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Impact of COVID-19 on electricity energy consumption: A quantitative analysis on electricity

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\textbf{A B S T R A C T}

In addition to the tremendous loss of life due to coronavirus disease 2019 (COVID-19), the pandemic created challenges for the energy system, as strict confinement measures such as lockdown and social distancing compelled by governments worldwide resulted in a significant reduction in energy demand. In this study, a novel, quantitative and uncomplicated method for estimating the energy consumption loss due to the pandemic, which was derived from epidemiological data in the beginning stages, is provided; the method bonds a data-driven prediction (LSTM network) of energy consumption due to COVID-19 to an econometric model (ARDL) so that the long- and short-term impact can be synthesized with adequate statistical validation. The results show that energy loss is statistically correlated with the time-changing effective reproductive number ($R_t$) of the disease, which can be viewed as quantifying confinement intensity and the severity of the earlier stages of the pandemic. We detected a 1.62\% decrease in electricity consumption loss caused by each percent decrease in $R_t$ on average. We verify our method by applying it to Germany and 5 U.S. states with various social features and discuss implications and universality. Our results bridge the knowledge gap between key energy and epidemiological parameters and provide policymakers with a more precise estimate of the pandemic’s impact on electricity demand so that strategies can be formulated to minimize losses caused by similar crises.

\section{1. Introduction}

The ongoing COVID-19 pandemic is one of the most impactful global public health emergencies in recent years, spreading rapidly worldwide and causing a catastrophic global tragedy. Up to 2021/12/05, the pandemic had caused 266,138,021 confirmed cases of infection and 5,270,900 confirmed deaths, with suspicions that both numbers are strongly underestimated \cite{1} (Fig. 1). In addition to the tremendous loss of life, the pandemic has created an enormous challenge for the energy system, as most governments around the world instituted strict confinement measures such as lockdowns and social distancing to try to reduce transmission and minimize the pandemic’s impact \cite{2}, which resulted in a significant negative influence on both the demand and supply sides of the energy industry, especially in the earlier stages of the pandemic. For instance, this pandemic is believed to be responsible for the uncertainty in the energy market in the first half of 2020, specifically in the fluctuation of crude oil prices, as the anticipated energy consumption is supposed to be substantially lower than prepandemic predictions \cite{3}.

When confinement measures are executed, people tend to stay at home, causing a significant suppression of commercial and industrial activities, which results in an instantaneous negative impact on electricity consumption. For instance, the International Energy Agency reported that during the first few months of the pandemic when Wuhan, China, was under lockdown, China’s electricity consumption was reported to be 13\% lower than it was the year before \cite{4}. When restrictive measures were gradually softened, the electricity demand steadily recovered \cite{4}. A sudden change in electricity demand can negatively affect both power utilities and financial activities, as it causes challenges in electric grid reliability and fluctuations in the energy supply chain. Therefore, it is vital for policymakers/managers to anticipate the impact...
of public health crises on electricity demand in the beginning stages and to have plans in place to make a cautious adjustment and to formulate strategies or policies that will minimize losses. This pandemic-power relationship can be especially helpful for countries/regions that are still suffering through the COVID-19 pandemic or regions experiencing other public health crises.

There have been several studies attempting to qualitatively discuss how the pandemic affected the power system, especially in the early stages. For instance, Elavarasan et al. [5] present comparisons of electricity consumption in 2019 and 2020 to analyse the impact of COVID-19 on power grids. Abu-Rayash and Dincer [6] investigate the effects of the COVID-19 pandemic on the electricity sector mainly by comparing electricity consumption in the same periods of 2019 and 2020. Bahmanyar et al. [7] calculated the electricity demand variation index for European countries and compared the DVI in 2020 and 2019. Edomah et al. [8] analysed the impact of COVID-19-related lockdowns on electricity consumption by comparing time series data before and after lockdowns. To the best of our knowledge, most existing studies conclude that COVID-19 has negatively affected electricity consumption.

With the increasing accessibility of pandemic and electricity supply data over time, a growing number of studies containing quantitative analysis have gradually emerged. Some studies compare the energy consumption under the pandemic to that of the year before the pandemic (2019). For instance, Eryilmaz et al. [9] carry out a linear regression analysis to empirically test the impact of stay-at-home advisories on electricity generation from each fuel type. Costa et al. [10] analyse the impact of COVID-19 on the Brazilian distribution electricity market based on the optimization tariff model, detecting that both producers and consumers have been affected. Norouzi et al. [11] propose two hybrid methods for model construction and analysis through an autoregressive elasticity and neural network-based sensitivity analysis to explore the impact of COVID-19 on oil and electricity demand in China. Cui et al. [12] use the GDynE model to see how the COVID-19 pandemic has affected energy transition in different countries, concluding that the COVID-19 pandemic will lead to a dramatic reduction in this year’s energy consumption for all regions and countries. These studies usually neglect various effects, such as ecogrowth [13], seasonal effects [14], and fluctuations [15]. Other studies forecast electricity consumption or estimate the changes during the pandemic. For instance, Huang et al. [16] analyse the electricity consumption decrease in China under COVID-19 with a grey model and

| Nomenclature                                | Definition                                                                 |
|---------------------------------------------|-----------------------------------------------------------------------------|
| OLS                                         | Ordinary least squares                                                      |
| ARIMA                                       | Autoregressive Integrated Moving Average model                              |
| LSTM                                        | Long Short-term Memory neural network                                       |
| ARDL                                        | Autoregressive distributed lag model                                        |
| RNN                                         | Recurrent neural network                                                   |
| $R_0$                                       | Basic reproductive number                                                  |
| $R_t$                                       | Effective reproductive number                                               |
| $\sigma$                                    | Sigmoid function                                                           |
| $f_i$                                       | Forget factor                                                              |
| $i_t$                                       | Input gate                                                                  |
| $o_t$                                       | Output gate                                                                 |
| $\tilde{C}_t$                               | Intermediate value                                                         |
| $W_f, b_f, W_i$                             | Weight matrices of forget gate, input gate and output gate                 |
| $b_f, b_i, b_o$                             | Bias vectors of forget gate, input gate and output gate                     |
| $h_{t-1}$                                   | Inputs at the previous time ($t-1$)                                        |
| $x_t$                                       | Inputs at the current time ($t$)                                            |
| $\tanh$                                     | Hyperbolic tangent function                                                |
| $\lambda_n$ ($n=1,2$)                      | Long-run coefficients                                                      |
| $\alpha_i, \beta_i$                        | Short-run coefficients                                                     |
| $ECT_{t-1}$                                 | Lagged error correction term                                               |
| $RMSE$                                      | Root mean square error                                                     |
| $MAPE$                                      | Mean absolute percentage error                                             |
| $ECT$                                       | Error correction term                                                      |

