Effect analysis of the COVID-19 pandemic on the electricity consumption of Bangladesh

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ABSTRACT

The COVID-19 pandemic has disrupted our way of life and has brought challenges on a scale never seen before. Lockdown and various other social distancing rules have been implemented in order to slow down new infections. This has led to a drastic change in people’s lifestyle and has altered the pattern of electricity consumption. In this paper, the effect of lockdown on the overall electricity consumption of Bangladesh is analysed. Also, a neural network-based prediction model is developed to predict the electricity consumption during a lockdown or estimate the future consumption given a lockdown is announced in the future. Furthermore, in order to compare the change in electricity consumption for commercial, residential, and industrial areas, power measurements for the lockdown and the post lockdown period are analysed in detail. Results show a significant decline in the overall electricity consumption of Bangladesh during the period of lockdown. In addition, the commercial and industrial areas showed a considerable reduction in electricity consumption. However, the changes in electricity consumption in residential areas are found negligible. This study will aid in to provide a clearer understanding on the electricity consumption pattern in the case of further lockdowns or in the event of another outbreak in the future.

1. Introduction

The global pandemic caused by the novel coronavirus has had a significant effect on the way we live our everyday life. In order to slow down the spread of the virus, various containment measures were taken all over the world. Lockdowns were imposed, social distancing was observed, public gatherings were restricted to only a few people or were completely prohibited [1]. With such restrictions in place, it is no wonder that our day-to-day activities have changed a lot [2]. For instance, physical meetings have been replaced with online meetings and work from home has been encouraged wherever possible [3]. Additionally, physical classes in schools and universities were suspended and replaced with online classes [4]. All means of public transportations were suspended, and with lockdowns in place, people were mostly restricted to their homes [5]. Hence, a new way of living has evolved owing to the constraints imposed on the masses in order to curb the spread of the virus.

Bangladesh, a country known for its large population and high population density, was no exception to the effect of the pandemic. In the first lockdown, which started on the 26th of March 2020 and ended on the 30th of May 2020, millions were confined within their homes. Additionally, all non-essential businesses, offices, schools, universities, and industries were closed to contain the virus [6]. As such, work from home has now become the norm for a lot of professions [7]. This has led to increased demand on the cloud infrastructure, which witnessed a rise in energy consumption [8]. Such means have altered the pattern in which electricity is consumed throughout the nation.

Various existing literature have been published regarding the effect of the pandemic on the daily electricity usage. Abu-Rayash and Dincer have shown that there was an average, 14% reduction in electricity consumption during the pandemic in south-eastern region of Canada in 2020 for the month of April. Also, the daily load curve was flatter for the month of April 2020 compared to April 2019 [9]. Narajewski and Ziel analysed the electricity load demand of five European countries namely Germany, Italy, Spain, Poland, and France and have observed significant decline in the electricity consumption during the period of lockdown [10]. Santiago et al. has shown that in Spain, there was a 13.49% reduction in 2020 in the electricity consumption compared to the average of the previous five years from the beginning of lockdown on 14th of March to 30th of April. In addition, the working days saw an average of 14.53% reduction whereas weekends experienced a 10.62% reduction in electricity consumption [11]. Edoma and Ndulue studied the effect of lockdown on the transition of electricity usage in residential, commercial, and...
industrial areas. The study revealed an increase in home laundry, cooking, showering, and professional practices in the residential areas, whereas the industrial areas pertaining to food, personal care, and pharmaceuticals witnessed a decline in electricity usage. In contrast, the commercial areas saw a reduced electricity consumption due to the scaling down of trading services to only essentials [12]. Halbrügge et al. analysed the behaviour of German and other European electricity systems during the period of lockdown. The study shows that the electricity consumption decreases during the period of lockdown in all the countries except Sweden, where no lockdown was imposed [13]. In addition, the average day-ahead electricity price dropped to 17.60 EUR/MWh during the lockdown in Germany, a decline of almost 20 EUR/MWh from the same timeframe in 2019. The reduced price is the result of the increased generation of the onshore wind and solar energy during the period of lockdown [13]. Madurai Elavarasan et al. investigated the effect of the pandemic on Italy, Australia, India, and the USA. The study reports a significant reduction in electricity demand in these countries while in lockdown. In addition, a considerable shift in electricity consumption was observed, with commercial loads witnessing a substantial drop in demand, compared to residential loads which saw a spike in demand. Industrial loads also declined; however, the decline was insignificant as opposed to the commercial areas [14].

