Impact of Covid19 on electricity load in Haryana (India)

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Summary
As it is known that the whole world is battling against the Corona Virus Disease or COVID19 and trying their level best to stop the spread of this pandemic. To avoid the spread, several countries like China, Italy, Spain, America took strict measures like nationwide lockdown or by cordoning off the areas that were suspected of having risks of community spread. Taking cues from the foreign counterparts, the government of India undertook an important decision of nationwide full lockdown on March 25th which was further extended till May 4th, 2020 (47 days-full lockdown). Looking at the current situation government of India pushed the lockdown further with eased curbs, divided the nation into green, orange and red zones, rapid testing of citizens in containment area, mandatory wearing of masks and following social distancing among others. The outbreak of the pandemic, has led to the large economic shock to the world which was never been experienced since decades. Moreover it brought a great uncertainty over the world wide electricity sector as to slow down the spread of the virus, many countries have issued restrictions, including the closure of malls, educational institutions, halting trains, suspending of flights, implemented partial or full lockdowns, insisted work from home to the employees. In this paper, the impact analysis of electricity consumption of state Haryana (India) is done using machine learning conventional algorithms and artificial neural network and electricity load forecasting is done for a week so as to aid the electricity board to know the consumption of the area pre hand and likewise can restrict the electricity production as per requirement. Thus, it will help power system to secure electricity supply and scheduling and reduce wastes since electricity is difficult to store. For this the dataset from regional electricity boards of Haryana that is, Dakshin Haryana Bijli Vitran Nigam and Uttar Haryana Bijli Vitran Nigam were analysed and electricity loads of state were predicted using python programming and as per result analysis it was observed that artificial neural network out performs conventional machine learning models.

1 | INTRODUCTION

Covid-19 pandemic has caused an unprecedented global economic and social crisis. The pandemic has significantly affected all aspects of life, including the energy sector. Electricity demand has been significantly reduced worldwide as a result of lockdown measures been imposed and followed. Most of the countries were following the full or partial lockdown during the first quarter of 2020, leading to which Global electricity demand
decreased by 2.5%. The impact of electricity demand world-wide during Covid 19 is shown in Figure 1 below.

Therefore, sudden drift in electricity demand patterns are observed since the spread of Covid19 due to nationwide full or partial lockdown. During this phase industries were shut and people were insisted to stay at home to stay safe, which ultimately has increased the domestic consumption and decreased the industrial power consumption.

In India for all the states government undertook an important decision of lockdown on March 25th for 21 days, which was further extended on 14th April by 2 weeks that is, till third May 2020. Before the lockdown was announced, the Prime Minister of India insisted everyone in the country to follow a one-day curfew (named as “Janta Curfew”) of 14 hours on March 22nd from 7 AM to 9 PM in India, since “Janta Curfew” day that is, 22nd march, a significant change in the load patterns are observed.

Although apart from the change in life style of people during prevailing pandemic situation, there are other factors too that affect electricity load consumptions that is, weekdays, off days, holidays, meteorological or weather elements such as temperature, humidity, wind, rainfall, dew etc. A part from this electricity load depends a lot upon geographical factors, population, land use, city plans, industrial plans, community events, social events, development, construction etc.

Now a days knowing the electricity load consumption pre hand that is, electricity load forecasting is an essential and integral technique used by power companies so as to predict the power or energy which intern is needed to balance the supply and load demand at all times. Accurate electric load forecasting is essential for various operations of power systems such as purchase, production, transmission, transfer, distribution, as well as management of daily load demand and maintenance. Thus, during this pandemic time when electricity demand observed sudden drift, it is utmost important for the electricity power systems to forecast the demands.

