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A machine learning framework to quantify and assess the impact of COVID-19 on the power sector: An Indian context

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As the COVID-19 continues to disrupt the global norms, there is the requirement of modeling frameworks to accurately assess and quantify the impact of the pandemic on the electricity sector and its emissions. In this study, we devise machine learning models to estimate the pandemic induced reduction in electricity consumption based on weather, econometrics, and social-distancing parameters for seven major Indian states. As per our baseline electricity consumption model, we find that the electricity consumption dropped by 15–33% in 2020 (March-May) during the complete lockdown phase, followed by 6–13% (June-August) during the unlock phases and gradually reached the norms by September 2020. As a result, the net CO2 emissions from power generation in 2020 dropped by 7% and 5% compared to 2018 and 2019 respectively. Amidst the ongoing second wave since mid-April 2021, we projected the electricity consumption across states from May-August by accounting for two scenarios. Under the reference and worst-case scenarios, the electricity consumption approximates 106% and 96% of the non-pandemic situation, respectively. The modeling framework developed in this study is purely data-orientated, cross-deployable across spatio-temporal scales and can serve as a valuable tool to inform current and future energy policies amidst and post COVID-19.

1. Introduction

In an effort to slow down the spread of coronavirus disease 2019 (COVID-19), the first half of 2020 witnessed the imposition of stringent policies across the globe, including the closure of businesses and factories, travel restrictions, and issuing stay-at-home orders [1–3]. The pandemic induced closure of industrial, commercial, and social activities as well as the reduced people mobility resulted in an unprecedented drop in the electricity demand during most parts of the first and second quarter (Q1 and Q2) of 2020 [4,5] and also during the second wave which occurred in distinct timelines across various countries. Global energy security and sustainability are non-negligible issues; as such, it is essential to study and accurately assess the impact of the disruption caused by COVID-19 on the electricity sector and its associated emissions across spatio-temporal scales.

With over 246 million cases reported worldwide as of October 31st, 2021, India is one of the most affected countries by the pandemic with over 34 million infected cases which is next only to the US, and 458 K deaths [6,7]. In an attempt to ‘flatten the curve’ during the first wave, India underwent a complete lockdown from March 25th to May 31st 2020 [8,9], followed by partial lockdowns in the latter months. The recent resurgence of COVID-19 in April 2021 [10]: the so-called second wave, which was much worse than the first, raised uncertainty on its severity to public health and the extent of disruption it can cause to the economic activities and social norms. A few reports, including peer-reviewed articles and non-peer reviewed briefs, have presented insights on the impact of COVID-19 on major electricity markets across the globe and on the Indian electricity sector – but mostly based on initial approximations. Thus, from a scientific standpoint, there is a need for modeling frameworks which can assess the true impact of COVID-19 on the elec-
tricity sector and project the very same into the near-term and long-term future under the constantly evolving nature of the pandemic.

1.1. Literature review

With the onset of the pandemic in early 2020, Elavarasan et al. [8] reviewed the immediate impact of COVID-19 on a few major global electricity markets and described how electricity demands varied in India between March-May 2020. Similarly, Ruan et al. [4] studied the impact of COVID-19 on US electricity markets between Feb-June 2020 and developed an open-access database to map electricity consumption during the pandemic by including weather, and COVID-19 derived public health data. In related yet different studies, Bahmanyar et al. [11] and Werth et al. [12] investigated the impact of COVID-19 induced electricity changes across major European countries between March-April and March-June 2020, respectively, and both calculated the change in electricity consumption for 2020 with respect to the same time periods in 2019. A few other notable works in a similar context include studies done for Indonesia [13] and Turkey [14]. From a modeling perspective, Norouzi et al. [15] developed a hybrid ANN model to predict the national electricity consumption in China as a function of econometrics and COVID-19 induced variables. Hunang et al. [16] developed a univariate time-series model to calculate the electricity demand in the absence of the pandemic and benchmarked it against the actual consumption for 2020 for China, while Prol and Sungmin [17] developed harmonic regression models to predict the electricity demand from March to August in 2020 in a counterfactual scenario with no pandemic restrictions to show the reductions across several European countries and US states. Specific to India, Kanitkar [18] developed a simple input-output model to claim that the daily supply from coal-based thermal power plants in India reduced by almost 26% during the lockdown between April-May 2020, resulting in reduced emissions of about 15–65 MtCO2, while Deshwal et al. [19] described the impact of COVID-19 on the Indian renewable energy sector and the opportunities it holds in the power distribution mix in the post COVID era.

1.2. Objectives and contribution of this study

To their merit, the abovementioned studies presented a timely assessment of the pandemic impact on the country-specific electricity demand. However, a few common limitations exist among these studies. Firstly, most of the abovementioned works presented an immediate aftermath of the COVID-19 on the electricity sector (mostly during the first 2–4 months after the initial lockdown was imposed), and the long-term impact has not been studied. Moreover, most of these studies are descriptive in nature as they simply described how the electricity demand reduced under the pandemic influence. To this context, these studies have not presented a method to assess the baseline electricity consumption profile for 2020 in the absence of the pandemic. As such, these studies have not statistically quantified the reduction in electricity demand due to COVID-19 induced lockdown, nor have they proposed any methods to quantify the same. While the studies by Hunang et al. [16] and Prol and Sungmin [17] have made some effort in this direction, these are again limited in the fact that these models are either univariate in nature (i.e., depend only on the historical values of electricity consumption) or do not account for any pandemic induced variables, e.g., social distancing parameters respectively. Thus, they may not be able to capture the true impact of the pandemic on electricity demand. Lastly, given the continuous evolving nature of the pandemic and the uncertainty associated with its global impact in the near- and long-term, lockdown policies will need to continuously adapt. (For instance, a new and adverse strain of the virus such as Omicron identified as of November 2021, or lack of immediate medical supplies or ineffectively of the vaccines in long run could make the lockdown policies more stringent- as till date it is regarded as the most efficient containment step. Similarly with rise in vaccination, self-awareness in the global population on how to conduct oneself in personal and professional setting under the new norm—could decrease the spread of the pandemic and lockdown policies could be liberalized). This inadvertently increases the variability and uncertainty in the electricity consumption and calls for generic frameworks or modeling approaches that can map electricity consumption to the continuously changing nature of the pandemic. To this context, electricity consumption will have to be not only mapped with respect to weather [20,21] and econometrics [22,23] parameters as per current modeling practices, but also with COVID-19 induced social distancing parameters, which is the new norms at the time of the pandemic; and collectively affects electricity consumption. However, there is paucity in the literature that identifies such parameters collectively and proposes or devises modeling framework to predict electricity demand by using them. Building on these backgrounds, in this study we present a systematic, data-driven framework to quantify the impact of COVID-19 on the power sector and its emissions which addresses the above limitations. The contributions of this study are manifold as following:

1) By using the concept of predictive inference, we developed a year-long, Baseline Electricity Consumption Analysis (BECA). The BECA model is used to predict the electricity profile for 2020 in a non-pandemic scenario and benchmarked against actual electricity consumption. This model aids to statistically quantify the reduction in electricity consumption through the entire 2020 across the various phases of the pandemic. To the best of our knowledge this is the first year-long study of its kind in the literature.