The aim of this study is to analyse the impact of lockdown on electricity consumption and the key objectives are to analyse and examine the effect of the COVID-19 pandemic on the overall electricity usage pattern of Bangladesh as a whole and to study the effect of lockdown on commercial, residential, and industrial areas. In addition, a neural network-based prediction model is developed to predict the future electricity consumption in the event of further lockdowns. The following paper is divided into three sections. In the first section, the data collection and methodology are described, and in the second, the effect of the pandemic on the daily electricity demand is discussed in detail. The neural network model is also discussed in the second section along with its prediction accuracy. Finally, in the last section, the study is concluded with a brief discussion about the results.

2. Methodology

The study has been developed in three stages. In the first stage, the data was collected from the respective sources while in the second stage, it was combined, sorted, organized, and processed. Here, Excel was mainly used to process and clean the data from the spreadsheets which was then exported to MATLAB for plotting. In the final stage, the effect of COVID-19 on the electricity consumption was analysed and an artificial
Table 1. Summary of prediction models.

| Parameters                  | NARX and TDNN |
|-----------------------------|---------------|
| Inputs                      | [3 x 1] cell |
|                            | [Day of week; Hour; Temperature] |
| Target                      | Consumption during lockdown of 2020 |
| Number of days of training  | 62            |
| Hidden layers               | 1             |
| Hidden layer activation function | tansig  |
| Output layer activation function | purelin |
| Number of neurons           | 9             |
| Number of delays            | 3             |
| Maximum number of epochs    | 1000          |
| Maximum number of validation fails | 10       |
| Minimum gradient            | $1 \times 10^{-10}$ |
| Performance function        | Mean squared error (MSE) |
| Training function           | Levenberg-Marquardt |
| Data split ratio (Train-Val-Test) | 80-20-0** |

Note: ** Separate testing data has been included.
* TDNN has an extra row in the cell for consumption in 2019.
** Separate testing data has been included.

A neural network model was implemented to predict the future consumption during any further lockdown. Two separate neural network models have been adopted in this study. The first model is used to predict the electricity consumption while a lockdown is imposed, whereas the second model is used to estimate the overall consumption if a lockdown is announced in the future. The prediction models were built using MATLAB’s narxnet and timedelaynet functions. Figure 1 illustrates the three stages of development. As can be observed, the data is collected in the first stage and then aggregated and processed in the second stage. In the third and final stage, the effect of the COVID-19 lockdown on the electricity consumption is analysed and a neural-network-based prediction model is developed.

In order to carry out this study, electricity load data was collected from the power grid company of Bangladesh (PGCB) [15] which is publicly available to download. The study consists of the daily electricity load for the years 2019 and 2020. Using these data, the overall load curve of Bangladesh was aggregated together and analysed in section 3.1. The data consisted of the overall power consumption throughout the country at 30-minutes interval. The effect on the commercial, residential, and industrial areas are mainly discussed in section 3.2 and uses the substation data of the corresponding areas. Here, the maximum power consumed through each substation for that day were recorded. For the comparison, four commercial areas from the urban city centre, namely Bashundhara, Dhanmondi, Gulshan, and Magbazar were considered. As for the residential areas, it consisted of Maninkagar, Madartek, Kamrangirchar, and Kalyanpur, and lastly, the industrial areas comprised substations connected to steel industries, particularly GPH ispat, Modern steel, Rahim steel, and BSRM. In addition, the daily average temperature of Dhaka was included in order to study the effect of temperature on the electricity consumption. Here, temperature was mainly considered as it plays a dominant role in dictating the overall electricity consumption as compared to other factors, such as relative humidity, hours of sunshine, and wind speed [16]. Dhaka city was chosen due to its significance in terms of its population and overall percentage of electricity consumption. With a population of over 14 million, it is also the largest city of Bangladesh and is responsible for nearly 40% of the country’s total electricity consumption [17, 18]. In contrast, the population of the next biggest city, Chittagong, is nearly 7.6 million [19]. The temperature data were collected from a website called reliable prognosis [20] which is also freely available to download from the website. The temperature data is based on the temperature at Hazrat Shahjalal International Airport. Also, in section 3.3, a comparison of the change in the different sources of power generation due to the lockdown has been included.

