Assessing Solar Generation & Curtailment in California

Dianyi Li, Xiaoyueyan Yang, Yueyi Yang

Abstract

Solar power has long been adopted as a renewable energy in the electricity sector. With more renewable energy been part of the power system, problems like oversupply has been endangered the reliability of the power system. Solar curtailment has become an increasing trend to manage oversupply.

In this study, we assess and forecast daily solar share of generation and daily percent solar curtailed in the state of California. For daily solar generation share, there is a rapid growth in the beginning but levelled off in the recent two years. The chosen STLF shows that the solar share would still be similar with the last two years thus the increasing solar generation would only induce more curtailment. For daily percent solar curtailed, we see an increasing trend and enhanced seasonality in recent years; model forecasts predict that the increasing trend and enhanced seasonality will continue into the year-ahead.

Key Words: Solar, Curtailment

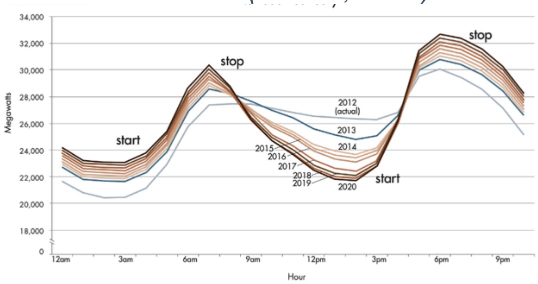
1. Introduction

Solar power is the power generated via the collection of sunlight. As the most populated state in the United State, California has a long history dealing with climate change and air pollution. Many goals have been set to drive electric grid changes for example control greenhouse gas emission. In September 2006, the California State Legislature passed AB-32, the Global Warming Solutions Act of 2006. Goal of this bill is to reduce California GHG emissions back to 1990 emission levels by 2020 (EDF, n.d.). In 2016, California stated passed the bill SB-32 as an extension to the AB-32. It sets a GHG emissions target for 2030 at 40 percent below 1990 levels (EDF, n.d.). In 2018, California sets an ambitious goal of 60% of its electricity from clean sources by 2030 and 100% by 2045 (SB-100) (Grizard, 2019).

Those bills and targets push California's electricity sector to go clean quickly. According to California Energy Commission (CEC), from 2010 to 2018 total renewable generation of CA in-state electricity generation has increased from 14.9% - 32.35% (CEC, n.d.). In 2019, California ranked first in the United States for solar power generation with solar installation of 27,405.89 MW (SEIA, 2019). Most solar installations are Utility PV, followed by residential solar PV.

However, the rapid rise in solar resources coming onto the system has created a new operating paradigm, oversupply. ISO explained this phenomenon as "Duck Curve" which is a Duck-shape load curve of non-renewable generations (Figure 1). Duck curve is the curve for net load which is the Total Forecasted Load subtracted by the Forecasted Load from variable generations (Solar and/or Hydro power). The curve reveals timing imbalance between peak demand and renewable energy production (CAISO, 2016). In the day, the system can generate too much solar power but without adequate customer demand. Oversupply of electricity in the day would decrease wholesale prices to a extremely low level or even negative. Non-renewable generators have to ramp down to stabilize price and maintain demand and supply balance. While after the sunset, solar generation goes to end but customer demand increase, which requires non-renewable generators to ramp up quickly to meet the shortage in supply. The variation solar power in a day challenge utility for a more flexible ramping up and down. On the other hand, during oversupply time, even though the market can remedy the imbalance and protect generators from the negative wholesale price, the frequent oversupply is not a sustainable condition for the grid and might push some generators out of the market.

Figure 1 Example of Duck Curve provided by CAISO (CAISO, 2016)



The common practice to manage oversupply is Curtailment. It is the reduction of output of a renewable resource below what it could have otherwise produced. Solar power go to the grid will be cut when the forecasted load is over the forecasted demand. According to CASIO, curtailment on Solar and Wind has been increasing quickly in recent years, and there exists some seasonality for the curtailment. For example, in Spring and Fall, it seems there would be more curtailment because the less demand for cooling or heating. This project is going to focus on the Solar Curtailment in California from 2014 to 2020 to assess the current solar generation its curtailment. Also, we expect this project can help us clearly identify the seasonality behind curtailment change.

2. Data Overview

2.1 Data Source

Generation and curtailment data at five-minute intervals were downloaded from the California ISO website. The dataset contained load, generation by source, wind and solar curtailment data, all in megawatts (MW), from May 2014 to March 2020. Though curtailment data is very limited while solar generation data can be found elsewhere dating back further, we wanted to match the timeframe of both series and decided to only use this dataset from CAISO.