In this work, impact analysis of electricity load in prevailing pandemic situation of various circles of state Haryana (India) is done. The electricity demand since “Janta Curfew” day is analysed and electricity load forecasting for state Haryana (India) is done using machine learning algorithms and Artificial Neural Network (ANN) which in turn is beneficial for the power systems to know the electricity demand for the day before hand and thus this will aid in reducing the wastage. For this dataset from state electricity boards that is, Dakshin Haryana Bijli Vitran Nigam and Uttar Haryana Bijli Vitran Nigam are considered. The related work, and approaches toward electricity load forecasting are discussed in subsequent section.

2 | STATE OF ART

Electricity load consumption is dynamic and diverse in nature. The initial research linear and non-linear regression techniques were applied in forecasting short term load. Apart from these curve fitting, least square approximation techniques, time series analysis statistical approaches were also explored by several researchers. A
A major breakthrough was seen with the advancement in the field of artificial intelligence for performing short-term load forecast. These techniques were capable of handling large data efficiently and effectively and catered to handle the diverse nature of electrical load. Various artificial intelligence techniques being popularly used for short-term load forecasting include ANNs,\textsuperscript{15} Fuzzy Logic Systems,\textsuperscript{16} Support Vector Machines\textsuperscript{17} and many others.

ANNs\textsuperscript{18} retains excellent non-linear mapping capabilities, which enable it for power load forecasting. Recently many researchers have applied deep learning methods\textsuperscript{9,19} for electricity load forecasting. Several other researchers have also applied machine learning models including Extreme Learning Machine Neural Network (ELMNN),\textsuperscript{20} Generalized Regression Neural Network (GRNN)\textsuperscript{21} and Support Vector Machine (SVM).\textsuperscript{22}

Many researchers have addressed various parameters like temperature, rainfall, humidity, holidays and other possible scenarios for more accurately predicting the electricity load. The effect of temperature and humidity were considered by Khotanzad et al,\textsuperscript{23} while the effect of humidity and wind speed were considered through a linear transformation of temperature was proposed in their improved version.\textsuperscript{24}

In this work, machine learning conventional methods and ANN are applied for electricity load prediction. The paper discusses about the impact analysis how energy consumption is affected by the COVID-19 pandemic in the India. The prevailing conditions of COVID-19 and restrictions imposed by the government to avoid the spread is causing devastating influence on the state’s energy sector. Thus, there is an urge for power systems to forecast the loads so as to prevent waste. In this paper, electricity load consumption drift in seven circles Ambala, Sirsa, Bhiwani, Gurgaon, Faridabad, Narnaul and Hisar of state Haryana are discussed. The work is novel as no previous work for electricity load predictions is done for state Haryana as of now. The observations and analysis of the same is shown in subsequent section.

3 | ELECTRICITY LOAD CONSUMPTION – OBSERVATIONS DURING FULL LOCKDOWN

Haryana\textsuperscript{25} is one of the 28 states in India located in the northern part of the country, it consists of 22 districts. State Haryana economy relies on agriculture, industrial sector and service sector. In this analysis some of the circles of Haryana that come under urban (Gurgaon), industrial (Faridabad, Hisar, Bhiwani) and agriculture (Narnaul) are considered so as know the energy consumption patterns during lockdown.

Considering the first circle that is,\textsuperscript{26} Ambala. It has area of 1569 km\textsuperscript{2} and population of 11.3 lakhs and cloth market is considered to be the largest textile market in the region; which remain closed due to nationwide lockdown which intern impacted the load of the city. The electricity load consumption of Ambala circle is shown in Figure 2 below (x axis depicts the dates and y axis load in MW). It can be clearly seen that there is decline in max and min load consumption after 20th march 2020 when the government announced the “Janta Curfew” which was followed by complete lockdown.

Considering the loads of next circle that is,\textsuperscript{27} Bhiwani with area 3432 km\textsuperscript{2} and population 16.3 lakhs and the city is majorly having textile industries. The load graphs are shown in Figure 3. In this graph, again the drift in
load is observed significantly majorly after 24th of March (x axis depicts the dates and y axis load in MW).

