

Analysis of Electricity Demand of Pakistan During the COVID-19 Pandemic

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ABSTRACT

With a population of 220 million, Pakistan is the sixth populous country in the world. The first case of COVID-19 in Pakistan was reported in late February 2020 but at least for the first wave the country managed to successfully flatten the curve by August 2020. It was observed that energy usage is correlated more to the lockdown rather than the COVID-19 peak. The nationwide lockdown in Pakistan was enforced in March 2020, which resulted in a year-on-year decrease in electricity consumption of 9% for the month. However, only an insignificant (0.09% year-on-year) increase in energy consumption was seen in June 2020, when the number of COVID-19 cases peaked. During the lockdown period, performance of the short-term load forecasting models was impacted negatively. This impact created unit commitment and dispatch uncertainties for grid operations. Following the curve flattening, we observe a shift to the normal daily energy demand in the country.

Keywords: covid-19, energy demand, power system planning, short term load forecasting, neural networks

NONMENCLATURE

Abbreviations

LM	Linear Model
SVR	Support Vector Regression
NN	Neural Network

Symbols

D	Electricity Demand
AT	Apparent Temperature of Pakistan
n	Number of observations
y	Predicted value of energy
x	True value of energy

1. INTRODUCTION

Energy consumption is vital for the prosperity of a region and electricity is one of the primary sources of energy that people require for day-to-day work. As technology progresses, more and more electricity dependent devices are being introduced and many previously mechanical processes have been made electrically driven. Compared to the year 2015, a 30% rise in global energy consumption is expected by 2035 [1]. In order to meet this increase in demand and handle its related disruptions, electric power systems need to evolve.

Disruptions in electric power grid can be defined as unexpected changes in electricity supply or demand [2]. Some of these disruptions have a short term impact, for example power grid faults, while others create a long lasting impact on the grid such as the introduction of electric vehicles [4]. These disruptions affect power grid and utilities across business functions including operations, finance and resource management [5].

The COVID-19 pandemic has been one of the more unprecedented of such disruptions. A study in Italy was conducted which shows the impact of COVID-19 on the country's electricity consumption with an emphasis on the drop in energy prices and reduction in CO₂ emissions [6]. A multidisciplinary study in India was conducted which discusses the impact of COVID-19 on utilities and on the Indian power system in retaining the grid frequency and voltages [7]. Another study in China discusses the effect of COVID-19 on the oil and electricity consumption of the country and shows the relation between oil and electricity consumption with the population of infected people in the country [8]. This paper will focus on the impact of COVID-19 and subsequent lockdown on electricity consumption of

Pakistan with an emphasis on the effect on the short-term load forecasting models.

2. PAPER STRUCTURE

2.1 Pakistan Electricity Demand Profile

Electricity consumption in Pakistan is highly dependent on the weather. Due to air conditioning, there is more electricity demand in summer than winter [9]. The Pearson correlation coefficient between demand and temperature is 0.93.