Fig. 1. Distribution of COVID-19 infection rate worldwide on 2021/12/05 [1].
monthly data. Cihan [17] predicts electricity and gas consumption in a Turkish industrial zone via ARIMA and Holt-Winters models. Obst et al. [18] adapted generalized additive models and predicted the electricity demand during the lockdown period in France and compared the results with several similar models. Lu et al. [19] forecast electricity demand in the U.S. with a hybrid multi-objective optimizer-based model and detected a declining trend. Wang et al. [20] calculated the difference in electricity consumption between the pandemic-free state and the actual state with the ARIMA and BP approaches, concluding that China’s electricity use dropped by 29% due to the COVID-19 pandemic. Fezzi and Fanghella [21] employ an econometric model to calculate the COVID-19 impact and detected reductions in both electricity demand and GDP. Table 1 lists the relevant works and provides information for the utilized models and places studied. All the studies presented in the table reveal a negative effect of COVID-19 on electricity consumption. With these exciting attempts, however, it is still challenging to formulate a model that includes a data-driven prediction of energy demand on COVID to a classic econometric model so that the long- and short-term impact could be synthesized with adequate statistical validation.

The workflow of our current attempt can be summarized as follows (Fig. 2): We first employ data on daily electricity consumption from 2016 to 2019 and project the energy demand for 2020 from pandemic data (hypothetical non-COVID-19 scenario). We then synthesize our results and compare them with key epidemiological indicators (updated regularly) so that the anticipation of energy loss can be viewed from a dynamic perspective. To validate our approach, we chose five different states in the United States, which is one of the most severely affected countries by COVID-19, and Germany. We believe these locations represent different regions with various population densities, political leanings, and COVID-19 policies. We took into account exposure to the pandemic and daily energy consumption data, and applied our model to these regions.

This paper is organized as follows: In section 2, we carry out a qualitative analysis of the early-stage COVID-19 impact on electricity consumption in the U.S. and Germany, including descriptions of COVID-19 trends and control policies, together with a general overview of electricity consumption data. In sections 3–4, we forecast electricity consumption without COVID-19 (hypothetical non-COVID-19 scenario) in 5 different states of the U.S. and Germany and then compare the actual consumption under COVID-19 (COVID-19 scenario). The traditional epidemiological model with practical conditions is then modified with key parameters present for different disease stages. We then analyze the specific impact of COVID-19 on electricity consumption by combining electricity demand reduction (from LSTM output and actual data) with the epidemiological model and finally propose a simple correlation for implications in energy policy/precautionary operation.

In summary, by providing the LSTM-ARDL estimation, this study calculates the energy consumption loss under COVID-19 and reveals the immediate effects of COVID-19 on energy qualitatively and quantitatively. The findings bridge the knowledge gap of the quantitative estimation of the relationship between energy consumption and effective reproduction number (R0), which can be taken as a basis for policy and supply adjustments to handle public health crises and minimize the negative impact. Additionally, as a data-driven model, LSTM-ARDL estimation can be taken as an approach to predict energy consumption or other time-series variables under different emergencies, including but not limited to COVID-19, providing a reference value for further research on different emergencies and their impact on energy, economy.

Table 1

| Author(s) | Place studied | Methods | Qualitative contents |
|-----------|---------------|---------|----------------------|
| Huang et al. [16] | China | Grey model | Correlation analysis of COVID-19 on electricity consumption reduction |
| Wang et al. [20] | China | ARIMA (BP) | Calculations on the electricity consumption reduction |
| Gulati et al. [23] | Some states in India | Machine learning | Predictions on electricity consumption under COVID-19 |
| Leach et al. [24] | Some provinces in Canada | Fixed-effects regression | Confirmation of impact of COVID-19-related factors on electricity consumption |
| Lu et al. [19] | U.S. | Machine learning | Predictions on electricity consumption under COVID-19 |
| Wang et al. [25] | U.S. | Grey model, ARIMA, BP | Calculations on oil consumption without COVID-19 |
| Obst et al. [18] | France | Generalized additive model | Predictions on electricity consumption under COVID-19 |
| Fezzi and Fanghella [21] | Italy | Econometric model | Calculations on the electricity consumption reduction percentage |
| Santiago et al. [26] | Spain | Percentage change calculation | Calculations on the electricity consumption reduction percentage |
| Sahin et al. [27] | Five European countries | GA based SFANGBM, machine learning | Predictions on electricity consumption under COVID-19 |
| Ceylan [28] | Turkey | Machine learning | Predictions on electricity consumption under COVID-19 |
| Cihan [17] | Industrial zones in Turkey | ARIMA (Holt-Winters) | Predictions on electricity consumption under COVID-19 |
and environmental indicators.

2. COVID-19 conditions and electricity consumption

2.1. COVID-19 trends in early stages

The first COVID-19 case within the United States was disclosed on 2020/1/19 in Washington [42], while the earliest COVID-19-associated death was confirmed on 2020/2/6 in California [43]. These two figures in Germany are 2020/1/27 and 2020/3/9, respectively [1]. During the epidemic, the transmission and incidences differ across states because of socioeconomic and demographic factors such as income inequality, age, disability, language, race, and urban status [44-46]. Meanwhile, prevention measures vary from state to state due to the U.S. federal system [47]. As a consequence, individual states show different epidemiological trends [48].

Therefore, we chose five typical states and a country in different situations to analyse the epidemic features more comprehensively. The target states were chosen based on (i) the magnitude of the outbreak of each country or state and (ii) daily electricity consumption data availability. By 2020/9, California, Texas, Florida, and New York had become the four U.S. states with the highest cumulative number of COVID-19 infections. Considering the impact of population size on the spread of the pandemic [49,50], a state with a smaller population size (Tennessee: 6,829,174) is also selected to extend the generalizability of the study. The number of confirmed cases in Tennessee is relatively small due to a much smaller population but remains significant in terms of the case rate per 100,000 [51]. Additionally, Germany, with more than twice the population of California, was also selected.