2) Given the dynamic nature of the pandemic, as witnessed during the second wave, along with the potential threat for the third wave; we devised the Pandemic Electricity Consumption Scenario (PECS) model to predict the near-term electricity under the continuously evolving COVID-19 pandemic and associated government policies.

3) While electricity consumption has primarily been mapped as a function of meteorology variables [20,21], economic variables [22,23], and to its lagged values, these variables cannot capture abrupt changes in socioeconomic behaviors during the pandemic and the resulting electricity demands. Mobility data can serve as proxies for the population behaviors with respect to social distancing measures. But where to look for relevant data and what data to look out for remains a challenge. Here, we address this issue and propose how to collectively map electricity consumption as a function of these abovementioned heterogeneous variables - where social distancing variables form the new norm.

4) Lastly, the framework developed is generic and cross-deployable in nature as it is purely data-driven and scalable across spatio-temporal scales. As such, this study will be useful to the regulatory bodies, policy makers, and associated stakeholders not just in India (which is the primary case study of this work) but also other states and countries across the globe to take precautionary measures and tackle the issues and challenges of the power sector amidst the pandemic, to ensure stable supply of electricity, safeguard the energy security of the future and meet the global emission targets during and post the COVID-19 era. The overall schematic of this work is represented in Fig. 1.

The rest of the paper is organized as follows: Section 2 rationalizes the selection of various algorithms and data used in this study. Section 3 provides an in-depth description of the modeling framework and the purpose they serve – which is the core of this study. Section 4 presents the main findings including the year-long quantification of the drop in electricity demand across states due to the varying degree of lockdown policies in 2020; followed by the emission analysis of the power sector for 2020. This is followed by an evaluation of the scenarios which project the electricity consumption under the varying influence of pandemic-based lockdown policies. Finally, we present a summary and essence of this work in Section 5.
2. Modeling intuitions

This study primarily focuses on the development of generalized modeling frameworks to map the electricity consumption as a function of weather, econometrics and COVID-19 induced social distancing parameters, under the past and continuously evolving futuristic pandemic situation. Thus, at the very core the models developed in this study fall under the general category of multi-variate time series models. To this end, in this section we provide an overview of various time series models that were used in this study and the reason for their selection. Moreover, we also explain the selection of various variables which ultimately serve as input to the models. Hence, the main objective of this section is to provide the readers with the rationalization of our modeling philosophy and intuitions, which then sets the tone for the rest of the paper. Here, it is worth a mention that our focus was not to develop new algorithms specifically for predicting electricity demand under the influence of pandemic and other relevant factors like weather and econometrics. Rather our primary motivation was to develop generic modeling frameworks using existing algorithms through appropriate and most relevant data to effectively assess and quantify the impact of the pandemic on electricity, based on the objectives described in Section 1.2.

A brief review of the literature suggested that multi-variate time-series modeling of electricity consumption fall within two main categories i.e., classical timeseries models (e.g. autoregressive integrated moving average (ARIMA), seasonal autoregressive integrated moving average (SARIMA), vector autoregression (VAR) etc.) and machine learning (ML) based timeseries model (e.g. Artificial neural networks (ANN), non-linear autoregression with exogeneous variables (NARX), long-short term memory (LSTM) etc. to mention a few) [24–26]. It is well established in the literature that these models present their own pros and cons. For instance, the classical models are interoperable, their coefficients have clear implication and are able to decompose the timeseries data to capture its seasonality and trend [24,26]. The ML methods on the other hand, do not require substantial data pre-processing as in the case of classical models, and offer greater potential to capture the non-linearity in the timeseries data [24,25]. To our observation, literature does not offer a very affirmative reason on the selection of a particular algorithm for a timeseries based problem, nor is there a single best performing timeseries algorithms that can be universally used [24,27]. Rather in most of the studies it is a common practice to evaluate multiple algorithms and choose the best performing one. To this aim, in this study we comparatively evaluated two classical (linear) models namely VAR and Facebook Prophet (FBP) and two ML models – NARX and LSTM models to devise our data-driven framework. A brief description of these algorithms and their mathematical formulation is presented below.
2.1. Algorithms for timeseries modeling

VAR: Vector autoregression is bi-directional timeseries model, which is extensively used in macroeconomics and various timeseries analyses. In a classical VAR model, the time series is modeled as a linear combination of its own lags. In the case of multi-variate timeseries, which includes exogenous inputs, the VAR relates to the previous (lag) values of the target variable, and also includes the past values of its input variables [4,26]. It is algebraically defined as:

\[ y_t = a + \beta_{11}y_{t-1} + \beta_{12}y_{t-2} + \ldots + \beta_{1m}y_{t-m} + \beta_{21}x_{1t} + \beta_{22}x_{2t} + \ldots + \epsilon_t \]  

(1)

Where, \( y_t \) represents the time-series variable to be forecasted, \( x_{it} \) represents the input variables, \( a \) and \( \beta_i \) represents the coefficients and \( \epsilon_t \) denotes the error. Since we are considering multi-variate timeseries forecasting, VAR outperforms the simple autoregression model, as it takes into consideration the dependence on the past values of the input variables.