It must be pointed out that for 2019 and 2020, 11 and 20 days of data out of the 365 and 366 days were missing from PGCB’s database, respectively. The missing days were filled by averaging the data of the previous, current and the next day of all the days in that month. For example, if a particular Monday were missing in January, that day was filled with the average of all the Sundays, Mondays, and Tuesdays of January.

The neural network model has been developed in section 3.4. Here, a type of recurrent neural network called Nonlinear AutoRegressive neural network with eXogenous inputs (NARX) and a time delay neural network (TDNN) was implemented for electricity consumption prediction. The NARX model was used to predict electricity consumption while a lockdown is taking place. It is a short-term load forecasting (STLF) model [21] and can accurately predict the consumption 30 minutes ahead. However, it can be remodelled to predict longer into the future, although this comes at the cost of lower accuracy. TDNN, on the other hand, can be used to estimate the consumption in any upcoming lockdown scenarios. Such types of predictions are known as time-series forecasting, and since NARX and TDNN perform better than traditional feedforward neural
networks in these aspects, it was selected as the prediction model [22, 23, 24].

NARX is a type of dynamic neural network which uses past values to predict an output into the future. There are two separate inputs in this model. The first is known as the exogenous input and the second input is the output of the prediction of the previous timestep. The exogenous inputs are the type of variables which can influence the prediction. The model can be mathematically expressed using Eq. (1).

\[ y(t) = f[y(t-1), y(t-2), \ldots, y(t-n), x(t-1), x(t-2), \ldots, x(t-n)] \]  

Here, \( y(t) \) is the output value, which in this case corresponds to the prediction of the electricity demand, and \( x(t-n) \) is the past external or exogenous variable which influences the output. In this particular model, the exogenous variables correspond to the day of the week, hour, and temperature. The term \( y(t-n) \) in the equation represents the electricity consumption values of the previous timesteps. Together, the variables \( x(t-n) \) and \( y(t-n) \) are fed into the neural network model to make a prediction.

Figure 2 shows the general architecture of a NARX model. As can be seen, the input layer contains a series of delay operators which are used to sequence the inputs into a series of timesteps. The input layers contain a number of nodes which are known as neurons, and each of these neurons are connected to the next layer known as the hidden layer. The connections from one layer to another are simply the weights or importance of the neurons. The input values of the neurons are multiplied with
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The weights and added with another value known as the bias. Both the biases and the weights are randomly generated at the beginning of the training and are updated to more accurate values as they are trained. The result of this multiplication and addition is then passed on to the neuron of the hidden layer which contains the activation function. Similarly, the output of the hidden layer is passed to the output layer which performs similar operations to generate the output. The advantage of using NARX is that it optimizes the time performance compared to other neural networks [25].

There are two different types of architecture for NARX systems. The first one is called a series-parallel (SP) connection (also known as open-loop configuration), and the other is known as a parallel connection. The key difference between the two types is that in the SP connection, the past values of $x(t)$ and the immediate actual past values of $y(t)$ are used to predict the future values, whereas in parallel connection, the past values of $x(t)$ are used but not the exact historical values of $y(t)$. Instead, the prediction is fed back to the network to predict the future. In other words, prediction is based on previous prediction. In this paper, the SP architecture has been used during the training period of the network as it is more efficient in training [26, 27]. This allows the network to use the actual past values as feedback input resulting in increased accuracy. The SP configuration has been used to model the short-term load forecasting while a lockdown is going on.

The second model that has been used is called a time delay neural network (TDNN). The architecture of TDNN is identical to NARX, except there is no $y(t-n)$ as input, rather, only the exogenous input is fed to the network to predict the future values. In this paper, TDNN has been used to estimate the future consumption during a lockdown when it is announced in the future.