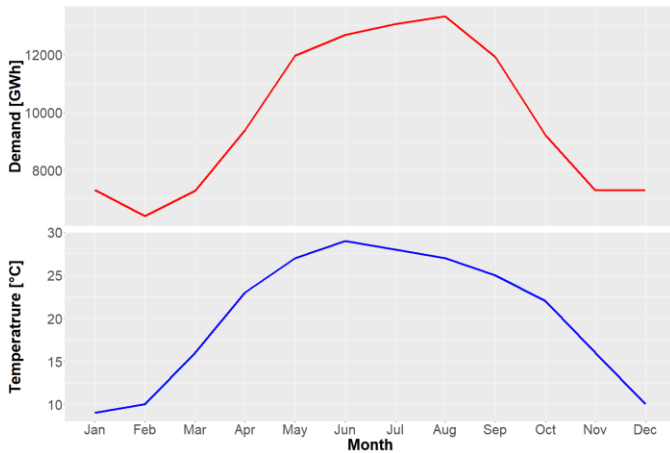


Fig 1 Correlation between Electricity Demand and Temperature of Pakistan

2.2 Pakistan Electricity Demand & Covid-19 Timeline

From the start of the year 2020, the electricity demand of Pakistan was low in both magnitude and variance. Due to change in weather, the electricity demand started increasing in March 2020. The initial lockdown was imposed on a provincial basis. Fig 2 shows some detail of the lockdown implementation times for various institutes in the country. The province of Baluchistan announced a lockdown on 22nd March 2020, with the province of Sindh following suit a day later, and the rest of the provinces another day later. Fig. 2. shows the daily electricity demand of Pakistan for years 2019 and 2020 and the daily new COVID-19 cases reported in the country. Even though there was a slight provincial variation in the implementation of the lockdown, most of the decisions were made at the national level by NCOG [10]. Therefore, the electricity demand data used in this study is also at national level.

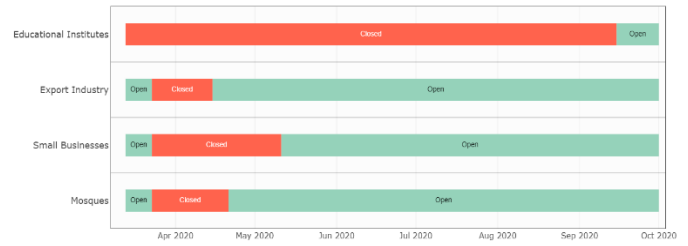


Fig 2 Lockdown Implementation Timeline

After the announcement of lockdown by all provinces, the electricity demand started dropping which reached its lowest point of 180 GWh on 28th March 2020. This valley is reflective of business activities coming to a halt [11]. The average daily energy demand drops from 247 GWh in March 2019 to 224 GWh in March 2020, a 9% decrease. Afterwards, the demand kept rising, as the government allowed essential businesses to reopen on 15th April 2020 [12].

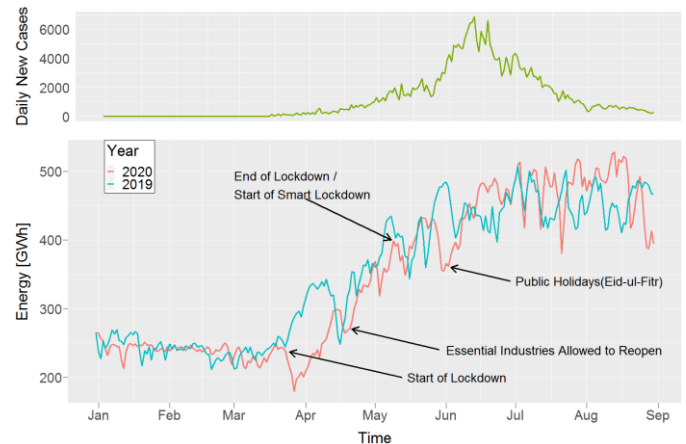


Fig 3 COVID-19 Cases and Electricity Demand of Pakistan

At the end of May 2020, the government of Pakistan decided to lift the lockdown and started containing infected areas using ‘smart lockdown’ protocols [13]. By this time the daily electricity demand started approximating to the electricity demand of year 2019. In parallel however, the number of daily new COVID-19 cases reported also started increasing towards its first wave peak. No positive correlation between number of COVID-19 cases and electricity demand was observed. Another valley in daily energy consumption was also observed during the public holidays of Eid-ul-Fitr, which lasted an extended period of six days [14].

Pakistan experiences high variation in apparent temperature as well as in electricity demand in the monsoon season. This high variation is evident for both 2019 and 2020. However, it can be observed that these

variations are steeper and have a short interval, evident by the spikes in electricity demand being short lived.

2.3 Daily Demand Pattern Before/After Covid-19

Other than the drop in daily electricity demand, the daily power consumption patterns also changed. For comparison, Fig. 3. shows boxplots [15] of hourly power consumption of 1 week before (14th-20th March) and 1 week after the initial lockdown (21st-28th March).