FBP: Facebook Prophet is an open-source time series forecasting algorithm designed by Facebook Inc., The FBP, which is a more recent introduction to the wide array of time series models, uses a Bayesian based curve fitting and is a linear decomposable time series model with three model components: trend, seasonality and holidays [28]. The equation if as follows:

\[ y_t = g_t + s_t + h_t + \epsilon_t \]  

(2)

Where the terms \( g_t \) is the trend function, \( s_t \) is the periodic changes and \( h_t \) represents the effects of holidays. The error term \( \epsilon_t \) represents any idiosyncratic changes which are not accommodated by the model. This model is chosen as it helps in forecasting time-series with non-linear patterns such as the yearly, weekly week and everyday regularity.

NARX: Non-linear autoregressive model is a non-linear regression model with exogenous inputs that can be used for time series forecasting. The non-linear function commonly used is the recurrent neural network (RNN) [29,30]. It is algebraically defined by

\[ y_t = f(y_{t-1}, y_{t-2}, \ldots, y_{t-n_y}, u_{t-1}, u_{t-2}, \ldots, u_{t-n_u}) \]  

(3)

Where \( y \) representsorelectricity consumption values, and \( u \) is the exogenous input variables vector, \( y_t \) is the current value of the electricity consumption which depends on the past \( n_y \) values of electricity and \( n_u \) past values of the external variables. Since the relation between the inputs and the output electricity consumption is not straightforward, complex models such as NARX help in mapping the inputs to outputs.

LSTM: LSTM is a type of recurrent neural networks (RNNs) used to solve the problems that require learning long-term dependencies. The fundamental principle governing the LSTM is that each cell (computational unit) is associated not only to a hidden state \( h_t \) but also to a state \( c \) of the cell which accounts for its memory [31,32]. The dynamic equations representing the computations within an LSTM cell are as follows:

The forget (f) gate is the first step in the computation of an LSTM cell and determines which information is to be retained and which to be removed. It is represented as follows:

\[ f_t = \sigma(w_{xf}x_t + w_{hf}h_{t-1} + w_{cf}c_{t-1} + b_f) \]  

(4)

The next gradual step is to determine the new information that needs to be stored in the cell state which is performed in a two-step sequence. The input gate (i) first determines the values to be updated and then is followed by a tanh (t) layer that generates a vector of new incoming candidate values \( c_t \). These are mathematically given by:

\[ i_t = \sigma(w_{xi}x_t + w_{hi}h_{t-1} + w_{ci}c_{t-1} + b_i) \]  

(5)

\[ c_t = f_t \circ c_{t-1} + i_t \circ \text{tanh}(w_{xc}x_t + w_{hc}h_{t-1} + b_c) \]  

(6)

The final outcome of the computation in the cell is determined by the output gate (o), Here, the cell state goes through another tanh (t) layer (to force the values to be between -1 and 1) and is multiplied by the output gate as follows:

\[ o_t = \sigma(w_{xo}x_t + w_{ho}h_{t-1} + b_o) \]  

\[ h_t = o_t \circ \text{tanh}(c_t) \]  

(7)

\[ (8) \]

Where \( f_t, i_t, c_t, o_t \) and \( h_t \) are the vectors to the forget gates, input gates, cell states, output gates and hidden states at any given time \( t \) and \( w_{ab} \) represents the weight factors of the \( a^b \) vector in the \( b^h \) gate and \( \sigma \) is the sigmoid function. The main difference compared to the NARX model is that LSTM units include a memory cell that can maintain memory for long periods of time.

2.2. Data and sources

Classically, the prediction of electricity demand (across various spatial-temporal scales) has been predominantly mapped as a function of weather and economic parameters. Among the weather parameters include variables such as daily mean temperature, humidity and wind-speed and calculated variables including heating degree days (HDD) and cooling degree days (CDD) [4,15,21]. While the econometric indicators include variables such as GDP, percentage GDP growth, manufacturing Purchasing Managers’ Indices (PMI), labour population, industrial productivity to mention a few [15,33]. In this study, both weather and economic parameters were used to develop the modeling framework. In addition to these variables, in the COVID-19 era, the lockdown policies also significantly impact the electricity consumption, as they lead to the closure of businesses, factories, and commercial buildings, travel restrictions and issuing stay-at-home orders [5,11], all of which are highly uncertain given the constantly evolving nature of the pandemic. Thus, it becomes of paramount importance to capture the impact of these variables on the electricity demand. In this study, we classify these variables as ‘social distancing’ variables. These variables correspond to the mobility and occupancy of the population of a given region (country/state/district/city) to their places of work or commercial buildings or travel or stay at home.

It is imperative to consider the importance of data when creating data-driven frameworks and more specifically while building data-driven models, as they decide the course of the overall modeling efficacy and the final insights. Since this study uses India as a case study, all the data used in the study were either obtained from respective regulatory agencies or purchased from professional services. Below are the relevant details:

Electricity data: The historical data on electricity generation in India was obtained from the Power System Operation Corporation Limited, India (POSOCO) [34]. POSOCO is the national level regulatory agency owned by the Government of India; and is responsible to monitor and ensure round the clock integrated operation of the Indian Power System. Typical data include state-level energy demand, peak demand, source wise generation split, electricity import and export by regions and frequency profile at daily resolution. (https://posoco.in/reports/daily-reports/).

Weather data: The historical data for weather parameters including daily mean temperature and mean humidity specific to the Indian states investigated in this study were purchased from Meteoblue [35]. Meteoblue is a professional service which provides historical and forecasted weather data for any location across the globe. (https://www.meteoblue.com).

Econometrics data: The econometrics data for India was purchased from Trade Economics (https://tradingeconomics.com/india) which provides historical as well as forecasted economic indicators for close to 200 countries [36]. The data purchased included National Gross Domestic Product (GDP), Manufacturing Purchasing Managers’ Indexes (MPMI), GDP from manufacturing and utilities (GDP H&U), Consumer Price Index (CPI), Inflation Rate (IR) and Minimum Labour Wage
The state-wise GDP contribution was obtained from the Ministry of Statistics and Programme Implementation, an enterprise by the Government of India (http://mospi.nic.in/data). Using the above data, the state-wise GDP was calculated using the formula below:

$$GDP_{State} = GDP_{National} \times x_{State}$$

(9)

Where $GDP_{State}$ and $GDP_{National}$ are the state and national GDP respectively in INR crores; $x_{State}$ is the contribution from each state towards the national GDP in percentage.

