Identifying the impact of COVID-19 from electricity demand patterns

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Codes used to produced the figures in this report can be found at

https://github.com/Metaming/COVID-19_impact/blob/master/COVID-19_Electricity_consumption.ipynb

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Abstract and Key Insights:

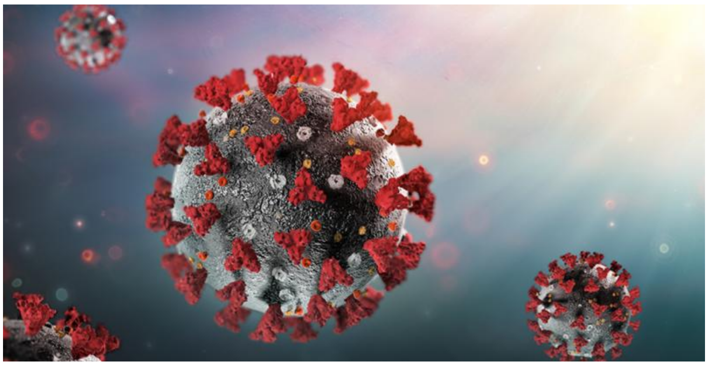
This report studies the impact of covid-19 on the electricity demand patterns in different states of Australia. We compared the total electricity demands this year over the past years, and developed models to taking into account the influence of temperature, gross state product (GSP) and distributed solar panels. Comparative studies and model prediction provide the following insights:

1. Weather temperature is the most significant impact factor for short-to-mid term (daily to monthly) electricity demands in Australia, even during the pandemic.

2. Despite the annual GSP growth rates of 1-4% in different states of Australia, the electricity demands have shown an overall decrease of around 1-5% over the past 5 years, due to the development of distributed solar panels.

3. The impact of COVID-19 on electricity demand is more noticeable when the temperature is mild during autumn and spring. While for states with a cooler winter this year, the impact is largely compensated by the increased residential demand.

4. There is a clear decreasing trend of electricity demand since September, which could be an indicator of economic recession.



Backgrounds and Data Sources

Backgrounds

The motivation of this study is to identify the possibility of tracing the impact of COVID-19 in a more 'real-time' manner using electricity consumption to complement other economic indexes [1].

There are already several studies that showed the impact of COVID-19 on energy consumption in different countries [2-4]. For countries with a strong electricity demand in manufacturing, like China, the impact of COVID-19 on electricity demand is obvious. However, does this also applied to Australia?

In this study, the focus will be on finding the impacts of COVID-19 on electricity consumption patterns in different states of Australia which have employed different strength of lockdown strategies.

Data sources

- For whole sale electricity demands in NEM (National Electricity Market) primarily in the east Australia: https://www.aemo.com.au/energy-systems/electricity/national-electricity-market-nem/data-nem/aggregated-data
- For whole sale electricity demands in WEM (Wholesale Electricity Market) primarily in the southwest Australia: http://data.wa.aemo.com.au/#load-summary
- The contribution of residential and non-residential contribution to electricity consumption in Victoria:
- For historic daily weather in Australia: http://www.bom.gov.au/climate/dwo/
- Economic indicators https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-state-accounts/latest-release
- Photovoltaic (PV) panels installation in different states: https://pv-map.apvi.org.au/postcode
- Major travel restriction and lockdown approaches: https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Australia

