Impact of COVID-19 Related Shutdowns on Utility-Scale Electric Demand and Forecasting: An Indian Metropolitan Area Case Study

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INTRODUCTION

The ongoing COVID-19 related shutdowns has had a profound impact on the electric demand profiles worldwide, as governments put strict mitigation and/or suppression measures in place. The global electrical demand has plummeted around the planet in the last few weeks, with countries such as Spain and Italy experiencing more than 20% decrease in their usual electric consumption[1]. In view of such massive electric demand changes, electricity network operators are facing unprecedented challenges in scheduling energy resources, as short-term energy forecasting systems struggle to provide an accurate demand prediction. In fact, power systems operational reliability highly depends on an accurate projection of the future demand and scheduling an appropriate mixture of generation resources accordingly. In particular, short-term forecasts such as day-ahead are critical in managing the market operation uncertainty. Thus, recent changes expose operators to severe technical and financial risks caused by the demand imbalance, further reinforcing the adverse economic impacts of the pandemic.

The current paper presents and analyzes the impacts of the COVID-19 related measures on electric demand of an Indian metropolitan area, referred to here as the City. The paper investigates the most recent data to provide a systematic analysis of the change in the electric demand. In addition, it proposes strategies to mitigate the impact on forecasting performance.

1 DEMAND CHARACTERISTICS: NORMAL VS. COVID-19 PERIOD

On March 19th, 2020 the Indian Prime Minister implored all citizens to observe a "curfew" from 7 am to 9 pm IST on March 22nd, 2020 to help reduce community spreading of COVID-19 in India. On March 24th, the Prime Minister announced that India would go under a total lock-down for the next 21 days[2]. Hence, the analysis presented in this paper is heavily focused on the electric demand profile during the month of March. To conduct the study, data for the City's electric demand for the past three years is used, along with the weather data obtained from multiple external weather streaming services.

The shape of electricity demand is influenced by several factors including month of the year, day of the week, time of day, and the weather[3]. Hence, in a systematic analysis of the impact of COVID-19 on the electric demand, these factors should be properly taken into consideration to guarantee the fidelity of the conclusion. Table 1 presents numerical statistics pertaining to the City's demand in the month of March, based on data from 2018-2019 in the first row and the data for 2020 in the second row. As shown in this table, the average, minimum, and maximum of the demand are considerably lower in March 2020 compared to the previous years, while the standard deviation remains almost the same.

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Electric Demand	Maximum (MW)	Minimum (MW)	Average (MW)	Std. Deviation (MW)
2018-2019	579	282	404	73
2020	503	231	344	74

Table 1. Numerical statistics of the City's electric demand during the month of March based on data from 2018-2020.

Figure 1 depicts the time-domain electric demand during March 2020 as compared to the average of March 2018 and 2019. Note that the demand during 2018 and 2019 is properly shifted to align the weekdays, and thus the date on x-axis is replaced by number of weeks. The impact of the nation-wide curfew can be clearly observed from March 22nd onward. In addition, traces of COVID-19 related shutdowns can be detected as early as the second week of March. Observe that the second Tuesday of March 2020 was a major holiday in India, resulting in a significantly low electric consumption. To ensure that the temperature is not playing a role, Figure 2 demonstrates the temperature during March 2020. As observed, the trend and variation of temperature cannot explain the behavioural change of electric demand, as no anomaly is present.