**Social distancing data:** With the onset and spread of the pandemic in early 2020 and associated global lockdown policies, Google Inc had introduced the Google Community Mobility Reports (https://www.google.com/covid19/mobility/) in February 2020 to keep track and record data on the population movement trends over time by geography [37]. This report includes social distancing factors such as the movement of population/people to groceries and pharmacies, parks, transit stations, retail and recreation, workplaces, and stay at home (residential). The Google Community Mobility Reports has proven to become one of the most reliable sources to capture social distancing data [3] and provides these data at the national, state and district level for over 200 countries.

To capture the effect of the pandemic induced lockdown and social distancing measures, in this study we used two parameters published from this report, namely % change in workplace population and % change in stay-home population. These parameters sufficiently capture the social distancing factors necessary to map them as a function of electricity consumption.

3. Scope and modeling framework

3.1. Defining the scope and timeline

In this study, seven Indian states namely Delhi (DL), Uttar Pradesh (UP), Maharashtra (MH), Gujarat (GJ), Tamil Nadu (TN), Karnataka (KA) and West Bengal (WB) were identified and the impact of lockdown on the state-wise electricity consumption was evaluated. Out of the total 37 states and union territories in India, these seven states account for approximately 48% of the total energy consumption [34], are representative of the four geographical zones, contribute to 56% of the national GDP [38] and have reported close to 80% of COVID-19 infected cases till date [6] as seen in Fig. 2.

In India, the lockdown policies are regulated at the state-level rather than by the central government. Except for the nationwide lockdown which was effective between March-May 2020, almost all states have maintained different levels of intensities and time-periods for the respective lockdown measures adopted. The major timelines for lockdown related policies adopted across Indian states is presented in Table 1. Here we would like to mention that barring the initial nationwide lockdown between March 25th – May 31st, 2020, the rest of the lockdown phases and corresponding timelines presented in Table 1 are not an absolute representation of lockdown measures across all the Indian states. Rather these provide the reader with the most indicative timelines of how various lockdown phases taken effect in India over the last 18 months.

3.3. Baseline electricity consumption analysis (BECA)

The baseline electricity consumption analysis (BECA) model is a multi-variate timeseries model devised to predict the electricity consumption for 2020, in a counterfactual or hypothetical situation had the COVID-19 not occurred. Once the predictions from the BECA model are obtained, they can be compared against the actual electricity consumption to statistically quantify the dip in electricity reduction for the entire year of 2020. This way, one can statistically quantify the reduction in electricity consumption that would have taken place due to the impact of the pandemic. The following steps were performed to develop the BECA model:

- The first step in the process of developing the BECA model was the selection of appropriate input variables. We used input time series from different categories of variables mentioned in Section 2.2. Under weather parameters, we chose temperature and humidity as these are major factors effecting electricity consumption, while for the econometric parameters, we considered state GDP values. In addition to state GDP, we also considered other economic parameters including Manufacturing Purchasing Managers’ Indexes (PMI), GDP from manufacturing and utilities (GDP H&U), Consumer Price Index (CPI), Inflation Rate (IR) and Minimum Labour Wage (MLW).
However, these variables were found to be highly correlated with state GDP values. (Please refer to SI Section S2 and Fig. S2 for details). Highly correlated variables do not tend to provide any new insights to a data-driven model, but rather they increase the dimensionality and complexity of the model leading to overfitting of the model. For this reason, only the GDP was considered as econometric variable. Lastly, we used the past time-series (lags) of the electricity consumption as input to the model. (The details of how the lag values of electricity were determined is presented in the SI Section S1 and Fig. S1). The final list of inputs and outputs for the BECA model is provided in Table 2.

• To develop the BECA model, four time-series models including VAR, FBP, NARX and LSTM were comparatively evaluated for their performance.

• All the models were trained on the daily data from January 2017–June 2019 and their prediction performance was assessed on the test period from July 2019–December 2019, where RMSE and MAE were used as the model evaluation metrics [25,32].

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{I} (y_i - \hat{y}_i)^2}{I}}
\]  
\[
MAE = \frac{\sum_{i=1}^{I} |y_i - \hat{y}_i|}{I}
\]  

Where \( I \) means the number of data points; \( y_i \) represents the \( i \)th data point and \( \hat{y}_i \) indicates the predicted value from the model; \( \bar{y} \) is the average of the \( I \) data points.

• Once the best-performing model was identified, the trained model was converted to a closed loop model and replacing the lag values of the electricity consumption with feedback input in order to carry out a multi-step-ahead prediction of baseline electricity consumption for 2020.

• The prediction interval for the time-ahead forecasting of 2020, under the non-pandemic counterfactual situation with 95% confidence was defined as:

\[
P_I = \hat{y} \pm 1.96 \times SE_f
\]  

Where \( \hat{y} \) is the predicted series and \( SE_f \) is the standard deviation of the best performing model [39].

• Finally, the BECA predicted electricity consumption was subtracted with actual electricity consumption for the entire 12 months of 2020, to determine the month wise reduction in electricity consumption throughout 2020 for each of the seven states.

3.3. ReCiPe for emission analysis

To assess the CO₂ levels due to the pandemic induced lower electricity demand in 2020, we made a direct comparison between electric-
ity generation and corresponding emissions quantified by global warming potential (CO₂-eq) using the ReCiPe (H) impact assessment method [40,41].

ReCiPe (H) is a life cycle impact assessment method which transforms the resources and its associated emissions into a limited impact score by the utilization of characterization factors (CFs) on midpoint and endpoint levels. The emission inventories in the Ecoinvent database [42] for power generation activities were aggregated to global warming potential (CO₂-eq) on midpoint level with corresponding CFs, to evaluate the overall environmental burden from CO₂-eq emission of the Indian energy sector from January 2018 to March 2021. Midpoint approach assigns environmental flows with identical impact mechanism to corresponding impact category, thus having a stronger connection to the environmental flows [43]. Hence, rather than applying endpoint approach with higher uncertainty level, midpoint approach was selected to provide a relatively more reliable analysis result.

Due to the diversity in power generation across various zones in India, relevant emission factors were collected based on data availability and the information provided in the report from the recently published pre-print [44]. Emission inventories of electricity production in regions with highest generation capacity for each energy source were assumed to be representative for the national-wide situation. Details of the emission factors and their sources corresponding to the energy sources are listed in SI Section S4 and Table S1.

