often used because it is consistent with the "monetary lifetime" of the equipment that will be on the utility's books with a depreciation schedule over 30 years, and is also compatible fully with present-worth (PW) or net-present value (NPV) calculations, which are most often done using that period.

4) There is no abiding reason to use any other length of period.

Considering the Valley North System and Valley South System load forecast must be designed for the long-term, the following assumption is made:

> *"All general plan land-use maps for Valley North and Valley South communities are assumed to be designed for the horizon year of 2048"*

3 TRENDING-BASED FORECAST

The approach for trend-based load forecasting of the Valley South and Valley North regions, starts by fitting S-Curves to historic distribution substation weather-normalized peak load data, and to an estimated horizon year load for that substation. Once the substation-level forecasts have been determined, results are then aggregated and adjusted to obtain the forecast at the radially-served transmission substation level at Valley Substation. The process is repeated for several sensitivity scenarios.

3.1 Determination of Horizon Year Load and Substation Load Forecasting

3.1.1 Step 1: First Estimation of Horizon-Year Load by Curve Fitting

The temperature-adjusted historic load information per distribution substation was utilized to make the first estimation of the horizon-year load. This analysis was done for all substations in the Valley South and Valley North regions. As an example, the results for Mayberry Substation 115/12 kV are shown in Figure 3-1, where it is shown how the historic load information for this substation is used to fit an S-Curve that estimates the future load at that substation. The first curve fitting results for all substations in the Valley South and Valley North regions can be found in the file **SCE Load Forecast.xlsx**, in the "**All Substations (I)**" sheet.

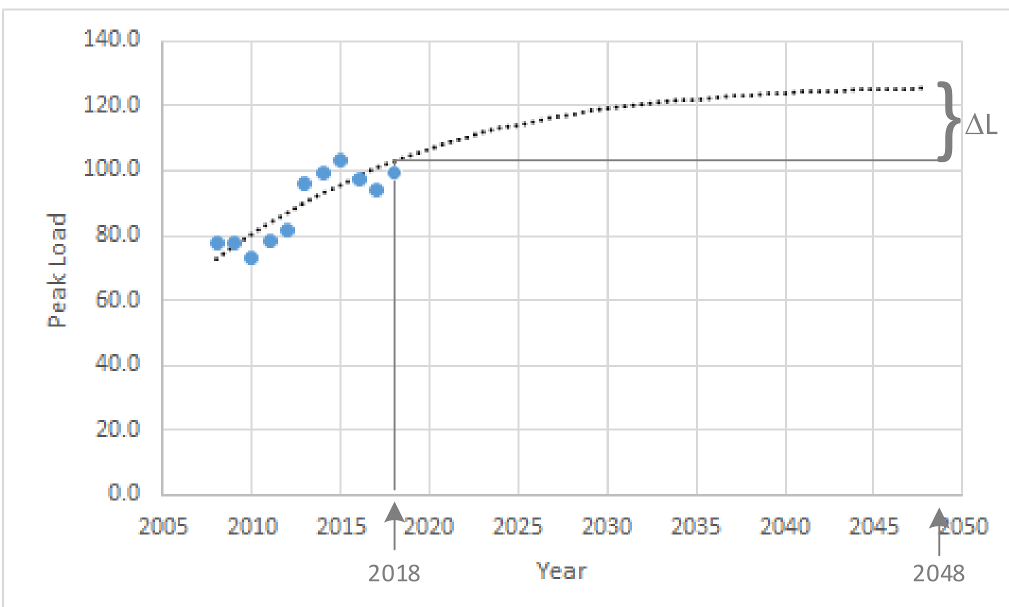

Figure 3-1. S-Curve fitting for Mayberry 115/12 kV Substation load.

The resulting curve is used to compute the expected load increment from the current year to the horizon year (ΔL). The way in which ΔL was applied, either to the maximum historic peak load of the last ten years or to the latest (2018) peak load, was considered as a variable in the sensitivity assessment for the load forecast.

3.1.2 Step 2: Estimation of Expected Load for Non-Traditional Developments

This step estimates those non-typical load developments that are not normally included in the historic peak load information. For this load forecast, the only type of future development that was identified as non-traditional was the expected new load that could result from cultivation of cannabis[4]. This type of load is expected to increase the energy demand of some existing loads or create new ones.

According to the estimates provided by SCE, the majority of load growth expected due to cannabis cultivation is expected to occur in other areas of its service territory, however, there is an expectation that a modest amount will occur in the Valley North and Valley South regions. SCE expects that the amount of this cultivation load is expected to be deployed from 2019 to 2021 in the amounts of approximately 5 MW in the Valley South region and 10 MW in the Valley North region. In this study, the expected new cultivation load was distributed in proportion to the number of metered customers in the substations of Elsinore in the Valley South System and Mayberry, Stetson, Nelson, Cajalco, and Moval in the Valley North System. The details of these results can be found in the **SCE Load Forecast.xlsx** file, in the "**All Substations (I)**" sheet.

The new cultivation load was considered as a variable in the sensitivity assessment of the forecast.

3.1.3 Step 3: Estimation of Expected Increment in Residential Load Density

As population grows in the Valley South and Valley North areas, the residential load density values may change which would affect the future load estimation. To quantify this effect, data from (Housing and Community Development. California, 2017), has been used to calculate the historic percentages by which "multi-family residential constructions" (mf) surpass the "single-family residential constructions" (sf). These percentages are listed in Table 3-1.

Table 3-1. Percentage by which Multi-family Residential Constructions (mf) Surpass Single Family Residential Constructions (sf)

Year	% mf > sf
2008	0.52%
2009	-13.13%
2010	-13.21%
2011	-6.74%
2012	-6.25%
2013	-0.70%
2014	2.79%
2015	4.27%

[4] The state of California approved approval of cannabis cultivation, but the level of acceptance is not expected to be uniform throughout the state, and some areas are more likely to increase load due to Cannabis cultivation, than others.

This information is used to approximate the percent difference between multifamily and single-family residential developments, by means of a trend line as shown in Figure 3-2. The resulting trend line allows inferring that by year 2048, multifamily residential developments will surpass by 59% the single-family residential developments.

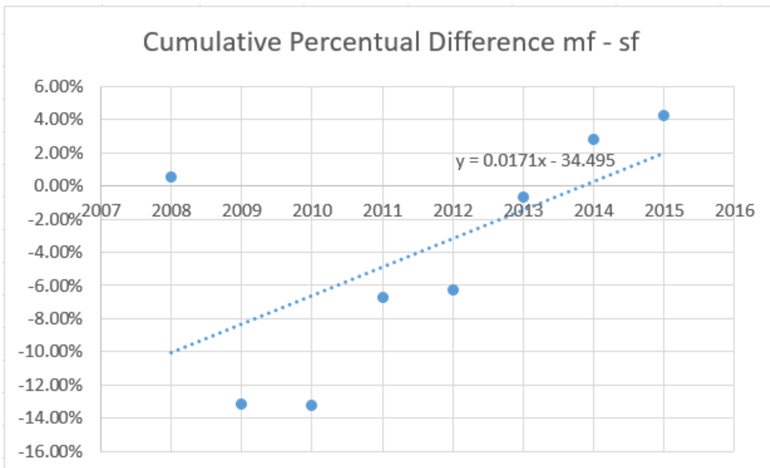

Figure 3-2. Trend of percent difference between multifamily and single-family residential developments

Considering a customer composition in the Valley North and Valley South areas as shown in Figure 3-3, and the multifamily and single-family proportions defined by the trend line of Figure 3-2, it can be estimated that in year 2018 there are approximate 411 MVA that correspond to multifamily residential load, and by year 2048 there will be approximately 207 MVA additional. This corresponds to an increase of 15% to the current multifamily proportion. This would result in an estimated future increase of 15% on the total load due to residential load density increase. This increase in residential load density is to be applied to the estimated growth ΔL determined in Step 1 (Section 3.1.1).

