Ancillary Service Requirements Analysis with Increasing Solar Generation in the ERCOT Interconnection.

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Abstract*—The increment of solar generation in an electric system will introduce significant variations to its generation supply, compromising the reliability of the system. These variations need to be balanced by counter actions that are provided by other system elements which are procured by the independent system operator (ISO). These counter measures are known as ancillary services. The Electric Reliability Council of Texas (ERCOT) procures ancillary services in order to reduce the instantaneous mismatch between generation and demand. This allows to maintain the frequency and reliability of the electric system [1]. In the last few years, there has been an exponential increase in solar capacity in the ERCOT system, increasing the need for ancillary services. This has lead to the creation of a new methodology to determine ancillary service requirements in order to accommodate the new variables in reliability that renewable generation capacity brings. This paper presents the methodology and associated tool to calculate the ancillary services requirements when solar generation capacity is increased in the system. The methodology and its implementation guide ERCOT and the Public Utility of Texas (PUCT) when evaluating reliability requirements in solar capacity. This allows the creation of policy and protocols to maximize solar energy's economic and electric benefits [2].

I. Introduction

In order to meet the demand, and maintain the frequency, the independent system operator has to dispatch generation instantaneously that will match the demand exactly. When the demand is not met, voltage and frequency problems arise, compromising the system. Ancillary Services must be deployed in order to make up for this discrepancy between instantaneous demand and load. There are three main types of ancillary services that ERCOT procures: Regulation Services, Responsive Reserve, and Non-Spinning Reserve Service [3]. Ancillary services are essential to ISO's since they provide frequency control, voltage control and reliability. Today, ERCOT is one of the most competitive electricity markets in the world. From the time that Senate Bill 7, Texas surpassed its goal of 2,880 MW of wind power capacity [1], Texas has since followed this trend and added more than 23,860 MW of wind power capacity to its system. However, in the next two years (2021, 2022), ERCOT is projected to add around 9,865 MW of solar capacity [4]. Along with the increase of renewable energy generation capacity, ERCOT has had to rethink how to determine the ancillary service requirements. ERCOT has developed methods to take into account the increase in renewable generating capacity and still procure sufficient ancillary services.

Similar studies have been performed at ERCOT in the past. In 2008, General Electric (GE) analyzed the increase of the wind capacity from 2008 to 2012, multiple potential scenarios were created from 5,000 MW to 15,000 MW of wind capacity increase and then analyzed how it would affect regulation up/down procurement [5]. Then, in 2012 a Matlab based script was developed to analyze the effect of the increase of wind capacity. The output were tables of 12 months by 24 hours that show the show how ancillary services must be procured [6]. For practical reasons, these tables are commonly referred in ERCOT as 'GE' Tables.

A. Motivation

This project was created based on the need to develop a method to easily calculate the impact of solar capacity generation on up/down regulation ancillary services. As non-constant renewable energy technologies market share increases in Texas (and the world), ancillary services must be adapted accordingly. This paper outlines the process of creating a new Python based tool to determine ancillary service requirements and validate its functionality. The tool has been designed to work with different data sets and it is to be used in current and future analysis. The final product of the tool are 'GE' Tables which only refer to how the increase of solar capacity will affect up/down regulation procurement.

B. Contribution

The contributions of this paper are the following: 1) Outline a new methodology to determine ancillary service requirements in relation with the increase of solar installed capacity.

2) Assess the impact of different scenarios for various solar installed capacity scenarios. 3) A flexible Python tool that can be used for current and future studies. 4) Provide a concrete recommendation for ancillary service requirements taking into account increasing solar installed capacity.

C. Paper Organization

The first section of the paper outlines the project's objective and motivation. Section II will overview the project and the Python tool. Section III describes the proposed methodology for regulation requirements calculation. Section V reports the results of the tool validations. Finally Section VII provides the conclusion, final recommendations and outlines the project's future work.

II. Project Overview

The ERCOT system has seen a large increase of solar installed capacity. As seen in Table 1, ERCOT expects to have 15,666 MW added by 2022. ERCOT must analyze and prepare for the impact of the new solar power injections in the ancillary service quantities (Regulation & Non-Spin). Table I contains the yearly amount of solar additions predicted by ERCOT [7].