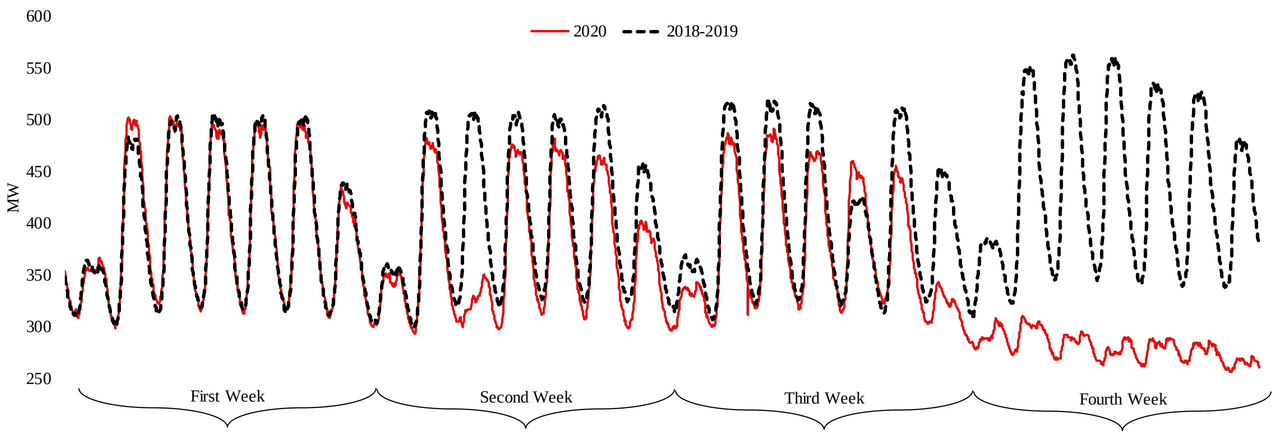

Figure 1. Electric demand during the month of March for 2018-2019 and 2020; week begins on Sunday.

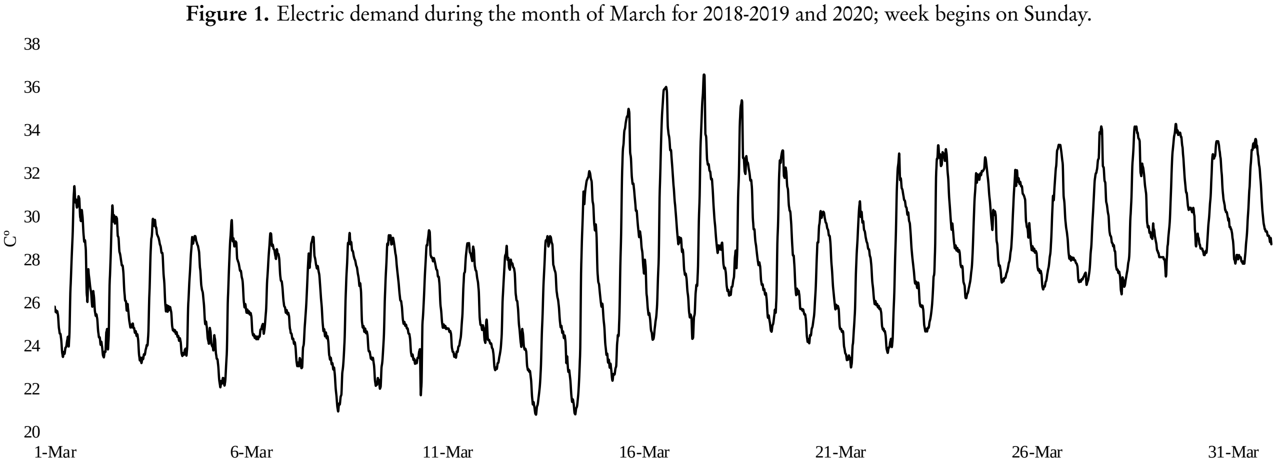

Figure 2. Temperature during March 2020; no anomaly is observed.

To further investigate the load trend, the normalized average weekly demand and average temperature in 2020 is shown in Figure 3. As seen in this figure, the load is on an increasing trend starting the week of February 2nd. Starting the week of March 8th, the electric demand experiences a noticeable drop, followed by a significant decrease in the weeks of March 22nd and 29th. Figure 4 demonstrates the load duration curve for five consecutive weeks starting March 2020. Based on this figure, the load in weeks of March 8th and March 15th has relatively followed the same shape as the week of March 1st, except for a quasi-uniform decrease. On the other hand, the load in weeks of March 22nd and March 29th has experienced a radical shape change, with a significant decrease in the average and variance.