Next Circle is Faridabad which is the major industrial hub of Haryana covering 742.9 km² and has population of 14 lakhs. The electricity load of the city is greatly impacted by the lockdown after 22nd of March 2020. The load graphs are shown in Figure 4.

Gurgaon city majorly comprise of IT sectors, corporate offices as well as leading industries. It is covering 732 km² and population of 8.77 lakhs. After the announcement of the lockdown electricity consumption has significantly decreased from 21st march 2020 shown in Figure 5.

Hisar also known as “the city of steel” city as it has a large steel industry. The major economy of the city is through industries. It is covering 3983 km² area with the population of 3.01 lakhs. The significant change in electricity load patterns can be observed after the announcement of lockdown (shown in Figure 6).

Figures 7 and 8 shown the Max and Min load patterns for various circles of Haryana.

Thus, it is clear from the graph; that lockdown in nation has significantly impacted the electricity loads. Future predictions over the load patterns can be made so that power systems can pre hand know about the production and consumption of the electricity of that circle.
In this paper conventional machine learning approaches such as Linear Regression (LR), Support Vector Regression (SVR), Decision Tree Regression (DTR), Random Forest Regression (RFR), and ANN is applied. The machine learning models are discussed below:

### 4.1 Linear regression

LR\(^3\) is an approach for modeling a linear relationship between features of given data. It is used in supervised machine learning. The LR equation is given below.

\[
Y_i = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} + \epsilon_i. \tag{1}
\]

In a multiple regression, the standard errors of the coefficients are also to be looked upon. The value of \(\beta_i\) need to be estimated in this. The regression as a complete may fit our data good enough, but if some of the independent variables are correlated (or irrelevant), their coefficients might not be useful.

### 4.2 Support vector regression

SVR\(^3\) is applied to solve nonlinear regression and time series problems. However, the application of SVR to electricity load forecasting is rare. Support vector machines attempt to pass a linearly separable hyperplane through a
dataset in order to classify the data into two groups. This hyperplane is a linear separator for any dimension; it could be a line (2D), plane (3D), and hyperplane (4D+). The best hyperplane is the one that maximizes the margin. The margin is the distance between the hyperplane and a few close points. These close points are the support vectors because they control the hyperplane.

4.3 | Decision tree regression

Decision tree is a decision support tool that predicts the output of a classification or a regression problem by passing the inputs to a tree-like model. One thing to note about decision tree is that they are very prone to overfitting.

The internal nodes of a Decision Tree consist of a test of an attribute for example “$x \leq 10$” based on the outcome of the result of this test, we proceed toward the leaf node of the tree which could be a continuous or discrete value. Decision Tree learns by “splitting” (conducting tests) on each attribute in the training set, and then this process is repeated for every ith row in the training set. The training is stopped either when all the target data is classified with 100% accuracy or when no more splits can be made.

In the above Figure 9, the splitting of the given data is done as following:
Split 1: $X_1 \leq 20,$

Split 2: $X_2 \leq 170,$

Split 3: $X_2 \leq 200,$

Split 4: $X_1 \leq 40,$

based on these splits, data is classified into five different groups.

4.4 | Random forest regression

If we try to classify data with the help of a single decision tree, then model might overfit model, so we instead use Random forests which are part of ensemble learning and uses multiple decision tree, which are made during training time and they are made using a method called bootstrapping, where a small chunk of data from training set is picked at random, then it is used to train a decision tree and then that chuck is added back to the training set, so that the data from that chunk could be picked again at random to train some other decision tree.