TABLE I
ERCOT Solar Additions by year as of May 31, 2020 (taking into account MW Installed, Synchronized, IA Signed-Financial Security Posted, and IA Signed-No Financial Security)

Year	PVGR MW Additions
2017	1,069
2018	1,858
2019	2,281
2020	5,801
2021	13,671

In order to account for various possibilities, six scenarios relative to the photo-voltaic generation (PVGR) were created. In addition, these PVGR forecast (PVGRF) scenarios have 2 different forecasting methods to increase the accuracy of the study. The PVGRF methods are covered in Section IV. The scenarios are:

- **Scenario 1:** Less than Expected Generation-(0% PVGR).
- **Scenario 2:** Less than Expected Generation-(33% PVGR).
- **Scenario 3:** Less than Expected Generation-(66% PVGR).
- **Scenario 4:** Expected PVGR Generation-(100% PVGR).
- **Scenario 5:** More than Expected PVGR Generation-(200% PVGR).
- **Scenario 6:** More than Expected PVGR Generation-(300% PVGR).

A. Calculation Tool Overview

The tool was developed in Python 3.6 using Jupyter Notebooks. The tool's **inputs** are: ERCOT's load and generation MW levels every minute along with PVGR capacity per month per year. This data comes from ERCOT's internal database. The **outputs** of the tool are: Raw Data, Regulation Requirements Tables, Scenario Comparison, 'GE' Regulation Tables, and 'GE' Regulation Tables Contour Plots. The tool and the input data are completely standalone, they do not rely on any other tool other than Python and the following Python libraries: NumPy [8], pandas [9], pylab, matplotlib [10], scipy [11], os and shutil. The methodology & tool workflow is shown in Fig. 1.

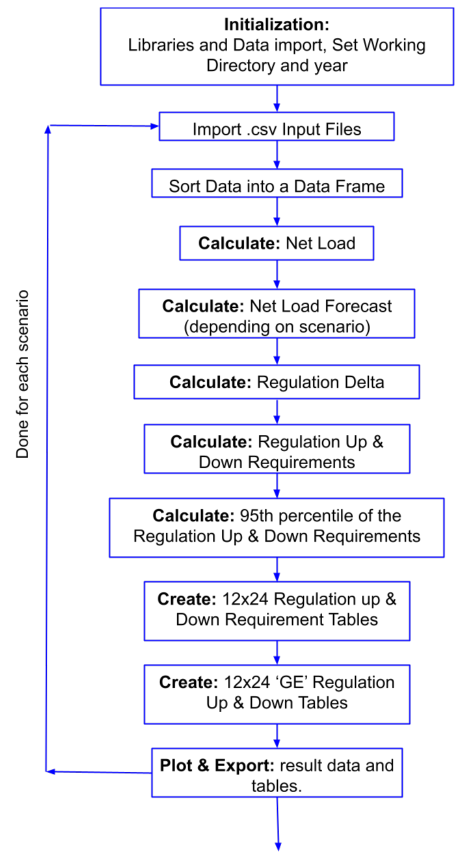

Fig. 1. Methodology & Python Tool Workflow.

B. Input

The tool calculates all of the scenarios iteratively given the year the user selected.The input files for the tool are .csv files where the columns are the different measurements(load, generation) and the rows are time stamps as seen in Fig. 2.

C. Output

Once the routine has been completed, the user will find a folder named after the year that was analyzed, and inside that, a folder per scenario. Finally, inside each of the scenario folders the user will find all of the results: Up/down regulation requirements tables, up/down regulation contour plots, sorted input data, 'GE' Tables for up/down regulation, 'GE' Requirements contour plots, input data visualization and a scenario comparison.

III. Regulation Requirements Calculation Methodology

In order to calculate the regulation requirements, the Python script will iteratively follow the workflow depicted in Fig. 1. The output of this process are regulation up and regulation down tables which state the amount of regulation needed for each hour of every month (for a given year). Here are the steps:

A. Data Import & Data Frame Time Sorting

For the desired year, 1 minute interval yearly Load, Wind Generation and Solar generation (PVGR) data was pulled and ordered into a 525,600 x 4 matrix. Once the script has imported the .csv matrix, the file will be imported into a Pandas Data Frame with Python. Then we will be able to produce a Data Frame that sorts all of the data into month, day, hour, 5 minute and minute intervals. This step is key in order be able to perform further statistical and mathematical calculations. Once sorted, the input data looks like Fig. 2.