In studies related to COVID-19, various epidemiological parameters are used as an effective means of quantifying the severity of the pandemic. A vital parameter for evaluating the initial prevalence of the disease [55]. Due to the improvement in various testing systems and the introduction of vaccines in the latter stages of the pandemic, other indicators can achieve a more visual representation of the extent of pandemic development. However, energy consumption was most uncertain at the earlier stages of the pandemic and gradually recovered in the latter stages when the pandemic became more manageable. Thus, there is a need to clarify the impact of energy consumption changes at the beginning of the pandemic and hedge macroeconomic and operational risks. It is reasonable and relevant to select $R_t$, which is more applicable to the early stage of the outbreak, to measure the energy consumption changes at the beginning of the pandemic.

We show the evolution of $R_t$ together with newly confirmed COVID-19 cases in 5 target states in Fig. 3. The effective reproduction numbers of the five states all started at high values, which is partly in tune with the initial upsurge of infections, especially in the case of New York. Shortly afterwards, the $R_t$ of each state drops below 1, after which the $R_t$ of different states starts to take diverse directions. California, Texas, and Florida experience another round of upick before stagnating and decreasing to below $R_t = 1$. At the same time, the $R_t$ values for New York and Tennessee fluctuated around $R_t = 1$ but remain $> 1$ until 2020/9/22. In Fig. 3, we can roughly visualize a delayed correlation between the effective reproduction number and newly confirmed cases: when $R_t$ decreases to below 1, an increasing number of cases is generated, indicating that the pandemic is still spreading with no tendency to vanish [53]. The $R_t$ value can be estimated by integrating the time intervals with the knowledge of the observed infection cases, the number of potential infectors, and the weighting function of transmission potential for a certain generation [54].

Despite the existence of other epidemiological indicators (e.g., number of hospitalizations, number of deaths, etc.), $R_t$ is most applicable to this study, as it is widely followed and observed at earlier stages as an indicator of the initial prevalence of the disease [55]. Due to the effective reproduction number ($R_t$), defined as the average number of secondary infections generated by a single index infection in a population at time $t$ [53], was introduced to track the disease spread. When $R_t < 1$, new infection on average is going to be caused by the current 1 case, which indicates an ongoing decrease in the number of cases with each generation; if $R_t$ remains $< 1$ constantly, the disease would be eliminated. When $R_t > 1$, an increasing number of cases is generated, indicating that the pandemic is still spreading with no tendency to vanish [53]. The $R_t$ value can be estimated by integrating the time intervals with the knowledge of the observed infection cases, the number of potential infectors, and the weighting function of transmission potential for a certain generation [54].

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amount of time (approximately 40 days), which confirms the supposition that \( R_t \) is an ideal precautionary factor for the upcoming wave of the pandemic.

2.2. Policies of COVID-19 prevention and control in earlier stages

To mitigate the economic and social impact of COVID-19, a number of intervention policies have been put in place by state and local governments. Based on the implementation data [47], the policies can be divided into various categories: state of emergency, physical distancing, shelter in place, mask wearing, business shutdown, reopening, and secondary closures (here, we mainly compare the differences among the 5 U.S. states, detailed in Fig. 4). California was the first state to declare a state of emergency among the states surveyed. Likewise, it was the first state to take the longest lasting prevention and containment measures, such as closing bars and restaurants and issuing a stay-at-home order. New York had a more restrictive policy than that of California and was the first of the states surveyed to mandate the use of face masks. The three states—Florida, Tennessee, and Texas—had the shortest duration and longest response time in placing restrictions on restaurants, gyms, and movie theatres, although their control measures in K-12 schools were not very different from the other two states. Furthermore, these three states did not implement precautions, such as stay-at-home orders and face mask requirements, as well as the other two states. For example, Tennessee and Florida did not mandate the use of face masks in public during the first wave of the COVID-19 pandemic but only encouraged it, whereas mask wearing is now viewed as the best defence against the spread of the coronavirus.

To better measure the impact of policy implementations on the development of the pandemic, we evaluated the relationship between epidemiological public health indicators (including \( R_t \) and newly confirmed cases) and policy implementation, concluding that policy implementation can change both the value and direction of \( R_t \). For instance, in New York, after the government declared a state of emergency on 2020/3/7, it attempted to lower the \( R_t \) value by implementing a series of intervention policies on social distancing, business shutdowns, and shelter-in-place mandates. In California, after reopening businesses and nonessential retail stores, the \( R_t \) value rose back above 1 until policies on masks and secondary closures were resumed and succeeded in lowering \( R_t \) values back below 1. However, as mentioned in the previous section, the number of new cases, compared with \( R_t \), reflects disease features with lags, showing that \( R_t \) is likely to be a better direct indicator of policy implementation for the characterization of pandemic development.

2.3. Electricity consumption during the prepandemic and earlier pandemic periods

Before quantifying the impact of COVID-19 on electricity consumption, we analyse long- and short-term trends in electricity consumption for the country and states studied. Fig. 5 shows the electricity consumption from 2016/1/1 to 2020/9/22 [57,58]. As electricity consumption is affected by users’ consumption habits, two levels of periodicity can be observed. In the short term, a 7-day fluctuation can be visualized in Fig. 5 for all selected states, and the serrated shape of the curve is likely due to the alternation of weekdays and weekends. On a longer-time scale, periodic peaks appear for each state studied, indicating the effects of seasons on users’ energy consumption habits due to changes in weather-related factors such as climate and seasonal market factors. For instance, the electricity consumption during June, July, and August is significantly larger than that of other months in all selected states. These periodic features are actually favourable in projecting future consumption using a data-driven method [59] and should remain periodical during the black swan events of a pandemic.