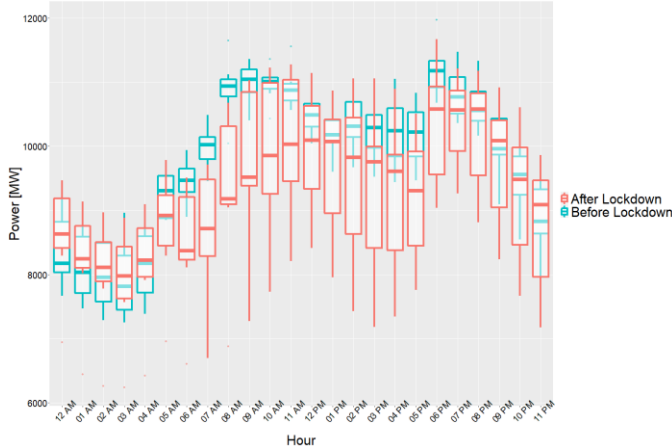


Fig 4 Hourly Demand Pattern Before/After Lockdown

The boxplots for the early hours of the day are mostly similar in length for both intervals but lower in magnitude after the lockdown. However, after 5 am in the morning, a significant difference can be observed between the boxplots of both weeks. The boxplots before lockdown are shorter and higher than the week after. However, after lockdown, there is a huge variation and drop in power consumption.

It can be observed that the intra-day power demand became significantly more uncertain after COVID-19. Taller boxplots imply an increased difficulty for the system operators to keep the power grid stable [16].

2.4 Short-term Load Forecasting

A Theory section should extend, not repeat, the background to the article already dealt with in the Introduction and lay the foundation for further work. In contrast, a Calculation section represents a practical development from a theoretical basis.

To further quantify the impact of COVID-19 on the electricity consumption of Pakistan, two variants of three regression models were trained with the objective of forecasting the electricity demand of the country. The first variant only included apparent temperature as the independent variable. The second also included a binary label of lockdown along with the apparent temperature.

For training the models without the lockdown label, historical data from 6th March 2020 to 20th March 2020 was used, which represents the time just before the lockdown started and simulates a model that is trained before lockdown. For training models with the lockdown label, data from 6th to 27th March 2020 was used, along with a binary variable indicating the status of lockdown. Both models were then tested on data from the time interval starting from 28th March to 10th April 2020.

2.4.1 Linear Regression

Ordinary least squares linear regression [17] is the first model used for forecasting electricity consumption of Pakistan. For our two type of models the linear equations are as follows:

$$D_{1(t)} = 6665 + 153AT_t \quad \text{Eq. (1)}$$

$$D_{2(t)} = 6365 + 169AT_t - 878L_t \quad \text{Eq. (2)}$$

Where $D_1(t)$ and $D_2(t)$ is the hourly power demand of Pakistan in MW for the two models, AT_t is average apparent temperature of Pakistan in degree Celsius and L_t is the lockdown label at any time t . In Equation (1) the coefficient of AT_t means that for every 1° C increase in apparent temperature the demand will increase by 153 MW on average. Likewise, in Eq. (2), the demand will increase by 169 MW on average for every 1° C increase in apparent temperature. However, in Eq. (2), coefficient of L_t means that if there is a lockdown in the country the power demand will decrease by 878 MW on average.

2.4.2 Support Vector Regression

The second type of model used is SVR (support vector regression) [18]. It is a variant of classification model SVM (support vector machine). By using the same principles of maximal margin, real numbers are predicted by setting a threshold, epsilon. Using the eps-regression type, radial basis kernel and epsilon of 0.1, both models were trained using their respective data.

2.4.3 Neural Network

The third type of model used is a simple neural network with resilient backpropagation with weight backtracking [19]. Both models have two hidden layers with three and eight neurons respectively. The neural networks are treated as black box, as the weights of each perceptron is randomly initialized and updated through backpropagation using our loss function.

2.5 Results

The objective of training these six models is to show the impact of COVID-19 on short term load forecasting models with and without information about lockdown.

Fig. 4. shows that the models with lockdown label perform better in forecasting the two weeks of lockdown, in comparison to their respective models without the lockdown label.