In order to develop the ideal NARX model, multiple simulations were run. The number of hidden layers was set to 1 since a greater number of layers does not necessarily increase the prediction accuracy and may lead to overfitting. Also, there is no straightforward rule to find the ideal number of neurons and delays. Therefore, a two-phase simulation was run to find the ideal number of neurons and delays. In the first phase, 5 simulations were run from 1 to 25 neurons and 1 to 25 delays. The results of the first phase suggested that the highest accuracies were clustered within the range of 1–10 delays. Then, in the second phase, the simulation was rerun 50 times from 1 to 25 neurons and 1 to 10 delays, and it was found that the network with 9 neurons and 3 delays performed the best in terms of prediction accuracy. The external inputs were a vector of 3 variables namely, temperature, time, and day of the week. The days were encoded with integers from 1 to 7 with Sunday being 1. The time, on the other hand, was converted to a numerical value ranging from 0 to 1 with a step of $\frac{1}{24}$. For training the network, 62 days of load consumption data of the lockdown period from March 2019 to May 2019 were used. The feedback values were the normal load consumption values which were synchronised according to their day of the week. For instance, the first Monday of June 2019 will correspond to the prediction of the first Monday of June in 2020. The training function used to update the weights and biases of this network was the Levenberg-Marquardt algorithm (LMA), also referred to as the damped least square method. LMA interpolates between the Gauss-Newton algorithm and the method of gradient descent. This algorithm has been used as it generally converges faster than other available functions such as Bayesian regularization (BR) or stochastic gradient descent (SDG) [28, 29]. Moreover, another benefit of this function is that even if the initial weights and biases are somehow quite far from the mark, it can still find an optimal solution [30]. Table 1 summarizes the training parameters of the two networks.

3. Results

3.1. Overall effect on Bangladesh

Figure 3 illustrates the comparison of the daily electricity consumption from the month of March to July for the year 2019 and 2020. The government of Bangladesh imposed nationwide lockdown on 26th of March 2020 [31]. As it can be seen that until mid of April, the electricity consumption for both the years is identical. However, the lockdown period shows a steep decline in the consumption of electricity in 2020. This is expected as all non-essential businesses, offices, industries, factories, schools, and universities were ordered to shut down as stay-at-home orders were imposed. Also, it can be observed that the electricity consumption again begins to rise in the second week of May.

Figure 6. Boxplots of the load curves of different months. (a) April 2019, (b) April 2020, (c) May 2019, (d) May 2020.
during this time, with people from Cox's bazar, Jessore, Khulna, Satkhira, and Barisal suffering the most [35, 36]. Almost 200 electric poles were severely damaged, and a significant number of power lines were destroyed in the cyclone [36]. In addition, almost 740 houses were washed away by the cyclone in Patuakhali [35]. Some parts of the country saw an increase in the voltage level after power went out in other cyclone-hit areas, therefore electricity supply to such areas were also shut down in order to protect from further damage [37]. Hence, due to the cyclone, the country’s daily consumption of 10,000 MW of electricity, plummeted to about 2500 MW of electricity [37].

Additionally, the effect of the season can also be felt as there is a rise in electricity consumption after the lockdown restrictions have been eased compared to the pre-lockdown periods when the weather was comparatively cooler. On 31st of May, the government began to lift the restrictions on all public and private offices, businesses, and factories [38]. Subsequently, the daily electricity consumption returned to pre-lockdown levels and the curve again became comparable to the previous year.

Figure 4 shows the percentage change in electricity consumption from 2019 to 2020. From the graph, it can be observed that the average percentage change fluctuates within 25 percent before the lockdown whereas the post-lockdown period shows a fluctuation of more than 50 percent. Again, the signs of recovery in the electricity consumption can be observed in May where the variations gradually return to normal with the inclusion of the sudden dip during the period of cyclone landfall on 18th of May when most of the region of West Bengal was cut off from the grid [36].