TIME	MONTH	DAY	HOUR	FIVEMINUTE	MINUTE	LOAD	PVGR	WIND
2019-01-01 00:00:00	1	1	0	0.0	0	36947.06784	0	14114.89714
2019-01-01 00:01:00	1	1	0	0.0	1	36923.13438	0	14119.72572
2019-01-01 00:02:00	1	1	0	0.0	2	36901.43307	0	14172.24603
2019-01-01 00:03:00	1	1	0	0.0	3	36873.80938	0	14214.50117
2019-01-01 00:04:00	1	1	0	0.0	4	36861.11862	0	14217.50182
...	...	...	...	...	...	...	...	...

Fig. 2. Example of time sorted data.

B. Regulation Requirements Calculation

Once the input data is sorted, the regulation requirements must be determined. For this, Net Load (NL), Net Load for Regulation, and the Regulation Delta are going to be calculated.

1) Net Load: Net Load is defined as the aggregate load demand minus aggregate wind generation minus aggregate PVGR generation. All of these values come from 1 minute data. Therefore, Net Load is a 1 minute instant value. Equation 1 outlines Net Load 1 minute calculation:

$$Net\ Load = Load - Wind - PVGR \tag{1}$$

2) Net Load Forecast: Since Security Constrained Economic Dispatch (SCED) is run every 5 minutes at ERCOT, a PVGRF will be produced for every 5 minute interval. Net Load Forecast (NLF) is described in Equation 2 which depends on the different PVGRF methods that may be chosen for the particular study [12].

$$NLF = Load - Wind - PVGRF \tag{2}$$

3) Regulation Delta: Once the Net Load and NLF have been calculated, Regulation Delta is defined as: the difference between the 1 minute Net Load (that does not take into account any PVGR addition) and the Net Load values from taking into account the different PVGRF scenarios (NLF). This mismatch is the regulation requirements at each 5 minute interval for the year.

$$Regulation\ Delta = Net\ Load - NLF \tag{3}$$

4) Regulation Up & Regulation Down Tables: Once the Regulation Delta has been determined for every 5 minute interval of the year, Regulation Up and Regulation Down are calculated. Requirements are defined as: **Regulation Up -** 95^{th} percentile of the positive portion of the Regulation Delta that is smaller than 1,000 MW. **Regulation Down -** 95^{th} percentile of the negative portion of Regulation Delta values that are greater than -1,000 MW. The cap on 1,000 MW on Regulation Up and -1,000 MW on Regulation Down get rid of any excessive deviation from normal regulation values. The 95^{th} percentile calculation of the each monthly 5 minute interval results into one regulation (up/down) value for each hour of every month. Therefore, the result is a 24 x 12 matrix that represents the up/down regulation requirements for each hour of each month of the year that is being analyzed.

5) Regulation Requirements Tables & Contour Plots: Regulation Requirements Tables are 12x24 tables that show how much Up/Down Regulation must be procured at different hours of the day for a specific month and year. In order to easily visualize the regulation tables contour tables have been created to compare Regulation Up as seen in Fig. 3.

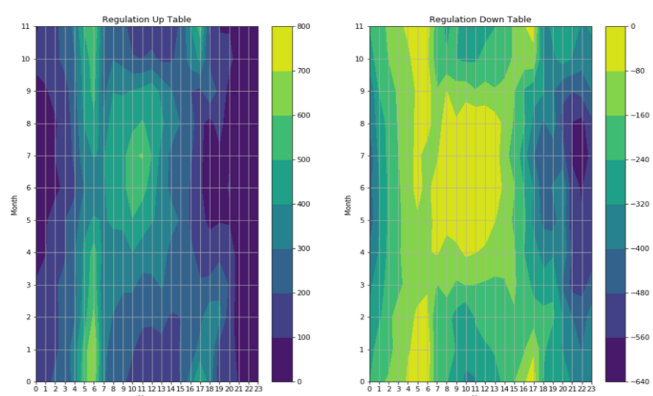

Fig. 3. Sample Regulation Up/Down Contour Plot.