Under COVID-19, electricity consumption from 2020/3 to 2020/9 (shaded) is affected in all five states studied, and this effect is dominated by a reduction in consumption, although it is hard to visualize directly from the data given by U.S. Energy Information Administration (EIA)’s Hourly Electric Grid Monitor [57] and partly cleaned by Ruggles et al. [58] (visualized in Fig. 5). Compared with the same period in 2019, three main changes can be observed: (i) the decrease in seasonal peaks and troughs, which is more apparent for Tennessee (from late March to early July, with lower peaks and troughs); (ii) higher volatility, mostly visible in California; (iii) an overall similarity with partial declines, specifically in Texas, California, and Florida. Note that the baseline

Fig. 3. Evolution of effective reproductive number \( (R_t) \) and the number of newly confirmed cases in the five selected states. Coloured lines show the trend of \( R_t \) using the left vertical axis with green segment: \( R_t < 1 \) and red segment: \( R_t > 1 \). The grey line indicates the daily number of newly confirmed cases on the right vertical axis.
electricity consumption has trended upwards in some states over the years (for instance, Texas). Therefore, when estimating the absolute loss of electricity load solely due to COVID-19 and subsequent measures, it is important to separate all other causes. In contrast with approaches using baseline correction by estimated equations or data for economic growth or others, we do so via an LSTM network trained by prepandemic data detailed in the following section.

3. Estimation models and data sources

3.1. Model specification

3.1.1. LSTM network: Prediction and comparison of electricity consumption

Long short-term memory (LSTM) networks were first introduced by Hochreiter and Schmidhuber [60] based on recurrent neural networks (RNNs). When processing data with large timesteps, error signals in RNN tend to “blow up” or “vanish” [61], giving rise to oscillating weights or prohibitive training times [60]. LSTM was developed to solve such error backflow problems. Compared with common RNN, an LSTM network contains cell memory units, which are capable of storing new information as well as forgetting previously stored memory, making LSTM a suitable fit for making predictions based on data in time series in which lags of varying duration can be present between repeated or irregular events. In energy fields, LSTM is becoming increasingly important in forecasting energy supply and consumption [59] for various categories of energy, such as natural gas [62], wind power [20], and electricity [31]. In these studies, the forecasting results from LSTM are reported to have better accordance with reality in various standard performance metrics compared to other prediction models.

In the typical chain structure of an LSTM network (Fig. 6), two transfer states are embedded in the flow of main repeatable units: the cell state, denoted as \( C_t \), which represents the historical information (long-term memory) that changes slowly based on factors computed from the current input \( x_t \) and the previous cell state \( C_{t-1} \), and the hidden state, denoted as \( h_t \), which represents the flow of short-term memory that is updated at a faster pace by factors computed based on the current input \( x_t \) and the previous hidden state \( h_{t-1} \). In each unit, 4 neural network layers containing weight matrices and layer bias vectors are trained to generalize 4 key vectors: forget gate vector \( f_t \), input

Fig. 4. Timeline of COVID-19 prevention and control policies in earlier stages. Policies in 5 states and Germany are categorized according to the colour of the bars. Grey, pink and green bars illustrate the time frames of business shutdown implementation, social distancing orders (including shelter-in-place orders in the United States and contact ban in Germany) and face mask requirements. States are asterisked when a certain policy is implemented for the second time. Data are obtained from Raifman et al. [47] except for the date of K-12 school closure in California, which is defined as the date most schools closed according to Johnson [56].
candidate values $i_t$ and $C_t$, and output gate vector $o_t$. These four vectors are all used for computing the current $C_t$, $h_t$, and the network output from a combination of pointwise operations ("\(x\)", "+" in Fig. 6) and activation functions, such as sigmoid functions (\(\sigma\)) or hyperbolic tangent functions (tanh). Eqn. (1) to (6) are details of the calculating structure in each repeating unit, with variables defined in Table 2 [64].

\[
\begin{align*}
  f_t &= \sigma(W_f[h_{t-1}, x_t] + b_f) \\
  i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i) \\
  C_t &= \tanh(W_c[h_{t-1}, x_t] + b_c) \\
  C_{t-1} &= f_t \times C_{t-1} + i_t \times C_t \\
  o_t &= \sigma(W_o[h_{t-1}, x_t] + b_o) \\
  h_t &= o_t \times \tanh(C_t)
\end{align*}
\]  

These four vectors are all used for computing the current $C_t$, $h_t$, and the network output from a combination of pointwise operations ("\(x\)", "+" in Fig. 6) and activation functions, such as sigmoid functions (\(\sigma\)) or hyperbolic tangent functions (tanh). Eqn. (1) to (6) are details of the calculating structure in each repeating unit, with variables defined in Table 2 [64].

In this study, the LSTM networks are initialized and trained using MATLAB R2020a (Deep Learning Toolbox). We first applied a zero-mean normalization to our data input to the interval \([1,1]\). Then, we set the hyperparameters based on the approach provided by Yang et al. [65] and calculated a random range for each hyperparameter. We kept the same training parameters for all experiments: maximum epochs randomized \([900, 1200]\), initial learn rate \([0.005, 0.02]\), learn rate drop period \([100, 150]\), and learn rate drop factor \([0.02, 0.04]\). Finally, we executed a call of the deep learning toolbox by employing the function net, carried out predictions of the test set, and applied denormalization.

After testing our trained network with historical data from 2019/11/1 to 2020/1/31, a period without the pandemic effect, we generalized the model to predict electricity consumption for the non-COVID-19 scenario in 2020 and used it as the reference state for quantification of the COVID-19 impact on electricity consumption. Note that in the face of the COVID-19 shock, any other parameters, especially macroeconomic parameters, were influenced by the crisis to a greater or lesser extent. Therefore, such parameters are not considered in the LSTM model in this study.

### Table 2

| Variable | Def. | Country/State | Mean | St. dev. | Observations |
|----------|------|--------------|------|----------|--------------|
| $R_t$    | Effective reproduction rate | California | 0.9898 | 0.1033 | 188 |
|          | Florida | 1.0191 | 0.1627 | 187 |
|          | New York | 0.9091 | 0.1516 | 191 |
|          | Tennessee | 0.9149 | 0.0704 | 184 |
|          | Texas | 1.0286 | 0.0961 | 184 |
|          | Germany | 0.9857 | 0.1180 | 190 |
| $CDPC$   | Average change in demand per capita per day (kWh) | California | 1.7280 | 3.9046 | 188 |
|          | Florida | 1.8135 | 2.3470 | 187 |
|          | New York | 1.6803 | 2.4257 | 191 |
|          | Tennessee | 1.5302 | 5.2187 | 184 |
|          | Texas | 1.6053 | 3.7741 | 184 |
|          | Germany | 0.4420 | 0.8452 | 190 |

Notes: The difference in the observed values of $R_t$ among selected states is due to the difference in the appearance of the first case in each state during the study period.