Figure 5(a) and Figure 5(b) compare the histograms of the daily load consumption of Bangladesh for 2019 and 2020 for the month of January and February, respectively. As can be observed, the histograms for the months prior to the lockdown give a nearly identical distribution which suggests that the load consumption before lockdown was similar to the previous year, and thus minimal change was observed here. Similarly, Figure 5(c) and Figure 5(d) illustrate the histograms for April and May. A clear contrast can be observed for the change in load consumption for both the months following the lockdown as the distribution shifts to the left. Moreover, the months before the lockdown show a lower deviation compared to the months during the lockdown. The reduced deviation also happens to occur at the lower end of the histogram, suggesting the lower electricity consumption as compared to April and May. This is due to the cooler climate that existed before the lockdown was imposed. In addition, the month of April shows a narrower distribution of the loads for the year 2020 which indicates a narrower range of load consumption compared to the previous year. However, this phenomenon is not noticed for the month of May which display identical deviation of loads for both the years. Lastly, it is noteworthy that all histograms contain identical percentage change fluctuation of more than 50 percent. Again, the signs of recovery in the electricity consumption can be observed in May where the variations gradually return to normal with the inclusion of the sudden dip during the period of cyclone landfall on 18th of May when most of the region of West Bengal was cut off from the grid [36].

Figure 6(a) and Figure 6(b) show the boxplot of the daily load curve for April 2019 and April 2020 and Figure 6(c) and Figure 6(d) show the boxplot of the daily load curve for May 2019 and May 2020. From the boxplots, the average electricity demand for the months of 2019 and 2020 can be juxtaposed easily for comparison. The bottom and the top edge of the boxes represent the 25th and 75th percentiles of the load, respectively. The boxplots for both the months show that the total electricity demand was higher in 2019 compared to 2020 as indicated by the higher median line. Moreover, for the month of April, the heights of the boxes in 2020 were less than those of 2019, indicating less variance and thus greater predictability. In contrast, the month of May showed less variability in 2019 than in 2020. From the month of May, most of the industries and offices were reopened. Furthermore, shopping malls and other small businesses were also allowed to reopen. Hence, the mean electricity demand of May 2020 was greater than April 2020. This is especially noticeable during the office hours as most of the offices, businesses, and industries operate during this timeframe.

This is due to the fact that from 10th of May, the government allowed businesses such as shopping malls and shops to run on a limited scale [32]. On the other hand, online classes for educational institutions were businesses such as shopping malls and shops to run on a limited scale. This is due to the fact that from 10th of May, the government allowed

Figure 7. Electricity load profiles from February to July for Fridays and Mondays. (a) Friday 2019, (b) Friday 2020, (c) Monday 2019, (d) Monday 2020.
Figure 7(a) and Figure 7(b) illustrate the daily load curve for all the Fridays from February to July for the year 2019 and 2020, respectively. It is to be noted that Friday and Saturday are considered as the weekend in Bangladesh, however, some offices and businesses remain open on Saturdays. Therefore, Friday has been chosen for comparison. For the weekends of 2020, a gradual rise in the load curve for the weekends can be observed which begins to decline in April, forming a valley. However, the curve begins to rise again in May as lockdown measures are eased. On the other hand, the rise in electricity consumption in 2019 is much smoother and does not form a valley. A similar trend can be observed in Figure 7(c) and Figure 7(d) which is a plot for all the Mondays (working days) from February to July for 2019 and 2020, respectively. Nonetheless, the plot for Monday shows a much steeper recovery of the load curve compared to Friday as it is a working day. The effect of the weekend can easily be seen by looking at both the graphs during the month of June and July. From morning to evening, which corresponds to the working hours, the load demand is higher for Mondays as compared to Fridays. Additionally, the load gradually increases over time as lockdown restrictions are lifted in May. Comparing the period before the lockdown starts (February and March) and the period after the lockdown ends (June and July), a clear distinction can be seen between them, with an increased consumption in the latter part which can definitely be attributed to the seasonal effects as the temperature gradually rises as summer approaches.

3.2. Effect on residential, commercial, and industrial areas

Figure 8 shows the daily plot of maximum power recorded at the substations of four commercial areas of Dhaka city. The areas are Bashundhara, Dhanmondi, Gulshan, and Magbazar. These are the areas where the majority of the offices, businesses, schools, and universities are located, all of which consume a significant amount of power. According to the plot, it can be seen that all four areas see a significant decline in the maximum power consumed after the lockdown measures were implemented. A small rise can be observed at the beginning of May which can be explained by the decision taken by Bangladesh garment manufacturers and exporters association (BGMEA) on 25th of April. From 26th of April, garments factories resumed operation with 30% of the workforce.
1427 export-oriented companies reopened on 26th with an additional 1820 on the following day. With so many factories reopening at the beginning of May, it can be inferred that the slow rise was the result of the decision by BGMEA [39]. Nevertheless, the electricity demand begins to return to normal levels by June when lockdown measures are relaxed. Additionally, the daily average temperature of Dhaka is also included to show the relationship between the load consumption and the gradual rise in temperature due to the incoming summer from March onwards. According to the observation, there is a strong correlation between the temperature and the amount of power consumed, with a higher temperature corresponding to an increase in consumption of electricity.