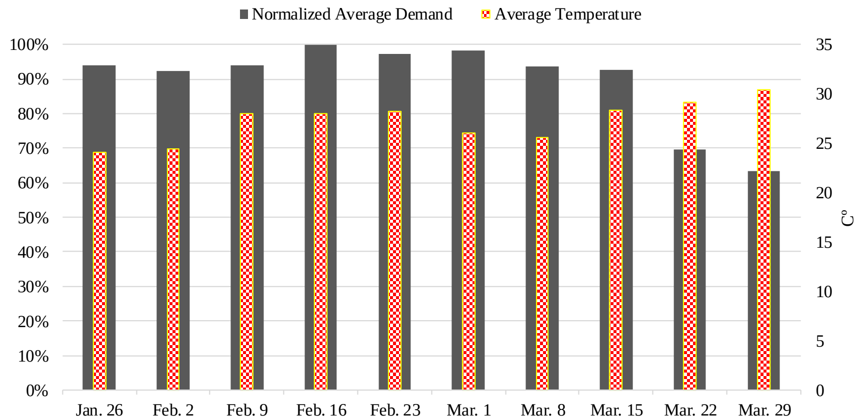

Figure 3. Normalized average weekly demand for 10 consecutive weeks in 2020.

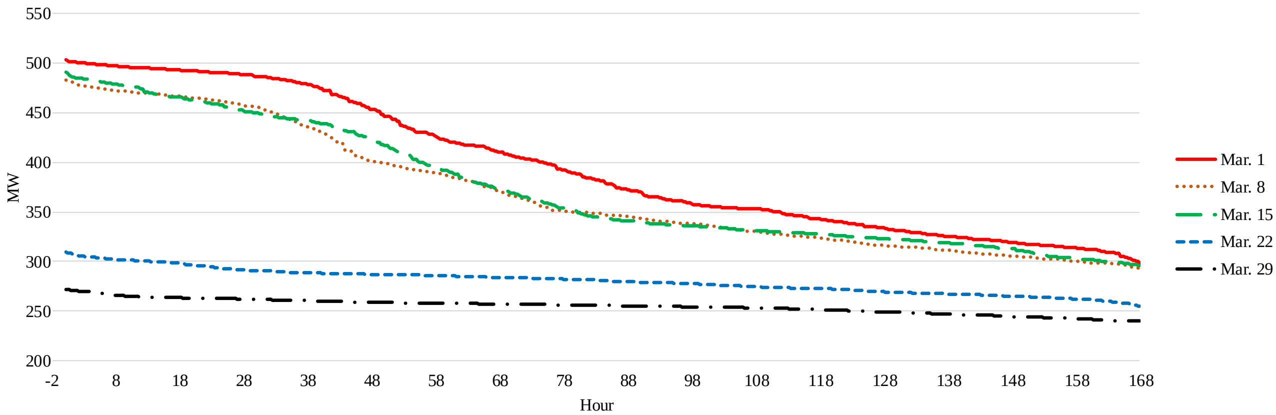

Figure 4. Load duration curve for five consecutive weeks in 2020.

In conclusion, the impact of COVID-19 related shutdowns is clear and significant for the weeks of March 19th and March 26th. The impact is less dominant but present for the weeks of March 8th and March 15th. There is no conclusive evidence on any COVID-19 related impact on the electric demand for the week of March 1st and its prior weeks.

2 IMPACT ON DAY-AHEAD FORECAST

BluWave-ai deployed the first version of its day-ahead forecasting system in February 2020, predicting 96 consecutive 15-minute intervals, i.e., a day, 15 to 39 hours ahead. The predictor is referred to as Version Alpha herein. Version Alpha primarily relies on the long-term seasonality patterns, and thus has large inertia against changes in the ultra-recent trend of the demand. Figure 5 shows the performance of Version Alpha in March and early April. It can be observed that the model exhibits an acceptable performance until around the week of March 8th, where it starts to over-predict. To better understand the model's performance, the prediction period is divided into two sub-periods of "before March 7" and "after March 7", and the model's key performance metrics are calculated for each sub-period as reported in Table 2.

Version Alpha	Average Load (MW)	MAE (MW)	RMSE (MW)	Largest Error (MW)
Before Mar. 7	396	6.58	8.16	29
After Mar. 7	326	44.62	60.83	219

Table 2. Version Alpha's performance metrics for two sub-periods; MAE is mean absolute error and RMSE is root mean squared error.