Exploratory Data Analysis

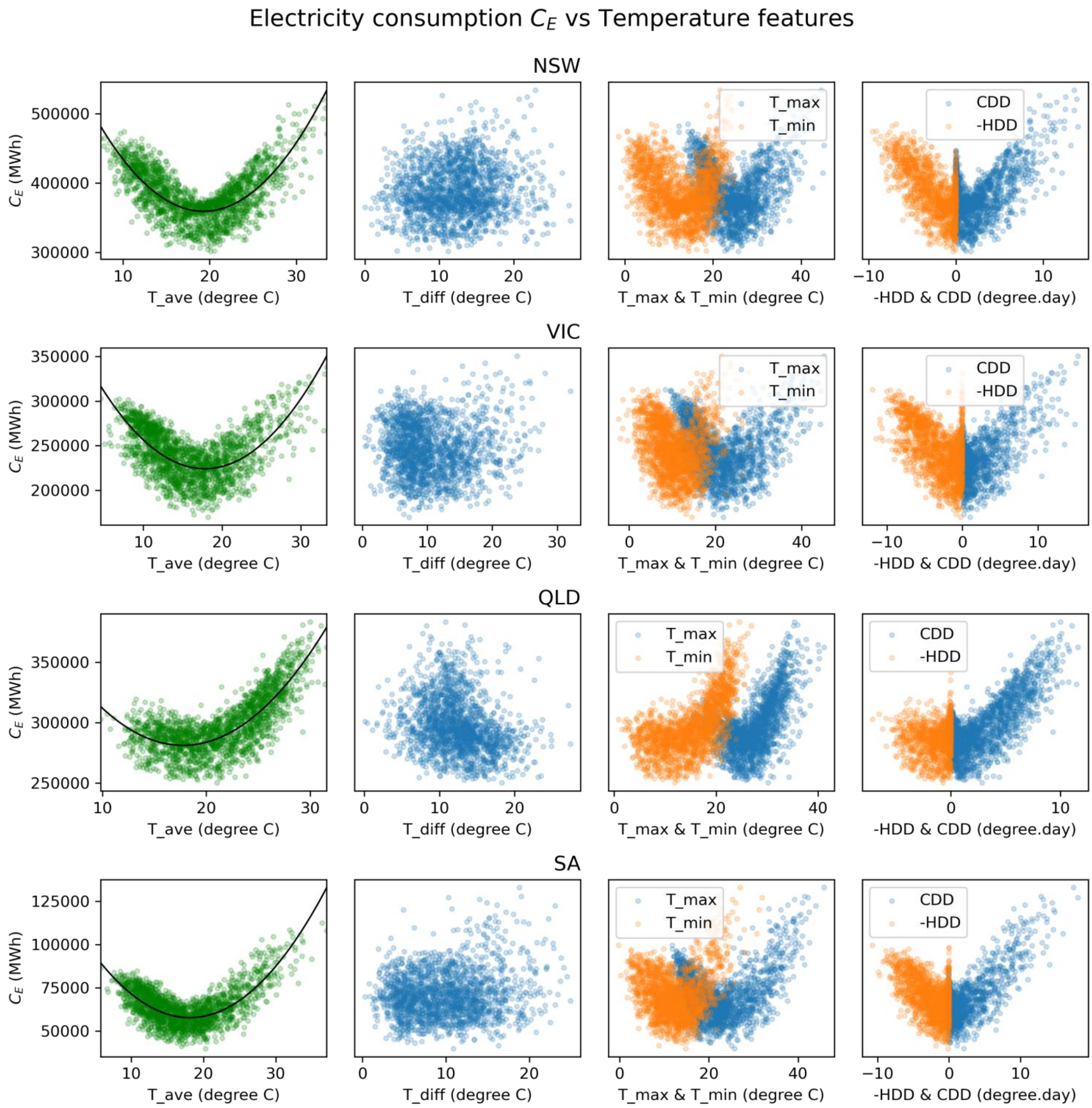


Figure 1. Distribution of daily electricity consumption C_E vs Temperature features, including daily averaged temperature T_{ave}, daily temperature variation T_{diff}, daily maximal and minimal temperature T_{max} and T_{min}, and daily heating degree day HDD and cooling degree day CDD. For clarity, HDD are plot in negative values.

Key observations from Figure 1

★ There is a nonlinear relation between the daily averaged temperature T_{ave} and electricity consumption C_E. There is a comfort temperature range around 18-20 degrees with minimal electricity demand. This justifies the use of critical temperatures to calculate heating degree days HDD and cooling degree days CDD, and use them as variables for prediction.