2.2 Data Prep

We aggregated the data by sum for total generation, solar generation and solar curtailment to a daily level from 5-minute intervals, and took the minimum of load each day as the daily baseload value. We then calculated solar's daily share of total generation and the daily percentage of solar that was curtailed. For these tasks, we used packages ***tidyr*** and ***dplyr***.

2.3 Data Overview

2.3.1 Solar share

We calculated the fraction of solar generation from the total electricity generation data. This series shows an obvious upward trend in the beginning yet seems to be stabilize after the year 2018. From Figure 2, it can be concluded that the seasonality pattern is similar in each year. After decomposing the data, it can be seen in Figure 3 that the trend is continually upward before 2018 and after 2018 it is stable overall with some fluctuation. In addition, the seasonality is super obvious and the same of each year. As can be seen clearly in Figure 4, the share reaches its peak in the late spring and drops greatly in the summer, then a slight upturn occurs in the fall, finally the lowest point occurs in the winter. The reasons may be that in the summer and winter, the electricity demand is highest because of cooling in the summer and heating in the winter. However, since solar generation is as reliable as generation of other resources, the high demand of electricity would be dependent more on the generation from other resources to avoid black out. In this way, the solar share would be lower in summer and winter.

Figure 2 Daily Solar Generation Share

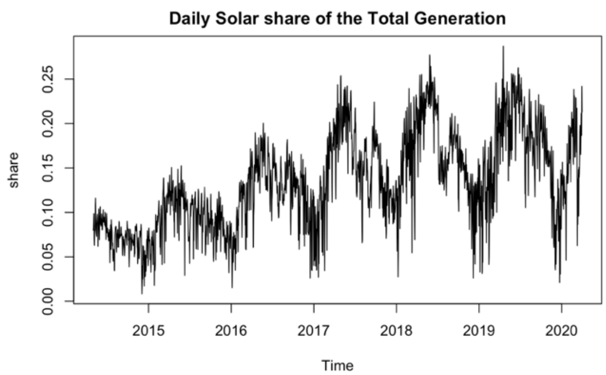


Figure 3 Decomposition of Solar Share

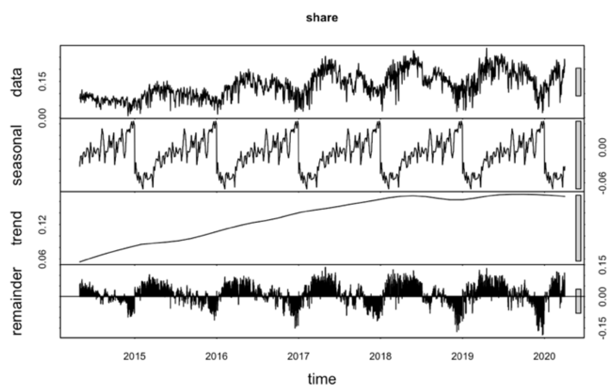
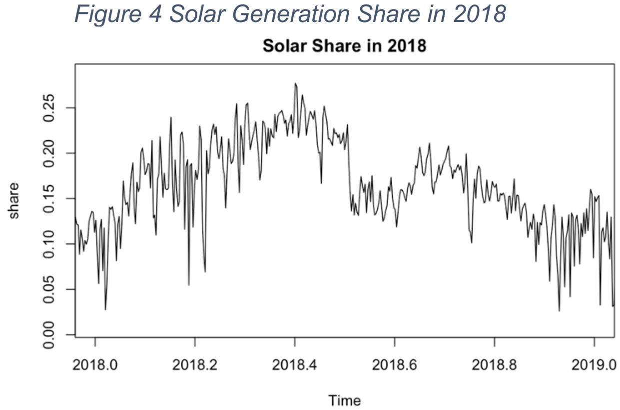