In this study, the LSTM networks are initialized and trained using MATLAB R2020a (Deep Learning Toolbox). We first applied a zero-mean normalization to our data input to the interval \([-1,1]\). Then, we set the hyperparameters based on the approach provided by Yang et al. [65] and calculated a random range for each hyperparameter. We kept the same training parameters for all experiments: maximum epochs randomized \([900, 1200]\), initial learn rate \([0.005,0.02]\), learn rate drop period \([100, 150]\), and learn rate drop factor \([0.02, 0.04]\). Finally, we executed a call of the deep learning toolbox by employing the function net, carried out predictions of the test set, and applied denormalization.

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3.1.2. ARDL method: Relating COVID-19 and electricity consumption

The autoregressive distributed lag (ARDL) model and its bound test approach, proposed by Pesaran et al. [37,66,67], is a widely used econometric model for estimating the relationship of time series variables. It is capable of (i) estimating the relationships with underlying variables integrated at both levels and differences, (ii) presenting efficient estimations for small samples [38]; and (iii) solving problems associated with nonstationary time series data [39] (i.e., spurious regression). Here, we introduce a CDPC variable that is calculated by the predicted electricity consumption per capita in the hypothetical non-COVID-19 scenario minus the observed consumption in the real world (COVID-19 scenario) and adopt the ARDL model to describe COVID-consumption relations.

To employ the model, a series of tests should be carried out first to ensure the statistical significance, existence of cointegration, and estimation accuracy. Unit root tests should be conducted to ensure the satisfaction of an important model assumption that the variables selected should be integrated into I(0) or I(1) [37]. We adopt the ADF approach, one of the most widely used unit root tests to reject the null hypothesis of existing unit root(s). Then, the following step examines the existence of a cointegration relationship between Rₜ and CDPC. Both the F value test and ECT₁ (error correction term with a lag) can be applied to serve the target, that is, to reject the null hypothesis of no level relationship.

With the cointegration relationship proven, Rₜ and CDPC can be further analysed by using the ARDL approach to estimate both the long- and short-run models, with which we can obtain more comprehensive and objective relationships. The relationships can be estimated by using Eqs. (7) to (9).

(i) Detection of long-run relationships among the variables (via ordinary least squares) [68]:

\[
\Delta CDPC_t = c + \lambda_1 (R_t)_{-1} + \lambda_2 CDPC_{t-1} + y \sum_{i=1}^{p} a_i \Delta (R_t)_{-i} + \sum_{i=1}^{q} \beta_i \Delta CDPC_{t-i} + \mu_t
\]

where \(\Delta\) indicates the correction to CDPC, \(c\) represents the drift component, \(\lambda_0 (n = 1,2)\) depicts long-run coefficients, \(a_i\) and \(\beta_i\) denote short-run coefficients, \(i\) signifies the optimal number of lags, \(p\) and \(q\) indicate the maximum lags included in this equation, and \(\mu_t\) represents the white noise error term. The null hypothesis for the nonexistence of a long-run relationship can be described as \(H_0 : \lambda_1 = \lambda_2 = 0\), and its alternative is \(H_1 : \lambda_1 \neq \lambda_2 \neq 0\).

(ii) Long-run relationship:

\[
CDPC_t = c + \sum_{i=1}^{p} a_i \Delta (R_t)_{-i} + \sum_{i=1}^{q} \beta_i CDPC_{t-i} + \mu_t
\]

(iii) Short-run relationship:

\[
\Delta CDPC_t = c + \sum_{i=1}^{p} a_i \Delta (R_t)_{-i} + \sum_{i=1}^{q} \beta_i \Delta CDPC_{t-i} + \delta ECT_{t-1} + \mu_t
\]

where \(ECT_{t-1}\) represents the lagged error correction term that characterizes the equilibrium speed under short-run shocks of explained variable(s) to reach the long-run cointegration in the current period [69]. It is supposed to be negative and statistically significant. The long-run coefficients of \(R_t\) calculated by Eq. (8) are the core coefficients in the model and can be interpreted as "elasticities" [70], which represent the sensitivity of change for CDPC in response to change in \(R_t\) (Eq. (10)).

Thus, once the fit is statistically significant, the long-run impact of \(R_t\) on CDPC can be described quantitatively in the form of a percentage change, and a quick estimation of CDPC can be reached based on \(R_t\) using Eq. (10).

\[
\frac{CDPC_t - CDPC_{t-1}}{CDPC_{t-1}} = \text{Elasticity} \times \frac{(R_t) - (R_t)_{-1}}{(R_t)_{-1}}
\]

3.2. Data acquisition and description

In this study, the impact of COVID-19 on energy consumption in the earlier stages of the pandemic were studied. Therefore, when selecting the data and the time span of the datasets, the validity of the epidemiological indicator as well as the spread of the pandemic itself should be considered. Following this principle, we limited the length of the study period to 180–190 days. We first collect electricity consumption per capita for the five selected states from 2016/1/1 to 2020/9/22, following which the effective reproduction number (denoted by \(R_t\)) of the selected country and states throughout 2020/2/25 to 2020/9/22 was selected as the indicator for pandemic severity. The acquisition approaches and pretreatment procedure of raw data in this study are listed as follows, and some statistical descriptions of data acquired are summarized in Table 2.

1. \(R_t\), a dimensionless quantity commonly employed by epidemiologists, is acquired from Systrem et al. [55].

2. Electricity consumption per capita, measured in kWh and calculated by daily electricity consumption divided by population (assuming that the population remains constant except for deaths related to COVID-19 in the pandemic). For electricity, (i) the data of 5 states in the U.S. are accessed through EIA’s Hourly Electric Grid Monitor [57], which collects electricity data from balancing authorities (BAs) across the contiguous United States and compiles regional datasets. For the small percentage of data that were found missing or implausible (negative or outlier values) from the original source, we adopted the cleaned database published by Ruggles et al. [58], specifically, the cleaned data from 2016/1/1 to 2019/7/1; while the data from 2019/7/2 to 2020/9/22 came directly from the Energy Information Administration (EIA) [57], they were screened under the same principles proposed by Ruggles et al. [58]; (ii) the data for Germany are from the transparency platform [71]. The resident population of selected states was obtained from the United States Census Bureau [72] and for Germany from the German Federal Statistical Office [73], corrected with the death toll due to COVID-19 [1].