★ The maximal and minimal temperatures also follow a similar trend. They can be used as additional features

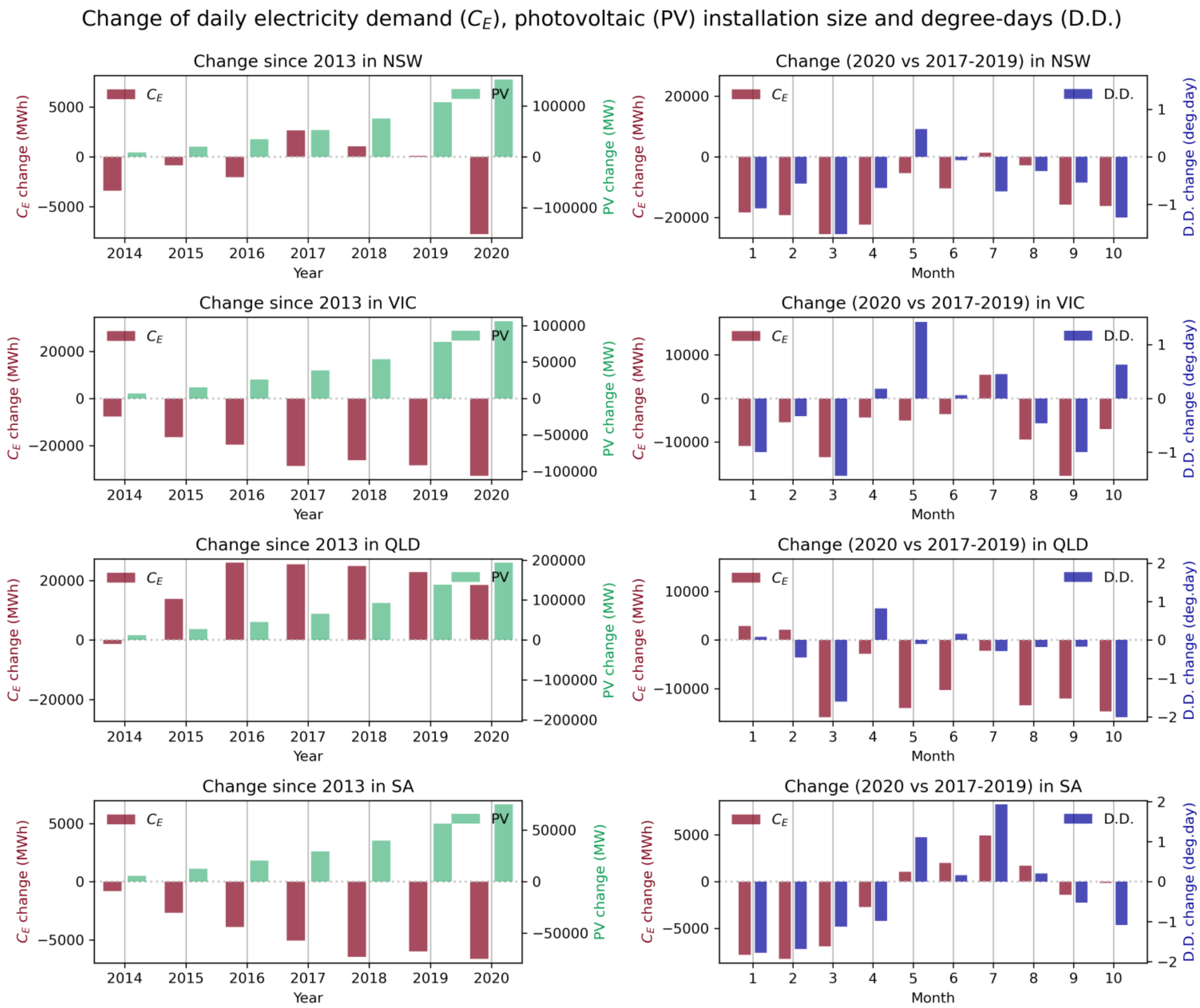


Figure 2. (left columns) Change of mean daily electricity demand C_E and the cumulative PV panels installation size compared to 2013. (right columns) Change of the mean daily electricity demand C_E and the degree-day D.D. (HDD + CDD) over months in 2020, compared to the same months over 2017-2019.

Key observations from Figure 2

★ The increasing photovoltaic panels is associated with the decreased electricity demands over the years. The change of weather temperature (total degree day D.D. = heating degree day HDD + cooling degree day CDD) is correlated with the change in electricity demands. Calculation showed that the electricity demand and the degree day has a correlation around 0.77 to 0.83.

★ The impact of these two features should be taken into account to reflect the short-term and seasonal change when identifying the impact of COVID-19.