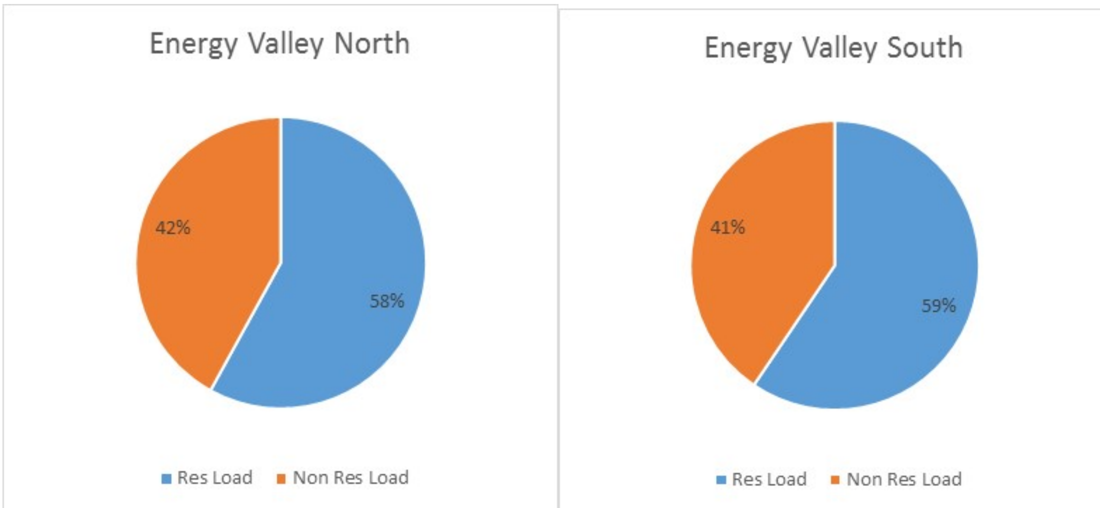

Figure 3-3. Residential and non-residential energy consumption in the Valley area.

The addition of the results from the three previous steps provides an estimate of the horizon-year load for each distribution substation. To complete the load forecasting at the substation level, S-Curves are fit to historic and horizon-year data to estimate the amounts of growth in all intermediate years. Figure 3-4 shows the results for the Mayberry 115/12 kV Substation. The results for all the substations in the Valley South and Valley North areas can be seen in the **SCE Load Forecast.xlsx** file, in the "**All Substations (II)**" sheet.

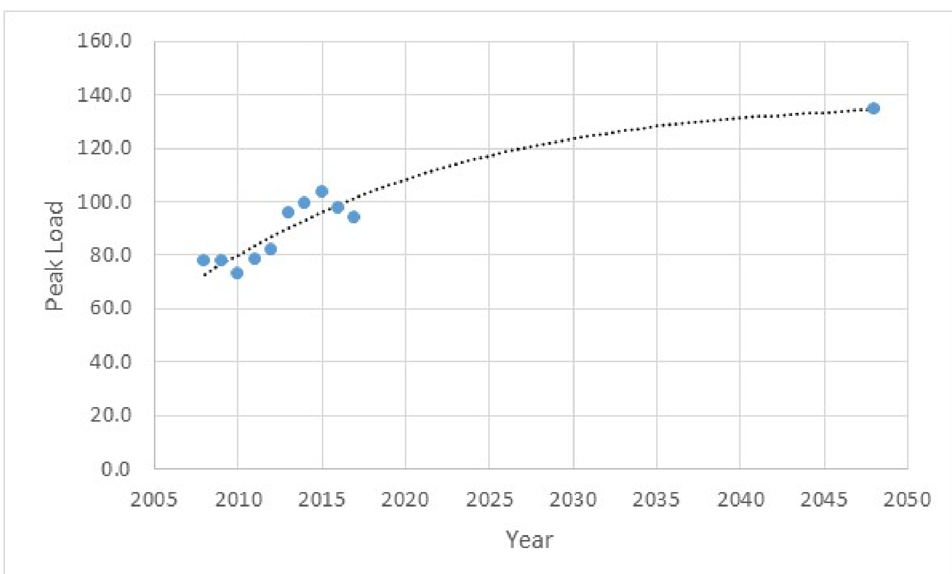

Figure 3-4. S-Curve fitting for the Mayberry 115/12 kV Substation.

3.2 Determination of Horizon-Year Load and Valley Load Forecasting

The summation of the estimated distribution substation horizon-year loads, for all substations in the Valley South and in the Valley North areas, produces a non-coincident horizon-year load at the Valley South and Valley North System levels, corresponding to normal-weather conditions. In order for these area load estimates to represent the coincident area load, a coincidence factor of 0.976 has been applied to Valley North, while 0.953 has been applied to Valley South[5].

A second adjustment is necessary to refer the normal-weather peak load estimates to those peak load values expected during 1-in-5 year heat storm temperatures. The Temperature – Load quadratic relationships shown in Figure 2-4 and Figure 2-6, were used in Section 2.2 to calculate the 1-in-5 weather-normalized load at Valley level. Each historic year from 2008 to 2018 resulted with a weather adjustment factor, dependent on the maximum temperature of each year. The maximum of those individual year factors is 1.175, and the average is 1.028. The maximum and the average weather adjustment factors were used in sensitivity scenarios: The maximum weather adjustment factor was applied to the Current Trend Scenario, and the average weather adjustment factor was used for the Reduced Trend, and for the Low forecasts.

After an appropriate horizon-year load was determined for the Valley South and Valley North areas, an S-Curve fitting was developed to estimate the forecasted load at all intermediate years between 2017 and 2048. Complete results for the Valley South and Valley North areas can be found in the **SCE Load Forecast.xlsx** file, in the "**Valley Historic**", and "**All Substations (II)**" sheets.

3.3 Sensitivity Analyses and Summary of Results

In order to account for the level of uncertainty that every long-term load forecast involves, a sensitivity analysis has been performed considering three variables:

- The way in which ΔL was applied, either to the maximum historic peak load of the last 10 years, or to the latest (2017) peak load
- New cannabis cultivation load considered or not considered
- Two different temperature adjustment factors: maximum or average

Cannabis cultivation load were considered as follows.

For the Valley South area, the planned cultivation load of 5 MW allocated to Elsinore Substation. For the Valley North area, the planned cultivation load was 10 MW allocated in proportion to the number of connected customers at the following substations: Cajalco, Mayberry, Moval, Nelson, and Stetson. The new cultivation load was assumed to grow linearly from year 2019 until year 2021. The Reduced Trend forecast accounts for 50% of the new cannabis cultivation load (i.e., 2.5 MW in Valley South and 5 MW in Valley North to be installed from year 2019 to year 2021). Three scenarios resulted from the combination of these variable considerations, as detailed in Table 3-2.

[5] Coincidence factors were computed by dividing historical total Valley North and Valley South System peak loads by the sum of the peak loads (at a coincident time) of all substations in each area respectively.

Table 3-2. Scenarios Resulting from the Sensitivity Analysis of Load Forecasting

Maximum Temperature Adjustment	Cultivation Load	ΔL Added to Maximum	Resulting Scenario	Results File
YES	YES	YES	Current Trend	SCE Load Forecast Current Trend, 2018_V21.xlsx
NO	50%	YES	Reduced Trend	SCE Load Forecast Reduced Trend, 2018_V21.xlsx
NO	NO	NO	Low Forecast	SCE Load Forecast Low, 2018_V21.xlsx

The three forecasts are labeled Current Trend, Reduced Trend, and Low Forecast. These represent scenarios of various expected economic and social conditions leading to different rates of growth and are described as follows:

- Current Trend: represents growth during a period of reasonably robust economic activity and growth. It represents a long-range growth rate over time where there is likely to be short periods of growth that exceeds the current trend and brief periods of economic downturn. Therefore, this forecast can be considered an extension of growth under a scenario of "current growth conditions continue" and is reasonable to carry forward as the likely expected trend.
- Reduced Trend: represents growth under a scenario of conditions in between current trend and low forecast.
- Low Forecast: represents growth under a scenario of substantially less growth, as would occur under a severe recession or other significant slowdown in the economy.

Table 3-3 summarizes the obtained results for the Valley South and Valley North System forecasts for the three studied sensitivity cases.

Figure 3-5 shows a comparison between the Current Trend, Reduced Trend, and Low Forecast for the Valley South region.

Table 3-3. Summary of Results for the Valley South and Valley North Forecasts for All Sensitivity Cases

Year	Current Trend		Reduced Trend		Low Forecast	
	Valley South [MVA]	Valley North [MVA]	Valley South [MVA]	Valley North [MVA]	Valley South [MVA]	Valley North [MVA]
2019	1081.0	777.4	1076.5	775.5	1072.6	773.1
2020	1093.5	788.0	1084.4	784.1	1076.7	779.3
2021	1107.8	802.0	1093.3	794.5	1080.8	785.6
2022	1122.3	816.2	1102.2	805.0	1084.9	792.0
2023	1136.9	830.6	1111.2	815.6	1089.1	798.4
2024	1150.1	841.8	1119.5	824.7	1093.2	804.8
2025	1163.4	853.1	1127.7	833.8	1097.4	811.3
2026	1176.9	864.6	1136.1	843.1	1101.6	817.9
2027	1190.5	876.3	1144.5	852.5	1105.8	824.5
2028	1204.4	888.2	1153.1	862.0	1110.0	831.2
CAGR	1.09%	1.34%	0.69%	1.06%	0.34%	0.73%