4.5 | ANN model

An ANN is a set of simple computational units called nodes which are interconnected. The Figure 10 shows how the output of a single neuron is computed, the inputs to the neuron are stored in form of a vector, and for every input there exist a corresponding weight. The extra input, called the bias input is appended; which is always equal to +1, in the Figure 10, bias is denoted with $x_0.$

Now, to compute the output of a neuron, the Hadamard product of input vector and its corresponding weight vector is computed, and the result of that product is stored in a resultant vector. Further the sum of every the resultant vector is the computed and assign it to a variable, in this case, we assigned it to variable called “$a$” and then, an activation function is applied on “$a$,” the output of that activation function is stored in variable “$z.”” Mathematically the above explanation can be written as shown in Equations (2) and (3):

$$a_k = \sum_{i=0}^{m} w_{ki} x_i,$$  (2)

$$z_k = f(a_k).$$  (3)

4.5.1 | Designing of ANN model for forecasting electricity load

In this work for electricity load forecasting, a four layered Sequential model is used which is densely connected. Each layer is denoted by $l_k,$ where $l_0$ is our input layer
and $l_3$ is our output layer and $l_1$ and $l_2$ are hidden layers. In the model input layer $l_0$ consists of 12 neurons, and the shape of the input vector $X$ is $(m, 8)$, and the shape of its corresponding weight matrix $w^{(0)}$ is $(9, 12)$, mathematically, it can be written as:

$$X \in \mathbb{R}^{(m,8)},$$

$$w^{(0)} \in \mathbb{R}^{(9,12)}.$$  \hspace{1cm} (4)

To make input compatible for multiplication with weight matrix, we add a bias element to the input vector. After that we multiply our input vector $X$ with $w^{(0)}$ to get $a^{(1)}$ and then apply the activation function which is ReLU in this case to obtain $z$, mathematically it can be written as shown in Equations (6) and (7):

$$a^{(1)} = w^{(0)} \times X \left(\text{where} , a^{(1)} \in \mathbb{R}^{(m,12)}\right),$$

$$z^{(1)} = \operatorname{ReLU}\left(a^{(1)}\right) \left(\text{where} , z^{(1)} \in \mathbb{R}^{(m,12)}\right).$$

The hidden layer $l_1$ consists of eight neurons, and its corresponding weight vector $w^{(1)}$ is of shape$(13, 8)$, and the activation function used in this layer is $\tanh$ and $a^{(2)}$ and $z^{(2)}$ as can be computed as shown in Equations (8) and (9):

$$w^{(1)} \in \mathbb{R}^{(13,8)},$$

$$a^{(2)} = w^{(1)} \times z^{(1)} \left(\text{where} , a^{(3)} \in \mathbb{R}^{(m,8)}\right),$$

$$z^{(2)} = \operatorname{tanh}\left(a^{(2)}\right) \left(\text{where} , z^{(3)} \in \mathbb{R}^{(m,8)}\right).$$

Similarly, the hidden layer $l_2$ consists of eight neurons, and its corresponding weight vector $w^{(2)}$ is of shape $(9, 8)$, and the activation function used in this layer is $\operatorname{ReLU}$ and $a^{(3)}$ and $z^{(3)}$ can be computed as follows (Equations [10] and [11]):

$$w^{(2)} \in \mathbb{R}^{(9,8)},$$

$$a^{(3)} = w^{(2)} \times z^{(2)} \left(\text{where} , a^{(3)} \in \mathbb{R}^{(m,8)}\right),$$

$$z^{(3)} = \operatorname{ReLU}\left(a^{(3)}\right) \left(\text{where} , z^{(3)} \in \mathbb{R}^{(m,8)}\right).$$

Finally, the output layer $l_3$ consists of one neuron, with no activation function because this being a regression problem. The weight matrix $w^{(3)}$ is of shape $(1, 9)$ and $z^{(4)}$ can be computed as:

$$w^{(3)} \in \mathbb{R}^{(9,1)},$$

$$z^{(4)} = w^{(3)} \times z^{(3)} \left(\text{where} , z^{(4)} \in \mathbb{R}^{(m,1)}\right).$$

Now, after the data is gone through our neural net, it needs to be backpropagated, so as to adjust the weights to make predictions as accurate as it can be. For this loss function is used to minimize, in this case mean squared error as out loss function is used.

