Reaction order and neural network approaches for the simulation of COVID-19 spreading kinetic in India

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A R T I C L E   I N F O

A B S T R A C T

COVID-19 has created a pandemic situation in the whole world. Controlling of COVID-19 spreading rate in the social environment is a challenge for all individuals. In the present study, simulation of the lockdown effect on the COVID-19 spreading rate in India and mapping of its recovery percentage (until May 2020) were investigated. Investigation of the lockdown impact dependent on first order reaction kinetics demonstrated higher effect of lockdown 1 on controlling the COVID-19 spreading rate when contrasted with lockdown 2 and 3. Although decreasing trend was followed for the reaction rate constant of different lockdown stages, the distinction between the lockdown 2 and 3 was minimal. Mathematical and feed forward neural network (FFNN) approaches were applied for the simulation of COVID-19 spreading rate. In case of mathematical approach, exponential model indicated adequate performance for the prediction of the spreading rate behavior. For the FFNN based modeling, 1-5-1 was selected as the best architecture so as to predict adequate spreading rate for all the cases. The architecture also showed effective performance in order to forecast number of cases for next 14 days. The recovery percentage was modeled as a function of number of days with the assistance of polynomial fitting. Therefore, the investigation recommends proper social distancing and efficient management of corona virus in order to achieve higher decreasing trend of reaction rate constant and required recovery percentage for the stabilization of India.

1. Introduction

Currently spreading of novel coronavirus (SARS-CoV-2) has created a very distressing situation in the whole world. World Health Organization (WHO) has declared it as a global public health disaster due to its highly contagious behavior (Wang, Wang, et al., 2020). After reporting a case of unidentified pneumoniain Wuhan, Hubei Province, People's Republic of China (PRC) in late December 2019, the origin of the disease was identified.

The pneumonia was declared as novel coronavirus pneumonia (NCP) by the experts of the PRC Centers for Disease Control (CDC) (Huang et al., 2020). However, the virus was named as acute respiratory syndrome coronavirus 2 (SARS-CoV-2) by the International Committee on Taxonomy of Viruses (ICTV). With many potential natural hosts, intermediate hosts and final hosts, this disease is a class of β-coronavirus. Hence, prevention and treatment of the virus infection is a great challenge as because of these characteristics (Vellingiri et al., 2020).

This virus is considered as highly infectious and transmissible in spite of the large number of cases worldwide and low mortality rate as compared to SARS and the Middle East respiratory syndrome (MERS) (Liu et al., 2020; Statista, 2020). Maintaining the social distancing, frequent washing of hands, avoiding touch of the mouth, nose, and face are the main preventive measures for COVID-19 (WHO, 2020).

With origin from China (PIB, 2020), on 30th January the first case of COVID-19 was reported. In the maximum states of the country, this disease has been spreaded. As on 23rd May 2020, the total cases reported in India are 131422 with 54409 recoveries with 3867 deaths. In order to accommodate patients with possible symptoms of COVID-19, there is a lot of stress on the part of administration and health officials. Hence, for predicting the number of cases in the coming days, efficient predictive tool must be used. This will benevolently help the administration and health officials for making preparations.

Therefore, the objectives of the present study were enumeration of the effect of lock down stages on the COVID-19 spreading rate in India and mapping of its recovery percentage by applying feed forward neural network (FFNN) and mathematical modeling approaches.

3. Materials and methods

3.1. Data collection

For the present study, the data were collected from 1st Feb 2020 to 23rd May 2020 (Covid-19. in, 2020). Among the data, 75% was used for the training purpose and rest 30% were used for the validation and forecasting purpose. To enumerate the effect of lock down on the COVID-19 spreading rate, data of lockdown 1 (25th March to 14th April 2020), lockdown 2 (15th April-3rd May 2020) and lockdown 3 (4th May-17th may, 2020) were used.

3.2. FFNN modeling for the prediction of COVID-19 spreading rate

Feed forward neural network (FFNN) was used for the simulation of the lockdown effect on the COVID-19 spreading rate in India. FFNN was applied for the mapping of number of total cases (NTC), number of active cases (NAC), number of recovered cases (NRC), number of deceases persons (NDP) as a function of number of days. FFNN based relationship was used for the prediction and forecasting of COVID-19 spreading rate (Apostolopoulos & Mpesiana, 2020; Desai et al., 2008; Jiang & Schotten, 2020; Tomar & Gupta, 2020). Total data of 99 days starting from 1st Feb 2020 were used for the mapping of FFNN modeling. Forecasting of FFNN was performed for the 14 days data (from 101 to 115 days i.e. up to 23rd May 2020). The FFNN analysis was performed in the MATLAB environment (MATLAB R2015 a).