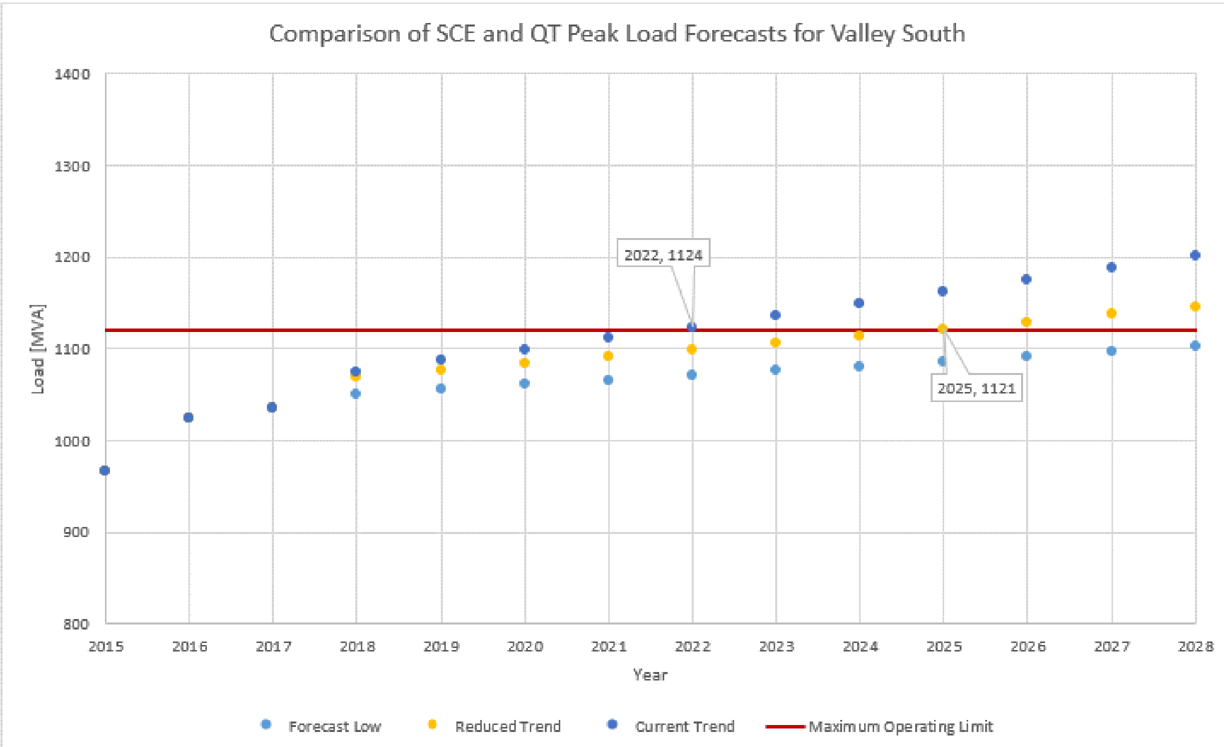

Figure 3-5. Comparison of Current Trend, Reduced Trend, and Low Forecast for the Valley South area.

4 SPATIAL LOAD FORECAST

The spatial load forecast developed for the Valley North and Valley South areas of the SCE System is based on land-use and is intended to forecast the peak load in the area for the future 30 years. Forecast results are estimations of future peak load values in the Valley South and North areas, with a resolution of 150 acres. The spatial load forecasting process is an improved S-Curve trending method that utilizes current land use and distribution peak load information, to determine load densities for each customer class or land uses[6]. This result, assisted by the planed land use of the region, is used to infer the horizon year load in a small-area basis. Results are then aggregated to give an estimated future peak load for the whole Valley South and Valley North regions.

The spatial load forecasting process has been conducted with INSITE. For further references on this software tool refer to Section 2.3.

4.1 Data Retrieval

The spatial load forecasting method requires much of the same information used in the trending-based forecast of Chapter 3. For example, temperature records, and historic peak load for the Valley North and Valley South Systems and their respective distribution substations, were utilized as part of the base information for the spatial method. Nevertheless, the addition of the spatial element and the increased confidence for the determination of horizon-year peak load, required a commensurate amount of additional information, as described in the following subsections.

4.1.1 Current and Future Land-Use Information

Current and future land-use information was compiled from several sources, including zoning and general and specific plan documents retrieved from publicly available documentation. SCE provided zoning and general plan information for the Riverside County; the rest was obtained from planning department websites for cities and communities of the Valley South and Valley North areas. Figure 4-1 and Figure 4-2 respectively show excerpts of the current and future land use maps that were compiled for all the study territory.

As mentioned in Section 2.4, general plan land-use maps corresponded to planning horizon ranging from year 2030 to year 2045. Considering that community plans for long-term periods are usually ambitious to certain extent, it is reasonable to assume a common planning land use horizon year which is farther in the future than that of the original plan. The following assumption was made:

> *"All general plan land use maps for Valley North and Valley South communities are assumed to be designed for the horizon year 2048"*

[6] Land uses are defined in Section 4.2.2

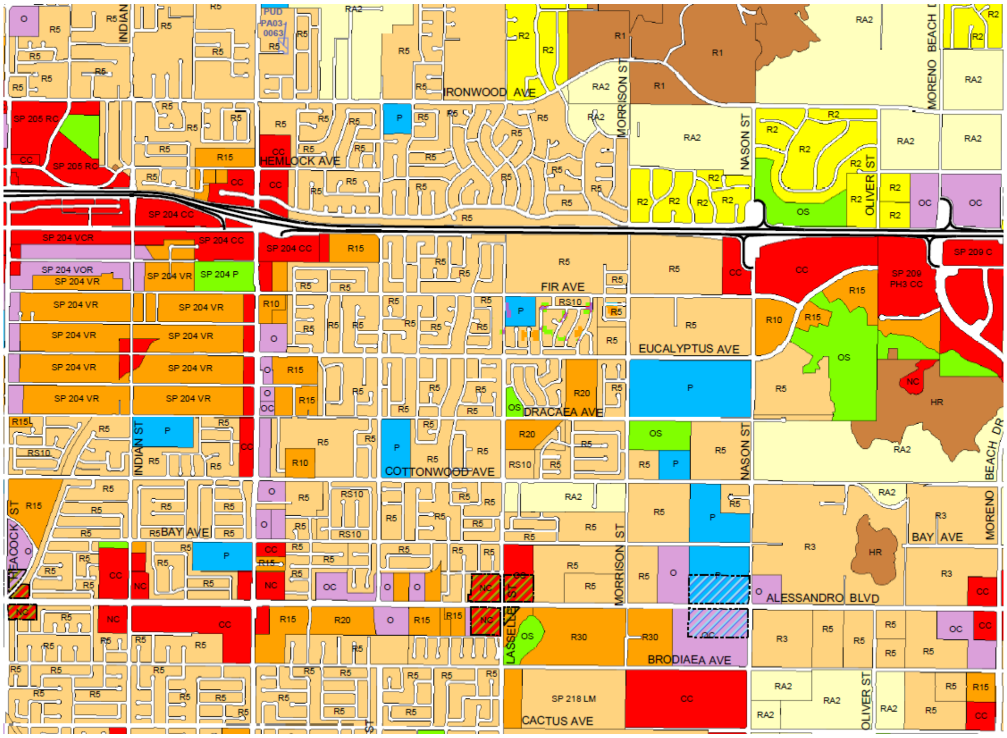

Figure 4-1. Excerpt of Current Land Use for Moreno Valley

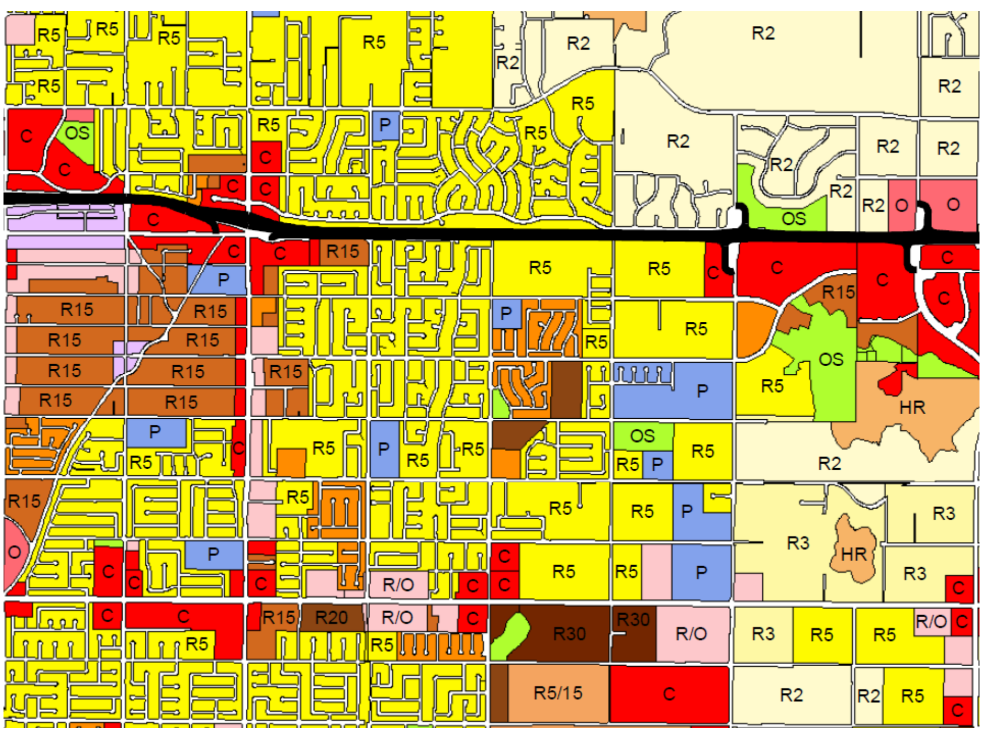

Figure 4-2. Excerpt of general plan for the City of Moreno Valley in the Valley North area.