Figure 9 illustrates the plot of the maximum power recorded at the substations of four steel industries, namely GPH Ispat, Rahim Steel, Modern Steel, and BSRM. Again, a sudden drop can be observed after 15th of March. However, the recovery of the steel industries is at different times as a lot of the industries were not completely shut down during the lockdown period, rather, most of them were totally off only during the first half period from April to May and this is noticed in the plot as well which dips to its minimum in April. Later, some of them reopened during the 1st week of May and which resulted in the rise in the power consumption again and after the lockdown was completely over, everything returned to normal. It is interesting to note that unlike the commercial areas, whose consumption increases with the approaching summer months, the industrial areas show a constant demand for electricity throughout the year.

Figure 10. Load consumption for residential areas.

Figure 11. Energy generation mix for 2019.

Similarly, Figure 10 shows the electricity demand for the residential areas. The residential areas display quite a bit of diversity as far as electricity demand is concerned. For instance, some areas exhibit significant decline after the lockdown while others show little to no change. This stems from the fact that none of these areas are purely residential and are often accompanied by a number of small shops, restaurants, and bazaars. This is the general picture of the residential areas of Bangladesh where a small number of businesses exist alongside the residential buildings. Therefore, the areas which saw a greater fall in demand constituted more businesses than other areas. In general, as people were bound to reside within their homes due to the lockdown, it can be theorised that residential demand should increase as suggested by other studies [12]. However, a considerable number of the people who earn their living in Dhaka do not live there permanently and left for their hometowns just before the lockdown was imposed. This may explain the
reason as to why the figure differs from what it should be in first sight. Moreover, the rise in electricity consumption of the residential areas due to the onset of summer is not as prominent as their commercial counterparts which might be due to the fact that the residential areas generally contain only a handful number of air conditioners as compared to the commercial areas. This is not surprising since most of the households of Bangladesh use ceiling fans as their primary means of cooling.

3.3. Effect on overall energy generation mix

Figure 11 and Figure 12 illustrate the energy generation plots for the years 2019 and 2020, respectively. As can be observed, the primary sources of electricity come from non-renewable sources such as gas and oil. It must be pointed out that P. Gen stands for private generation companies while HVDC and Tripura are the electricity imported from Bheramara and Tripura of India, respectively. From the plots, a clear distinction can be made in the generation patterns between the two years as a result of the lockdown. In both the years, the generation increased during the summer months. However, the disruption in the generation caused by the pandemic can be easily noticed in 2020. As most of the industrial and educational institutions were shut down after the lockdown began, some of the power plants generated less power than they usually do. This is especially noticeable for the private generation companies and the HVDC transmission from India, which experienced considerable reduction during the lockdown period. After the lockdown ended, the industrial and commercial institutions were gradually reopened, and the generation began to recover. Surprisingly, it is also evident that after the lockdown ended, the overall power demand is comparatively more stable compared to the previous year. Additionally, in many developed countries, the demand for renewable energy sources for power generation has increased quite significantly during the lockdown period because of the low operating cost and reduced electricity demand [40]. Bangladesh, however, did not experience any growth in consumption of renewables. The only major source of renewable energy that is connected to the grid is a hydroelectric power plant, which accounts for just 230 MW compared to the overall generation, and as opposed to other countries, the increase in generation mix is not noticeable. Unlike intermittent renewable sources like solar photovoltaic and windfarm, hydroelectricity is predictable and hence, it can be seen that during the lockdown, the generation from hydropower are often kept low.
3.4. Prediction results of NARX neural network and TDNN model

Figure 13 shows the performance plot of the training phase of the NARX neural network. As can be seen, the training process quickly converges to a validation performance (Mean squared error) of 80604 within just 38 epochs. This fast convergence can be attributed to the Levenberg-Marquardt training function that was used to train the network.