Both the input and output layers were consisted of one neuron for each FFNN. The output neuron was considered among NTC, NAC, NRC and NDP during each FFNN. Total four FFNN analyses were performed. Feed forward algorithm was used for development of the neural network (NN) architecture. A forward direction based data flow viz. from input to output layer was accentuated for the implementation of the FFNN architecture. As an adaptable parameter of the network, a real number quantity namely weights were associated with the connections of two neurons. The input data were introduced to the hidden layer with the help of weights and input layer neurons. Two types of tasks were performed by the neurons of the hidden layer. At first summation of the weighted inputs were done along with bias values by using the following equation

$$O_{il} = \sum_{i=1}^{n} X_i w_i + T_i \tag{1}$$

where, O_{il} stands for output of input to hidden layer, W_i (W_{ih} for connecting input and hidden layer, whereas W_{ho} for connecting hidden and output layer) denote the connection weights, T_i (T_h are the bias values for the hidden layer, whereas T_o are the bias values for output layer) refers to bias and x_i stands for input parameter for ith neuron.

After the summation, weighed output (O_{il}) is passed through an activation function. The output of the hidden layer is denoted by O_{hl}. The space in the non-linearity of the input data is shifted with the aid of the activation function. For the present study activation function namely logsig was used during execution of the FFNN. The mathematical expression for the estimation of the hidden layer (O_{hl}) output is given by the following equation:

$$O_{hl} = logsig\ (O_{il}) \tag{2}$$

Equation (3) was used for the estimation of final output of FFNN. The mathematical expression for the final output is given as follows:
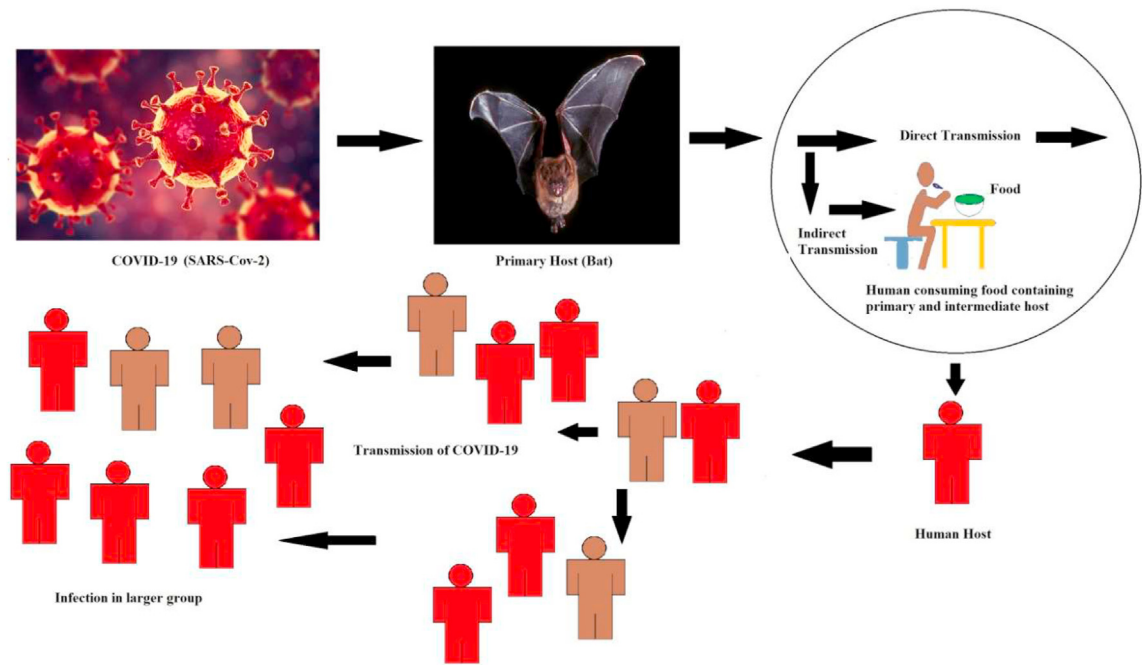
Fig. 1. Scenario for the transformation of COVID-19.
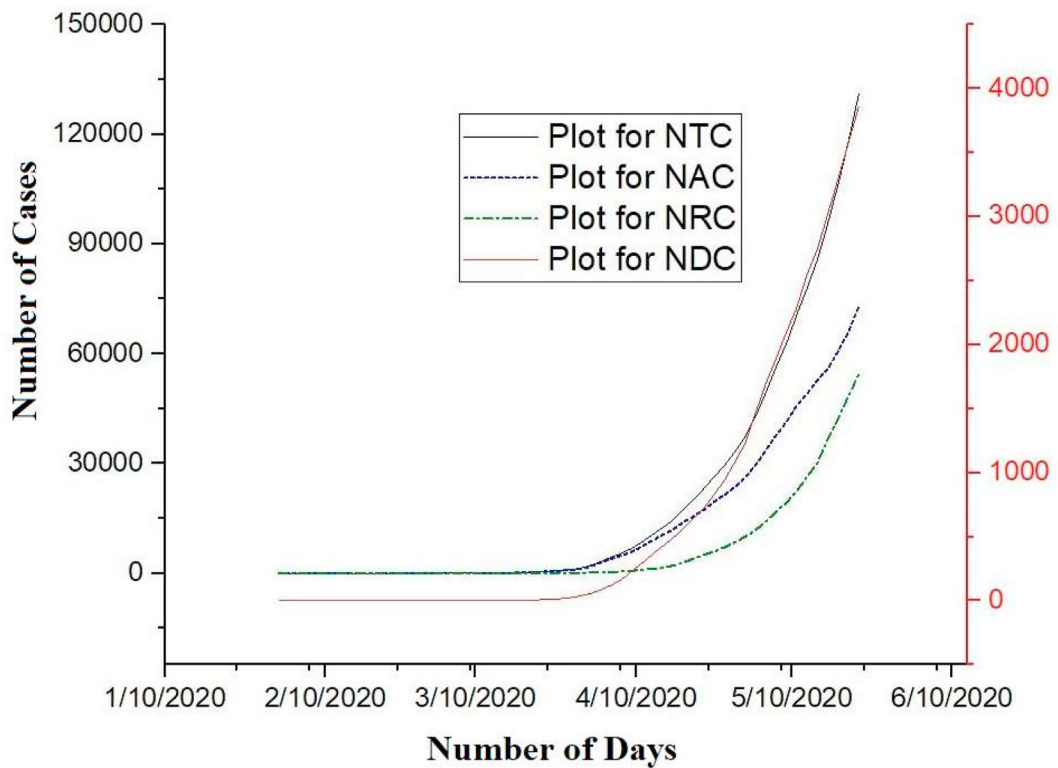
Fig. 2. COVID-19 spreading rate of India under the categories of NTC, NAC, NRC and NDC.