4.1.2 Geo-referenced Peak Load Information

SCE provided annual peak demand and energy consumption information for 352,125 metered customers disseminated throughout the Valley South and Valley North regions. This information for each meter was accompanied by the corresponding address, customer class type, as well as the circuit and substation from which each customer was served.

4.2 Conditioning of INSITE

INSITE is the tool used to do most of the forecast calculations, and its conditioning consisted in adapting its format to the size and characteristics of the Valley System area. The size is defined by the grid resolution and the number of small areas to consider, and the characteristics are related to the number and type of defined land uses.

4.2.1 Grid Resolution and Small Areas

A grid covering the approximate 1,200 square mile area served by Valley Substation was defined with a resolution of 150 acres, which provides an adequate definition for a transmission-level load forecast. A resolution of 150 acres also happens to approximately match with the block size defined by main streets in urban areas, as shown in Figure 4-3. In total, the Valley South region was divided into 2,851 small areas, and the Valley North region was divided into 2,541 small areas; the forecasts were executed separately for each of the two regions.

Using geographic information system (GIS) data analysis tools, each small area was assigned with a sequential code number to serve as unique identifier. At the same time, geographic attributes were defined for each small area to mark their position in the study territory, as well as their area of coverage.

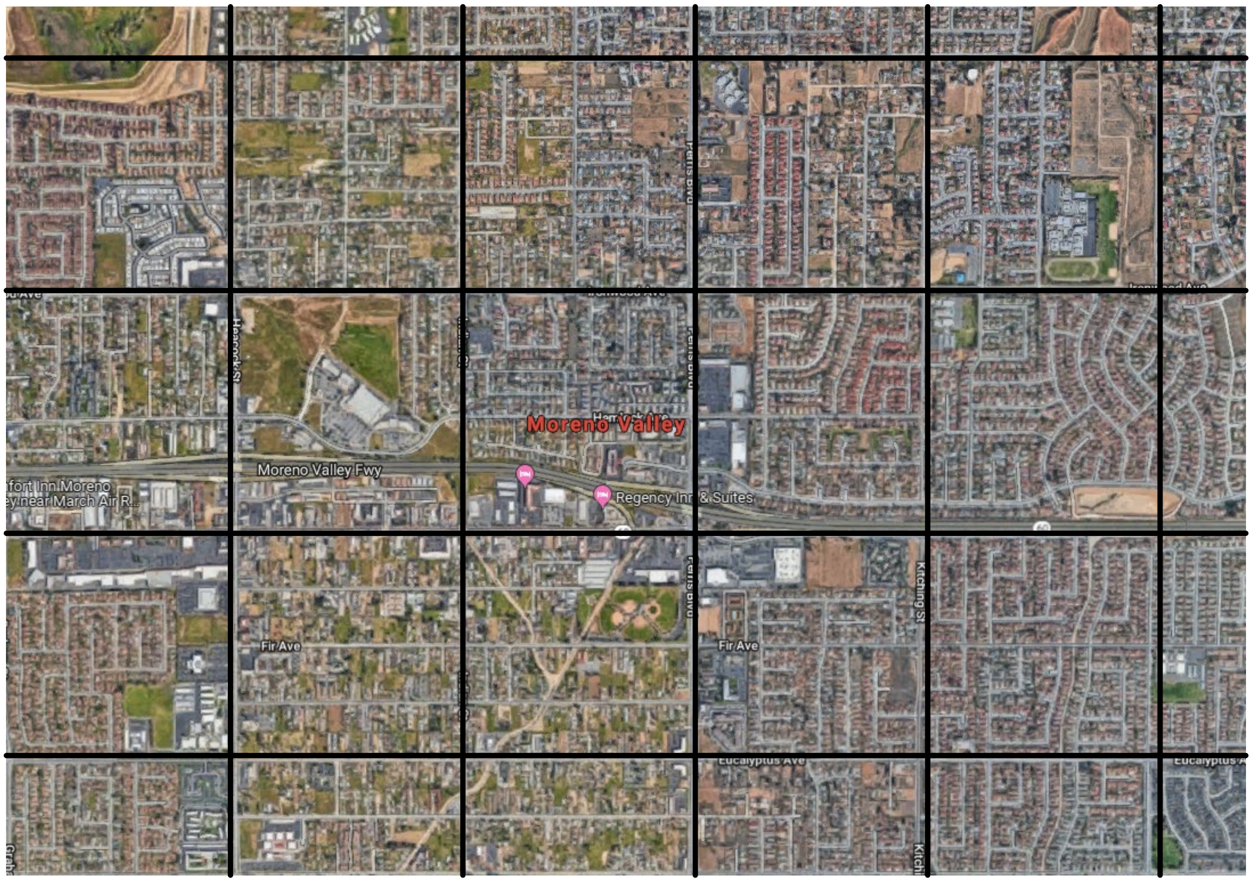

Figure 4-3. 150-acre grid resolution.

4.2.2 Land use definition

The current and future land-use maps were divided into 14 classes common to all communities. Each land-use was assigned a code number, where the composition of each small area was defined as a function of the land uses that fell within. Results were converted to the INSITE tabulated format. The list of land uses defined for the Valley South and Valley North areas are:

- High density residential
- Medium density residential
- Low density residential
- Retail commercial
- Industrial park
- Business park
- Public offices
- Airport
- Mixed use area
- Agriculture
- Open space
- Water space
- Highway
- Average load

Among the retrieved land use information for different communities, some cases were found to be of difficult classification under a common-to-all-communities list; for this reason, the average load category was created.

Using the retrieved maps described in Section 4.1.1, and assisted by GIS data processing, the current and future land use of each small area was defined. Figure 4-4 shows an example of the land-use definition for a particular small area comprised of 30% of public offices space, 25% of residential space, and 45% of open space. Table 4-1 shows the land use definition for a group of small areas as defined in INSITE.

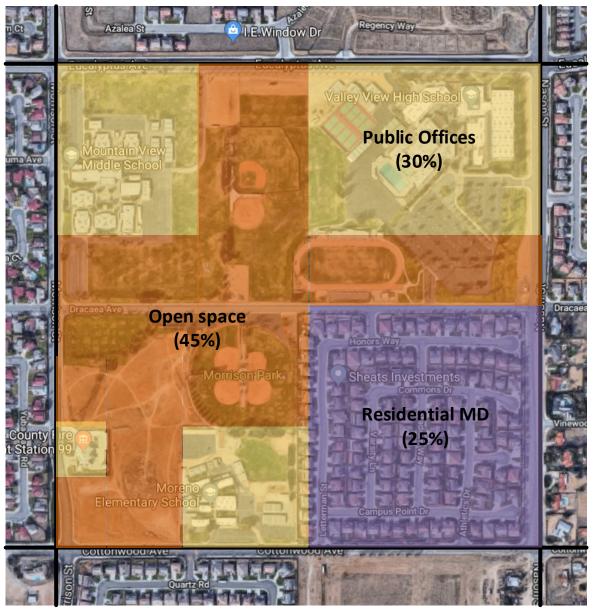

Figure 4-4. Example of land use definition for a single small area.

Table 4-1. Sample of land use definition in INSITE format

	Land Use Type					
	2	3	4	7	11	13
SHAPE NUMBER	Medium Density Residential	Low Density Residential	Retail/Community Commercial	Public Offices (including school)	Open Space	Highway
247	30%	3%	2%	0%	63%	2%
248	93%	1%	0%	0%	5%	0%
249	66%	0%	8%	13%	13%	0%
250	99%	0%	0%	1%	0%	0%
251	80%	0%	0%	0%	20%	0%
252	60%	0%	0%	0%	40%	0%
253	63%	34%	0%	0%	3%	0%

4.2.3 Distribution of Load in the INSITE Grid

The geographically referenced peak load information received from SCE consisted of peak demand and energy readings for 352,125 customer meters disseminated throughout the Valley South and Valley North regions; load information was accompanied with the physical address of the service points, meter classification type, and circuit and substation to which each meter is associated. The geo-referenced peak load data was used to proportionally distribute the Valley North and Valley South System load throughout the small areas. Results were converted to the INSITE tabulated format. The distribution of load throughout the study regions was done following the steps below.

