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An evaluation of the impact of COVID-19 lockdowns on electricity demand

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Abstract

The COVID-19 pandemic has given rise to significant changes in electricity demand around the world. Although these changes differ from region to region, countries that have implemented stringent lockdown measures to curtail the spread of the virus have experienced the greatest alterations in demand. Within Australia, the state of Victoria has been subject to the largest number of days in hard lockdown during the COVID-19 pandemic. We conduct an exploratory data analysis to identify predictors of demand, and have built a time series forecasting model to predict the half-hourly electrical demand in Victoria. Our model distinguishes between lockdown periods and non-restrictive periods, and aims to identify a variety of patterns that we show to be influential on electricity demand. The model thereby provides a nuanced prediction of electrical demand that captures the shifting demand profile of intermittent lockdowns.

Keywords: Statistical modeling, Time series, Load demand pattern, Victoria

1. Introduction

The onset of the COVID-19 global pandemic has had far-reaching and lasting effects. In addition to the devastating health toll and loss of life, there has been massive social and economic upheaval, as businesses have been forced to close, and many regular daily activities have come to a standstill. Across the globe, significant reductions in the electrical demand have been observed, which have been attributed to a variety of mitigation strategies designed to contain the spread of the virus, including lockdowns, industrial shutdowns, and travel restrictions [1, 2, 3, 4, 5].

Electricity is an essential commodity for the efficient running of all economic sectors, as well as residential households. To ensure that electricity supply can meet the demand, energy providers must use forecasting methods to plan for the future [6]. When an end-use customer requires power, the electricity retailer supplies this power by purchasing the electric load. The electricity retailer will pre-purchase the electricity load they require based on demand forecasts at the wholesale price. In the case of under-predictions, the retailer can purchase additional loads from the National Electricity Market

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(NEM) at a typically high, volatile spot price. However, overestimating the demand can lead to wasted electricity and the disposal of the unused load [7]. Improved demand predictions lead to a reduction of additional costs for electricity retailers incurred by over and under predicting the demand. On a macroeconomic scale, this could potentially allow electricity costs to fall as the cost to the providers is reduced, and pricing becomes more competitive. Additionally, there is an environmental benefit to improving electricity demand predictions, as the waste from generating excessive electricity is minimized.

Governmental responses to the pandemic have been quite varied across the world, but a correlation has been observed between the stringency of the mitigation strategies (ie. restrictions such as lockdowns) and the magnitude of the decline in electrical demand [8]. Countries that imposed heavy restrictions have generally experienced greater declines in electrical demand than countries that took a less restrictive approach [9, 8]. More specifically, for countries such as Italy and the UK, where strict lockdowns were implemented, the electrical demand on workdays (Monday to Friday) was comparable to the pre-pandemic weekend demand [9]. Conversely, the demand profile in Sweden, a country that did not lock down its population, exceeded its corresponding pre-pandemic levels on occasion. This indicates that identifying the severity of restriction measures imposed in response to the pandemic is important for analysing variations in the expected electrical demand. Consequently, it is important for the analysis of pandemic-related impacts to be region specific. Studies investigating the COVID-19 impact on load demand have been conducted for India [10, 11], China [12], France [13], Turkey [14] , and United States [15, 16]. In Australia, the state of Victoria has experienced the largest proportion of COVID-19 cases to date, and has thus been subjected to the most days under lockdown rules. The effect of COVID-19 on electricity demand in the state has been visualized by Chetty et al. [17], but the effect has not been quantified. Here, we use Victorian electrical demand data to build a statistical model for demand forecasting, and show that the inclusion of COVID-19 related predictors is essential for forecasting accuracy.

We first conducted an analysis of the electricity demand in Victoria before the pandemic, using data from 2016 and 2019. This analysis provided us with insights into the pre-existing trends, such as daily and weekly patterns, which informed the types of predictors used in our model. We then compared trends in the raw data during lockdowns, and outside of lockdowns. The differences observed here gave us confidence that the lockdown status of the state of Victoria influences the half-hourly electrical demand, and that including this information in the forecasting model will improve predictions of the future demand. Having amassed an array of predictors, we estimated the optimal forecasting model for the Victorian electrical demand data. Using these results, we estimated the change to the half-hourly demand predictions as a result of our additional predictors. Most importantly, we found that our model makes significantly different forecasts at certain times of the day during lockdown periods.

The remainder of this article is organised as follows. In Section 2 we perform an exploratory data analysis to identify trends in the electrical demand data. In Section 3 we look specifically at the effects of COVID-19 restrictions, including lockdowns, on electrical demand, and compare the daily and weekly demand profiles to see how these have changed from the regular (non-lockdown) profiles. In Section 4 we compile a list of predictors based on our analysis in the previous two sections, and formulate an optimal forecasting model for our dataset and compare this model with some benchmarks. In Section 5 we show how the additional predictors that came from our analysis make the model predictions more accurate, and more specific to a variety of factors. Section 6 concludes the paper.

2. Material and Preliminary analysis

Half-hourly forecasts of electricity demand are useful for reducing the cost of power generation, and allow for more effective planning [18]. We have collected historical half-hourly demand data for Victoria from the Australian Energy Market Operator (AEMO) website to form the basis of our dataset. Our data points include every half hour from 01/01/2016 0:30 to 30/07/2021 0:00. Here, it should be noted that more historical data points are investigated to eliminate the fluctuations from a meteorological episode such as a mild or severe winter. The historical demand will provide autoregressive predictors for our model. We have also performed additional analysis to identify patterns in the demand data that could inform the curation of other independent predictor variables, thereby improving our model.

There are many factors that can affect the electrical demand, such as social activities, changes in climate and seasonal cycles and trends [19]. An example of these trends can be seen in the daily, yearly, weekly and seasonal demand patterns shown in Figure 1.

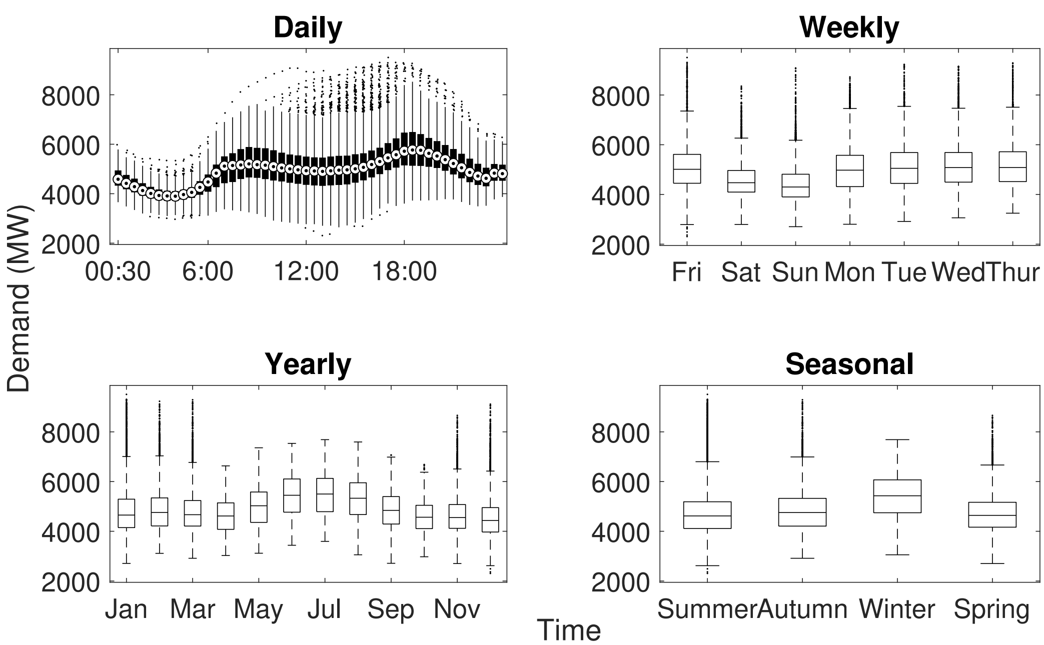

Figure 1: Electrical demand pattern

From the plot of the daily demand in Figure 1 we see that there are two peaks in electrical demand, the first occurring around 08:30, with an average demand of 5272.19 MW, and the second, higher peak of 5834.74 MW at approximately 18:30. The morning and evening peaks may correspond to the time that the majority of people wake up and return home at the end of the day. Between these two peaks, there is a dip in demand which reaches a minimum of 4929.56 MW at 13:00. This dip may occur because of the break most people take around lunch time. Additionally we find that consumption is much less variable at night because most people are asleep.