★ This winter is overall cooler, as can be seen from the increased degree day data in VIC and SA. But the electricity demand in VIC does not increased proportionally to be more than past years (unlike SA), this could be due to the reduced demands from business and industry.

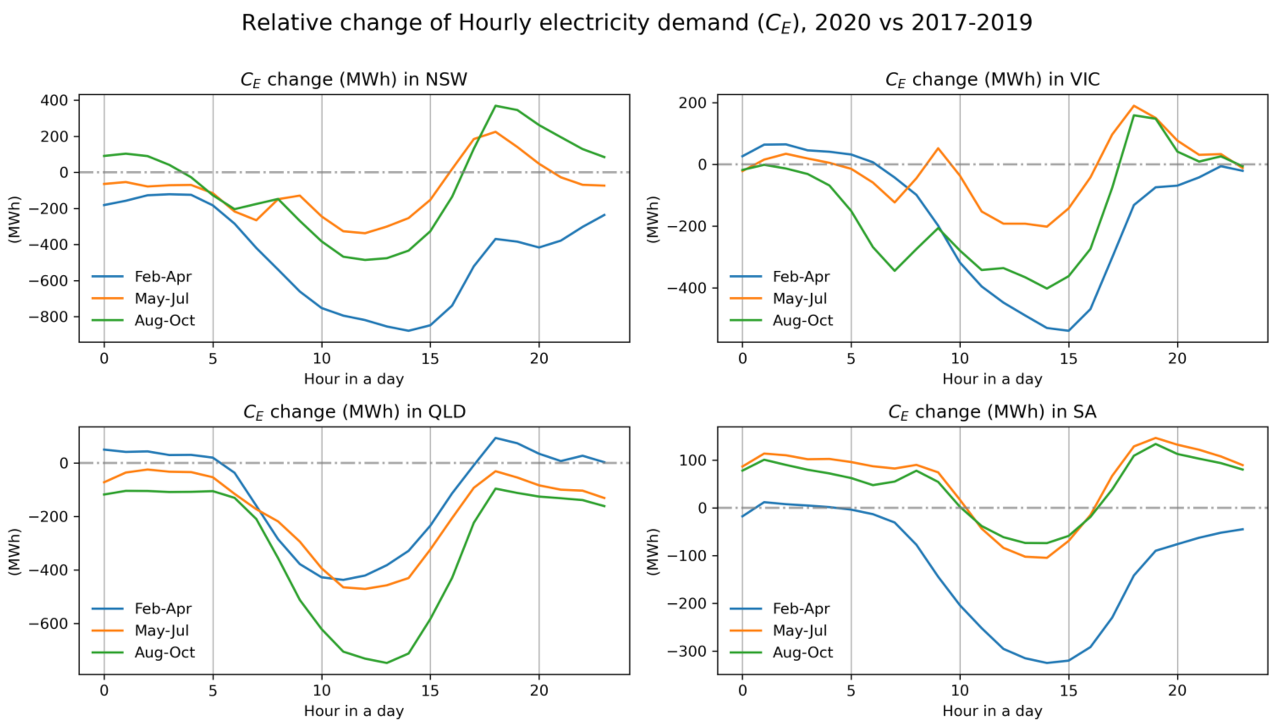


Figure 3. Mean hourly electricity demand change in autumn (Feb to Apr), winter (May-Jul) and spring (Aug-Oct) in 2020 compared to the mean values from 2017-2019.

Key observations from Figure 3

★ Overall the demand has decreased in 2020 compared to the past 3 years. The major drop in the day time is due to the increased installation of distributed PV panels, which reduces the demands at day time.

★ In NSW and VIC, there is a decrease in the day time peak (around 8 am) but an increase demands at night time peak hour (around 18 pm) after the pandemic. This is probably due to the less demands to go to work in the morning, but an increase demands for cooking at night.

★ In QLD, the overall demand keep dropping since last Autumn; while in SA, the demand increase due to cold winter this year.

Models for Predicting Electricity Demand

We have employed two models:

(1) linear regression model

(2) boosting regression model using Catboost.

The two models used R^2 as the evaluation metric and RMSE as the loss function for gradient boosting.