Step 1: Distribution of the Valley South and Valley North areas recorded peak loads for year 2018 (Table 2-1) into meters in the whole study territory. To do this, the recorded peak load for individual meters was used as a proportionality factor. As a result, each meter was assigned with a portion of the coincident 2018 recorded peak load for the study region.

Step 2: Distribution of the historic recorded peak load (Table 2-1) into meters in the whole study territory. The same proportionality factors for meters computed in Step 1, were used to distribute the historic peak load information into the dispersed meters.

Step 3: Assignation of peak load to small areas. Assisted by GIS data processing and analysis, addresses associated to each meter in the study territory were positioned in a map, and linked to the specific small area. The approximated peak load (current and historic) for each small area resulted from the addition of all the adjusted meter loads that fell within the small areas.

Table 4-2 shows the distribution of peak load for a group of small areas, in the format used for INSITE.

Table 4-2. Sample of the load history in kVA distributed for a group of small areas

SHAPE NUMBER	COORD. X	COORD. Y	Year							
			2011	2012	2013	2014	2015	2016	2017	2018
2522	6271615	2205520	2135	2144	2072	2137	2036	2180	2188	2299
2523	6274171	2205520	5628	5652	5463	5634	5366	5746	5768	6060
2524	6276727	2205520	1430	1437	1389	1432	1364	1460	1466	1540
2525	6279283	2205520	1687	1695	1638	1689	1609	1723	1729	1817
2526	6281839	2205520	1912	1920	1856	1914	1823	1952	1960	2059
2527	6284395	2205520	581	584	564	582	554	594	596	626
2528	6286951	2205520	1172	1177	1137	1173	1117	1196	1201	1262
2529	6289507	2205520	1237	1243	1201	1239	1180	1263	1268	1332
2530	6292063	2205520	617	619	599	617	588	630	632	664
2531	6294619	2205520	47	47	46	47	45	48	48	51

4.3 INSITE Execution

The INSITE process is based on three modules: Weather Normalization, Horizon Year, and the main engine. The tool flowchart is depicted in Figure 4-5.

a. Weather Normalization module: takes the most recent eight years of system level total load to calculate the weather-normalized load.
b. Horizon Year Load (HYL) Solver module: takes the most recent historical load and the corresponding current land-use information to calculate the load densities of each land use type, and then based on the future land- use information calculates the HYL for each small area.
c. Engine module: takes the historical load and HYL as the inputs to execute a hierarchical trending method through a bottom-up aggregation and a top-down allocation to obtain the raw forecast for each small area, and then performs post-process on the raw forecast to generate the final forecast in both data and map format.

The following sections cover the process and results for the three INSITE modules.

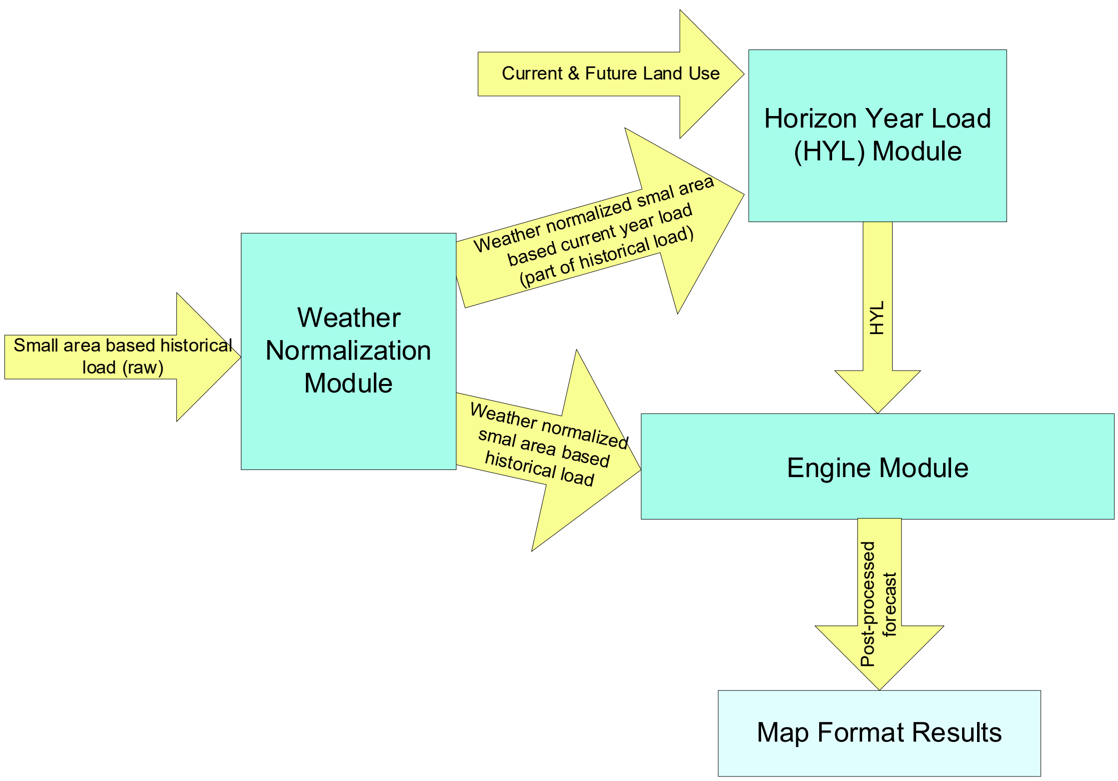

Figure 4-5. Overview of INSITE structure.

4.3.1 Weather Normalization

The Weather Normalization module requires temperature[7], number of cooling degree days, and demographic information. The reference temperature for 1-in-5 year heat conditions was determined from historical temperatures as described in Section 2.2. The number of cooling degree days was computed based on historical temperature data. Population statistics were obtained from publicly available sources. The result of this step is a weather-normalized historic load data set at the small-area level. Additional details on weather normalization is presented in Section 2.2.

The output of the Weather Normalization module is a table of the historic load information as described in Section 4.2.3, but with adjusted values after compensating for weather variations. A sample of the results of the Weather Normalization module are shown in Table 4-3, for the same small area reported in Table 4-2.

Table 4-3. Sample of the load history in kVA distributed for a group of small areas after weather normalization

SHAPE NUMBER	COORD. X	COORD. Y	Year							
			2011	2012	2013	2014	2015	2016	2017	2018
2522	6271615	2205520	2039	2069	2106	2153	2194	2236	2279	2322
2523	6274171	2205520	5375	5455	5553	5674	5784	5894	6006	6120
2524	6276727	2205520	1366	1387	1411	1442	1470	1498	1527	1556
2525	6279283	2205520	1612	1636	1665	1702	1734	1767	1801	1835
2526	6281839	2205520	1826	1853	1887	1928	1965	2002	2041	2079
2527	6284395	2205520	555	564	574	586	598	609	620	632
2528	6286951	2205520	1119	1136	1156	1181	1204	1227	1250	1274
2529	6289507	2205520	1182	1199	1221	1248	1272	1296	1321	1346
2530	6292063	2205520	589	598	609	622	634	646	658	671
2531	6294619	2205520	45	46	47	48	49	49	50	51

4.3.2 Horizon Year Load Module

The Horizon Year Load module includes a solver that estimates the load for each small area in the service territory, as it is forecast to be in the horizon year, which in this case is year 2048. To do this task the module requires the weather-normalized, small-area based historical load that comes from the Weather Normalization module (Section 4.3.1), and the current and future land-use definitions for each small area (Section 4.1.1).

The Horizon Year module considers all small areas to compute the total area corresponding to each land-use type, as well as the total peak load for each land-use type. These results are then used to compute equivalent load densities for each land–use type, corresponding to current year. Load density results for the Valley South region are summarized in Table 4-4.

[7] Reference temperature was based on historic temperature records as explained in Section 2.2.

Table 4-4. Summary of land use information and load density

Type	Current Acreage	Future Acreage	Load Density [kW/acre]	Load Percentage
High Density Residential	1905	6418	33.9	12.9%
Medium Density Residential	28389	46860	15.1	42.0%
Low Density Residential	89407	116211	1.8	12.4%
Retail/Community Commercial	4555	8598	18.3	9.4%
Industrial Park	7027	11709	11.5	8.0%
Business Park	1928	2990	19.2	3.4%
Public Offices (including school)	5662	8455	8.2	4.1%
Airport	38	38	34.5	0.1%
Mixed Use Area	2806	3284	1.0	0.2%
Agriculture	27949	20698	0.4	0.5%
Open Space	254745	188888	0.0	0.0%
Water Space	2625	3458	0.0	0.0%
Highway	599	2161	0.5	0.1%
Average Load SP	0	7869	15.0	7.0%

Horizon year load values for each small area are determined based on load densities and future land uses. It is worth noting that the horizon year load values are computed assuming a constant load density. For this reason, results at this stage are carefully reviewed to make sure they correspond to realistic expectations. A sample of results obtained out of the Horizon Year module of INSITE are shown in Table 4-5. These values were used for S-Curve fitting in the next module.