3. CDPC, defined as daily changes in demand per capita (in kWh), is the subtraction of actual electricity consumption in the COVID-19 scenario from LSTM predicted electricity consumption (hypothetical non-COVID-19 scenario).

4. Results

4.1. Prediction & comparison of electricity consumption

4.1.1. The validation of LSTM network using backtesting

Prior to predicting electricity consumption without the impact of the COVID-19 pandemic, we first verify the application of the LSTM network by using known real-world data as the validation set and test the feasibility of the current model. We train the LSTM model using daily data from 2015/7/1 to 2019/10/31 and test the projection results using daily data from 2019/11/1 to 2020/1/31. Here, neither the training set nor the validation set are relevant to the pandemic. We then run the LSTM neural network 150 times for each state and pick 100 runs with the lowest RMSE as the model output. We calculate the confidence intervals and relative errors of the daily average prediction for the 100 runs picked and summarize the results (in Table 3) for the five states.
Here, the average relative errors in the states studied (except Florida) are below 10%. In Florida, significant errors are observed on days with large electricity consumption shocks, increasing the overall average. According to the results, projections using the current LSTM model have no significant systematic error but a rather random error of relatively low magnitude. Therefore, the current LSTM network can be hypothesized to be applicable for predicting the non-COVID scenario, as the backtesting results shown in Table 3 depict successful projection on historical data.

### 4.1.2. Prediction and comparison

Here, we perform predictions for CDPC in pandemics (from the selected beginning date, SLEL in Fig. 4, to 2020/9/22) using a validated LSTM network trained by daily data from 2015/7/1 to 2019/11/1 and tested with data from 2019/11/1 to 2020/1/31 before the onset of the pandemic. We show in Fig. 7 the predicted changes in demand in the selected beginning date, SLEL in Fig. 4, to 2020/9/22) using a validated historical data.

Forecast results of the test set (2019/11/1 to 2020/1/31).

| States     | Observed value | Forecasted value (95% Confidence Interval) | Average relative error (Absolute values) |
|------------|----------------|---------------------------------------------|------------------------------------------|
| California | 687,915.25     | 692,440 – 696,997                            | 1.80%                                    |
| Florida    | 554,328.79     | 604,356 – 613,657                            | 10.73%                                   |
| New York   | 417,018.92     | 418,034 – 425,288                            | 3.70%                                    |
| Tennessee  | 423,582.61     | 408,849 – 416,661                            | 4.35%                                    |
| Texas      | 933,191.39     | 913,646 – 943,925                            | 6.35%                                    |
| Germany    | 1,236,966.33   | 1,269,525 – 1,275,983                         | 2.82%                                    |

For the selected runs with seasonal fluctuation features, specifically with peak electricity consumption repeatedly appearing in June-Aug each year. It can be seen clearly from the figure that while the electricity demand recovers the prediction for roughly the same time that CDPC rises to > 1. It is interesting to see that, as measures are taken, an almost immediate change in CDPC can be seen. For instance, in the case of New York, as the reopening of businesses happens on 5/15, the CDPC stops declining and starts rising (with fluctuation), showing a strong recovery of electricity demand. This trend strengthened when restaurants and retail outlets were reopened on 6/22. Note that in the neural network, the confinement measures are NOT considered (i.e., real demand and predicted demand are totally independent).

However, as CDPC describes the average number of secondary infections generated by a single index infection, in the earliest stage of the pandemic when there is a relatively small number of infected cases, a very high R0 can be acquired in calculations [55]. For instance, if the first person infected in a state passes the virus to five people, the instantaneous R0 value would be 5, which is an unrealistically large number but does not represent an already widely transferred disease, as there are only 6 people infected for now. R0 can only be used as a quantitative measure for confinement and pandemic severity after implementing the first prevention and controls. This effect is also evidenced by Fig. 7, as fewer distinguishing effects of the pandemic on electricity consumption might be observed in the very beginning, but strong correlations between R0 and CDPC can be seen from the start of the state of emergency. The following section will further quantify and analyse these relations and the impact of the COVID-19 pandemic on electricity consumption.

### 4.2. Impact of R0 on electricity consumption

To quantify the correlation between R0 and CDPC, the ARDL model is adopted in this section; however, to obtain statistically significant results, a set of validation tests on time series data need to be passed before the implementation of ARDL, first of which is the unit root tests that guarantee the stationarity of variables. The second is cointegration tests to ensure the existence of a cointegration relationship between R0 and CDPC.

#### 4.2.1. Results of unit root tests

In this section, the augmented Dickey-Fuller (ADF) test was employed to test for the stationarity of each variable. Granger and Newbold [74] proposed that because of possible stochastic trends, economic time series tend to be nonstationary, i.e., unit root exists, which may lead to “spurious regression”. A widely used unit root test method is the ADF test [75]. The outputs in Table 4 indicate that both variables (R0 and CDPC) in each state studied are confirmed to be stationary at I(0) or I(1), meeting the assumptions of the model.

#### 4.2.2. Results of cointegration tests

The concept of cointegration was first formalized by Engle and Granger [76]. It is a statistical tool to assess the long-run equilibrium relationships between variables. For two nonstationary time series, if the linear combination of these two tends to stay within a fixed distribution instead of varying, cointegration exists [77]. The cointegration results are presented in Table 5. First, for each state selected, the calculated F-statistics are higher than the upper bound critical values at the 1% level of significance, rejecting the null hypothesis. Therefore, the existence of a cointegration relationship can be proven. Moreover, ECT(1) has been introduced to present double illustrations of the cointegration relationship when CDPC is the explained variable. The results demonstrate significant and negative ECT(1) values for all 5 states, satisfying the statements by Rafindadi and Ozturk [78] and confirming the conclusions of F value cointegration tests again.