The box plots of the yearly and seasonal demands in Figure 1 both demonstrate that electricity demand is at its highest during the winter months. The highest average half-hourly demand is in July, at 5468.74 MW. This is nearly 1000 MW higher than the lowest average demand of 4554.05 MW, which occurs in December. Considering the low temperature in Victoria, we can infer that the higher consumption of electricity in winter may be due to the use of heating.

The weekly demand plot in Figure 1 shows that over the course of a week, the electrical demand is consistently higher on working days (Monday to Friday) compared to the weekend. The average half-hourly demand during working days ranges from 5020.17 MW on Monday, to 5166.89 MW on Thursday. The average demands from Saturday and Sunday are significantly lower: 4566.51 MW and 4417.24 MW, respectively. The reduced electricity demand on weekends is likely a result of businesses and factories being closed.

We use all this information to create predictor variables in Section 4 for building our forecasting model.

3. Lockdown effects

Given that our data spans the time period from 2016 to 2021, it is important that we consider the impact of COVID-19, and lockdowns in particular, on the electrical demand, as we know that the population's activity has shifted significantly in response to the pandemic. At the onset of the COVID-19 pandemic in Australia, a nation-wide lockdown was imposed on the 23$^{\text{rd}}$ of March 2020. Restrictions were eased in Victoria on May 15$^{\text{th}}$ of the same year. The capital city of Melbourne underwent a second lockdown on July 20$^{\text{th}}$ 2020. This lockdown was eventually lifted on the 26$^{\text{th}}$ of October 2020. The third lockdown began on the 13$^{\text{th}}$ of February 2021 and ended on the 17$^{\text{th}}$ of February. A fourth lockdown began on the 28$^{\text{th}}$ of May and ended on the 10$^{\text{th}}$ of June. Most recently, Melbourne entered its fifth lockdown, beginning on the 16$^{\text{th}}$ of July and ending on the 27$^{\text{th}}$ of July. All the lockdown information was retrieved from ABC news [20]. Using this information, we created a dummy variable, "lockdown", which takes the value 1 for all data points that fall within the lockdown period, and 0 otherwise.

In Figure 2 we show the percentage change in demand in 2020 and the first half of 2021, relative to the demand at the corresponding times in 2019. The lockdown periods are highlighted. The total demand in Victoria decreased by 3.0% in 2020 relative to 2019, and in January to July 2021 it was reduced by 1.81% from the 2019 demand during the same period. This figure shows us that describing the effect of

COVID-19 and lockdowns as simply lowering the electrical demand is too reductive, and it conceals the nuance behind the daily demand profile. Here, it should be noted that we investigate the data points from 2016 to 2019 to eliminate the fluctuations from a meteorological episode in our work. We can more clearly see the effects of the lockdown measures by comparing the average daily demand profile during lockdown and out of lockdown. This is shown in Figure 3.

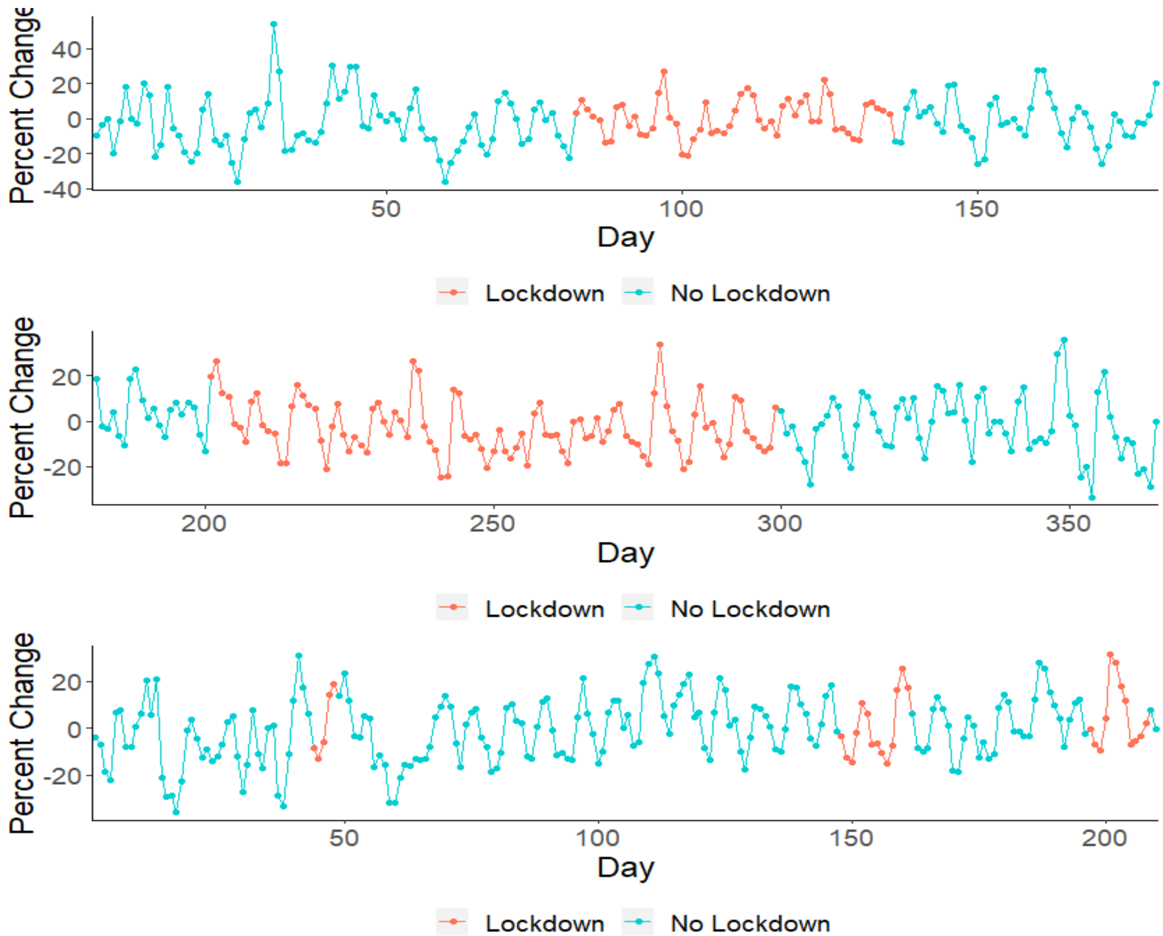

Figure 2: Comparing the electrical demand in 2020-2021 Relative to 2019

Top: Percentage change in demand in Jan-June 2020 relative to the same period in 2019. Middle: Percentage change in demand in Jul-December 2020 relative to the same period in 2019. Bottom: Percentage change in demand in Jan-July 2021 relative to the same period in 2019.