Table 4-5. Sample of results out of the Horizon Year module

Shape Number	Horizon Year Load [MW]	Base Year Load [MW]
2556	176	175
2557	329	328
2558	270	80
2559	167	127
2560	0	0
2561	4	0
2562	0	0
2563	79	78
2564	12	11
2565	1760	9
2566	1736	903
2567	1900	1899
2568	1700	1699
2569	532	411
2570	439	331
2571	24	23

4.3.3 INSITE Engine

Based on the outputs from the Weather Normalization and Horizon Year Load modules, at this point of the process all the necessary information is available for the INSITE Engine module to perform the S-Curve fitting task for each small area. This is to say, each small area has an associated set of data representing weather-normalized historic peak load and horizon year peak load.

S-Curve fitting computes a set of parameters K_1, K_2, K_3, and K_4 for the generic function:

$$f(t) = \frac{K_1}{1 + e^{K_2(t-K_3)}} + K_4$$

One S-Curve is obtained for each small area, representing the estimated evolution of load from the base year until the horizon year (2048). After careful revision of the module's raw outputs, the results of this step include a detailed forecasted of peak load values for each of the small areas as well as for the entire Valley Substation service territory.

Table 4-6. Results at Valley-level without additional effect of future DER

Year	Spatial V. South (No added DER) [MVA]	Spatial V. North (No added DER) [MVA]
2019	1092	787
2020	1116	804
2021	1142	825
2022	1162	845
2023	1181	857
2024	1193	866
2025	1205	874
2026	1217	882
2027	1229	893
2028	1242	904

4.3.4 Adjustment for future DER developments

The final step of the forecast consists in aggregating to the spatial forecast data obtained in Section 4.3.3, the effects of future developments on Photovoltaic, Electric Vehicles, Energy Efficiency, Energy Storage, and Load Modifying Demand Response, as defined in the IEPR 2018 forecast (California Energy Commission, 2018). These additional DER resources are expected to result in a net reduction of peak load.

For the years through 2028, the 2018 IEPR forecasts at the state and SCE system levels, are brought to Valley North and Valley South level. The IEPR 2018 forecasts were disaggregated (by SCE) to the level of the Valley South and Valley North Systems, for Additional Achievable Energy Efficiency (AAEE), Additional Achievable Photovoltaic (AAPV), Electric Vehicles, Energy storage, and Load Modifying Demand Response (LMDR). SCE provided the inputs for this task, and are summarized in Table 4-7. These load values should be interpreted as peak-modifying elements, which in general result in a reduced future load forecast when compared to the forecast described in Section 4.3.3.

Table 4-7. Disaggregated peak load reduction for future DER developments in MVA

	DER Type	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028
Valley North	AAPV [MVA]	-4.9	-4.9	-4.9	-4.9	-4.9	-4.5	-4.0	-3.7	-3.7	-2.9
	Electric Vehicle [MVA]	0.3	0.4	0.3	0.4	0.4	0.4	0.4	0.2	0.2	0.3
	AAEE [MVA]	-2.3	-2.1	-2.6	-2.8	-3.2	-2.9	-2.8	-2.7	-2.8	-2.9
	Energy Storage [MVA]	-0.5	-0.1	-0.1	-0.2	-0.2	-0.2	-0.1	-0.1	-0.1	-0.1
	LMDR [MVA]	0.0	-0.5	0.0	-0.1	-0.2	-0.1	-0.1	0.0	0.0	0.0
Valley South	AAPV [MVA]	-5.7	-5.0	-4.2	-3.4	-3.0	-2.8	-2.7	-2.4	-2.1	-1.9
	Electric Vehicle [MVA]	0.8	0.9	0.8	0.6	0.7	0.6	0.6	0.4	0.4	0.4
	AAEE [MVA]	-3.4	-2.9	-3.6	-2.6	-3.0	-2.8	-2.7	-2.5	-2.6	-2.8
	Energy Storage [MVA]	-1.0	-0.1	-0.2	-0.2	-0.2	-0.1	-0.1	-0.1	-0.1	-0.1
	LMDR [MVA]	0.6	-1.4	0.0	-0.2	-0.2	-0.1	-0.1	0.0	0.0	0.0
	Total	**-16.2**	**-15.6**	**-14.4**	**-13.4**	**-13.7**	**-12.4**	**-11.6**	**-10.8**	**-10.7**	**-10.1**

The peak-load modifying amounts of Table 4-7 are applied to the Valley South and Valley North system level base case spatial forecast of Section 4.3.3. The resulting adjusted forecast at high-level is then scaled down proportionally to the small area level, attaining the outcome of the higher-level spatial load forecast while also being consistent with the IEPR forecast.

Table 4-8 shows the results for the spatial load forecast at the level of the Valley South and Valley North Systems, after the effect of future DER developments have been considered. Figure 4-6 to Figure 4-8 show the forecasted spatial load forecast distribution of load for years 2019, 2022, and 2029 for the Valley South region. Similarly, Figure 4-9 to Figure 4-11 show the forecasted spatial distribution of load for the same years for the Valley North region.

Table 4-8. Spatial forecast results at Valley South and North System level

Year	Spatial Forecast Valley South [MVA]	Spatial Forecast Valley North [MVA]
2019	1083	779
2020	1099	789
2021	1118	803
2022	1132	816
2023	1146	820
2024	1152	821
2025	1159	823
2026	1166	825
2027	1174	829
2028	1183	834

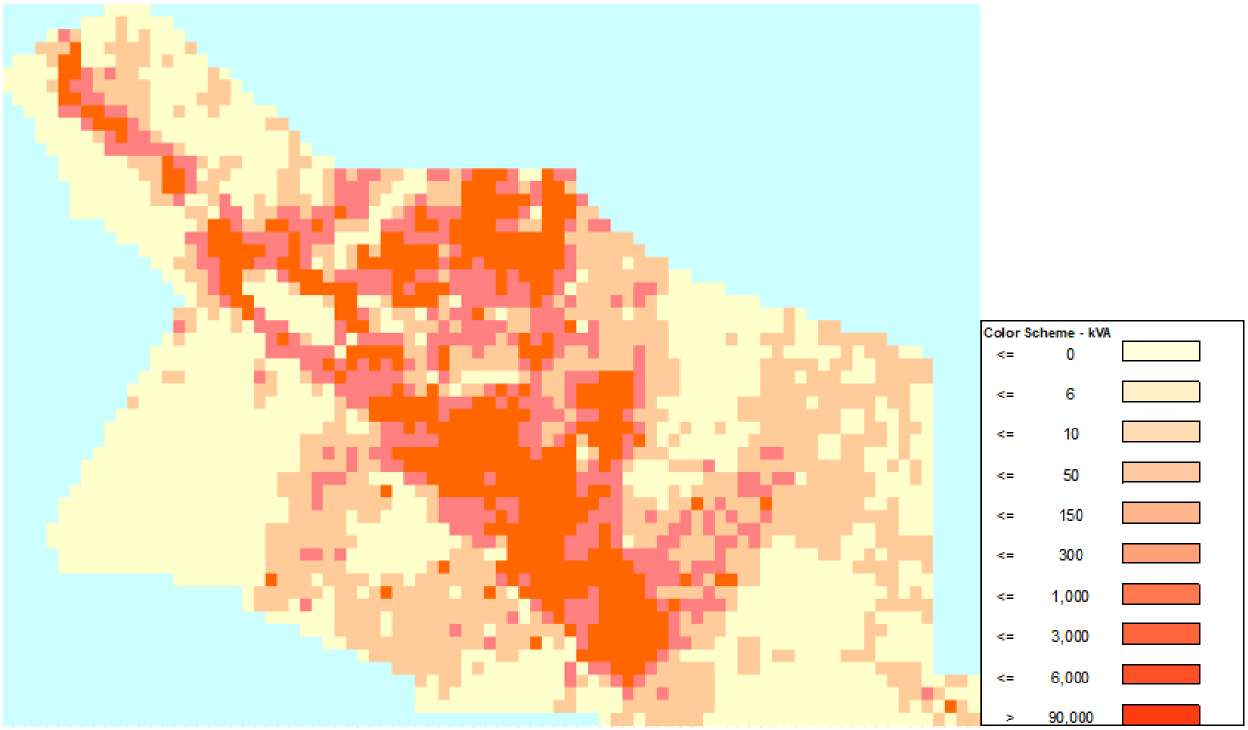

Figure 4-6. Spatial load forecast distribution for Valley South, year 2019 (1,083 MVA)