6) 'GE' Tables: From the Regulation Tables that were derived per scenario, the 'GE' Tables are calculated. The 'GE' Tables are defined as: incremental change between two scenarios. Mathematically, the 'GE' Table value for a given month and hour is the slope of the curve fit of the line that passes through that scenario and the base scenario. Since the goal is to analyze how the regulation requirements change as installed PVGR capacity increases. Then, each scenario is compared to the base Scenario 1. Equation (5) outlines the

$$NLF_{M1,M2,M3,M4} = Load_{Constant\ or\ Ramp} - Wind_{Constant\ or\ Ramp} - PVGR_{Constant\ or\ Ramp} \quad (4)$$

$$Num_{x,y} = \frac{Regulation\ Up/Down_{x,y(Scenario\ 2)} - Regulation\ Up/Down_{x,y(Scenario\ 1)}}{Capacity_{x(Scenario\ 2)} - Capacity_{x(Scenario\ 1)}} \quad (5)$$

method to calculate each 'GE' Table value where x is the month, y is the hour and $RegulationUp/Down_{Scenario1}$ is the Up/Down Regulation value at month x and hour y from the base scenario (0% PVGR). After all of the scenarios are calculated contour tables for each scenario are graphed next to each other in order to better analyze which method performs best as seen in Fig. 6.

IV. Forecasting Method Comparison

In Section III-B2 the NLF calculation is introduced. However, in order to adjust and analyze the different calculation possibilities (and how they differ from one another), four different types of NLF methods were studied. In order to illustrate this approach, Fig. 4 depicts (graphically) different PVGR forecasting methods. In the Data frame it is called SCED. These methods can be run by executing the appropriate python (.py) file. To calculate the Regulation Delta, use Equations 6 and 7:

$$Net\ Load = Load - Wind - PVGR \quad (6)$$

$$Regulation\ Delta = Net\ Load - NLF \quad (7)$$

We begin by defining the two types of forecasting:

- **Constant -** sample the desired Data column every 5 minutes (0, 5 10, ...) and for the next 4 minutes the value is constant.

$$...y_7 = y_5, y_6 = y_5, y_5 = y_5, y_4 = y_0, y_3 = y_0...$$

- **Ramp -** the value is depend on the slope of the past two (in 5 minute interval) values where Δ is the slope and is defined as:

$$\Delta = y_t - y_{t-5} \quad (8)$$

Therefore the next value would be:

$$y_{t+5} = y_t + \Delta \quad (9)$$

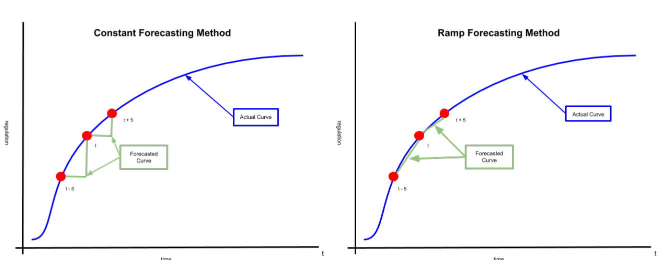

Fig. 4. PVGR Forecasting Methods.

Once PVGRF has been determined with one of the methods, we can combine forecasts (for Load, Wind, PVGR) and create four potential Net Load Forecasting Methods (NLF). This will create a more comprehensive analysis. The methods are presented:

1) NLF = $Load_{Constant}$-$Wind_{Constant}$-$PVGR_{Constant}$
2) NLF = $Load_{Constant}$-$Wind_{Constant}$-$PVGR_{Ramp}$
3) NLF = $Load_{Ramp}$-$Wind_{Ramp}$-$PVGR_{Constant}$
4) NLF = $Load_{Ramp}$-$Wind_{Ramp}$-$PVGR_{Ramp}$

All scenarios for the years 2017, 2018, 2019 and 2020 were performed with the four methods.

V. Linear Interpolation Validation

A. Overview

Once all of the scenarios and all of the years (2018 and 2019) have been calculated with the four NLF methods, we proceed with the validation. However, instead of manually finding the slope as seen in section III-B6, the slope will be calculated using a linear least squares regression with the *linregress* function in the SciPy library [11]. This way if the results match up, then it is clear that the 'GE' Tables values have been calculated correctly. In addition, a final more 'robust' 'GE' table has been created called 'GE' Curve Fit. The new table consists on taking into account the slope between all the scenarios as the new value for the 'GE' Regulation table. This will allow for better procurement regardless of how much solar capacity is installed in the end (more/less than expected). Fig 5 shows a sample analysis where the blue points are the regulation data points, orange data points are the GE regulation data points based on slope calculations. Each of the points on the x axis are the different scenarios from 0% to 300% PVGR Scenarios. The curve fit is successful for all scenarios and both tables, therefore they are verified. The validation was successfully done for each hour, for all of the months of all of the years of all of the methods.