In comparing the daily demand profiles for lockdown and non-lockdown periods, it is that the lockdown demand profile is slightly more 'stretched' than the normal profile, in the sense that local demand minima are slightly become much lower 04:00 and 14:00) and local demand maxima 09:30 and 18:30) are the about same for lockdown periods. However, the average of demand is 224.92 MW higher at this time during a lockdown than on a regular day. The mid-day dip in demand is the location of the second largest difference in demand. Moreover, Figure 3 shows clear differences for both minimum and maximum demand before 5:00am. It is interesting to note that the difference in average demand for this period does not seem

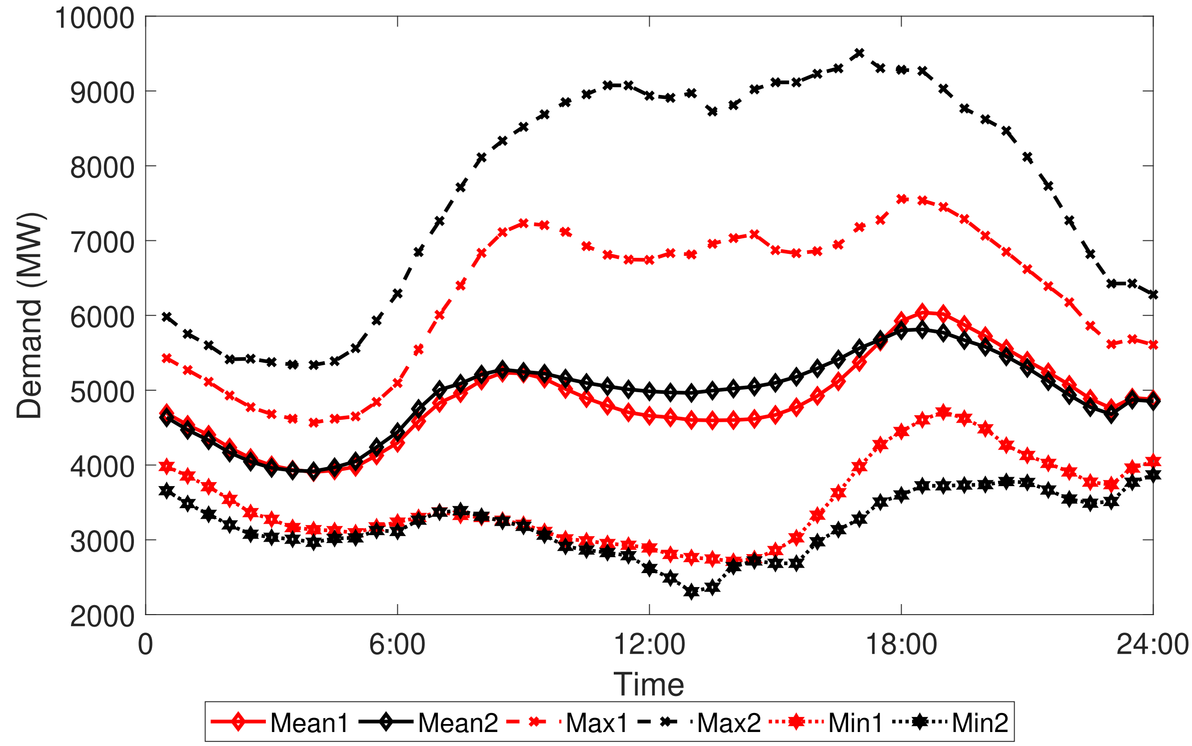

Figure 3: Daily observed electrical demand profile. Mean 1, Max 1, and Min 1 are the average, maximum, and minimum of the half-hourly demand with lockdown (in red colour), respectively. Mean 2, Max 2, and Min 2 are the average, maximum, and minimum of the half-hourly demand with no lockdown (in black colour), respectively.

to be there. Therefore, we need to quantify the difference while taking account of many other variables including the seasonality and other cyclic patterns.

From Figure 4, based on the average values for each day, we can see that there is very little difference in demand on the weekends during lockdowns and outside of lockdowns. Monday, Thursday and Friday show that the lockdown demands seem lower than usual. The largest difference of the average is observed on Thursday, where the average half-hourly demand during lockdown is 155.12 MW lower than a non lockdown day. Here, we can infer that the consumption of electricity demand generally increases with time and many complex patterns are interactive; thus, the impact of lockdown is under-evaluated according to the simple analysis.

It should be noticed that observed patterns here based on the data summary in Figure 3 and 4 are inaccurate because the daily/weekly pattern is not accounting for the other effects (such as the seasons).

4. Data Modeling

In this section, we first introduce the predictors built according to the analysis in the former two sections. Next we construct two linear regression models with and without COVID-19 predictors and

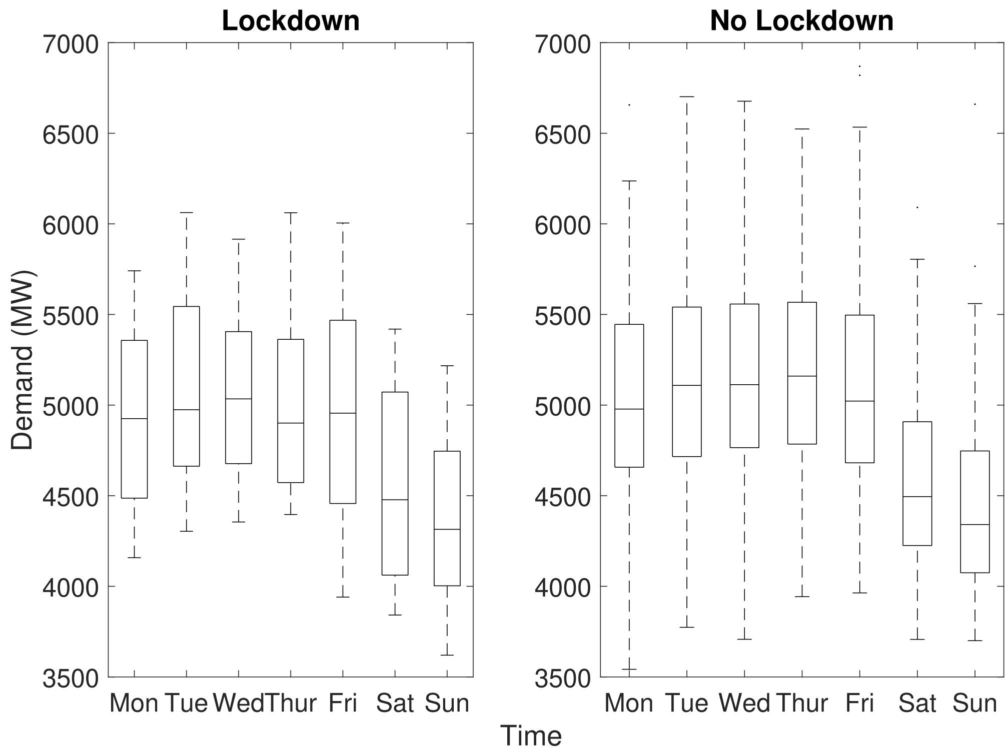

Figure 4: Weekly observed electrical demand profile. The average values of electricity demand (unit: MW) from Mon. to Sun. with lockdown are 4925.30, 5060.52, 5058.89, 5026.17, 4983.97, 4555.43, and 4396.49, respectively, while those with no lockdown are 5030.67, 5117.59, 5155.52, 5181.29, 5100.87, 4567.69, and 4419.45, respectively.

show the improvement by modeling with COVID-19 predictors. Then we diagnose the residuals from the selected linear regression model and further extract the temporal correlation by using a time series modelling approach. Finally we assemble the sub-predictions from the selected linear regression and time-series model together for our final predictions.

From an operational perspective, we have access to consumption data at $t-30$ intervals, which has been noted in our recently published work in Wu et al. [18]. In this work, we divided the investigated dataset of electricity demand into two parts: the training set (61296 observations) from 01/01/2016 0:30 to 30/06/2021 0:00 and the remaining test set (1392 observations) from 01/07/2021 0:30 to 30/07/2021 0:00. It should be noted that we have 8784 data points with COVID-19 impact in our training set while we have 576 data points with COVID-19 impact in our test set.

4.1. The construction of predictors

To build models which capture some of the patterns found in our preliminary analysis, we used certain harmonic functions as predictors. Using these functions as load forecasting predictors was proposed by Wu et al. [7]. We considered a number of cyclical trends including those noted in Section 2: daily, weekly, seasonal, and yearly. We also included half-daily and monthly patterns and, motivated by Figure 1, we added a dummy variable, "Workday", which takes the value 1 if the day is Monday to Friday, and

0 on the weekends. Most importantly, we included the variable "Lockdown", which was introduced in Section 3. We also included eight interaction variables that are formed by taking the product of the Lockdown variable with the two harmonic functions for the daily, half-daily, weekly, monthly, seasonal, and yearly patterns, as well as the product of Lockdown and Workday variables.