We used the data from 2015-07-01 to 2019-06-30 as the train set, and 2019-07-01 to 2019-12-31 as the validation. Within the train set we used time-series splitting as a cross-validation approach for training. We use data from 2020-01-01 as the test set. The data are normalized based on the train set using RobustScaler.

We have selected and employed the following features:

Feature name	Meaning & Note
year	year
month	month
HDAY	If the date is a public holiday of the state
weekend	If the date is weekend
solar	Variation of solar flux over the year
PV	Installation size of PV panels
solar_PV	'solar' × 'PV'
GSP	GSP of the state. The daily GSP is normalized to the yearly GSP and interpolated to approximate daily variation. Since GSP for 2019-2020 financial year is not available, we approximate it with a constant equals to the value at 2019-06
T_max	Daily maximal temperature
T_min	Daily minimal temperature
T_ave	(T_max + T_min)/2
T_diff	(T_max – T_min)/2
HDD	Heating degree day calculated using Eq. 1 with T = T_ave
CDD	Cooling degree day calculated using Eq. 2 with T = T_ave
HDD_m	Heating degree day calculated using Eq. 1 with T = T_min
CDD_m	Cooling degree day calculated using Eq. 2 with T = T_max
HDD_5d , CDD_5d	HDD and CDD 5 day moving averaged
HDD_2 , CDD_2	HDD^2 , CDD^2
HDD_m2, CDD_m2	HDD_m^2 , CDD_m^2
HDD_exp_5d, CDD_exp_5d,	$HDD \times \exp[(d_i - d_0)/\tau]$, $CDD \times \exp[(d_i - d_0)/\tau]$. d_0 is the current day, d_i is *i* days ago. τ is chosen such that $\exp[(d_{i=5} - d_0)/\tau] = 0.1$

Table I. Features generated and selected for training models

For the calculation of the heating and cooling degree days, we use the following equations:

$$\mathrm{HDD} = \max(\mathrm{T_{HDD}} - \mathrm{T}, 0) \quad (1)$$

$$\mathrm{CDD} = \max(\mathrm{T} - \mathrm{T_{CDD}}, 0) \quad (2)$$

T_{HDD} and T_{CDD} are critical temperatures for heating and cooling [5], which differ slightly in different states.

Results and Insights

We developed independent models for each state to adapt the state-specific situation. The two models got the following results.

State	Linear regression Train set R^2	Linear regression Test set R^2	Catboost Train set R^2	Catboost Test set R^2
NSW	0.8838	0.8446	0.9608	0.809
VIC	0.8486	0.7955	0.9598	0.8456
QLD	0.8907	0.8648	0.9897	0.8288
SA	0.7903	0.7855	0.9401	0.7951

Table II. R^2 values for different models when applied to training set and test set