To further compare the performance of Version Alpha before and after March 7th, Figure 6 depicts the mean absolute error (MAE) distribution for the two sub-periods. It can be observed that the decay of residuals is around 10 times faster for the period before March 7th, with only 20% of residuals higher than 10 MW as compared to 75% afterwards. Such strong discrepancy verifies the adverse impact of COVID-19 on the day-ahead predictor tuned on the long-term seasonality.

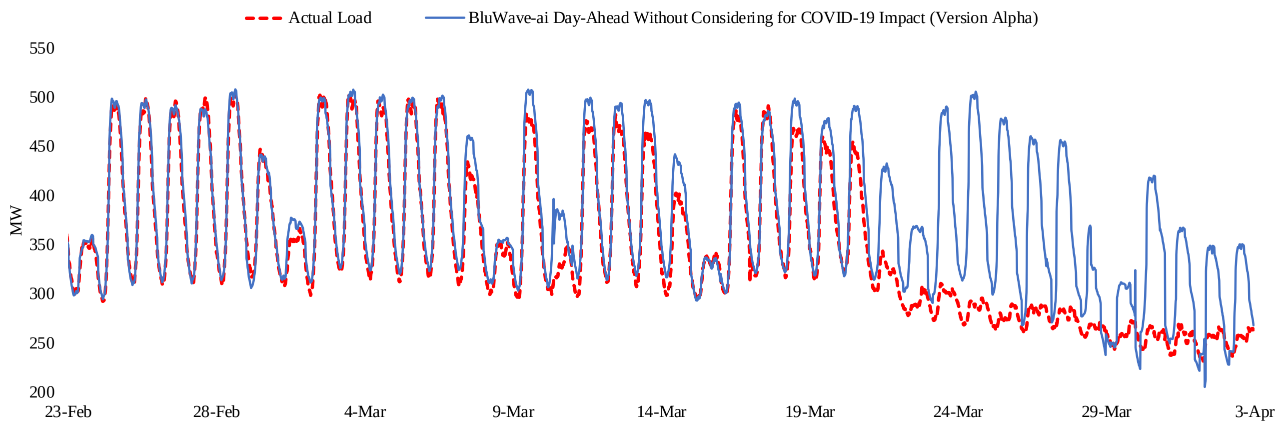

Figure 5. Actual load vs Version Alpha's prediction from February 23rd, 2020 onward.

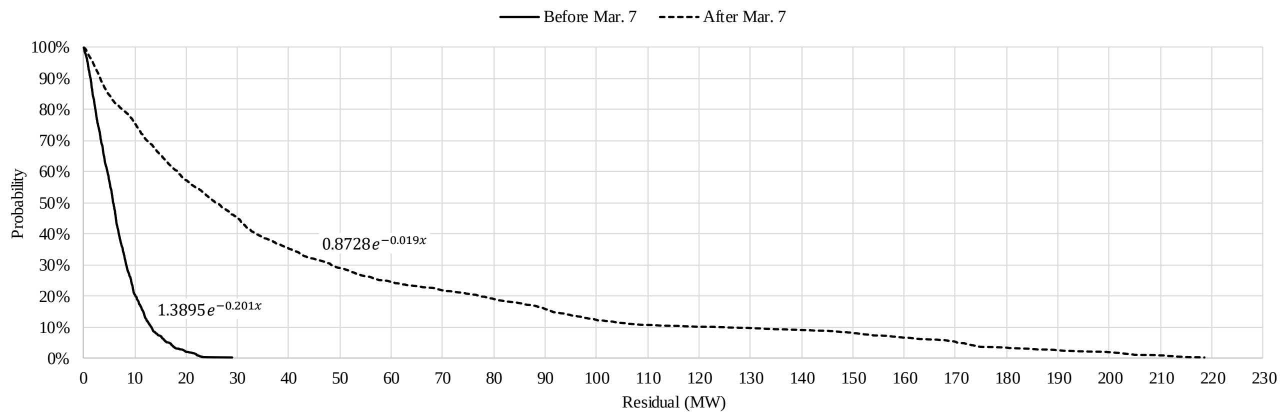

Figure 6. Version Alpha MAE distribution for the two sub-periods.