#### 4.2.3. Results of long- and short-run ARDL models

With the advantages of integration at both I(0) and I(1), the ability to deal with small samples, and the solving of nonstationary time series data problems, the ARDL model, which can be used to estimate the long-run elasticities better, is applied when estimating the relationship between R0 and CDPC. The estimation of both long- and short-run ARDL models and their diagnostic statistics are presented in Table 6 and visualized in Fig. 8.

The upper part details the long-run relationship of the two variables in selected states, and the lower part indicates the speed of adjustment computed in the short-run relationship. As CDPC (demand change per capita, calculated by predicted consumption minus observed consumption) has been selected as the explained variable, a negative relationship between observed electricity consumption per capita and R0 can be described when the elasticity of R0 is positive. The results in Table 6 illustrate that both variables are statistically significant. The positive elasticities of R0 indicate the positive effects of pandemic severity (and confinement) on electricity demand reduction, indicating that a 1%
increase in $R_t$ may cause approximately 1.40% growth in CDPC in Germany, and 1.70% growth in California and Tennessee. In comparison, this may lead to a 1.67% rise in New York and a 1.73% increase in Texas, which has a relatively higher average $R_t$ and variance of $R_t$. In other words, an increase in $R_t$ might mitigate actual electricity consumption per capita by a similar percentage. Similar relationships can be found in existing studies, such as Abu-Rayash and Dincer [6] for Ontario, Norouzi et al. [11] for China, Eryilmaz et al. [9] for the U.S. The model passed the diagnostic tests, indicating that there was no heteroskedasticity or serial correlation in the model among the 5 states studied. The results of the D.W. test also showed no autocorrelation in the residual series. Finally, the error correction term (ECT) demonstrates the speed of the adjustment process to restore a deviation from the long-run equilibrium [79]. In this study, the ECT coefficients of the countries and states studied are all negative and statistically significant, indicating speeds of 9.66%, 9.68%, 25.70%, 20.23%, 17.53% and 100.06%,

Fig. 7. Results of electricity consumption predictions. Coloured lines show the trend of $R_t$ using the left vertical axis with green segment $R_t < 1$ and red segment $R_t > 1$. The blue line indicates a typical LSTM output of CDPC. Dates with notes illustrate the implementation of COVID-19-related policies by the governments.
Table 4
Results of unit root tests.

| Variable | State | Level | 1st difference |
|----------|-------|-------|----------------|
| \( R_t \) | California | –0.5829 | –6.2593*a |
| Florida | –0.2515 | –3.2090*a |
| New York | –0.5168 | –7.0785*a |
| Tennessee | –0.7296 | –4.2559* |
| Texas | –0.1635 | –3.2243* |
| Germany | –1.8687 | –4.6824* |
| CDPC | California | –2.6964*a | –11.536* |
| Florida | –2.5605*a | –12.9698* |
| New York | –1.5267 | –8.1617* |
| Tennessee | –0.0557*a | –9.4695* |
| Texas | –2.4352*a | –9.4519* |
| Germany | –2.7753* | –6.7567* |

Notes: *a, b and c denote statistical significance at the 1%, 5%, and 10% levels, respectively. Optimal lag lengths are selected automatically using the Schwarz information criteria for the ADF test.

4.2.4. Discussions
At the beginning of the pandemic, social distancing and the resulting change in lifestyle led to a change in the structure of energy consumption by reducing productive activities related to energy consumption (e.g., public transport, industry, etc.). Therefore, a decrease in total energy consumption expressed as a negative change in the model, and a positive long-run elasticity are observed in each location studied. To explore the similarities and differences among the locations studied, 8 social and economic indicators have been selected and visualized in Fig. 9 and Fig. 10.

Under the combined effect of numerous social, economic, and policy factors, differences in the long-run elasticity of each location studied can be observed (the 2 most significant ones visualized in as an instance in Fig. 11). For instance, locations studied (except Florida) with higher population density have shown smaller long-run elasticity and may suffer less from electricity consumption loss, probably because the negative impact of COVID-19 on the grid is partly counteracted by the positive contribution of population density to electricity intensity [82]. Taking age group as another example, locations with higher percentage of residents above 25 years old are likely to be impacted less negatively. However, this finding seems to contradict other research findings in which working age population has repeatedly been acknowledged as a propellant of electricity consumption [84]. In addition to the social and economic factors, we suspect that policies can also have an impact on the coefficient. For Florida, a relatively less stringent policy response (for instance, lack of mandatory rules for mask wearing in public places) may also have had an impact on CDPC and the long-run coefficient. Such potential correlations can also be observed in other indicators (for instance, the GDP percentage of different industries as COVID-19 decreases the energy consumption in different industrial zones [171]). Thus, the difference in long run elasticity is influenced by a combination of these factors which are also not necessarily independent, but in general the range of elasticity we visualized is fairly narrow (1.40–1.73).

In addition to its application in COVID-19, as shown in this paper, this data-driven method can also be applied to future pandemics, as \( R_t \) has been calculated in different disease outbreaks. Although diseases with different transmission capacities may have different long-run

Table 5
Results of cointegration tests.

| Country or State | F value | 10% | 5% | 1% | ECT(1) (t-stat.) |
|------------------|---------|-----|----|----|-----------------|
| \( R_t \) model |         |     |    |    |                 |
| California      | 5.8553a | 2.44 | 3.28 | 3.15 | 4.11 | 4.81 | 6.02 | –0.0916 (-3.4315)a |
| Florida         | 8.5366a |      |     |    |                 |
| New York        | 6.9807a |      |     |    |                 |
| Tennessee       | 14.2862a|      |     |    |                 |
| Texas           | 8.5586a |      |     |    |                 |
| Germany         | 46.9877a|      |     |    |                 |

Notes: *a and b denote statistical significance at the 1% and 5% levels, respectively.