The CO₂-eq missions from the various sources in the generation mix were calculated based on the equation below:

\[ CO₂ - eq \ emission = \sum \ P_i \cdot CF_{i,j} \]  

Where \( P_i \) is power generated from the \( i \)th energy resource (kWh) and \( CF_{i,j} \) is the emission characterization factor of impact category \( j \) for energy resource \( i \) (kg/kWh).

Our analysis revealed that, emissions from thermal power production alone contributes to more than 99% of the total emissions. To this rationale, the CO₂ emissions from thermal power production at a unit process level as provided by the Ecoinvent database was chosen to represent the uncertainty with respect to emission analysis for the entire Indian power sector. According to Ecoinvent, the selected unit process is assumed to follow the log-normal distribution with geometric mean at 1.1993 kg CO₂/kWh thermal power with a standard deviation of 1.0046 kg CO₂/kWh. Therefore, within 95% confidence interval, the corresponding CO₂ emission for 1 kWh thermal power would range from 1.1883 kg CO₂/kWh to 1.2104 kg CO₂/kWh approximately, which are 99.08% and 100.93% of the geometric mean value respectively. By multiplying the above two percentage values, the lower and upper limits of the CO₂-eq emission results within a 95% confidence interval were calculated.

3.4. Pandemic electricity consumption scenario (PECS)

During the months of April and May 2021, India experienced unprecedented second wave of the COVID-19, the largest outbreak in the world since the beginning of the deadly pandemic last year [45,46]. As such, many states once again undertook lockdown measures from mid-April onwards to curb the further outbreak of the pandemic. In India, the lockdown policies are regulated at the state-level rather than by the central government. As such, there is considerable variability in the duration, stringency and policies associated with the lockdown across states, which inadvertently increases the variability in electricity consumption. Given the abovementioned uncertainties, which is also applicable to any global economy, we devised the Pandemic Electricity Consumption Scenario (PECS) model to predict the near-term electricity under the constantly changing lockdown policies.

The following steps were performed to develop the PECS model:

• The PECS model primarily maps electricity consumption as a function of weather, past electricity demand data and lockdown induced
social distancing parameters. Specifically, the social distancing parameters were mapped via two variables i.e., % change in daily workplace population and % change in daily stay-home population from the Google Mobility Reports as described in Section 2.2. This report also provides data on other social distancing factors such as movement of population/people to groceries and pharmacies, retail and recreation and travel to transit stations during the pandemic. However, all these variables were found to be strongly correlated to the aforementioned variables and hence omitted from being used in the model as highly correlated variables do not tend to add meaningful insights to the model. (Please refer to SI Section S5 and Fig. S4 for details). The list of inputs and outputs for the PECS model is provided in Table 3.

- To develop the PECS model, four time-series models including VAR, FBP, NARX and LSTM were comparatively evaluated for their performance, like the one explained in the BECA model.
- All the models were trained over the period from January 2019–December 2020 using the evaluated for their prediction performance on the test period from January 2021–April 2021, where RMSE and MAE were used as the model evaluation metrics as described in Eqs. (2) and (3).
- Once the best performing model for each state was identified, it was used to forecast the electricity consumption for the period from May – August 2021. For each of the state, two specific scenarios were developed: worst-case and reference which represented hypothetical projections of how lockdown measures could evolve in the above-mentioned period and thereby affect the electricity consumption. The details of the scenarios are as follows:

1. Worst-case: This scenario assumes that strict lockdown and social distancing measures will be undertaken in the entire duration from May-August. Under these assumptions the % change in the daily workplace population and % change in the daily stay-home population follows the trend from April -May 2020, when the first complete and strict lockdown was imposed. Specifically, the mean values of % change in workplace population and in stay-home population for each of the states is calculated between April-March 2020 and the same mean values are used as inputs in the PECS models to project electricity consumption from May-August 2021. The weather parameter for the forecast period was obtained by averaging the mean temperature and humidity for the respective days from the past 4 years.

2. Reference: This scenario assumes that strict lockdown and social distancing measures will be undertaken for the entire month of May followed by a gradual relaxation of measures – a trend as observed last year. Specifically, the mean values % change in workplace population and in stay-home population for each of the states is calculated between April-May 2020 and the same mean values are used as social distancing inputs in the PECS models to project electricity consumption from May 2021. Similarly, the mean values of the parameters from June-July 2020 and August-September 2020 are used as input for the months of June-July 2021 and August 2021 respectively. The weather parameter for the forecast period was obtained by averaging the mean temperature and humidity for the respective days from the past 4 years.

4. Results

4.1. Quantifying electricity consumption during the first wave

To statistically quantify the impact of COVID-19 on electricity consumption across each state, we use the concept of predictive inference and develop a year-long, baseline electricity consumption analysis (BECA) for each of the states investigated. Based on the demographics of the state, the BECA estimates the electricity consumption profile for 2020 under a hypothetical, non-pandemic situation which is then used as a benchmark against the actual electricity consumption.

Among the four algorithms evaluated, the NARX model resulted in the best overall performance closely followed by the LSTM model, on both the training and test period. On the contrary the classical linear models including VAR and FBP, had an acceptable performance on the training set, but failed to predict in the test set and had a considerable error, as witnessed through large RMSE values compared to the NARX and LSTM. (The overall training and test performance of the algorithms are presented in SI Table S2). It is well reported in the literature that classical timeseries models are found to be limited in their performance compared to the ML models specifically as they do not capture non-linearity trends in the data. This becomes even more evident in the case of multi-variate timeseries predictions such as in this study. The input variables used to develop the BECA model were non-correlated (please refer to SI Section S3 and Fig. S3 for details). Thus, the ML models were more likely to capture the non-linearity among input variables better than the classical models, which eventually hampered the final predictions of the latter. Between the ML models, it is worth a note that for each of the seven states, a single algorithm was not observed to be the best performing. For instance, in the case of MH, GJ, UP and TN the NARX model outperformed the rest of the algorithms, whereas in the case of DL, WB and KA, the LSTM was the best performing. Also, an interesting observation was that while the LSTM model had the overall best performance on the training set, the NARX model bettered the predictions on the test set. To this cause and the fact that the NARX model had an overall better performance on the test set, it was identified as the best performing model and identified as representative for the BECA model. The accuracies of the algorithms on the test period averaged across seven states is provided in Fig. 3. The state-wise accuracy of the BECA model (which is derived from the best performing NARX model) is presented in Table 4.