To address the COVID-19 related curfew, BluWave-ai deployed an updated version of its day-ahead predictor tuned on an ensemble of long-term and short-term seasonality. This predictor is referred to as Version Beta herein. Figure 7 demonstrates the performance of Versions Alpha and Beta during the curfew period, i.e., from March 22nd onward. As observed, Version Beta quickly adjusts itself to the curfew period, achieving an acceptable performance within a few days. On the other hand, Version Alpha struggles to provide a meaningful day-ahead forecast. Table 3 quantifies the performance metrics of the two predictors from March 26th onward. In this table, naïve refers to a predictor that uses the actual values of two days ago as its prediction. It can be seen that Version Beta defeats the naïve benchmark by 34%. To further investigate Version Beta's performance, Figure 8 depicts the predictor's residual distribution. It can be observed that more than 80% of residuals are lower than 10 MW, while almost none are higher than 20 MW, indicating a highly competent performance for Version Beta.

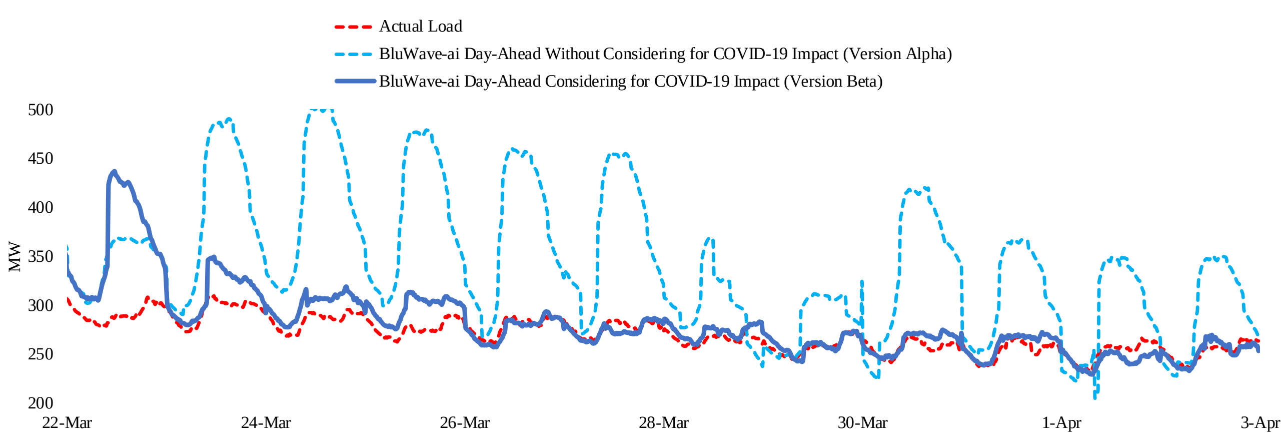

Figure 7. Actual load vs Version Alpha's and Version Beta's predictions from March 22nd, 2020 onward (curfew period).

Version	Average Load (MW)	MAE (MW)	RMSE (MW)	Largest Error (MW)
Alpha	261	63.12	81.51	174.67
Beta	261	5.75	7.18	22.10
naïve	261	8.70	10.86	29

Table 3. Versions Alpha and Beta performance metrics from March 26th, 2020 onward.