Finally, we add the dummy variable, "COVID", which can assess the general impact of COVID-19 on electrical demand in Victoria. An entry ban was announced by the Prime Minister of Australia to take effect on Friday the 20$^{\text{th}}$ March 2020 at 21:00 AEDT, blocking all non-citizens and non-residents from entering the country. For all data points after this event, we set the "Covid" variable to be equal to 1.

Table 1 below summarizes the predictor variables used in our model.

Table 1: The details of predictor construction

Type	Predictor	Formula	Predictor	Formula
Basic	Time	$t = 1, 2, \ldots$	Workday	$\begin{cases} 1 & \text{if day is Mon-Fri} \\ 0 & \text{otherwise} \end{cases}$
	DailySin	$\sin(2\pi t/T)$, $(T = 1 \times 48)$	DailyCos	$\cos(2\pi t/T)$, $(T = 1 \times 48)$
	HalfDailySin	$\sin(2\pi t/T)$, $(T = 1 \times 48/2)$	HalfDailyCos	$\cos(2\pi t/T)$, $(T = 1 \times 48/2)$
	WeekySin	$\sin(2\pi t/T)$, $(T = 7 \times 48)$	WeeklyCos	$\cos(2\pi t/T)$, $(T = 7 \times 48)$
	MonthlySin	$\sin(2\pi t/T)$, $(T = 365.25/12 \times 48)$	MonthlyCos	$\cos(2\pi t/T)$, $(T = 365.25/12 \times 48)$
	SeasonalSin	$\sin(2\pi t/T)$, $(T = 365.25/4 \times 48)$	SeasonalCos	$\cos(2\pi t/T)$, $(T = 365.25/4 \times 48)$
	YearlySin	$\sin(2\pi t/T)$, $(T = 365.25 \times 48)$	YearlyCos	$\cos(2\pi t/T)$, $(T = 365.25 \times 48)$
COVID-19	COVID	$\begin{cases} 1 & \text{if after travel ban} \\ 0 & \text{otherwise} \end{cases}$	Lockdown	$\begin{cases} 1 & \text{if in lockdown} \\ 0 & \text{otherwise} \end{cases}$
	LockdownDailySin	Lockdown×DailySin	LockdownDailyCos	Lockdown×DailyCos
	LockdownHalfDailySin	Lockdown×HalfDailySin	LockdownHalfDailyCos	Lockdown×HalfDailyCos
	LockdownWeeklySin	Lockdown×WeeklySin	LockdownWeeklyCos	Lockdown×WeeklyCos
	LockdownMonthlySin	Lockdown×MonthlySin	LockdownMonthlyCos	Lockdown×MonthlyCos
	LockdownSeasonalSin	Lockdown×SeasonalSin	LockdownSeasonalCos	Lockdown×SeasonalCos
	LockdownYearlySin	Lockdown×YearlySin	LockdownYearlyCos	Lockdown×YearlyCos
	LockdownWorkday	Lockdown×Workday		

4.2. Regression with predictors

In this subsection, we build two linear regression models with and without COVID-19 predictors to demonstrate how considering the effects of COVID-19 can improve the model predictions. The regression coefficient estimates for the predictors are reported in Table 2 and the results of the ANOVA test comparing the two models are given in Table 3.

As illustrated in Table 2, most of the coefficient estimates for the two models are significant. In the work, our focus is not on the hypothesis tests but prediction with lockdown in place. Given that the number of predictors is not large, it is unclear whether the removal of insignificant explanatory variables would lead to better predictions because of potential type I and II errors incurred. On the other hand, all the explanatory variables are selected or created meaningfully. We therefore did not remove the 2 insignificant variables as potential bias can be introduced upon their removal.

Upon further exploration of the differences between the parameter estimates, two interesting observations can be made. Firstly, the estimate for the intercept of the regression model without COVID-19 impacts is 4766.19, which is much greater than 4742.25, the intercept of the model with COVID-19

Table 2: The regression coefficient estimates for the model predictors[a]

	Without COVID-19 impact	With COVID-19 impact
Intercept	4766.19***	4742.25***
Time	0.00***	0.00***
Workday	486.82***	496.11***
DailySin	-516.36***	-517.21***
DailyCos	-256.39***	-278.00***
HalfDailySin	-371.32***	-360.76***
HalfDailyCos	-151.69***	-146.97***
WeeklySin	-90.68***	-88.57***
WeeklyCos	78.27***	81.71***
MonthlySin	-21.65***	-21.72***
MonthlyCos	-9.06***	-11.01**
SeasonalSin	-31.69***	-34.20***
SeasonalCos	-67.95***	-53.88***
YearlySin	-8.00**	-8.19**
YearlyCos	-323.38***	-315.78***
COVID	-	-23.94**
Lockdown	-	-210.55***
LockdownWorkday	-	-110.72***
LockdownDailySin	-	9.36
LockdownDailyCos	-	237.16***
LockdownHalfDailySin	-	-115.83***
LockdownHalfDailyCos	-	-51.83***
LockdownWeeklySin	-	-32.78*
LockdownWeeklyCos	-	-57.11***
LockdownMonthlySin	-	-29.04**
LockdownMonthlyCos	-	12.84
LockdownSeasonalSin	-	93.03***
LockdownSeasonalCos	-	-40.69***
LockdownYearlySin	-	-44.95***
LockdownYearlyCos	-	-444.03***

Significant codes: '***': 0.001; '**': 0.01; '*': 0.05.

impacts. In other words, the COVID-19 impact significantly decreases the electricity demand baseline. Secondly, the coefficient estimate for Workday in the model without COVID-19 impacts is 486.82 and 496.11 in the model with COVID-19 impacts. This means that more electricity is consumed on workdays impacted by COVID-19 than regular workdays. In addition, the ANOVA test recorded in Table 3 shows that introducing 15 predictors based on the impact of COVID-19 significantly improves the model fit to the data, giving an extremely small p-value ($< 2.2e-16$).

Table 3: The ANOVA test results showing the difference between the two regression models

Model 1: Regression without COVID-19 impact

Model 2: Regression with COVID-19 impact

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
Model 1	96369	3.4658e+10				
Model 2	96354	3.3866e+10	15	792546580	150.33	$< 2.2e-16$

According to the coefficient estimates for the regression model with COVID-19 impacts in Table 2, the following conclusions can be drawn. The intercept coefficient estimate gives the average half-hourly demand, which is 4742.25 MW. The workday coefficient estimate tells us that on average, the half-hourly demand on Monday to Friday is 496.11 MW higher than the weekend demand. We can also see that the general impact of COVID-19 is to reduce the average half-hourly electrical demand by 23.94 MW, while the average reduction to the half-hourly demand due to lockdowns specifically is 210.55 MW. Our findings and contributions to the understanding of the electrical demand in Victoria are as follows:

a. Generally, the estimated daily electricity demand profiles show that there are two peaks in demand, occurring at approximately 09:30 and 18:30. Between these peaks, there is a reduction in demand, and it is at its lowest around 04:00 in the morning. The estimated weekly profile shows a decrease in the variation of half-hourly demand from Monday to Friday and more dramatically during the weekend. Thus, demand is higher on weekdays compared to weekends. In terms of annual trends, the winter season is associated with higher electricity demands, with the month of July showing the highest average half-hourly demand.

b. Lockdowns, and to a lesser extent the pandemic in general, have caused a net reduction in the average half-hourly electricity demand. Moreover, we examined the daily demand profile during lockdowns to gain a more nuanced understanding of the effects of lockdowns. During lockdown demands exhibit the peaks and troughs at about the same time points as demands without lockdown (as shown in Figure 6). However, the values at peaks or troughs appear to vary at two time points. During the mid-day dip, the lockdown effect becomes the largest, and disappears after 19:30.

c. We have proposed 29 predictors that capture the trends in the demand profile, as well as the effects of the pandemic and lockdowns. According to the ANOVA results in Table 3, we show the predictors considering COVID-19 impacts can significantly improve data modelling.

d. Our model adjusts the predictions of electricity demand according to three possible states; normal (pre-pandemic), lockdown, and no lockdown, as well as the specific time of day and the day of the week.