A state-wise comparison with both the mean and prediction interval of electricity consumption is shown in Fig. 3. The interval estimation is derived from the root mean squared error (RMSE) estimation of the BECA model on the test dataset and hence can be considered as a reliable estimation boundary of the prediction. The close overlay between the line plots of the BECA and the actual electricity consumption in the period from Jan–March 2020 and the divergence from April through June 2020, demonstrates the efficacy of our model. It is quite evident

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**Table 3**

List of input and output parameters for the PECS model.

| Input                | Parameters                          | Frequency  |
|----------------------|-------------------------------------|------------|
| Weather              | Mean temperature                    | Daily      |
| Parameters           | Mean humidity                       | Daily      |
| Pandemic             | Percent change in workplace population | Daily    |
| Parameters           | Percent change in stay-home population | Daily    |
| Electricity Parameter| Lag values of electricity           | Daily**    |
| Output               | Electricity consumption             | Daily      |

** Please refer to SI Section S1 and Fig. S1 for details.

**Table 4**

State wise accuracy of the BECA model (NARX) on the training and test periods. The model was trained on the period from January 2017-June 2019 and was evaluated on the test period from July -December 2019.

| States    | Train RMSE (GWh) | Test RMSE (GWh) | Train MAE (GWh) | Test MAE (GWh) |
|-----------|------------------|-----------------|-----------------|----------------|
| Delhi     | 5.96             | 6.35            | 4.64            | 5.10           |
| Maharashtra | 14.60           | 17.26           | 10.91           | 13.54          |
| Gujarat   | 17.60            | 19.24           | 12.77           | 14.46          |
| UP        | 12.17            | 13.35           | 8.47            | 10.00          |
| Tamil Nadu | 12.78           | 12.89           | 10.03           | 10.20          |
| West Bengal | 18.23           | 16.79           | 14.49           | 13.58          |
| Karnataka | 9.53             | 8.49            | 7.09            | 6.76           |
that all the states experienced a significant reduction in electricity consumption starting in April through the end of May. However, the magnitudes of reduction varied from state to state, depending on the landscape, industrial activities and population dynamics. The period from April to May, witnessed the maximum dip ranging between 15%–33% across the different states, given the stringent lockdown measures and closure of essential industries, factories, commercial establishments and transportation. The impact was more pronounced in the states of Maharashtra, Gujarat and Delhi, which are the industrial and commercial hub of the country. States like Karnataka and Tamil Nadu, with a relatively dominance in agrarian and IT economy experienced a lesser dip of 10–15%.

The electricity consumption began to rebound during the unlock phases, where again the trend varied across the states. The drop in the actual consumption as compared to the BECA ranged between 6% to 15%; given the differences in the level of partial release across states, and the varied level of social distancing measures such as reopening of heavy and manufacturing industries, office buildings and commercial activities. The months of June-August experience significant variations in temperature and humidity across states, depending upon the geographical zones, which also causes significant variation on electricity consumption. The estimated changes in electricity consumption across states, during the various phases of lockdown are presented in Fig. 4. (Detailed state wise estimates for the entire year of 2020 is presented in the SI Table S3). As per the BECA model, the cumulative of actual electricity consumption across the seven states was 23 TWh lesser than the baseline model for the entire year of 2020.

By the start of 2021, the electricity consumption fell back to the norms as most of the lockdown measures were gradually released. The reopening of the economy and intensive measures to counter the incurred losses to the economy during 2020 led to increased industrial and commercial activities and long work hours (including home office) resulting in a steep rise in electricity consumption. The net electricity consumption by the states investigated was found to be 170 TWh during the first quarter (Q1), 2021, which was 8% and 6.5% more than the values during the same time period in 2019 and 2020, respectively. The states of Uttar Pradesh, Maharashtra, and Gujarat saw the highest increase in electricity consumption during Q1, 2021 (increase by 11.5% and 13.4% w.r.t to 2019 and 2020, respectively for UP, increase...
by 15.4% and 8.1% w.r.t to 2019 and 2020, respectively for Maharashtra and increase by 10.3% each w.r.t to 2019 and 2020 for Gujarat).

4.2. Assessment of CO₂ emissions from the power sector

The reduced electricity consumption across the various states stemming from the pandemic induced restrictions on industrial, commercial and social activities inadvertently implied reduced demand, which in particular had a significant impact on power sector emissions. Under reduced electricity demands, thermal-based generation (coal and lignite) plummeted, while the share of renewable energy sources (RES) increased, precisely due to the merit-order of the capacity mix of different generation technologies [5]. As a result, India managed to keep the RES mix of the grid at an annual mean value of 10.15% in 2020 as compared to 8.4% and 9.5% in 2018 and 2019, respectively. During the lockdown period between April–August 2020, the mean contribution of RES in the grid mix was found to 11.67%, while that of thermal feedstock plummeted down to 65.3%. The mean contribution of thermal generation in 2020 saw a drop to 70.21% in the total mix as compared to 74.98% and 72.29% during 2018 and 2019, respectively.

As a consequence of reduced electricity demands during the various lockdown phases and increased contribution of RES in the distribution mix, the emissions from the electricity sector also decreased. Through our analysis, we observed that the emission patterns closely matched with the electricity demand during the various lockdown phases of 2020 with respect to 2019. For instance, India experienced a stringent lockdown during the months of March-May 2020. During this phase the electricity consumption reduced by 9–26% across the various states, while the CO₂ emissions decreased by 22–31% during the same timelines from 2019. During the partial lockdown phase from June-August 2020, the electricity consumption reduced by 6–13%, while the emission reduced by 7–18% from the same periods in 2019. Lastly, with the gradual reopening of the economy between September – December 2020, while the electricity demand increased by 2–9% while the corresponding emission increased by 6–9% compared to the same months in 2019. Thus, we see a clear and consistent trend between electricity consumption and CO₂ emission during the various lockdown phases for 2020.