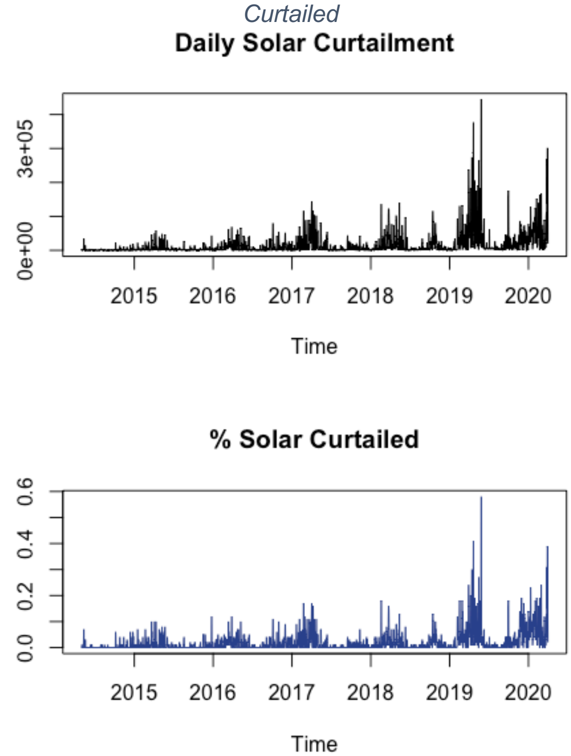
Figure 4 Solar Generation Share in 2018



2.3.2 Percent solar curtailed

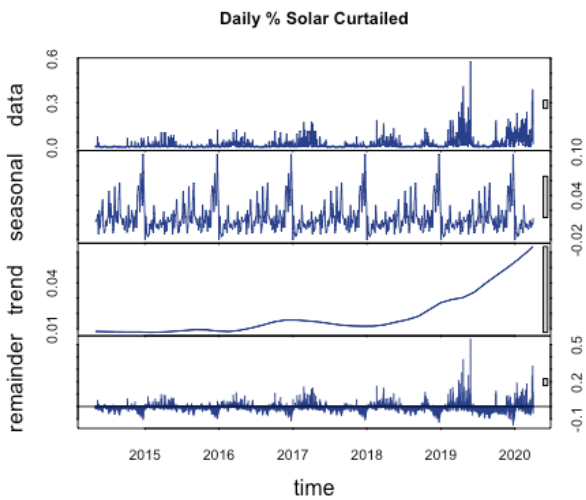
We calculated percent solar curtailed from curtailment and solar generation data, both series seem to follow each other and show similar increasing trend and dominating annual seasonality patterns (Figure 5). There tend to be a peak in the spring months, a low during the summer and another peak in the fall. This pattern can be explained by the mild afternoon temperature during those seasons. In the afternoon, the temperature is mild enough so that there is less of a need to turn on air-conditioning/ heaters. This reduces demand during solar's prime production time, leading to high curtailment. Starting in 2019, we see that the annual seasonality was enhanced in both series with much higher peaks in the spring. For example, 444 gigawatts of solar generation, equivalent to 58% of that day's total solar generation, was curtailed on May 27, 2019. This is was partially explained by the increased amount of hydroelectric generation in 2019 when experience a large amount of precipitation and more electricity been generated by hydropower.

Figure 5 Daily Curtailment (MW) and Percent Solar Curtailed



We decided to focus on modeling daily percent solar curtailed because we thought the percentage conveyed the magnitude of the problem better. Looking at the decomposition of the series using Loess Method, we see a sharp increasing trend starting in mid-2018(Figure 6). This rapid increase in daily percent solar curtailed shows that the curtailment problem will be of increasing significance and pose challenges to grid operators and policy makers if not dealt with promptly.

Figure 6 Decomposition of Daily Percentage Solar Curtailed



3 Methodology

As for the solar share dataset, it shows good seasonality and predictable trend, we focus on both model and forecast our series. In addition, since it shows good seasonality, we build our model on the data series with seasonal component.

Due to the limited availability of our data and the rapid change in curtailment over the past year, we will focus on modeling our series rather than forecasting into the future. Given the high frequency of our dataset, we used STLF and TBATS models during the fitting in addition to ARIMA models. STLF models and forecasts based on seasonal and trend decomposition using Loess Method. TBATS models are Exponential Smoothing State Space Model With Box-Cox Transformation, ARMA Errors, Trend and Seasonal Components; we considered it for its ability to handle high frequency data.

3.1 Solar share Model

We built three models to fit and forecast the data series including ARIMA, STLF, and TBATS model.

ARIMA: We used auto.arima to help determine the order of our series, and the fitted result is ARIMA(5,1,1) without seasonal components.

STLF: We also used the default function to fit the data series.

TBATS: We fitted TBATS model to the transformed data with different time periods, which are specified to be weekly, monthly and annually.

3.2 Percentage of Solar Curtailed Model

In the attempt of modeling the daily percent curtailed series, four models were tried – STLF, ARIMA, ARIMA with regressors and a TBATS model.

STLF: A system default STLF was used to fit our daily percentage of curtailed series.

ARIMA: We ran auto.arima to help determine the order of our series. It returned an order of (1,1,1) with no seasonal components which was expected given it can't handle such high frequency datasets.