Remark 1. The observed daily pattern in Figure 6 is different from the description based on the data summary in Figure 3 because of the additional seasonal effects inherited in Figure 3. Our proposed model can incorporate other effects as many as possible, thus the final estimated daily pattern is insensitive to any biased seasonal effects presented in the data. Roughly, Figure 6 represents the daily pattern after averaging over all the seasons (standardized) while Figure 3 is specific for the dates in the data without considering the nature of imbalanced seasonal design. To show the consistency to the observed data, we calculate the fitted demands for the same dates as used in Figure 3. We can see from the plot in Appendix 6 (lockdown vs no lockdown: daily average over the dates in the data) that the estimated pattern from these dates resulted in a consistent pattern to that in Figure 3.

Remark 2. The observed weekly pattern in Figure 6 is different from the description based on the data summary in Figure 4 because the weekly pattern from Figure 4 is not accounting for the other effects (such as the seasons) and the data do not have balanced seasonal effects for all seasons for locked and unlocked periods. Our proposed model takes account of other effects as many as possible so that the final estimated weekly pattern is not affected by any biased seasonal effects presented in the data. Furthermore, we calculate variations of the fitted demands for the same dates as used in Figure 4 as Monday (105.28), Tuesday (58.38), Wednesday (97.20), Thursday (154.40), Friday (117.93), Saturday (12.06), and Sunday (21.77). We can see the variations of the fitted demands exhibit a same pattern in the description about Figure 4. The discrepancy in this weekly pattern shown in Figure 6 is due to the additional seasonal effects inherited in Figure 4. Roughly, Figure 6 represents the weekly pattern after averaging over all the seasons (standardized) while Figure 4 is specific for the dates in the data.

4.3. Temporal correlation modelling

In this subsection, considering the model selection results in sub-section 4.2, we further explore the residuals estimated by the regression model with COVID-19 impact, specifically considering temporal correlation to improve data modeling.

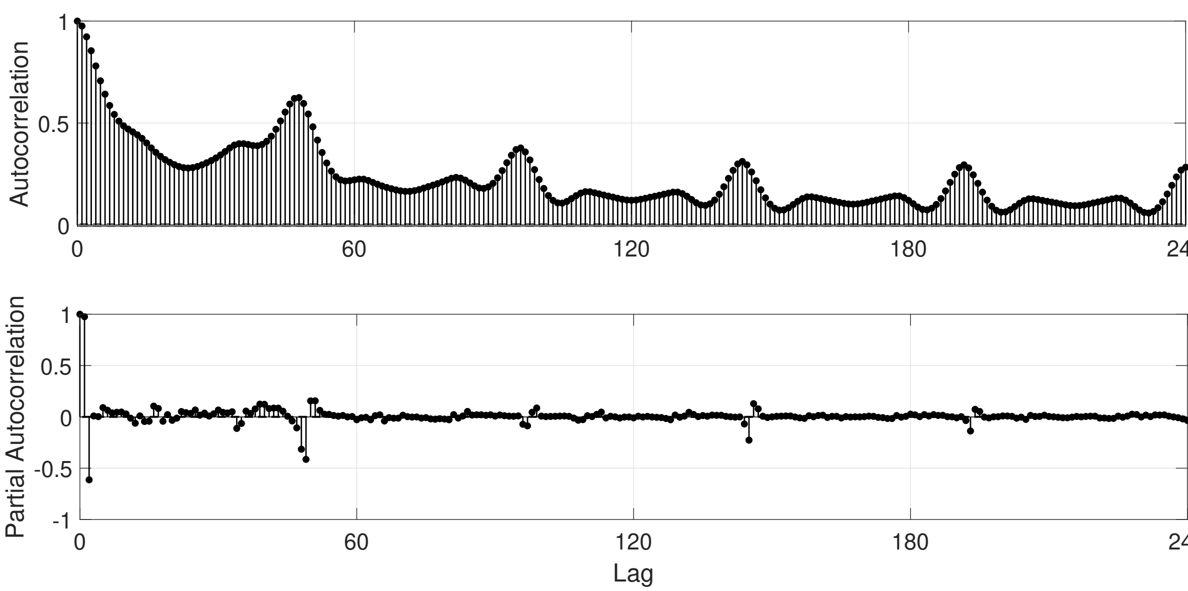

Figure 5: ACF and PACF for the residuals of the regression model with COVID-19 impact

The ACF and PACF results for the residuals of the regression model with COVID-19 impacts are plotted in Figure 5. Here we find that the PACF nearly tails off after the second-order lag and the ACF sine-wave decays. This means there exists a complex temporal pattern in our estimated residuals.

To obtain an optimal ARIMA model, we used the function "auto.arima()" in the R package "forecast" [21] to estimate the model coefficients, obtaining $p = 3$, $d = 0$ and $q = 1$ with the minimum AIC value as 1,165,638. These parameters represent the autoregressive order, integrated order and moving average order, respectively. The best model was estimated to be the ARMA(3,1) model, with coefficient estimates given in Table 4.

Table 4: The coefficient estimates of the ARMA(3,1) model

	ar1	ar2	ar3	ma1
	0.66	0.82	-0.55	0.92
s.e.	0.0095	0.0149	0.0066	0.0087

These estimates allow us to deduce how certain variables affect the electrical demand. From the autoregressive order of the model for instance, we find that the previous three observations are the most important lagged values for predicting future demand. Moreover, of the three autoregressive predictors, ar1 and a2 have positive effects on the demand, while ar3 has a negative effect on the demand. In details, additional megawatts of the first and second lagged values increase the current demand prediction by 0.66 megawatts and 0.82 megawatts, respectively. By contrast, the ar3 predictor has a negative coefficient estimate, meaning a one megawatt increase in the second lagged demand has the effect of reducing the current demand prediction by 0.55 megawatts. Moreover, ma1 has the most largest effect on the demand prediction as 0.92.

Finally, our proposed forecasting model for predicting the electricity demand that considers the impact of COVID-19 is given by:

$$
\begin{aligned}
y_{t+1} = \;& 4742.25 + 0.00\text{Time} + 496.11\text{Workday} - 517.21\text{DailySin} - 278.00\text{DailyCos} - 360.76\text{HalfDailySin} \\
& -146.97\text{HalfDailyCos} - 88.57\text{WeeklySin} + 81.71\text{WeeklyCos} - 21.72\text{MonthlySin} - 11.01\text{MonthlyCos} \\
& -34.20\text{SeasonalSin} - 53.88\text{SeasonalCos} - 8.19\text{YearlySin} - 315.78\text{YearlyCos} - 23.94\text{COVID} \\
& -210.55\text{Lockdown} - 110.72\text{LockdownWorkday} + 9.36\text{LockdownDailySin} + 237.16\text{LockdownDailyCos} \\
& -115.83\text{LockdownHalfDailySin} - 51.83\text{LockdownHalfDailyCos} - 32.78\text{LockdownWeeklySin} \\
& -57.11\text{LockdownWeeklyCos} - 29.04\text{LockdownMonthlySin} + 12.84\text{LockdownMonthlyCos} \\
& +93.03\text{LockdownSeasonalSin} - 40.69\text{LockdownSeasonalCos} - 44.95\text{LockdownYearlySin} \\
& -444.03\text{LockdownYearlyCos} + 0.66u_t + 0.82u_{t-1} - 0.55u_{t-2} + 0.92\nu_t + \nu_{t+1},
\end{aligned}
$$

where y_{t+1} is the predicted demand at time $t+1$, with white noises, ν_{t+1} and ν_t, and regression model (with COVID-19 impact) residuals u_t, u_{t-1}, and u_{t-2}. Here, it should be noted that all constructed predictors are at time $t+1$.