Furthermore, between March to August in 2020, when India was either in complete lockdown or partial lockdown, the mean CO₂ emissions between reduced to 99.3 (85.2 to 109.7) Mt CO₂-eq month⁻¹. This accounted for a drop of approximately 14% (5% to 26%) and 12% (3% to 24%) of the generation emission as compared to the monthly mean of 2018 and 2019, respectively. For the entire year of 2020, the mean CO₂ emissions from electricity generation was found to be 107.4 (85.2 to 118.8) Mt CO₂-eq month⁻¹ which was 7% and 5% drop from the mean annual emissions due to generation in 2018 and 2019, respectively. These findings are consistent with the claims made by Bertram et al. [5] and Le Quere et al. [2], on the global power sector emission reduction in 2020 as compared to 2019 by 6.8% (4.9% to 9.0%) and 7% (3% to 13%) respectively. The main findings of this section are presented in Fig. 5. The details of the monthly emission per energy source and the total emission along with the 95% confidence interval as calculated from the ReCiPe analysis are presented in the SI Table S4.
Given the increased electricity consumption during the Q1 of 2021, we estimate that the net CO₂ emissions from fossil-fuel generation would be at 382 Mt CO₂-eq, an increase by 11.9% in comparison to the same time period in 2020. These emission levels even surpass the non-pandemic Q1 of 2018 and 2019 by 9.2% and 9.1%, respectively. We observe that the emissions reached a record high of 135 Mt CO₂-eq month⁻¹ which is the highest monthly emission observed since 2018. As an emerging economy, India’s emissions have steadily and linearly increased by approximately 4% per year in the last decade; of which the power sector has contributed between 65–70% [8,18]. However, the recent trends observed are unprecedented and closely mimic the emissions patterns post the global financial recovery of 2010, when the CO₂ emission increased by 9.4% in 2010 compared to 2009 [47]– mainly driven to revive the economy, which inadvertently resulted in a rebound of coal demand.

### 4.3. Projecting the electricity consumption during the second wave

The power consumption during the Q1 of 2021 grew almost by 20% as compared to the same timeline from last year [48], indicating a robust recovery in industrial, manufacturing and commercial growth and economic revival. However, this recovery could be hampered by the unprecedented second wave of the COVID-19. Many states began to undertake lockdown measures from mid-April to curb the further outbreak of the pandemic and partial lockdown measures are still implied in major Indian states. Given the considerable variability in the lockdown duration, its stringency and policies associated with the lockdown across states, the variability in electricity consumption increases. The PECS model is devised to capture this variability and to provide an estimation of electricity consumption through scenarios as the pandemic induced lockdown measures evolves over the period of time.

For the PECS model, four timeseries models namely VAR, FBP, NARX and LSTM were comparatively evaluated for their prediction accuracies. Unlike in the case of the BECA, a clear distinction was observed as the LSTM model unanimously outperformed all the other algorithms on the training and test set for each of the 7 states investigated. The accuracies of the algorithms on the test set averaged across seven states is provided in Fig. 6. (Overall training and test performance of the algorithms are presented in SI Table S5; and the comparison of the actual electricity consumption v/s electricity predicted by PECS is shown in SI Fig. S5). The state-wise accuracy of the PECS model (which is derived from the LSTM model) is presented in Table 5. The near-term electricity consumption projections under the various scenarios modeled via PECS are shown in Fig. 7.

The reference scenario captures the lockdown trends such as that of 2020, which is the infliction of strict lockdown measures being imposed in May, followed by a gradual relaxation during the next 3 months. Under this scenario, though it is observed that electricity consumption gently dips in the beginning of May, but unlike last year it stays more or less in the range close to the non-pandemic scenario. The consumption tends to increase with the gradual relaxation of lockdown parameters and by the end of August, the electricity consumption under this scenario is anticipated to overshoot the non-pandemic scenario by 106% (87% to 122%). Accordingly, we project that under this scenario, 19 TWh of electricity out of the total 23 TWh deficit from last year, could be offset by the end of August 2021.

In the worst-case scenario, the pandemic induced lockdown measures are presumed to become more stringent and prolonged till the end of August, either due to the inability to curb the spread of the second wave for various reasons [49] or because of the potential threat of the third wave [50,51]. In this scenario too, given that May 2021 did not witness a substantial drop in consumption despite strict lockdown being imposed, the drop is anticipated to be at a marginal 96% (78 to 107%) in comparison to the non-pandemic scenario. While the possibility to offset the deficit from last year is reduced to a meagre 0.5 TWh under this scenario, the overall outlook still remains positive with respect to electricity consumption – due to both economic resilience and weather dynamics coming into play in the near term.

During the month of May 2021, most states underwent a strict lockdown similar to the one of during April-May in 2020. (At the time of submitting this work, most Indian states are still in lockdown – strict or partial). However, despite the strict lockdown measures imposed during the entire month of May, an initial assessment of the electricity consumption suggests that the electricity dip consumption was subtle and meagre this year. The model prediction under the reference scenario was validated against actual electricity consumption across states, where it was observed that the trends and consumption as predicted by the PECS model across the various states investigated, was in close alignment with the actual consumption. The average drop in electricity consumption across states in May of 2021 was found to be a bare 4% in stark contrast to the 20%–33% drop from last year when the strict lockdown was imposed. As such, we anticipate that the near-term electricity consumption could potentially experience a minimal collapse, yet less pronounced and anticipate a faster recovery as compared to the first wave.

### 4.4. Validating the pecs forecast

While ambiguity on the progression of the second wave and the potential threat for the third wave by November of 2021 still looms, we have validated the projections of the PECS model till the end of July at the time of submitting this work. Starting in April of this year, when the second wave of the pandemic inflicted India, we developed the PECS models and made the forecast for the near-term future as described in Section 4.3. However, since the PECS model uses the concepts of recurrent neural networks (i.e. LSTMs are a form of recurrent neural networks) we have been continuously updating this model on a biweekly basis based on the evolution of the pandemic and the associated lockdown polices forecasting it for at least a month ahead. Based on the lockdown policies of Indian states, most Indian states again underwent a strict lockdown measure during the months of April and May 2021, and more specifically in May – all the states investigated in this study were in complete lockdown. Fig. 8 presents the comparison of the of the PECS forecast under reference scenario to that of the electricity actual consumption across various states till the end of May. Here it can
Table 5
State wise accuracy of PECS model on the training and test period. The model was trained for a 2-year period from January 2019- December 2020 and was evaluated on 4 months test period from January-April 2021.