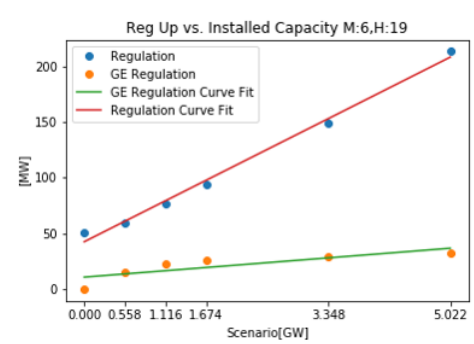

Fig. 5. Sample Curve Fit Analysis for June at 7 PM.

VI. Method Comparison & Selection

A comparison table between all of the methods was created called 'GE' Curve Fit tables (both Regulation Up and Regulation Down), can be seen in Fig. 6. The figure highlights the requirements and variability difference between the four different methods.

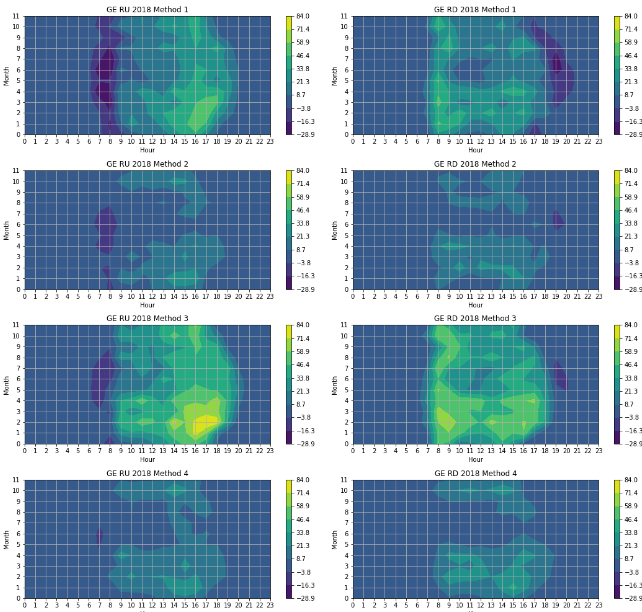

Fig. 6. Forecasting Method Contour Comparison Graph.

VII. Recommendation, Conclusion & Future Work

A. Recommendation

The best way to come up with the most robust 'GE' Table is to take into account all of the years and scenarios possible and average them. This is done by taking all of the 'GE' Curve Fit Table for various years and averaging the 'GE' Down/Up Regulation tables by the number of years used.

After careful consideration the final recommendation is to use *Method 2* due to its flexible and accurate results. The Regulation up and Regulation Down GE Recommendation Tables for 2021 are shown in Fig. 7 and Fig. 8.

	Hour																							
Month	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Jan.	0	0	0	0	0	0	0	0	0	11	5	6	10	12	14	15	12	4	1	0	0	0	0	0
Feb.	0	0	0	0	0	0	0	0.3	4.3	13.8	18.4	17.4	16	17.3	23.3	22.3	22	14	4.6	0.8	0	0	0	0
Mar.	0	0	0	0	0	0	-0.1	0.3	5.6	12.6	15.4	15.4	16.6	16.6	18.1	17.9	18	16.8	13	5.4	0.6	0	0	0
Apr.	0	0	0	0	0	0	-0.1	-0.6	3.4	12	13.3	13.5	14.5	15	16.9	21.4	19.3	18.8	16.1	7.1	0.9	0	0	0
May	0	0	0	0	0	0	-0.3	-1.4	3.4	14	13	11.1	12.9	14.4	14.5	17.3	17	14.8	12.6	6.1	1	0	0	0
Jun.	0	0	0	0	0	0	-0.4	-1.9	1.8	7.1	7	5.3	6.1	7.3	8.9	10.3	12.4	10.8	9.9	5.3	1.8	0.3	0	0
Jul.	0	0	0	0	0	0	-0.5	-3	-1.4	2.1	2.1	2.8	5	6.5	8.3	8.9	8.3	7.3	6.9	3.5	1.1	0.1	0	0
Aug.	0	0	0	0	0	0	-0.4	-2.6	-2.6	2.6	2.6	3	3.4	5.8	9.1	10.8	8.8	7	5.8	2.6	0.5	0	0	0
Sep.	0	0	0	0	0	0	-0.1	-1.4	-2.1	4.5	7.3	6.4	5.5	8	11.1	11.8	12.1	10	5.9	1.1	0	0	0	0
Oct.	0	0	0	0	0	0	0	-0.5	-0.5	4.8	8.1	7.3	7.9	10.5	13.4	11.9	12.6	9.6	5.1	0.8	0	0	0	0
Nov.	0	0	0	0	0	0	-0.1	0.1	3.8	10.8	13	11.6	12.8	16.9	22.5	18.6	12.9	4.4	1	0	0	0	0	0
Dec.	0	0	0	0	0	0	0	0	-1	7	10	10	10	15	18	16	18	4	0	0	0	0	0	0