4.4. The model comparison

In this sub-section, we investigate three benchmark models to demonstrate the effectiveness of our proposed model for electricity demand forecasting with COVID-19 impact. These models include: regression without COVID-19 impact (Model 1), regression with COVID-19 impact (Model 2), and temporal regression without COVID-19 impact (Model 3). Moreover, two error indicators, mean absolute error

(MAE) and root mean square error (RMSE), are used to measure the forecasting performance as follows:

$$\text{MAE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|},$$

and

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2},$$

with data size n, i-th observation y_i and i-th prediction $\hat{y}_i$.

To illustrate the performance of demand forecasting during a lockdown period, we further distinguish the data points occurring during a lockdown (576 observations) from the test set. The forecasting results are reported in Table 5.

Table 5: Error indicators for forecasting performance in test set

	The whole Period		Lockdown Period	
	MAE	RMSE	MAE	RMSE
Without COVID-19 impact				
Model 1	685.81	822.72	662.53	809.57
Model 3	98.55	136.48	102.59	142.84
With COVID-19 impact				
Model 2	619.78	763.36	489.02	620.04
Proposed.	98.52	136.22	100.38	136.44

They show our proposed forecasting model with MAE = 100.38 and RMSE = 136.44 is more effective than the other three benchmark models for electricity demand forecasting during a lockdown period. Several other observations can be made from the results in Table 5. Firstly, compared to Model 1 (regression without COVID-19 impact), Model 2 provides better predictions with smaller error indicators, especially for forecasting demand during lockdown periods. This further demonstrates the effectiveness of our model selection in sub-section 4.2 and that considering the impact of COVID-19 can greatly improve model predictions. Furthermore, we can conclude that including the temporal correlation can significantly improve the forecasting accuracy. For example, in the case of forecasting during the whole period, the MAE and RMSE with our proposed model (considering temporal correlation) are 98.52 and 136.22, respectively, while those with Model 2 (regression with COVID-19 impact) are 619.78 and 763.36, respectively. Finally we shall note that Model 3 (where COVID-19 impact is not considered) provides good predictions for the whole period and has an MAE and RMSE of 98.55 and 136.48 respectively. The main reason behind this is that the temporal correlation can correct predictions by sufficiently considering the lag information.

It is noteworthy that using the intercept value of 4742.25 as a basis, the largest difference between the forecast errors is around 0.13% (difference of RMSE during lockdown between the proposed model (136.44) and Model 3 (142.84)). Here, to illustrate the significance of the results reported in Table 5, we further take the difference between final estimated residuals with Model 3 and our proposed model. Then, we conduct the t-test on the difference during the lockdown period and the whole period, respectively, and record their results in Table 6. Here, the null hypothesis is: the average of differences between Model 3 and the proposed model is 0.

Table 6: Results of the t-test between Model 3 and the proposed model

Panel A: The differences during the whole period				
	Mean	t	Df	Sig.(2-tailed)
Differences	0.01	0.40	97775	0.69
Panel B: The differences during lockdown period				
	Mean	t	Df	Sig.(2-tailed)
Differences	-3.25	-16.41	9359	$< 2.2e-16$

According to results from our statistical tests, two points can be concluded as follows. First, we obtain that our proposed model can provide great predictions during the lockdown period compared to Model 3 with p-value$< 2.23e{-}16$ in Panel B from Table 6. In other words, the reported error indicators with Model 3 and the proposed model during lockdown period in Table 5 are significant. Another point is there are no forecasting performance between Model 3 and the proposed model during the whole period. As illustrated in Panel A from Table 6, the p-value is 0.6898, and this means there is no significant difference between these two models. The result further shows temporal correlation containing underlying information can be extract with time-series modelling to improve forecasting performance.

In summary, our proposed temporal model with the impact of COVID-19 provides more highly accurate predictions when compared to the other investigated benchmark models for electricity demand forecasting particularly during lockdown periods.

5. Discussion

To analyze the effects of the pandemic, we have defined three states: (1) normal, where Covid=0 and Lockdown=0; (2) lockdown, where Covid=1, and Lockdown=1; and (3) no lockdown, where Covid=1, and Lockdown=0.

5.1. Modelling the daily and weekly average demand patterns for different states

We have extracted the predictors (and their corresponding coefficient estimates with our selected model from Table 2) that pertain to the daily and half-daily patterns, as well as the pandemic-related predictors to create a model for the change in average daily demand pattern. This demonstrates that the addition of these predictors significantly affects the forecasting estimates. The model for the change to the daily pattern is given by

$$\begin{aligned}\text{DailyChange} = &(-517.21\text{DailySin} - 278.00\text{DailyCos}) + (-360.76\text{HalfDailySin} - 146.97\text{HalfDailyCos}) - 23.94\text{COVID}\\ &- 210.55\text{Lockdown} + (9.36\text{LockdownDailySin} + 237.16\text{LockdownDailyCos}) + (-115.83\text{LockdownHalfDailySin}\\ &-51.83\text{LockdownHalfDailyCos})\,.\end{aligned} \quad (1)$$

Similarly, our model for the change in weekly pattern is given by

$$\begin{aligned}\text{WeeklyChange} =& 496.11\text{Workday} + (-88.57\text{WeeklySin} + 81.71\text{WeeklyCos}) - 23.94\text{COVID} - 210.55\text{Lockdown} \\ & - 110.72\text{LockdownWorkday} + (-32.78\text{LockdownWeeklySin} - 57.11\text{LockdownWeeklyCos})\,.\end{aligned} \tag{2}$$

We use these models to estimate the pattern of change to the predictions over a day, and over a week, as shown in Figure 6 below.

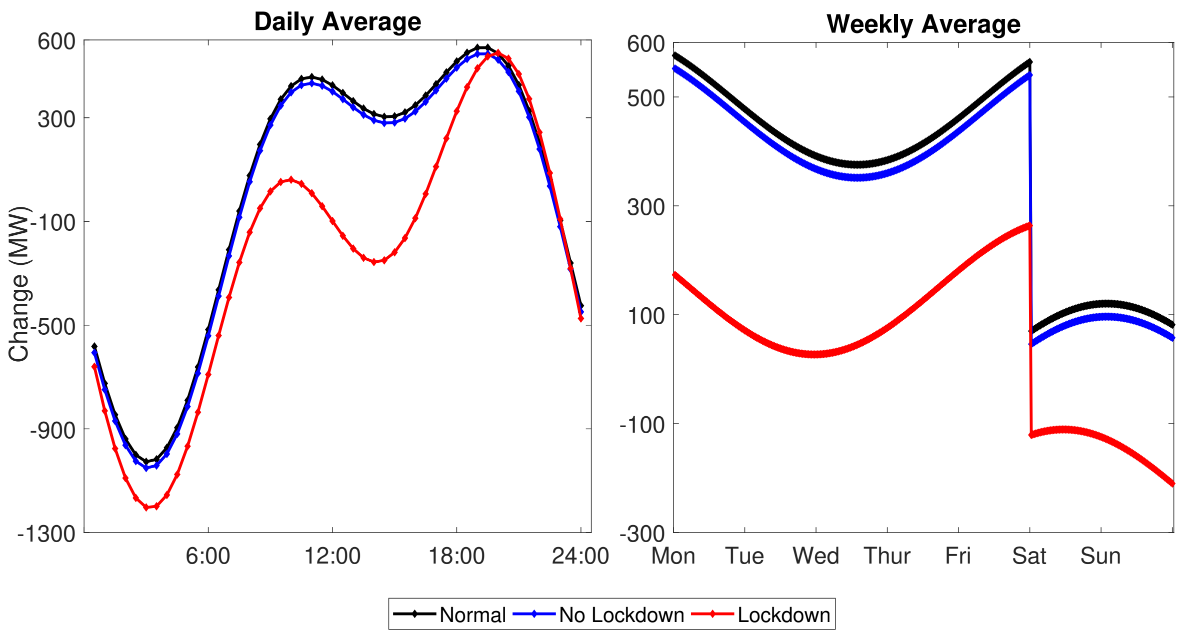

Figure 6: The daily and weekly average change patterns

5.1.1. Daily Changes

For the three states, the average daily change shows that our model follows the pattern of the daily demand profile found in Section 2, with the largest increase in prediction occurring around 19:00 to 20:00, and the largest decrease occurring around 02:30 to 03:00. These largest changes coincide with the global maximum and minimum in the daily demand profile.