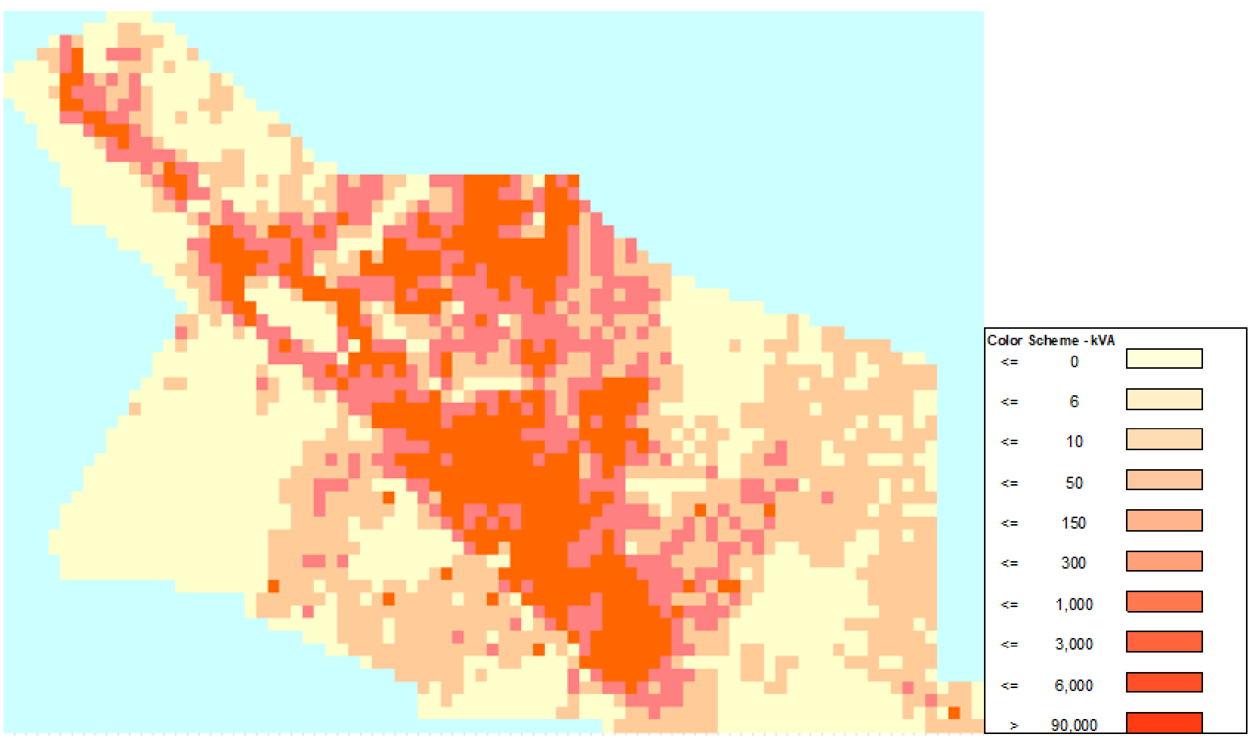

Figure 4-7. Spatial load forecast distribution for Valley South, year 2022 (1,132 MVA)

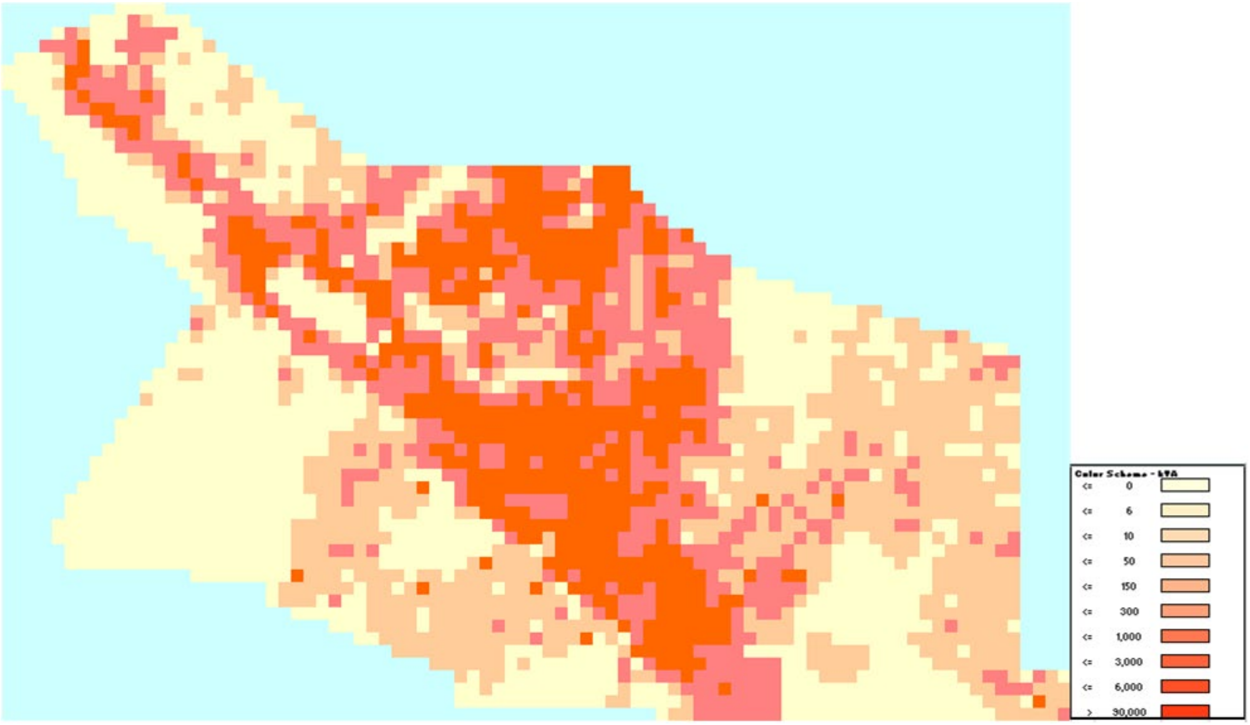

Figure 4-8. Spatial load forecast distribution for Valley South, year 2028 (1,183 MVA).

Figure 4-9. Spatial load forecast distribution for Valley North, year 2019 (769 MVA).

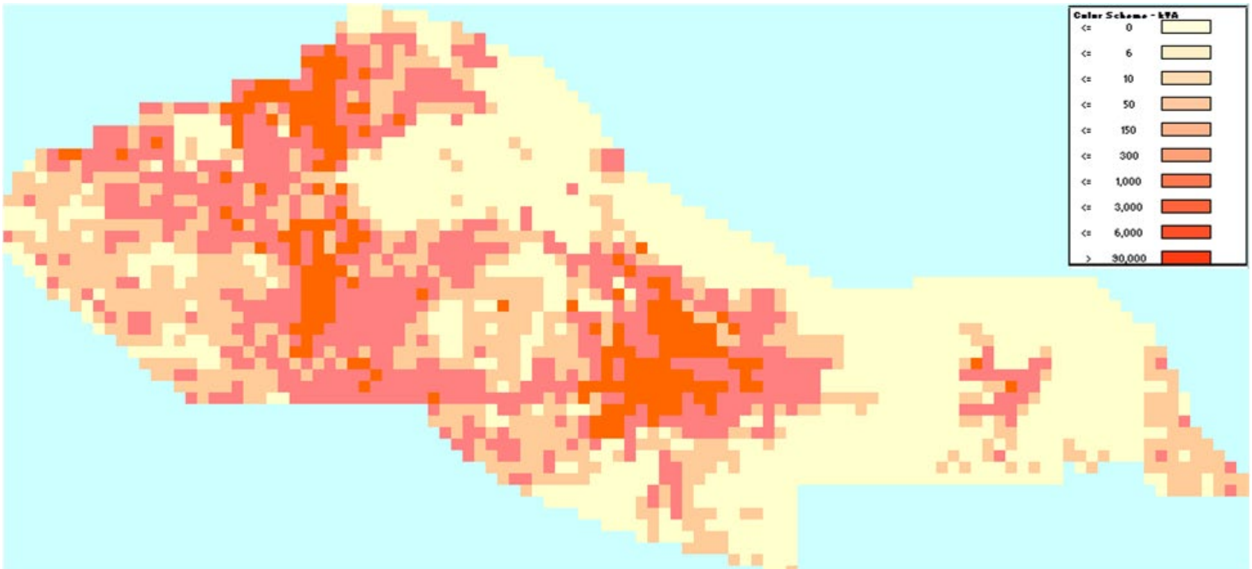

Figure 4-10. Spatial load forecast distribution for Valley North, year 2022 (816 MVA).