To analyze the results, three error metrics were used i.e. RMSE (root mean square error), MAE (mean absolute error) and MAPE (mean absolute percentage error). The equations for each are as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - x_i)^2} \quad \text{Eq. (3)}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - x_i| \quad \text{Eq. (4)}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - x_i}{y_i} \right| \times 100 \quad \text{Eq. (5)}$$

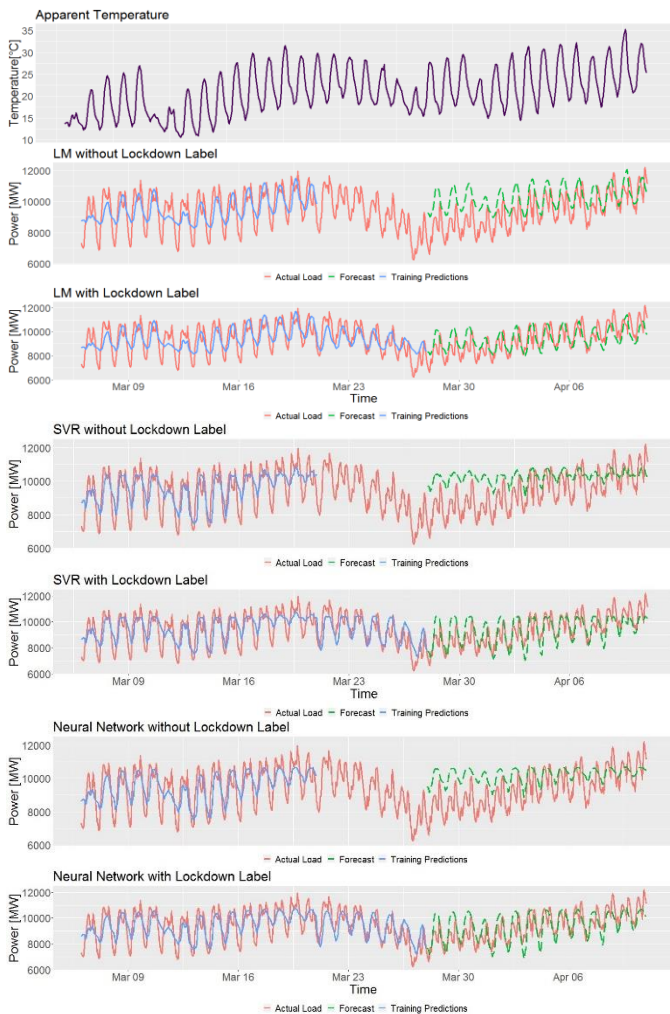


Fig 4 Hourly Demand Pattern Before/After Lockdown

Fig. 5. shows the RMSE over the training and testing time period for the neural network models. It is evident

from the bar plots that models without lockdown label and lockdown data are not capable of accurately forecasting power demand of Pakistan during lockdown.