To assess the general impact of COVID-19 according to our model, we consider the difference between the normal and the no-lockdown daily change. Our model estimates that the pandemic has the effect of reducing the average half-hourly demand by 23.94 MW. This reduction is consistent throughout the day.

The added effect of a lockdown is given by the difference between the no-lockdown and lockdown changes. This difference is dependent on the time of day, and reaches its maximum around 13:30, the mid-day demand dip. At this time, the effect of a lockdown is to further reduce the demand by 551.79 MW.

During the morning peak around 11:00, our model increases the demand prediction on average by 457.01 MW and 433.07 MW for the normal and no-lockdown days, respectively. However, it decreases the prediction at 11:30 for lockdown days by 41.29 MW. The reduction in demand is most pronounced during the daytime, and essentially disappears at night around 20:00 to 01:00.

5.1.2. Weekly Changes

Our model estimates the general impact of COVID-19 to be consistent throughout the week, however the effect of lockdowns is dependent on the day of the week. The effect of lockdowns over the course of a week is estimated to be greatest during the first half of the week, with the maximum reduction of 411.06 MW to the half-hourly demand occurring around 14:00 on Monday, and the smallest change of 190.74 MW occurring on Saturday around 00:30.

5.2. The change pattern from Monday to Sunday

Combining all our additional predictors, we have created a model for the total change to the half-hourly predictions due to our modifications. This model has the form given below.

$$\begin{aligned}\text{TotalChange} = {} & (-517.21\text{DailySin} - 278.00\text{DailyCos}) + (-360.76\text{HalfDailySin} - 146.97\text{HalfDailyCos}) - 23.94\text{COVID} \\ & - 210.55\text{Lockdown} + (9.36\text{LockdownDailySin} + 237.16\text{LockdownDailyCos}) + (-115.83\text{LockdownHalfDailySin} \\ & -51.83\text{LockdownHalfDailyCos}) + 496.11\text{Workday} + (-88.57\text{WeeklySin} + 81.71\text{WeeklyCos}) \\ & - 110.72\text{LockdownWorkday} + (-32.78\text{LockdownWeeklySin} - 57.11\text{LockdownWeeklyCos})\,.\end{aligned} \tag{3}$$

We have used this model to show the predicted changes over each day of the week for the three states. These results are shown in Figure 7.

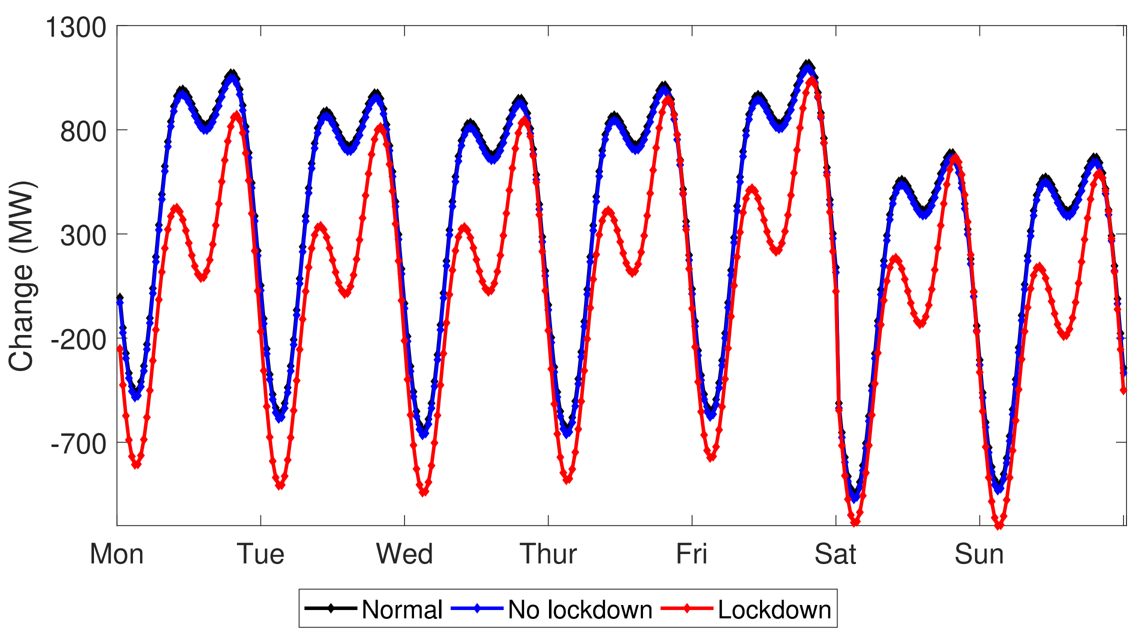

Figure 7: The total daily change pattern from Monday to Sunday

For each day of the week, we see a similar pattern for all three states, and the general impact of COVID-19 seems to be consistent throughout the day for each day of the week. The model estimates the evening peak to occur roughly an hour later during lockdowns compared to non-lockdown days. This lockdown peak is 199.29 MW and 161.91 MW higher on Monday and Tuesday, respectively, than the normal peak. The largest demand difference between lockdown and non-lockdown days occurs during the mid-day dip, which occurs around 13:30 every day, although the magnitude of this difference is larger during the first half of the week compared to the weekends. Interestingly, on Saturday night the predicted demand is 42.57 MW higher than the predicted demand on a normal day.

6. Conclusion

The COVID-19 pandemic has had caused unprecedented changes to the regular functioning of society. Although the response has differed around the world, the introduction of strict measures such as lockdowns in order to contain the virus has triggered large reductions in electrical demand in many countries. Our contribution has been to characterise the particular response of the electrical demand profile due to pandemic-related measures in the Australian state of Victoria, and to build a forecasting model for the data. More specifically, in this paper we have proposed a temporal regression model that accounts for the impact of COVID-19 on electricity demand forecasting. In our case studies we have shown that our proposed model can provide more accurate predictions compared to all other considered benchmark forecasting models when predicting demand during lockdown periods from the test set, with an RMSE of 136.44 and MAE of 100.38.

Among other benefits our model offers, its forecasting accuracy will presumably minimise the likelihood of power outages, for instance once restrictions are lifted. While our model is adequate in capturing the detailed lockdown patterns, further enhancement to the prediction accuracy could be made by including more local explanatory variables such as temperature. When applying our model to other regions, more specific conditions or power-related features can be easily included within the regression framework. A reliable predictive model of energy demand is a valuable tool for governments and electricity retailers to be able to manage the varying demands that will inevitably occur during times of economic disruption, such as pandemic-related lockdowns.

It is plausible that our findings may hold in locations other than Victoria, and as such it would be interesting to apply our modelling to other regions and countries. However, when doing this, it will be necessary to incorporate other local factors to the model in order to identify the specific impacts of COVID-19 on the demand profile. Statistical model checking and diagnosis will be needed to ensure validity of the results. Another limitation of our work is that we have not included public holiday information in our model. This would clearly improve predictions, however it should not change the patterns we discovered, due to very significant differences during lockdowns. It is well-known that the demand in households, industries and hospitals will all have different patterns, and therefore the COVID-

19 impacts will differ in each of these sectors. More detailed studies for different sectors at higher resolutions would be beneficial in better understanding the impacts of specific COVID-19 lockdown measures. This would ultimately be helpful in supporting the planning of power usage.

CRediT authorship contribution statement

Jinran Wu: Investigation, Methodology, Software, Writing-original draft, R coding. **Noa Levi:** Validation, Formal analysis, Visualization, Writing-original draft, R coding. **Robyn Araujo:** Writing-review & editing. **You-Gan Wang:** Supervision, Conceptualization, Funding acquisition, Project administration, Writing-review & editing.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The result to illustrate the proposed method

See Figure .8.