ARIMA with regressors: The third model is an ARIMA model with exogenous variables – daily baseload, solar share of generation and dummies for month February, March and April. After examining the regression of daily percent curtailed against 11 monthly dummies, we found that only February, March and April had significant results. For the sake of keeping our model sophistically simple, we left out the other monthly dummies. After fitting a time series multiple linear regression model on the exogenous variables, we examined the residuals and fitted an ARIMA(1,1,1) model. Combining both parts, we ended up with an ARIMA(1,1,1) model regressed against daily baseload, % solar curtailed and 3 monthly dummies.

For the purpose of forecasting, future year-ahead forecasts for the exogenous variables daily baseload and solar's share of generation are produced using stlf forecasts. Monthly dummies starting in April are saved and transformed to another ts object starting April 2020.

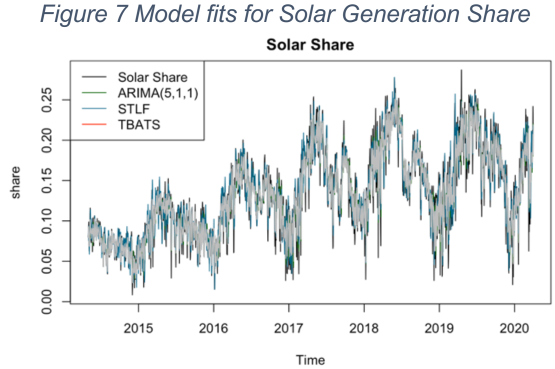
TBATS: We first transformed the daily percent curtailed series into a multiple season time series. Seasonal periods were specified to 7,12,365.25 to present weekly, monthly and annual seasonality. Then a TBATS model was fitted.

4 Results

4.1 Solar Generation Share Model Fitting

As can be seen from Figure 7, all the three models do a decent job in fitting the original data series because they all almost coincide with the original data. Among them, the STLF model with the blue line seems to be the best one since it captures more peak and bottom spikes fitting the data series. To further compare these three models, we would like to see the forecast results of them.

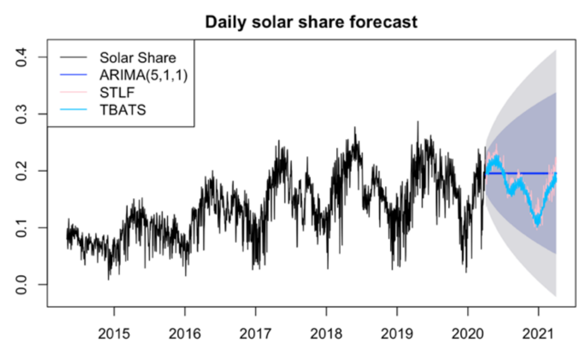
Figure 7 Model fits for Solar Generation Share



Forecasting

As can be seen from Figure 8, the STLF model with pink line seems to be the best one. Firstly, the ARIMA model with blue line is straight, without any trends or seasonality. Therefore, this one is the worst to forecast. As for the TBATS model with blue line, it shows seasonality pattern and its values would vary with time. However, it still has some disadvantages such as it does not capture spikes and does not show volatility in the smooth line. Compared to these two models, the STLF model does the best job to both show seasonality pattern and capture spikes as many as possible. In consequence, the STLF model is the best model thus it can be used to fit solar generation share and forecast the future pattern.

Figure 8 Daily Solar Generation Share Forecast



4.2 Percent Solar Curtailed Model Fitting

Figure 9 shows the four model fits. Overall, the four models have similar performance fitting the data, though the STLF model have the lowest error metrics (Table 1). Since the spikes in 2019 were unprecedented, the models were not able to match the spikes; they all seem to be a good fit otherwise. All but the ARIMA model failed to stick with the theoretical zero lower bound of this series.