Fig. 7. Regulation Up Recommendation for the year 2021.

	Hour																							
Month	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Jan.	0	0	0	0	0	0	0	0	0	11	5	6	10	12	14	15	12	4	1	0	0	0	0	0
Feb.	0	0	0	0	0	0	0	0.3	4.3	13.8	18.4	17.4	16	17.3	23.3	22.3	22	14	4.6	0.8	0	0	0	0
Mar.	0	0	0	0	0	0	-0.1	0.3	5.6	12.6	15.4	15.4	16.6	16.6	18.1	17.9	18	16.8	13	5.4	0.6	0	0	0
Apr.	0	0	0	0	0	0	-0.1	-0.6	3.4	12	13.3	13.5	14.5	15	16.9	21.4	19.3	18.8	16.1	7.1	0.9	0	0	0
May	0	0	0	0	0	0	-0.3	-1.4	3.4	14	13	11.1	12.9	14.4	14.5	17.3	17	14.8	12.6	6.1	1	0	0	0
Jun.	0	0	0	0	0	0	-0.4	-1.9	1.8	7.1	7	5.3	6.1	7.3	8.9	10.3	12.4	10.8	9.9	5.3	1.8	0.3	0	0
Jul.	0	0	0	0	0	0	-0.5	-3	-1.4	2.1	2.1	2.8	5	6.5	8.3	8.9	8.3	7.3	6.9	3.5	1.1	0.1	0	0
Aug.	0	0	0	0	0	0	-0.4	-2.6	-2.6	2.6	2.6	3	3.4	5.8	9.1	10.8	8.8	7	5.8	2.6	0.5	0	0	0
Sep.	0	0	0	0	0	0	-0.1	-1.4	-2.1	4.5	7.3	6.4	5.5	8	11.1	11.8	12.1	10	5.9	1.1	0	0	0	0
Oct.	0	0	0	0	0	0	0	-0.5	-0.5	4.8	8.1	7.3	7.9	10.5	13.4	11.9	12.6	9.6	5.1	0.8	0	0	0	0
Nov.	0	0	0	0	0	0	-0.1	0.1	3.8	10.8	13	11.6	12.8	16.9	22.5	18.6	12.9	4.4	1	0	0	0	0	0
Dec.	0	0	0	0	0	0	0	0	-1	7	10	10	10	15	18	16	18	4	0	0	0	0	0	0

Fig. 8. Regulation Up Recommendation for the year 2021.

B. Conclusion & Future Work

The tool is extremely flexible, transparent and needs minimal user input or maintenance. Features include: **Reusability**, **No Data Modification**, **Minimal User Input**, **Thorough Documentation**, **Raw Data Export**, and**Adaptable & Flexible**. The script has created an easy to use framework that can be reused for different power scenarios and studies. **Ordered & Sorted Results**.

The tool and analysis were successfully completed and deployed. The years and forecasting methods were successfully inspected. This new method has also set a good framework for other similar scenario based or method based sequence calculations. This tool could be used to calculated different years (both past and future). In future work, the data information should be updated to be able to handle future years, and perform the same regulation requirements for future solar capacity additions as well as other possible studies (i.e. wind capacity).

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