References

[1] Stephanie Halbrügge, Paul Schott, Martin Weibelzahl, Hans Ulrich Buhl, Gilbert Fridgen, and Michael Schöpf. How did the german and other european electricity systems react to the covid-19 pandemic? *Applied Energy*, 285:116370, 2021.

[2] Monica Carvalho, Danielle Bandeira de Mello Delgado, Karollyne Marques de Lima, Marianna de Camargo Cancela, Camila Alves dos Siqueira, and Dyego Leandro Bezerra de Souza. Effects of the covid-19 pandemic on the brazilian electricity consumption patterns. *International Journal of Energy Research*, 45(2):3358–3364, 2021.

[3] I Santiago, A Moreno-Munoz, P Quintero-Jiménez, F Garcia-Torres, and MJ Gonzalez-Redondo. Electricity demand during pandemic times: The case of the covid-19 in spain. *Energy Policy*, 148: 111964, 2021.

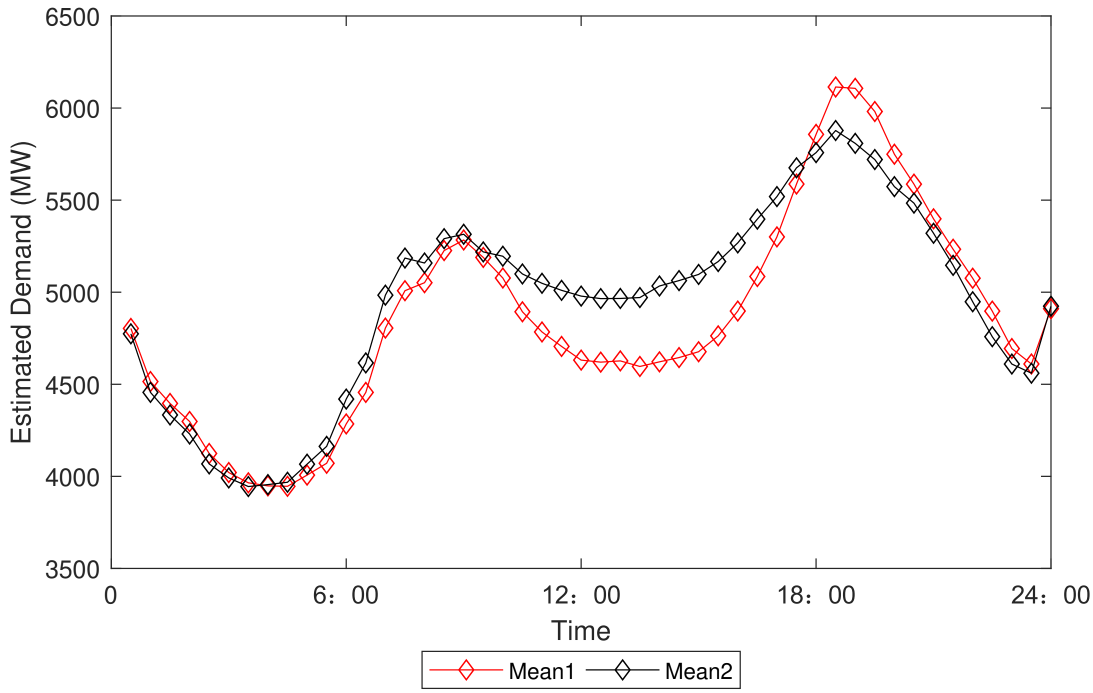

Figure .8: Estimated daily electrical demand profile with our proposed model. Mean 1 is the average of the half-hourly demand with lockdown (in red colour), and Mean 2 is the average of the half-hourly demand with no lockdown (in black colour).

[4] Duzgun Agdas and Prabir Barooah. Impact of the covid-19 pandemic on the us electricity demand and supply: An early view from data. *IEEE Access*, 8:151523–151534, 2020.

[5] Nima Norouzi, Gerardo Zarazua de Rubens, Saeed Choupanpiesheh, and Peter Enevoldsen. When pandemics impact economies and climate change: exploring the impacts of covid-19 on oil and electricity demand in china. *Energy Research & Social Science*, 68:101654, 2020.

[6] L Suganthi and Anand A Samuel. Energy models for demand forecasting—a review. *Renewable and Sustainable Energy Reviews*, 16(2):1223–1240, 2012.

[7] Jinran Wu, You-Gan Wang, Yu-Chu Tian, Kevin Burrage, and Taoyun Cao. Support vector regression with asymmetric loss for optimal electric load forecasting. *Energy*, 223:119969, 2021.

[8] Javier López Prol and O Sungmin. Impact of covid-19 measures on short-term electricity consumption in the most affected eu countries and usa states. *Iscience*, 23(10):101639, 2020.

[9] Alireza Bahmanyar, Abouzar Estebsari, and Damien Ernst. The impact of different covid-19 containment measures on electricity consumption in europe. *Energy Research & Social Science*, 68: 101683, 2020.

[10] Rajvikram Madurai Elavarasan, GM Shafiullah, Kannadasan Raju, Vijay Mudgal, Mohammad Taufiqul Arif, Taskin Jamal, Senthilkumar Subramanian, VS Sriraja Balaguru, KS Reddy, and

Umashankar Subramaniam. Covid-19: Impact analysis and recommendations for power sector operation. *Applied Energy*, 279:115739, 2020.

[11] Payal Gulati, Anil Kumar, and Raghav Bhardwaj. Impact of covid19 on electricity load in haryana (india). *International Journal of Energy Research*, 45(2):3397–3409, 2021.

[12] Liqiao Huang, Qi Liao, Rui Qiu, Yongtu Liang, and Yin Long. Prediction-based analysis on power consumption gap under long-term emergency: A case in china under covid-19. *Applied Energy*, 283: 116339, 2021.

[13] David Obst, Joseph De Vilmarest, and Yannig Goude. Adaptive methods for short-term electricity load forecasting during covid-19 lockdown in france. *IEEE Transactions on Power Systems*, 36(5): 4754–4763, 2021.

[14] Pınar Cihan. Impact of the covid-19 lockdowns on electricity and natural gas consumption in the different industrial zones and forecasting consumption amounts: Turkey case study. *International Journal of Electrical Power & Energy Systems*, 134:107369, 2022.

[15] Guangchun Ruan, Dongqi Wu, Xiangtian Zheng, Haiwang Zhong, Chongqing Kang, Munther A Dahleh, S Sivaranjani, and Le Xie. A cross-domain approach to analyzing the short-run impact of covid-19 on the us electricity sector. *Joule*, 4(11):2322–2337, 2020.

[16] Guangchun Ruan, Jiahan Wu, Haiwang Zhong, Qing Xia, and Le Xie. Quantitative assessment of us bulk power systems and market operations during the covid-19 pandemic. *Applied Energy*, 286: 116354, 2021.

[17] Shaylin Chetty, Hao Wang, and Sarah Goodwin. Visualising the effect of covid-19 on electricity consumption in victoria, australia. In *Workshop of Energy Data Visualisation (EnergyVis) 2021*, pages 367–371. Association for Computing Machinery (ACM), 2021.

[18] Jinran Wu, Zhesen Cui, Yanyan Chen, Demeng Kong, and You-Gan Wang. A new hybrid model to predict the electrical load in five states of australia. *Energy*, 166:598–609, 2019.

[19] Eric Ofori-Ntow Jnr, Yao Yevenyo Ziggah, and Susana Relvas. Hybrid ensemble intelligent model based on wavelet transform, swarm intelligence and artificial neural network for electricity demand forecasting. *Sustainable Cities and Society*, 66:102679, 2021.

[20] ABC. Victoria to enter five-day snap lockdown as more COVID-19 cases recorded, jul 2021. URL https://www.abc.net.au/news/2021-07-15/melbourne-lockdown-response-to-covid-outbreak/100296220.

[21] Rob J Hyndman and Yeasmin Khandakar. Automatic time series forecasting: the forecast package for r. *Journal of Statistical Software*, 27(1):1–22, 2008.