Figure 9 Model Fits for Daily Percent Solar Curtailed

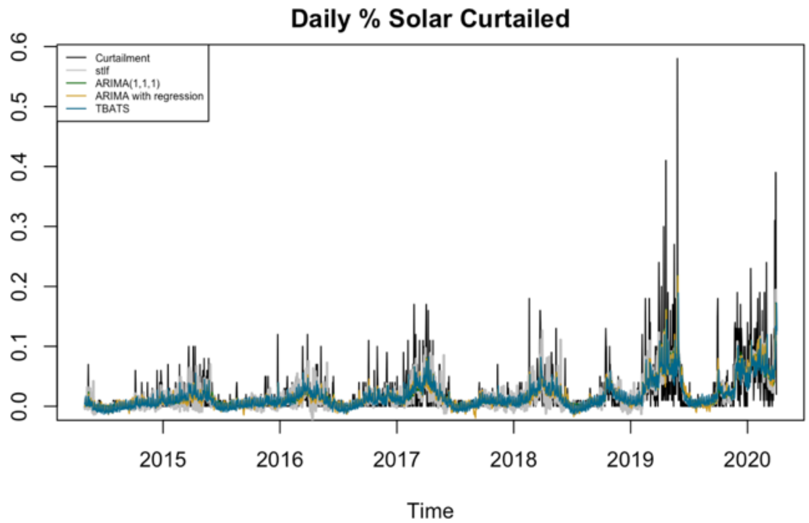


Table 1 Accuracy of Daily Percentage Solar Curtailed Models

Model	ME	RMSE	MAE
STLF	0.0004	0.0274	0.0154
ARIMA(1,1,1)	0.0005	0.0313	0.0161
ARIMA with Reg	0.0005	0.0308	0.0167
TBATS	0.0012	0.0306	0.0166

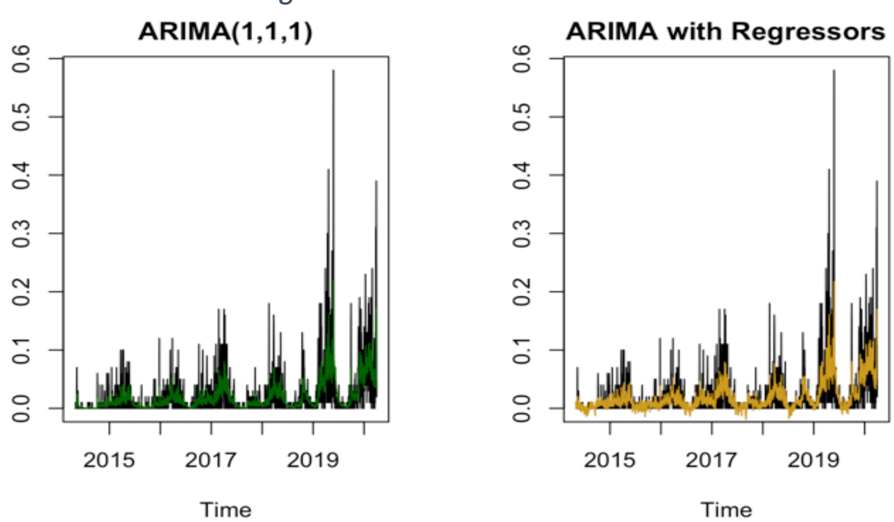
STLF

As indicated by the grey lines in Figure 9, STLF model does the best job at capturing the volatility of the series. However, it violates the zero lower bound of percent solar curtailed series.

ARIMA

We can take a closer look at the ARIMA model fit in Figure 10 below. One notable thing is that the ARIMA model is the only model that has a zero lower bound.

Figure 10 ARIMA Model Fits

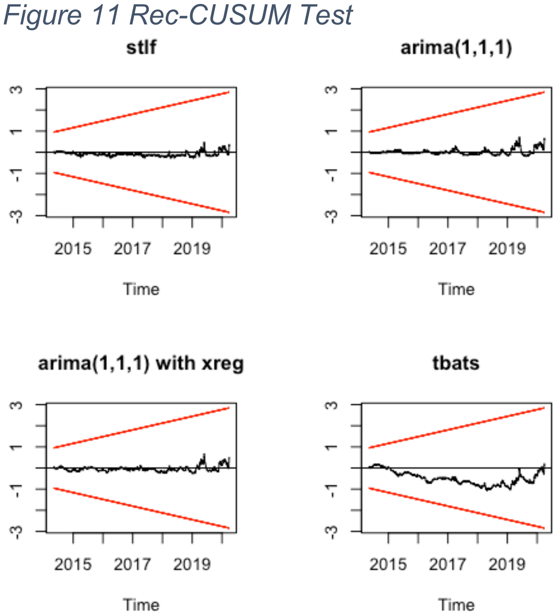


ARIMA with regressors
Compared to the ARIMA(1,1,1) model, this model seems to capture the volatility better while violating the zero lower bound of the series during the summer months(Figure 10).

TBATS
TBATS model fit is very similar to the ARIMA with regressors model. It captures some of the volatility and violates the zero lower bound of the series (Figure 9).

Due to concerns about the unprecedented high spikes, we examined the recursive residuals to make sure our models did not break. As **Error! Reference source not found.** shows, all our models were able to stay within the bounds during the Cumulative Sum of Recursive Residuals (Rec-CUSUM) test, indicating no structural breaks for our model.