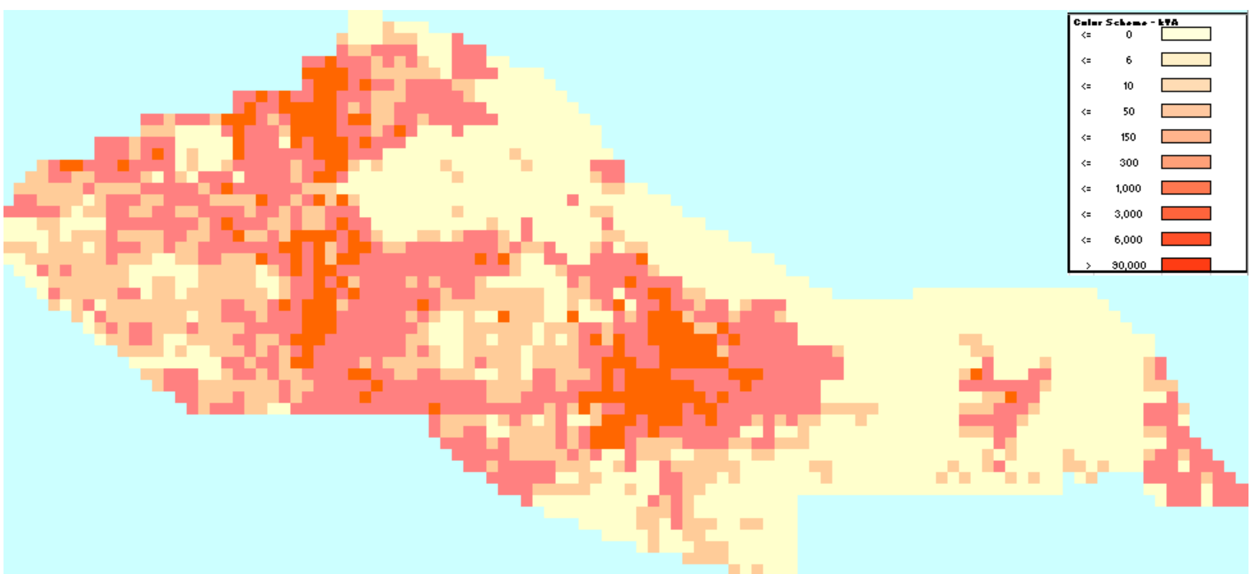

Figure 4-11. Spatial load forecast distribution for Valley North, year 2028 (834 MVA).

5 CONCLUSIONS

Two forecast methodologies have been implemented to the Valley South and Valley North regions within the SCE service territory served by Valley Substation. The aim has been to produce two long-term peak load forecasts using industry-recognized methods, to provide results that can be used confidently (with reasonable assumptions and expectations) to assess the electrical system needs of the area served by Valley Substation and for use in evaluating a range of alternative projects required to meet those needs.

The first method is a trending-based forecast that relies on historic peak load data. S-Curve fitting has been used to emulate the natural behavior of load evolution over time. The second method adds the spatial element for the interpretation of land-use information. It produces results with a higher degree of certainty and resolution, based on the fact it is supported by community general and specific plans for land future development.

The results for the two forecasting methods are summarized in Figure 5-1 and Figure 5-2 for the Valley South and Valley North Systems, respectively. It can be observed that the spatial method starts with a rate of growth that reduces after 5 to 6 years. With respect to the Valley South System, both sets of results are consistent, identifying the year 2022 as the year when the total area peak demand load is expected to exceed the amount of installed transformation capacity (1,120 MVA).

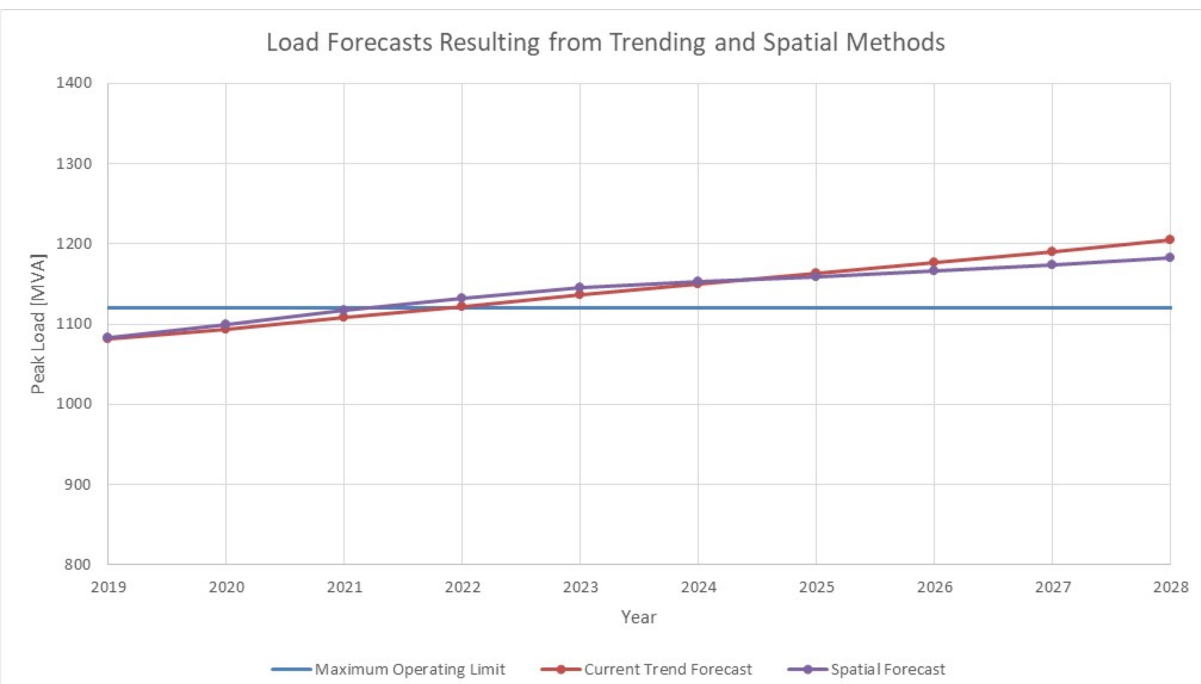

Figure 5-1. Comparison of Trending-based and Spatial load forecasts for the Valley South System.

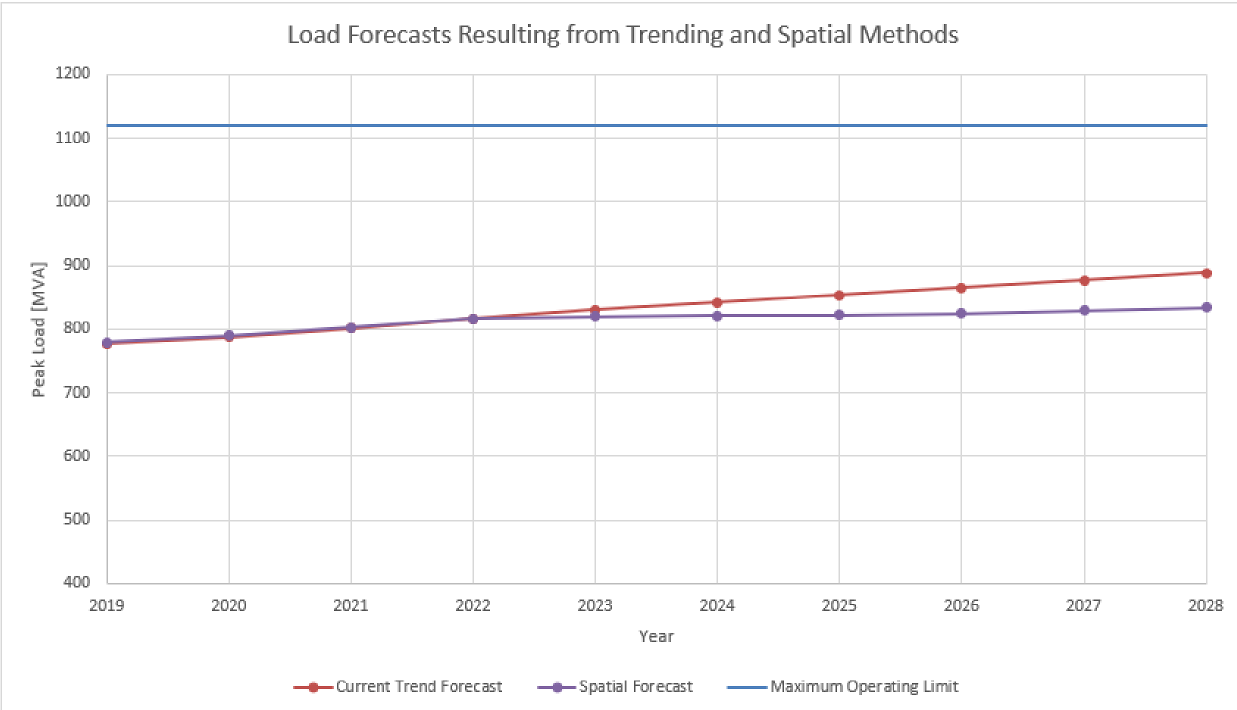

Figure 5-2. Comparison of Trending-based and Spatial forecasts for Valley North.

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