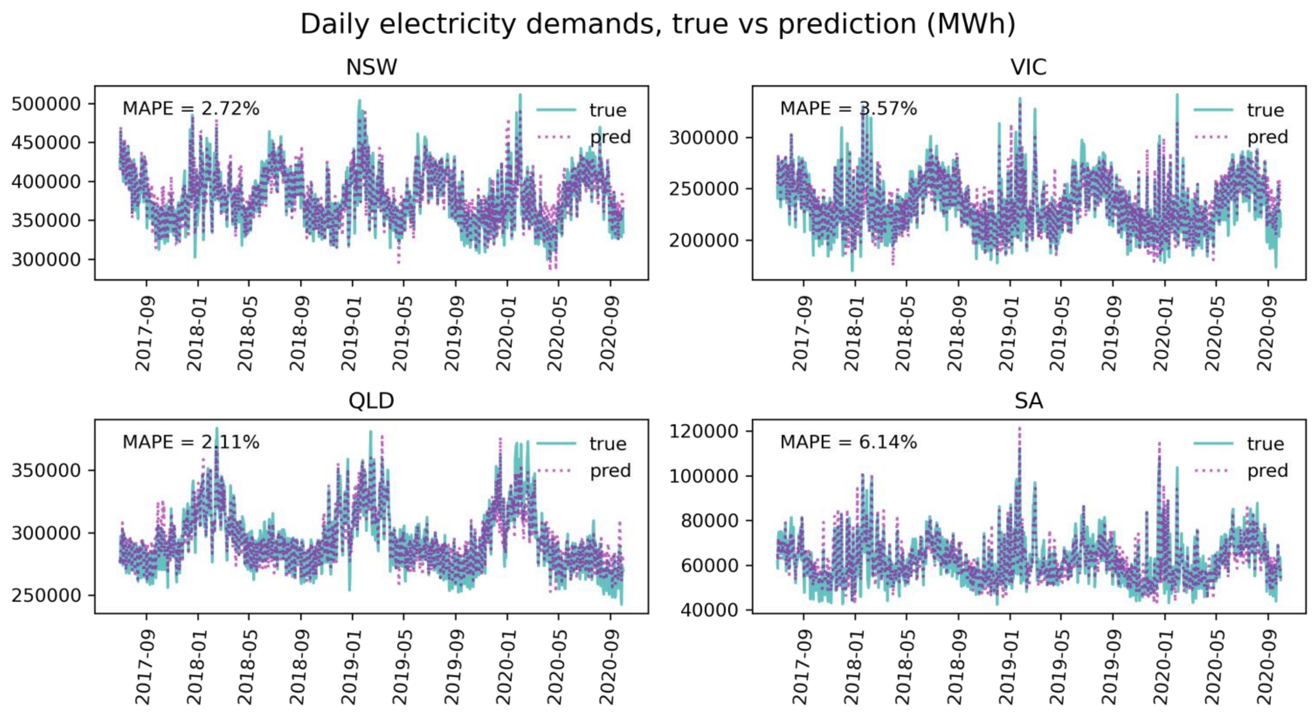


Figure 4. Comparison of true and predicted daily electricity demands using linear regression model. MAPE is the mean absolute percentage error within the date range from 2017-07-01 to 2020-10-10.