Figure 11 Rec-CUSUM Test



Forecasting
We forecasted the daily percent solar curtailed series one year into the future (Figure 12). The STLF model generates forecasts with more volatility; ARIMA with regressor model and TBATS model generate forecasts with a lower dip in the upcoming summer months, which is more consistent with historical seasonality patterns. None of the model forecasts are violating the theoretical zero lower bound constraint into the future, we think this can be explained by sharp increasing trend over 2019.

STLF
The STLF forecasts shows high volatility, which is consistent with historical trends. It did not forecast high spikes going into the spring season, and the lower bound of the year-ahead forecast is at 0.068.

ARIMA
The ARIMA(1,1,1) can not handle seasonality and generate year-ahead forecasts given its short-term memory characteristic. It spikes quickly then flatlines after one week.

ARIMA with Regressors
The ARIMA(1,1,1) with regressors model forecasts decrease in percent solar curtailed into the summer months, which is consistent with historical seasonality.

TBATS
The TBATS model forecasts are more volatile, but are the lowest compared to the other three models. It also forecasts a dip into the summer, consistent with historical seasonality.

Figure 12 Daily Percent Solar Curtailed - One Year Forecast

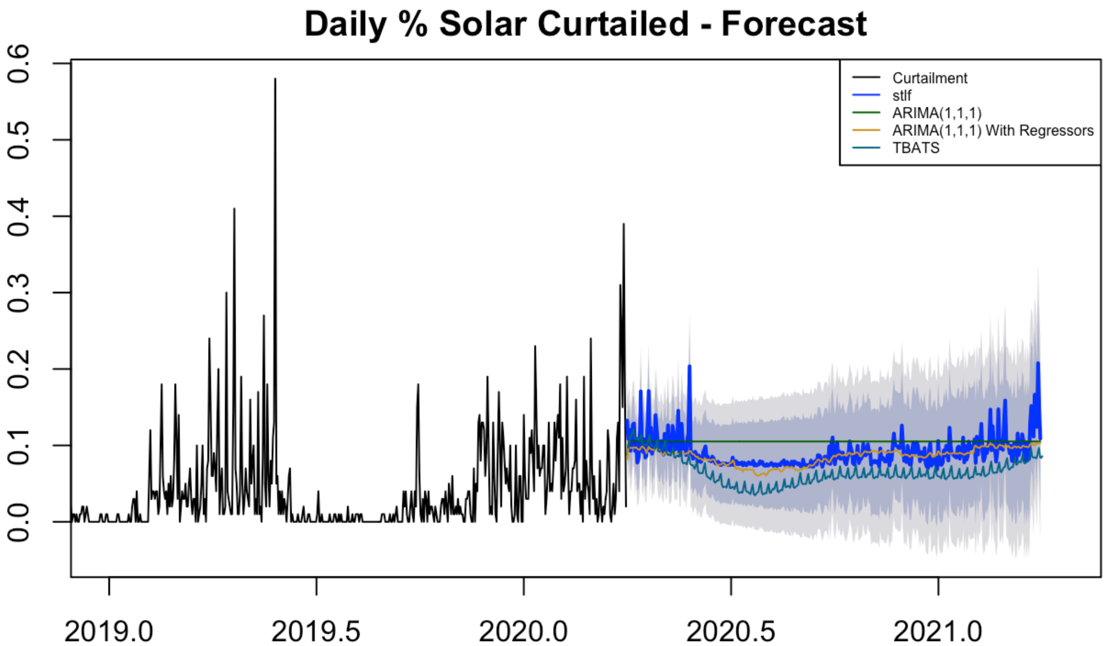
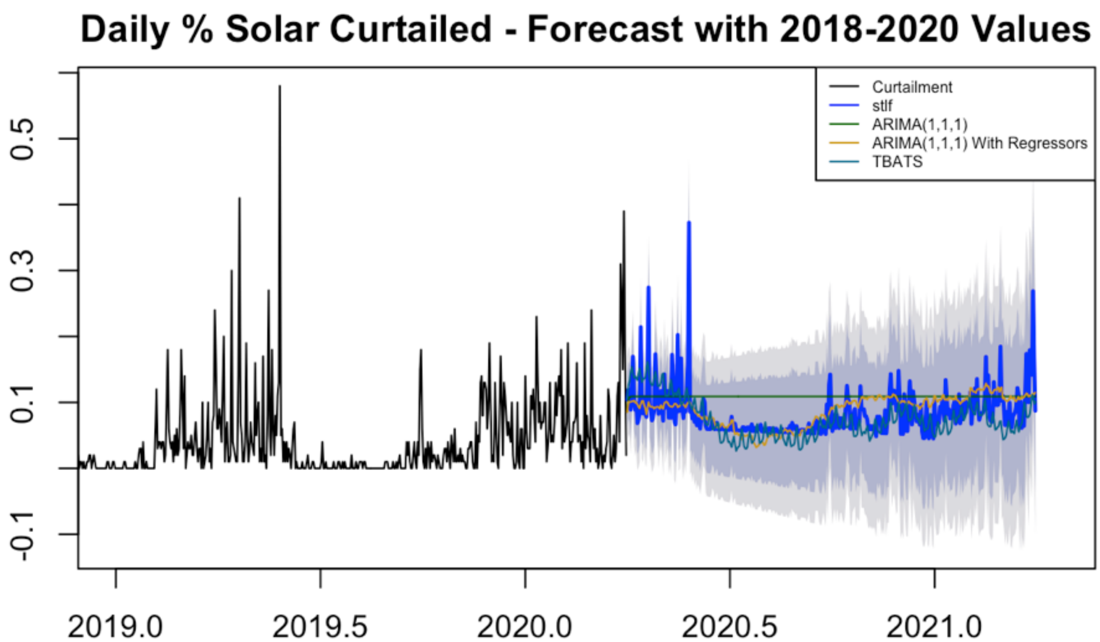