$$\mathcal{L}(y, \hat{y}) = \frac{1}{m} \times \sum (y - \hat{y})^2.$$  \hspace{1cm} (13)

To adjust $w^{(3)}$ loss function is differentiated with respect to $w^{(3)}$ and it could be done as follows:

$$\frac{\partial \mathcal{L}}{\partial w^{(3)}} = \frac{\partial \mathcal{L}}{\partial z^{(4)}} \frac{\partial z^{(4)}}{\partial w^{(3)}},$$

$$\frac{\partial \mathcal{L}}{\partial z^{(4)}} = -\frac{1}{2m} \left(y - z^{(4)}\right),$$

$$\frac{\partial z^{(4)}}{\partial w^{(3)}} = z^{(3)},$$

$$\frac{\partial \mathcal{L}}{\partial w^{(3)}} = -\frac{1}{2m} \left(y - z^{(4)}\right) \left(z^{(3)}\right).$$

Now, we have to find derivative of our loss function with respect to $w^{(2)}$ and it is computed below:

$$\frac{\partial \mathcal{L}}{\partial w^{(2)}} = \frac{\partial \mathcal{L}}{\partial z^{(4)}} \frac{\partial z^{(4)}}{\partial z^{(3)}} \frac{\partial z^{(3)}}{\partial a^{(3)}} \frac{\partial a^{(3)}}{\partial w^{(2)}},$$

$$\frac{\partial z^{(4)}}{\partial z^{(3)}} = w^{(3)},$$

$$\frac{\partial z^{(3)}}{\partial a^{(3)}} = \begin{cases} 1, & \text{if } z^{(3)} > 0 \\ 0, & \text{otherwise} \end{cases},$$

$$\frac{\partial a^{(3)}}{\partial w^{(2)}} = z^{(2)},$$

$$\frac{\partial \mathcal{L}}{\partial w^{(2)}} = -\frac{1}{2m} \left(y - z^{(4)}\right) \left(w^{(3)}\right) \left(\frac{\partial z^{(3)}}{\partial a^{(3)}}\right) \left(z^{(2)}\right).$$
Similarly, the derivatives of our loss function w.r.t $w^{(1)}$ & $w^{(0)}$, can be computed as

\[
\frac{\partial L}{\partial w^{(1)}} = \frac{\partial L}{\partial z^{(4)}} \frac{\partial z^{(4)}}{\partial z^{(3)}} \frac{\partial z^{(3)}}{\partial a^{(3)}} \frac{\partial a^{(3)}}{\partial z^{(2)}} \frac{\partial z^{(2)}}{\partial a^{(2)}} \frac{\partial a^{(2)}}{\partial w^{(1)}}.
\]
\[
\frac{\partial L}{\partial w^{(1)}} = -\frac{1}{2m} \left( y - z^{(4)} \right) \left( \frac{\partial z^{(3)}}{\partial a^{(3)}} \right) \left( w^{(2)} \right) \\
\left( 1 - \tanh^2 a^{(2)} \right) \left( z^{(1)} \right)
\]

\[
\frac{\partial L}{\partial w^{(0)}} = \frac{\partial L}{\partial z^{(4)}} \frac{\partial z^{(4)}}{\partial z^{(3)}} \frac{\partial z^{(3)}}{\partial a^{(3)}} \frac{\partial a^{(3)}}{\partial z^{(2)}} \frac{\partial z^{(2)}}{\partial a^{(2)}} \frac{\partial a^{(2)}}{\partial z^{(1)}} \frac{\partial z^{(1)}}{\partial a^{(1)}} \frac{\partial a^{(1)}}{\partial w^{(0)}}
\]

\[
\frac{\partial L}{\partial w^{(0)}} = -\frac{1}{2m} \left( y - z^{(4)} \right) \left( w^{(3)} \right) \left( \frac{\partial z^{(3)}}{\partial a^{(3)}} \right) \left( w^{(2)} \right) \\
\left( 1 - \tanh^2 a^{(2)} \right) \left( w^{(1)} \right) \left( \frac{\partial z^{(1)}}{\partial a^{(1)}} \right) X
\]