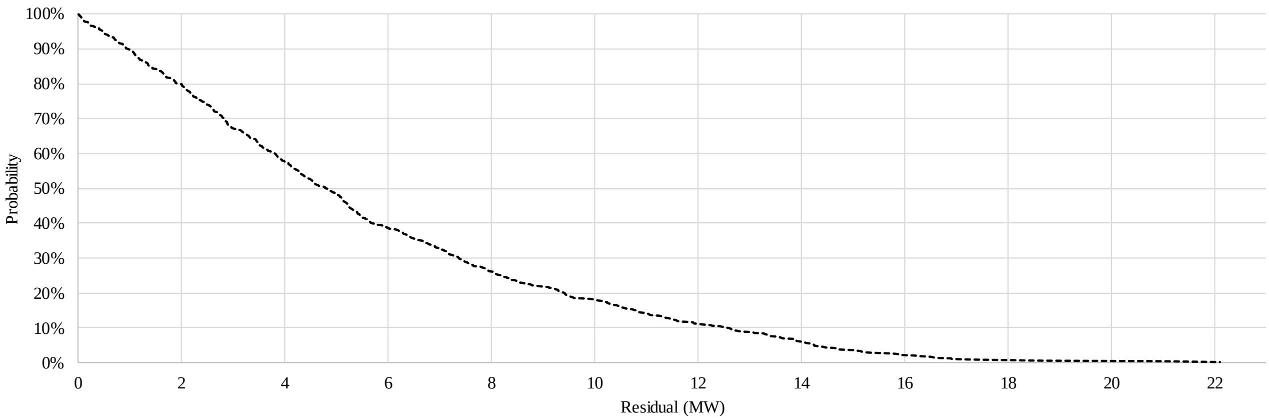

Figure 8. Version Beta MAE distribution for March 26th, 2020 onward.

3 IMPACT ON VERY SHORT-TERM FORECAST

BluWave-ai has developed a 90-minute-ahead predictor for the City based on the historical data from 2017-2020. Figure 9 demonstrates the predictor's performance from February 23rd onward. As discussed before, the period is divided into two sub-periods; February 23rd to March 7th during which no COVID-19 related impact is observed, and March 7th onward, during which the impact of COVID-19 related shutdowns is present. Table 4 provides performance metrics of the predictor during these two sub-periods. It can be observed that the short-term model's performance is not significantly impacted by the COVID-19 related shutdowns. In fact, the increase in the MAE and RMSE during the second sub-period can be mainly attributed to the poor performance on the first day of curfew, rather than a general lower-quality performance.

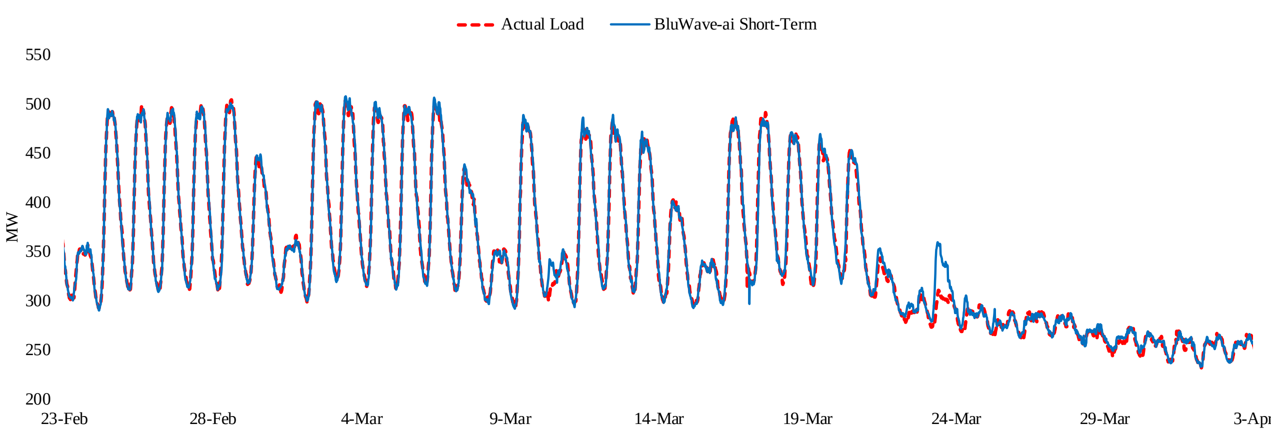

Figure 9. Actual load vs BluWave-ai short-term prediction from February 23rd, 2020 onward.

Short-Term Predictor	Average Load (MW)	MAE (MW)	RMSE (MW)	Largest Error (MW)
Before Mar. 7	396	2.83	3.63	14
After Mar. 7	326	4.62	7.91	57.43

Table 4. Short-term predictor's performance metrics for the two sub-periods.