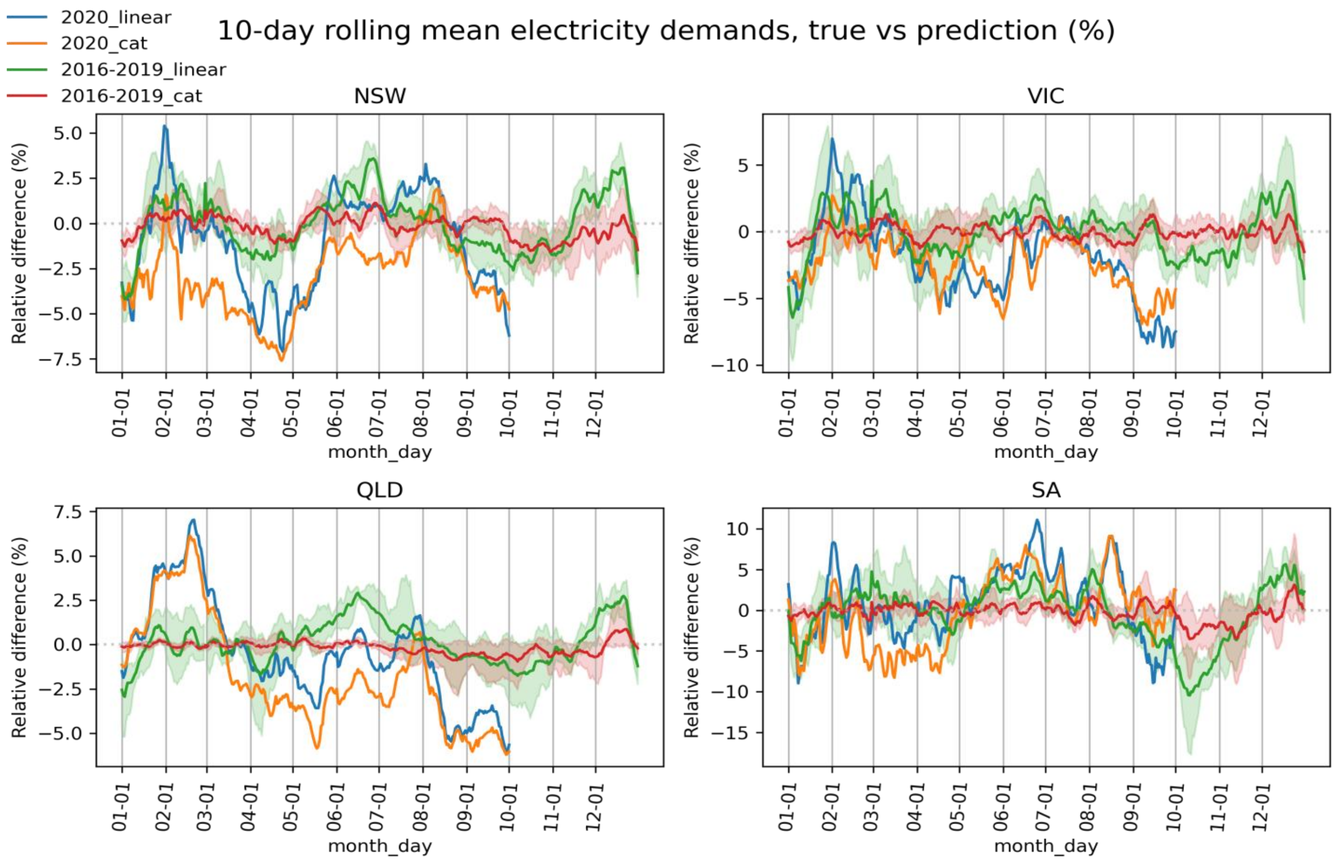


Figure 5. Comparison of true and predicted 10-day rolling mean electricity demands using linear regression and Boosting regression model. The relative difference is (true – pred) / pred. pred is the prediction using model trained with pre-COVID data.