Figure 13 Daily Percent Solar Curtailed Year-Ahead Forecast with 2018-2020 Values

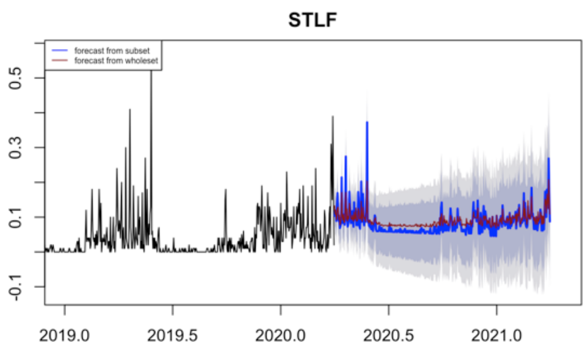


However, none of the forecasts seem to capture the magnitude of the problem, the spikes, if any, are still quiet low. We produced another set of forecasts using only data from 2018 on (Figure 13). We can see that with this subset of most recent data, all models other than the ARIMA(1,1,1) model forecast are more volatile. STLF forecasts seem to exhibit closer resemblance to 2019 data, while the other models forecasts are still relatively flat.

STLF

The new stlf forecasts are much more volatile, predicting high spikes in the spring season, which is more consistent with 2019 and early 2020 patterns; the forecasts have a lower bound around 0.045, which is lower than the forecast lower bound based on the whole set of historical data, but still higher than historical values(Figure 14).

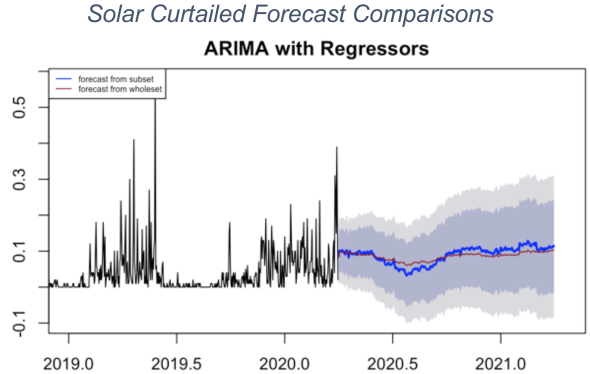
Figure 14 STLF Daily Percentage Solar Curtailed Forecast Comparisons



ARIMA(1,1,1) with Regressor

The model forecasts a lower dip into the summer compared to the forecast based on whole set data, and higher values for fall and winter seasons (Figure 15).

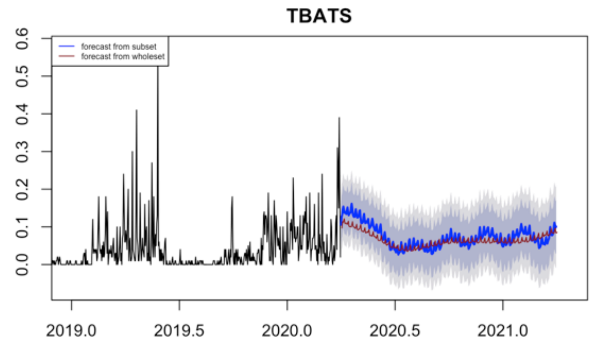
Figure 15 ARIMA With Regressors Daily Percentage Solar Curtailed Forecast Comparisons



TBATS

The new forecasts are more volatile compared to the previous forecasts, featuring higher values for the spring, and a more obvious seasonal pattern(Figure 16).