Note: \( \frac{\partial \text{ReLU}}{\partial x} \) and \( \frac{\partial \text{ReLU}}{\partial \text{ReLU}} \), are the derivatives of ReLU activation function and derivative of ReLU function is

\[
\frac{\partial \text{ReLU}(x)}{\partial x} = \begin{cases} 
1, & \text{if } x > 0 \\
0, & \text{otherwise}
\end{cases}
\]

Now using \( \frac{\partial L}{\partial w^{(1)}}, \frac{\partial L}{\partial w^{(2)}}, \frac{\partial L}{\partial w^{(3)}} \), and we can adjust our weight matrices as follow:

\[
w^{(k)} = w^{(k)} - \alpha \frac{\partial L}{\partial w^{(k)}}
\]

where, \( \alpha \) is the learning rate and is equal to 0.01 in our case.

Now, as it is known forward propagate and backpropagate once, it’s known as one epoch and this model is trained for 1000 epochs and to avoid overfitting, which could happen. In this model test data as validation data is
used, and training of the model is stopped as soon as the error on the validation data start to increase.

### 4.6 Electricity load forecasting model – Predicted results

In this work impact for Covid19 on electricity load of state Haryana is analysed and as per the historical data of the forecast variable 7 days ahead forecasting is done. The 4 months short term that is, day to day data as well as long term that is, week wise data is considered for the analysis. Further total seven circle load of state Haryana (ie, Ambala, Sirsa, Bhiwani, Hisar, Faridabad, Gurgaon and Narnaul) is considered in our analysis so as to know the impact on all industrial, rural, agriculture and urban sectors. As per the predicted results seen in Figure 11. ANN outperforms all the conventional machine learning methods such as LR, Random Forest, DTR, SVR.

In order to weight all features equally, the input data was normalized. Then the entire dataset is divided into two major parts that is, training and testing subset. The ratio 70 to 30 was applied in this case.

ANN involves in its optimization the number of neurons, in our case it was for only three hidden layer (hidden layer sizes), because more layers were not improving its performance (in our experiment). Two options were given for the parameter of neuron’s activation function that is, tanh and relu. The model is compiled using adam optimizer with a constant learning rate of 0.01. Further the model was trained for 1000 epochs and generally when the model is trained for these many epochs there is a chance of overfitting that was avoiding using early stopping. For early stopping to work validation data is required; for that test data is used.

Accuracy of the model is evaluated using following error mean squared error using the formula in Equation (17).

\[
\text{mse}(y, \hat{y}) = \frac{1}{m} \times \sum (y - \hat{y})^2.
\]  

(17)

The results of mean squared error for all the circles (minimum load and maximum load) using machine learning approaches and ANN are shown in Tables 1 and 2.

The above results are based on mean squared error on the test and train data, it is observed that ANN performs better than other algorithms, but in some cases Random Forest Regressor is outperforming ANN, but the reason why RFR is not considered is because it is more prone to overfitting of training data.

### 5 CONCLUSION

The current scenario of the Covid19 pandemic and prevailing government regulations of imposing full as well as
Partial lockdown leading to drift in energy consumption patterns. The energy consumption in India plummeted dramatically in March after the announcement of “Janta Curfew.” In this paper, electricity load forecasting is done for a week so as to know the required electricity load pre-hand which will aid the regional power systems to plan accordingly and avoid unnecessary power wastage. For this, ANN proved to do better predictions as compared to conventional machine learning models. Since the effects of COVID-19 are changing day by day and even the government now has eased the lockdown measures, it is to be noted that the results are likely to change when the same analyses are performed for different periods. Further in future work, we will be investigating how and by when India will recover its energy consumption after this sudden decline.

**DATA AVAILABILITY STATEMENT**

Data available on request from the authors

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