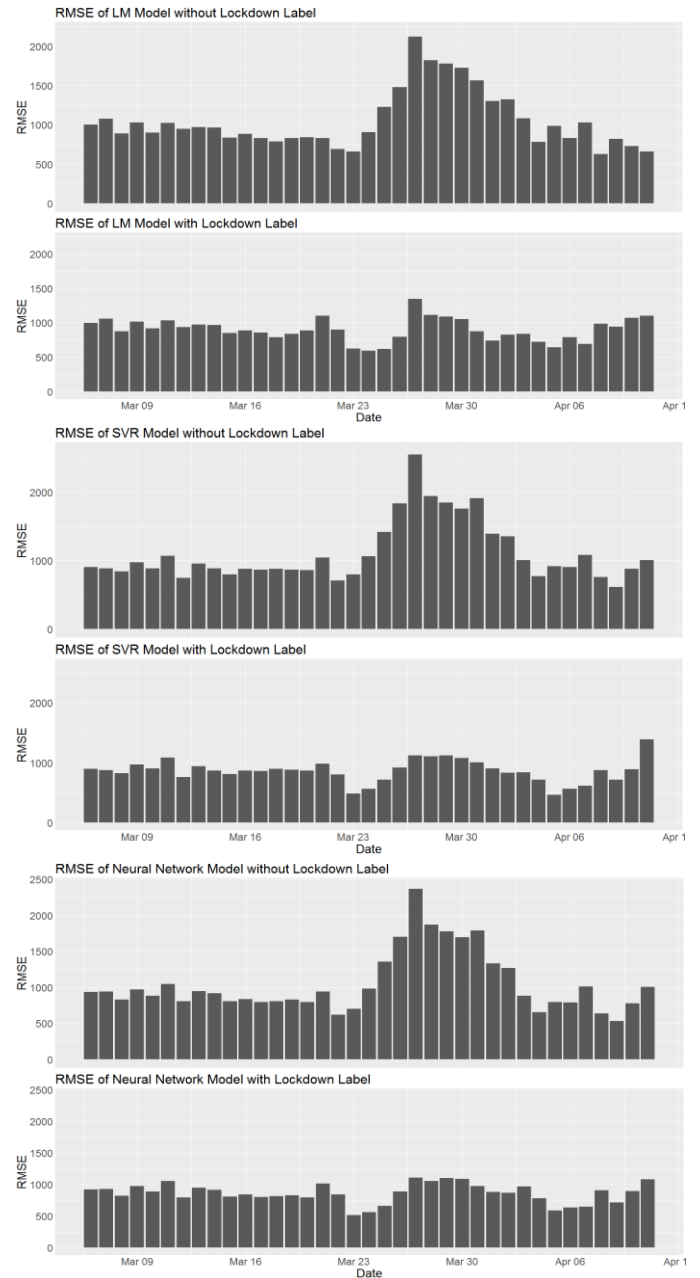


Fig 4 Hourly Demand Pattern Before/After Lockdown

Table 1. shows the performance metrics of each model for time periods before and after lockdown. For the models without the lockdown labelled data, the RMSE increased by 33.84%, 46.62% and 38.68% after the initial lockdown for the LM, SVM and NN models respectively. For the models with the lockdown labelled data, the RMSE increased only by -1.96%, -0.99% and

Table 1 Model Performance

	<i>Error Metric</i>	Without Lockdown			With Lockdown		
		<i>LM</i>	<i>SVR</i>	<i>NN</i>	<i>LM</i>	<i>SVR</i>	<i>NN</i>
Before Lockdown	<i>RMSE</i>	924.08	889.73	878.19	916.81	868.32	859.49
	<i>MAE</i>	792.93	707.87	725.48	775.52	692.68	700.28
	<i>MAPE</i>	8.53	7.57	7.84	8.38	7.46	7.59
After Lockdown	<i>RMSE</i>	1236.81	1304.49	1217.88	898.81	859.66	907.61
	<i>MAE</i>	1003.45	1095.80	1004.62	729.06	677.08	716.55
	<i>MAPE</i>	9.79	10.78	9.95	7.63	7.15	7.67

5.60% after lockdown for the LM, SVM and NN models respectively. A comparable difference in the MAE and MAPE values is observed. This difference emphasizes the need for newer and more disruption-aware load forecasting models.

2.6 Conclusions

In this paper we discussed the impact of COVID-19 and subsequent lockdown, on electricity consumption of Pakistan. A significant drop in daily electricity demand is observed in early stages of the lockdown compared to the same time in the previous year. Change in daily usage pattern is also observed and variation in intra-day power consumption increased after the lockdown was imposed due to the change in lifestyle. This had a negative impact on performance of short-term load forecasting models which creates a need for re-modeling them to better accommodate disruptions. The power sector faced grid stabilization issues. The number of COVID-19 cases in Pakistan escalated after the government decided to lift the lockdown. However, the major disruption in electricity demand occurred before the pandemic acceleration. So unlike other countries such as Italy [6] and China [8], in Pakistan a strong relation between the electricity consumption and the number of COVID-19 cases is not observed. Instead the drop in electricity consumption has been observed to be strongly related to the strictness of the lockdown.

ACKNOWLEDGEMENT

We would like to thank the Central Power Purchasing Authority of Pakistan for their cooperation and for providing us the national level electricity consumption data which was crucial for this study.

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