Figure 16 TBATS Daily Percent Solar Curtailed Forecast Comparisons



5 Discussion

5.1 Solar Generation Share

The daily solar generation share data series shows a rapid growth in the first six years and has been levelled off in the recent two years. In addition, our STLF model shows that the future solar generation share would still keep the stable pattern without increase and even drop a little that could be considered as the forecast error. Overall, the seasonality would not change a lot and the growth in the fraction of solar generation in the total generation would be hard to see.

In conclusion, the future generation share is hard to exceed the present peak fraction. In other words, no matter how much the generation of solar resources increase, this generation that could be utilized is hard to increase in the near future. However, with the strong enthusiasm in developing solar generators in California, this forecasting result is frustrating and would lead to recognition of increasing curtailment problem. In this case, more solar generation would be wasted and this result could warn the policymakers to reconsider their renewable resources goal especially the curtailment problem.

5.2 Percent Solar Curtailed

Examining the daily percent solar curtailed series, we see an increasing trend with enhanced seasonality in recent years. Starting in 2019, the series became more volatile with much higher spikes. Our models were able to pick up some of the variances, but unable to match the unprecedented spikes.

The STLF model is best at capturing the volatility both when fitting the model and forecasting into the future. ARIMA and TBATS model forecasts seem be capturing at the long-term level of the series rather than daily volatility of the series. Forecasting one year into the future, none of the model forecasts (both based on the whole set and subset of historical data) violate the zero lower bound, or even came close to 0, suggesting that the models forecast curtailments happening everyday in the upcoming year-ahead.

In conclusion, our models suggest increasing trend in daily percent solar curtailed for the upcoming year and that curtailments will be happening everyday. In addition, the enhanced seasonality pattern will continue according to the STLF models.

6 Limitations

The high frequency of our dataset makes it hard to utilize some of package's fittings for seasonality in both models. Also, since curtailment is a relatively recent issue, there is very limited amount of data available. In addition, curtailment seems to be rapidly involving for the past year, and together with the limited amount of data, it makes it difficult for us to model accurately and forecast into the future. We are also unable to explore more exogenous variables due to time constraint; however, future work can include taking a closer look into the generation composition, especially hydroelectric generation, to better model curtailment series.

7 Looking Forward

This issue of oversupply and renewable curtailment has been getting a lot of attention since the act of curtailing is essentially wasting California's renewable energy resources and is counterintuitive to the state's ambitious renewable goals. It is an interesting time to be monitoring this issue as the power market is going through unprecedented changes – fleets are retiring, automation is happening, and large-size grid edge solutions are being incorporated into the system. With rapid growth in solar capacity and generation, policy makers and grid operators must take on the challenge to better integrate them into the grid such that these green energy potentials are not wasted.

References

California leads fight to curb climate change. (n.d.). Retrieved April 13, 2020, from https://www.edf.org/climate/california-leads-fight-curb-climate-change

Grizard, E. (2019, January 11). SB 100: California's Commitment to 100% Clean Energy. Retrieved April 13, 2010, from https://www.bloomenergy.com/blog/sb-100-californias-commitment-100-clean-energy

California Energy Commission. (2019, June 24). "Total System Electric Generation." California Energy Commission. Retrieved April 13, 2020 from https://ww2.energy.ca.gov/almanac/electricity_data/total_system_power.html

Solar Industry Energy Association (SEIA). (n.d.) “California Solar.” SEIA. Accessed April 24, 2020. https://www.seia.org/state-solar-policy/california-solar.

Paulos, Bentham (2017, April 3). “Too Much of a Good Thing? An Illustrated Guide to Solar Curtailment on California's Grid.” Too Much of a Good Thing? An Illustrated Guide to Solar Curtailment on California's Grid | Greentech Media. Greentech Media. https://www.greentechmedia.com/articles/read/an-illustrated-guide-to-solar-curtailment-in-california.

California ISO. (2016). “Fast Facts: What the duck curve tells us about managing a green grid” CAISO. Retrieved April 13, 2020 from https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf

California ISO. (2017, May). “Fast Facts: Impacts of renewable energy on grid operations” CAISO. Retrieved April 13, 2020 from https://www.caiso.com/Documents/CurtailmentFastFacts.pdf

California ISO - Managing Oversupply. “ Managing Oversupply.” Accessed April 13, 2020. http://www.caiso.com/informed/Pages/ManagingOversupply.aspx.