To better understand the COVID-19 related impact on the short-term predictor's performance, the residual distribution for the two sub-periods is demonstrated in Figure 10. Note that the first day of curfew is eliminated from the second sub-period to enhance the fairness of the comparison. As observed, the performance of the short-term predictor has been slightly influenced by COVID-19 related measures, but the impact is not significant enough to motivate mitigation techniques.

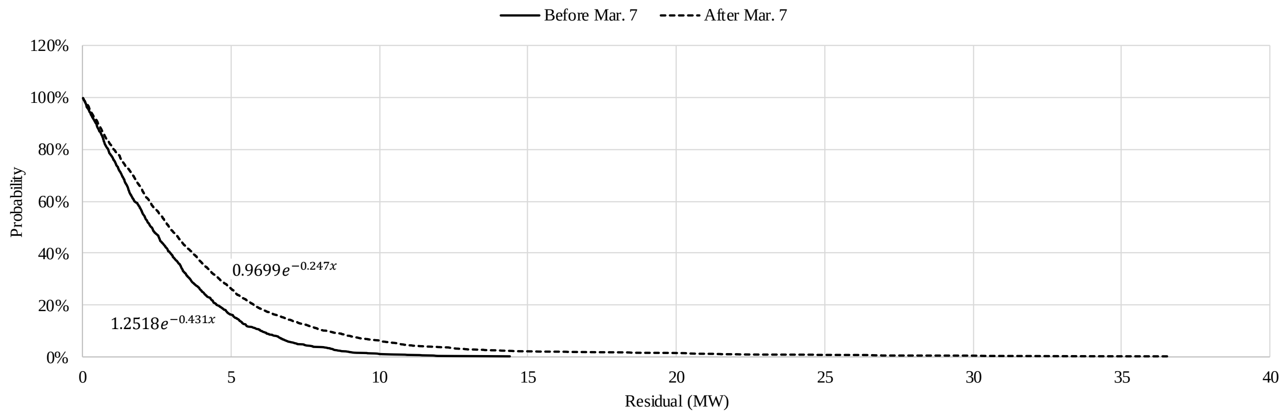

Figure 10. Short-term predictor MAE distribution for the two sub-periods.

4 KEY FINDINGS

- The City's electric demand has been significantly influenced by the COVID-19 related shutdowns. In particular, the demand has experienced a 40% decrease compared to the same period in previous years, as well as February 2020.
- The unprecedented change in the electric demand behaviour has a severe impact on the accuracy of day-ahead predictors. On the other hand, the changes seem to have a relatively mild impact on the accuracy of very short-term predictors in the range of a few hours ahead. This can be explained by the fact that very short-term predictors primarily rely on most recent trend as compared to longer-term seasonality, thus better adjust to recent changes.
- To mitigate the adverse impacts on day-ahead demand projections, electricity network operators can rely on naïve prediction techniques in the absence of more complex methodologies.
- It is shown that the naïve benchmarks can be defeated by a considerable margin, even in the absence of abundant data pertaining to the new paradigm of electric demand. BluWave-ai predictor Version Beta converged to accurate prediction within 2-3 days, defeating the naïve benchmark by 35%. This is achieved by an ensemble of methods that rely on both long-term and short-term seasonality.
- Electric utilities have been providing the essential service of power to end-consumers for more than a century. Within the last decade, utilities are becoming digitalized industries of tomorrow, embracing cutting-edge technologies to improve their operational efficiency and reliability. In this context, harnessing the power of big data by utilizing state-of-the-art data-driven techniques is the key enabler of the "Utility of the Future".

REFERENCES

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About BluWave-ai

BluWave-ai is leading the global energy transformation by facilitating the proliferation of distributed and renewable energy resources, electric transportation, and smart loads. Our SaaS-based solutions utilize artificial intelligence (AI) to optimize smart grids for increased affordability, reliability, and sustainability. Our customers – communities, corporations and utilities – have reported significant savings in capital and operational costs, as well as reductions in their carbon footprint. BluWave-ai is dedicated to working with partners and customers toward universal, affordable, and sustainable energy systems.