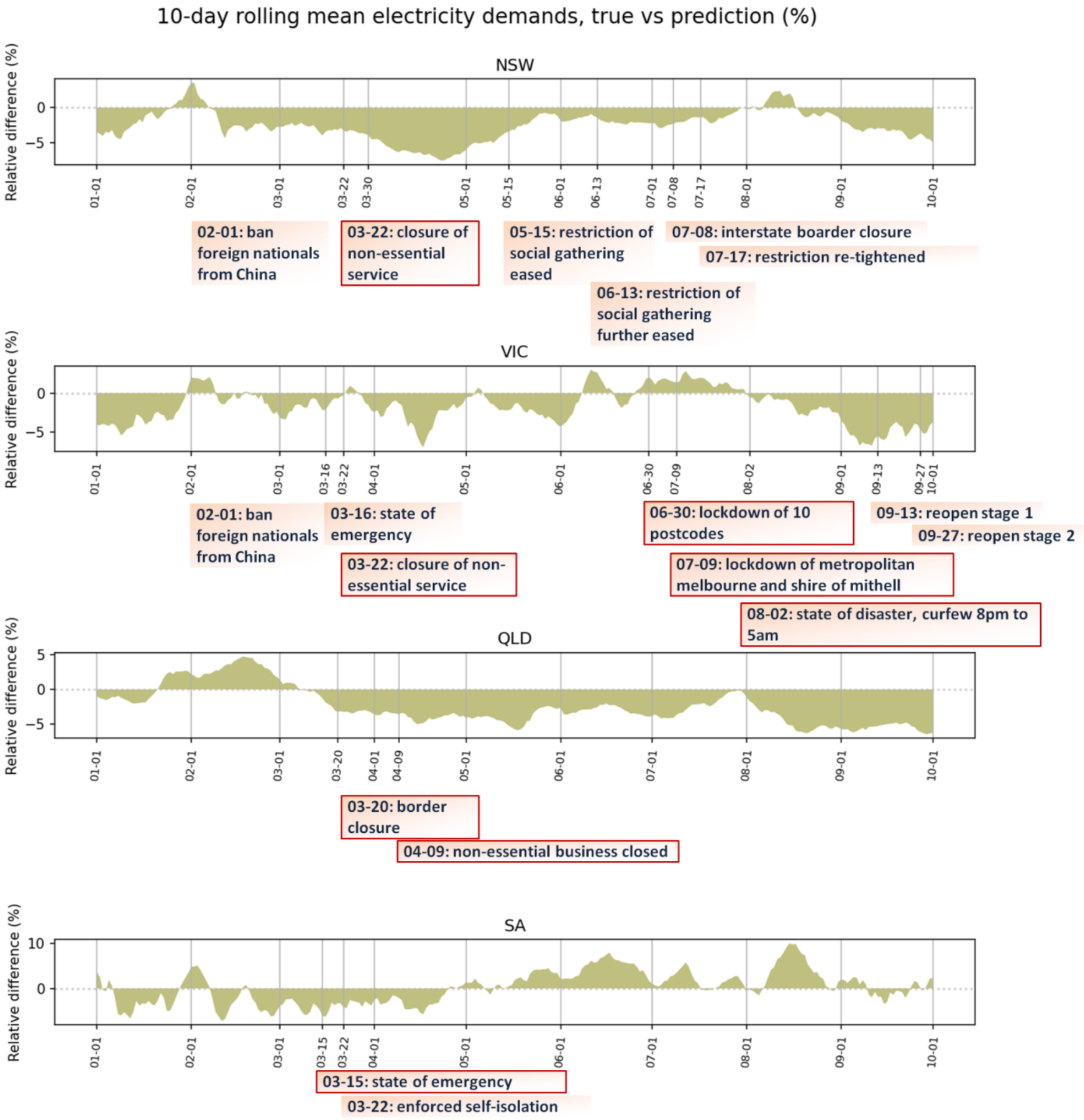


Figure 6. Timelines of COVID-19 restriction and the relative change of electricity demand in different states. The relative difference is defined as (true – pred) / pred. pred is the prediction using Catboost model trained with pre-COVID data. Red rectangles highlight major restriction approaches.

Our models provide an overall good fit for pre-COVID data (see Figure 4). By comparing the electricity demand from this year and past 4 years, as well as the prediction result from the model (see Figure 5 and Figure 6), we have the following observations that indicate the impact of COVID:

★ For New South Wales, the impact of COVID-19 is already noticeable as the Australia boarder closed, and the total electricity demand decreased by over 5% by late April. But the impact was reduced in winter season since June, and became obvious since mid-august as temperature becomes warmer.

★ For Victoria, even though it has closed non-essential business since late march, and has been in the lockdown state for more than 3 months, the overall electricity demand only showed a subtitle change during the winter season and even an increase during mid winter. But, the decline of electricity demand becomes more noticeable since August when temperature is warmer, in particularly after the curfew approach since 02-August. And the decline has been increased to around 7% in September. However, with the plan of recovery started from 13-September, there is a slow increase trend in the electricity demand.

★ For Queensland, the impact of COVID-19 on reduced electricity demand can be observed since late March after the boarder closure, even through the winter season, since heating demand is less significant in Queensland.

★ For South Australia, the cold winter and work from home requirement this year actually increased the overall electricity demand compared to last year.

Summary and Outlooks

In summary, we have examine the impact of COVID-19 on the electricity demands in different states in Australia. The impact is observable at the early stage of boarder closure, social distancing and remote working, before winter. The impact is largely compensated due to increased demands on heating during winter season, but there is a clear trend of electricity demand rapid dropping since September, when the temperature becomes warmer. This could be an indicator of economic recession.

The current study is still premature and several points required further improvement:

1. Currently, most of the data we have access to is the whole sale electricity demand data, which is the total demand amount from different sectors. To have a more accurate estimation of the COVID-19 on different sectors,, including residential, business and services, manufacturing, mining, etc., and the economy as a whole, it is necessary to obtain the electricity sample data from different sectors.
2. Currently we only used installation size of PV panels to estimate the increase contribution of distributed solar power. Since distributed solar panels can have a large impact on the electricity demands in the day time, it is necessary to obtain the actual hourly or daily contribution from the PV systems so that the impact can be more accurately estimated.
3. It could be possible to identify the impact of different restriction and lockdown approaches in the models by introducing dummy variables to characterize the effect of these approaches, like what has been done in our model using features 'weekend' and 'HDAY'.
4. There are some slow varying factor not considered in this study, such as population change, climate change, etc. can also be taken into account.
5. The current study used weather data from one observation site at each state, it should provide higher accuracy to include multiple sites.
6. The current study intends to have a taste of the problem and used simple and explainable models. We can also use more complicated models, but there is a balance between accuracy and explainability.

References

[1] 'CAN ELECTRICITY CONSUMPTION PATTERNS TELL US ANYTHING ABOUT THE PANDEMIC?' by Melbourne Datathon

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