| States      | Train RMSE (GWh) | Test RMSE (GWh) | Train MAE (GWh) | Test MAE (GWh) |
|-------------|------------------|-----------------|-----------------|----------------|
| Delhi       | 4.73             | 4.89            | 4.41            | 3.78           |
| Maharashtra | 13.82            | 18.03           | 10.29           | 13.31          |
| Gujarat     | 12.73            | 20.9            | 11.06           | 8.2            |
| UP          | 20.55            | 22.36           | 13.5            | 12.01          |
| Tamil Nadu  | 11.25            | 16.5            | 12.2            | 7.92           |
| West Bengal | 9.97             | 12.3            | 6.67            | 8.63           |
| Karnataka   | 9.8              | 11.76           | 7.5             | 10.31          |

Fig. 7. PECS model analysis depicting weekly projections for six states under the reference and worst-case scenario till the end of August.
be observed that the actual electricity consumption closely followed the trends to that of the PECS forecast with an RMSE and MAE of 15.25 ± 5.60 GWh/day and 11.11 ± 3.88 GWh/day respectively, across all the 7 seven states.

Further on, from June onwards the lockdown measures began to be relaxed and the states started going into partial lockdown mode (similar to the trends of 2020). This is precisely how we had devised our reference scenario i.e., to capture strict lockdown measures in April and May, followed by gradual relaxation from June onwards. Fig. 9 shows the comparison of the of the PECS forecast under reference scenario to that of the electricity actual consumption across various states between June and July. It is also evident here that the actual electricity consumption closely followed the trends to that of the PECS forecast with an RMSE and MAE of 14.23 ± 5.90 GWh/day and 11.17 ± 4.67 GWh/day, respectively, across all the 7 seven states. The PECS validation metrics with respect to the actual electricity consumption for each of the individual states between April till July 2021 is presented in SI Section S11 and Tables S7 and S8.

At the time of submission of this work, we have validated our PECS model till the end of July 2021 with the actual data. However, we are continuously updating our model based on the evolution of the pandemic and its lockdown associated policies. The models developed and the data are open sourced and can be found in the following GitHub link: https://github.com/ssuvarnamanu/COVID-19-and-India-Power-Sector. Additionally, a quantitative comparison of the PECS model with and without social distancing parameters is also presented in SI Section S12 with Table S9.

5. Conclusion and future implications

The primary contribution of this study is the development of a data-driven framework using tools of machine learning and LCA to investigate and quantify the impact of the COVID-19 pandemic on electricity consumption and associated emissions for 2020 and to project electricity demand amidst the ongoing second wave – by analysing the changes in mobility and demographic information across individual states. The inclusion of heterogeneous variables such as econometrics, weather and social distancing parameters in both the BECA and PECS can be used to understand the evolving effects on the power sector and can be leveraged at dual scale: bottom-up (daily power system operators) and top-down (policy making). However, the study is not without limitations and needs to be addressed. Currently the PECS model only accounts for weather and social-distancing parameters, under the assumption that any socioeconomic metrics which can potentially impact electricity demand is correlated or reflected by these parameters - might have its own limitations. However, it is a continuously evolving model and with updates on the model (i.e., training on most recent input data with time or with the addition of new input data) followed by subsequent iterative training the model provides a decent forecast for the near-term as presented in this study.

While we focus on India as a case study in this paper, the modeling framework developed is generic and cross-deployable in nature as it is purely data-driven and thus scalable across spatial-temporal scales. This is also an advantage of data-driven models compared to classical time-series and heuristic methods, provided the right data is available. From a spatial-temporal context we focussed on 'state-level' assessment and 'daily' temporal granularity, which we believe is a sweet-spot for such a yearlong assessment. Since all the models are purely data-driven, the framework can be scaled to various levels as it would be a matter of using appropriate data for the weather, econometrics and social distancing parameters by either, scaling up the spatial and temporal resolution to the national level and long-term horizon (weekly or monthly) respectively or scaling down to city or district level with hourly granularity.

Despite the reduction in electricity consumption experienced in 2020, the Indian power sector is very well on its way for a V-shape recovery in 2021 (till the end of August at the time of writing this paper. Please see SI Section S13 for more details). This is clearly evidenced by the fact that the electricity consumption of Q1 in 2021 increased by 6.5% as compared to the same timeline in 2020 (Q1 of 2020 was pandemic free). Moreover, the trajectory for electricity consumption during
the second and third quarter (Q2 and Q3) of 2021 as projected by the reference scenario in the PECS model suggests that electricity consumption will be on the rise with the potential to overshoot the electricity consumption in a non-pandemic scenario and that of the same time-period of 2020 (Q2 and Q3) by 6% and 12% respectively. While increased electricity consumption implies rebound of the economy, these are often accompanied with warranted risk of giving support to increase in fossil generated electricity. Such ventures tend to negate decreasing contribution of fossil sources (specifically coal) in the grid mix that has been on a downward hill since 2018; thus, countering and even offsetting the drop in emissions witnessed in 2020. However, the current situation also presents unique opportunities for the regulatory bodies and policy makers to direct the emissions towards a downhill trajectory, while the electricity demand experiences growth due to economic rebound and resilience. Approaches and policies that aid in the productive recovery and sustainable growth of the sector in the near-term future and post the pandemic is of paramount importance. While supplying secure and uninterrupted electricity to the growing needs of the nation along with penetration to the rural areas with fossil fuels, the emphasis will also have to play a crucial role from the global energy and emission context.

Notes

The authors declare no competing financial interests.

We open source the BECA and PECS models developed in this study on GitHub (https://github.com/ssuvarnamanu/COVID-19-and-India-Power-Sector). Two separate Excel datasheets are also attached in this repository, with essential details on the training and test data for each of the respective BECA and PECS models.

Declaration of Competing Interest

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.

CRediT authorship contribution statement

Manu Suvarna: Conceptualization, Visualization, Data curation, Formal analysis, Writing – review & editing. Apoorva Katragadda: Conceptualization, Visualization, Data curation, Formal analysis, Writing – review & editing. Zlying Sun: Conceptualization, Formal analysis, Writing – review & editing. Yun Bin Choh: Conceptualization, Formal analysis. Qianyu Chen: Formal analysis. Pravin PS: Formal analysis, Writing – review & editing. Xiaonan Wang: Conceptualization, Writing – review & editing.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.adapen.2021.100078.

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