Table 6
Results of short- and long-run relationships estimated by the ARDL model.

| Country or State | California | Florida | New York | Tennessee | Texas | Germany |
|------------------|------------|---------|----------|-----------|-------|---------|
| \( R_t \) model | (3,1)      | (2,1)   | (3,1)a   | (2,1)     | (4,1) | (2,4)   |
| \( y_2 \) (Heteroskedasticity) | 1.6951a | 1.5475b | 1.6735b | 1.7024b | 1.7271b | 1.3980b |
| \( y_2 \) (Serial Correlation) | [2.7068] | [2.1544] | [2.5165] | [1.7309] | [2.2592] | [2.3155] |
| R-squared | 0.8054 | 0.8079 | 0.7226 | 0.6529 | 0.7400 | 0.6081 |
| D.W. | 2.0536 | 1.813 | 1.9663 | 1.8897 | 1.9515 | 2.1040 |
| Diagnostic tests | | | | | | |
| \( y_2 \) (Heteroskedasticity) | 0.5570 | 0.434 | 0.4166 | 0.4071 | 0.8216 | 0.4007 |
| \( y_2 \) (Serial Correlation) | 0.5853 | 0.3822 | 0.1273 | 0.1666 | 0.1279 | 0.1094 |
| Speed of adjustment (in short-run relationship) | \( ECT(1) = -0.0966 \) | \( -0.0968 \) | \( -0.2570 \) | \( -0.2023 \) | \( -0.1753 \) | \( -1.0062 \) |

Notes: *a 1% level of significance. *b 5% level of significance. The values in ( ) represent t-statistics. The values in [ ] represent lag.
elasticity, the model is still effective in predicting trends in energy demand and objectively quantifying the extent of the impact of a public health crisis on energy consumption. For other black swan events, the model can possibly provide some ideas for subsequent quantification and forecasting of energy consumption effects. Since the explanatory variables in the ARDL model are not limited to epidemiological indicators, $R_t$ in this study can potentially be replaced with other variables to explain CDPC. Possible examples include the telework rate, which indirectly measures shifts in energy use and travel demand, and indicators such as the CBOE Volatility Index, which measures the investor “fear” gauge and can be used as a proxy to indicate risk and volatility in the financial market [85]. Quantifying changes in electricity consumption during other black swan events in this way is worth exploring.

5. Conclusions

5.1. Conclusions

Aiming to quantify the negative impact of the pandemic on electricity consumption in the earlier stages of the pandemic, this article employed an LSTM-ARDL model to link the epidemiological parameters to reductions in electricity consumption. The effective reproduction rate, $R_t$, was used as the quantitative measure for pandemic severity and the effectiveness of confinement policies. The electricity consumption reduction was calculated based on real-world data and LSTM projection using prepandemic data so that the current and predicted consumption were mutually independent. We first selected five states in the U.S., attempted to predict electricity consumption per capita in the non-

![Fig. 8. Results of the LSTM-ARDL model. The height of points demonstrates the elasticity of $R_t$ in the long-run cointegration, while the diameter of points manifests the population of selected states. Additionally, the shade of points illustrates the mean value of $R_t$.](image)

![Fig. 9. Population and social factors in the locations studied. Resident population, higher education rate, age group and population density data are from [80]. 2020 U.S. election results data are from [81].](image)
COVID-19 scenario, and calculated changes in electricity consumption per capita (CDPC) in the COVID-19 scenario by comparing predicted and observed values. Then, the impact of the COVID-19 pandemic on energy consumption was quantitatively identified by the relationship between changes in demand (CDPC) and effective reproduction number ($R_t$). The following conclusions were reached:

(1) $R_t$ and CDPC are positively correlated in all five states studied, demonstrating that fluctuations in $R_t$ have negative effects on electricity consumption. More specifically, a 1% rise in $R_t$ leads to a 1.62% average increase (1.40%, 1.69%, 1.55%, 1.67%, 1.70%, and 1.73%) in electricity demand, that is, a decrease in electricity consumption per capita of the same percent in Germany, California, Florida, New York, Tennessee, and Texas, respectively, despite their very different geographical features, social structures, and political tendencies.

(2) Under different intervention policies and social and economic development, different effects on electricity consumption can be detected, while all long-run elasticities of the country and states studied suggest that the impact fluctuates by approximately 1.62% (Fig. 8). Our results show good generalizability over countries or states with different population densities, economic development, political leanings, and COVID-19 control strategies. Our conclusions, especially the quantitative estimation of the...
relationship between $R_t$ and CDPC, facilitate a rapid estimation of energy consumption based on epidemiological data, which we find applicable as a measure for consequences of the confinement policies, in addition, to be taken as a basis for policy and supply adjustments to handle the crisis.

The COVID-19 pandemic has dramatically impacted various sectors of the world, including the energy sector. Various intervention policies have slowed the spread of the pandemic but have also significantly reduced energy consumption. The global COVID-19 pandemic has not abated significantly, as evidenced by the emergence of virus variants and further rises in new cases. In this context, the key contribution of this paper is even greater.

5.2. Policy implications

The results of this study show that electricity consumption suffered decreases under COVID-19, especially when $R_t$ increased. To minimize the negative impact of suddenly decreased electricity demand (especially on the economy and the energy sector), policymakers should adopt alternative fiscal and nonfiscal tools:

1. From the perspective of public management, according to the comparison in Fig. 9 and Fig. 10, authorities should (i) gradually increase the medical care budget and investment; (ii) plan industrial development rationally; and (iii) adjust pandemic prevention policies according to the expectation of negative effects.

2. On the electricity supply side, to ensure stable operation of the power system, it is recommended that governments should improve the emergency response capability of the grids in times of similar crises: (i) promoting infrastructure construction; (ii) detailing comprehensive emergency guidelines; and (iii) increasing investment in technological research and development and reducing the cost of power generation to hedge the losses caused by pandemics permanently.

3. On the electricity demand side, to reduce, shift or split risks across the power system, authorities are supposed to reduce or transform electricity consumption in areas of intensive power use by (i) encouraging the use of high-energy-efficient appliances and (ii) developing energy models less affected by macro factors, for instance, distributed energy systems.

4. In addition, COVID-19 and the lockdown policies implemented by the governments are changing the way people work, teleworking might become a permanent “new norm”, creating a demand for policies to (i) achieve sustainable electricity resources management; and (ii) encourage environmentally friendly life- and workstyles.

5.3. Limitations and future study directions

First, further estimations based on results from other locations can be carried out in the future, as the current study is limited by time and data availability. Second, the relationship between the long-run elasticities and other epidemiological public health indicators can also be quantified in subsequent studies to further illustrate the impact of the COVID-19 pandemic on energy consumption. Third, other measures not limited to epidemiological indicators can also be employed to estimate the impact of changes in external factors on energy consumption, for instance, long-term changes in individuals’ work habits, such as telecommuting.

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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.

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