Figure 14 illustrates the regression plot of the prediction results for the three parts of training the network, training, validation, and testing. The vertical axis is the prediction of the network while the horizontal axis is the actual value. All the three phases of the training process show an
excellent linear relationship with \( R \) value greater than 0.98. This translates to an accurate prediction despite the fact that the consumption of electricity was much more erratic compared to other times of the year. Figure 15 compares the predicted results with the actual consumption values. This plot consists of a separate data used for testing the network after the training process has finished. The test data accounts for the last four days of the lockdown. As mentioned earlier, open-loop prediction can be used for accurate prediction as it has access to the immediate actual values of the past. From the plot, it can be observed that this is indeed the case. The mean absolute percentage error (MAPE) of this prediction model on the test data was 2.03%, which suggests that it can be accurately used to forecast real-time lockdown electricity consumption.

Similarly, the TDNN model was trained on its own set of data and its performance was recorded. The performance plot of the validation segment resulted in a MSE of 820884 (in 31 epochs) with an \( R \)-value of 0.81 and 0.80 in training and validation, respectively. This model is generally less accurate compared to the NARX model. However, as this model is used to estimate the average electricity consumption in an upcoming lockdown and not accurately predict the consumption at every timestep, the result of MSE and regression plot can be considered acceptable. Figure 16 illustrates the result of the prediction on the test data which is the month of June in 2020. It must be noted that the lockdown had been lifted in May 2020, and the model here simulates the consumption if a lockdown were to be imposed on that particular month as well. According to the prediction, the average percentage reduction in electricity consumption due to lockdown being announced is 14.14% (daily average electricity consumption fell from 9402.3 MW to 8072.8 MW). The actual lockdown that was imposed from March 2020 to May 2020 experienced a reduction of 16.00% (comparing to actual values of 2019). Comparing the average percentage reduction of the TDNN model with the actual reduction due to the lockdown, the model can be considered accurate.

4. Conclusion

To conclude, it can be observed that there is a clear distinction between the year 2019 and 2020 in terms of the way we consume electricity. The pandemic has definitely affected the way we live our life and changes in habits due to the restrictions put in place to limit the spread of the virus can clearly be noticed by observing the load curve for both the years. The following points summarize the effect of the pandemic on the electricity consumption of Bangladesh and the contributions of this study:

- Imposing of the lockdown has significantly reduced the electricity consumption of the country, experiencing as much as 50 percent reduction in consumption as compared to the previous year. Also, the distribution of the monthly electricity consumption during the lockdown period has skewed to the left, indicating a lower consumption of electricity.
- The comparison of the commercial, industrial, and the residential areas show that the commercial and industrial areas observe the greatest decline in electricity consumption. However, the industrial areas do not show any response to the weather unlike the commercial areas whose consumption increases as summer approaches. In contrast, the residential areas show minimal change to both the lockdown and the weather as opposed to other studies.
- Two neural network-based model have been developed to predict the electricity consumption during a lockdown. The NARX model predicts the consumption while a lockdown is imposed while the TDNN model predicts the future consumption when a lockdown is announced in the future. The TDNN model predicted an average consumption of 8072.8 MW for the month of June 2020, which is a 14% reduction from the actual value.

The effect of the COVID-19 pandemic is still not over yet as the government announced a second lockdown starting from 5th of April [41]. Therefore, this comprehensive analysis of the daily load management can be helpful to understand the overall electricity distribution and consumption of this country or countries with similar demographics in the event of another disaster or pandemic as it will be convenient to predict the total amount of electricity that will be needed for the upcoming days.

Declarations

Author contribution statement

Abdullah Alavi: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.
Md. Shahriar Sadid & Moshiur Ahmed: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.
Fahim Abid: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.
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Data availability statement

Data associated with this study is available online. Electricity data is available at http://www.pgcb.gov.bd/site/page/0dd38e19-7c70-4582-95ba-078f6c690a8. Weather data is available at: https://rp5.ru/Weather_archive_in_Dhaka_airport, METAR.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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