Table 1

Effect of lockdown on the COVID-19 spread rate in India.

Types of Lockdown	Parameters	NTC	NAC	NRC	NDC
Lockdown 1	$k(day^{-1})$	0.13	0.13	0.16	0.15
	R^2	0.98	0.98	0.98	0.97
Lockdown 2	$k(day^{-1})$	0.06	0.05	0.1	0.06
	R^2	0.99	0.99	0.97	0.99
Lockdown 3	$k(day^{-1})$	0.05	0.04	0.07	0.04
	R^2	0.99	0.98	0.98	0.99
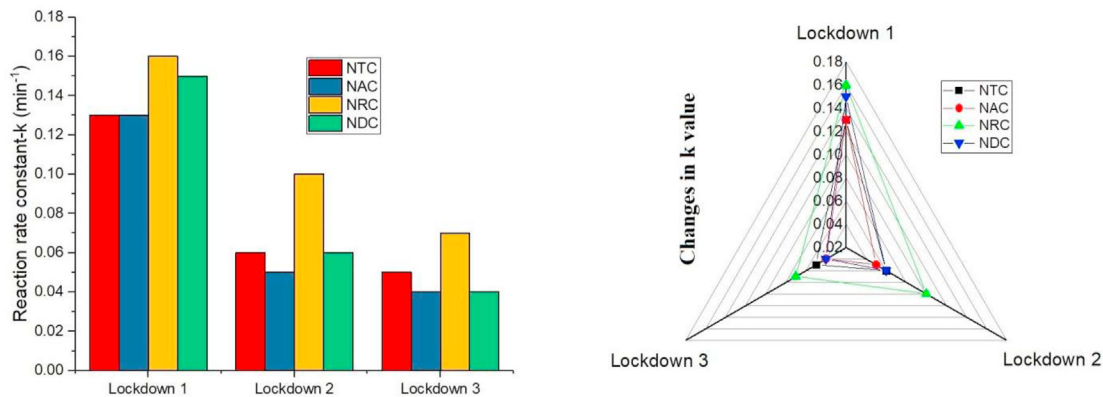
Fig. 3. Variation of reaction rate constant of COVID-19 spreading rate under different lockdown stages.
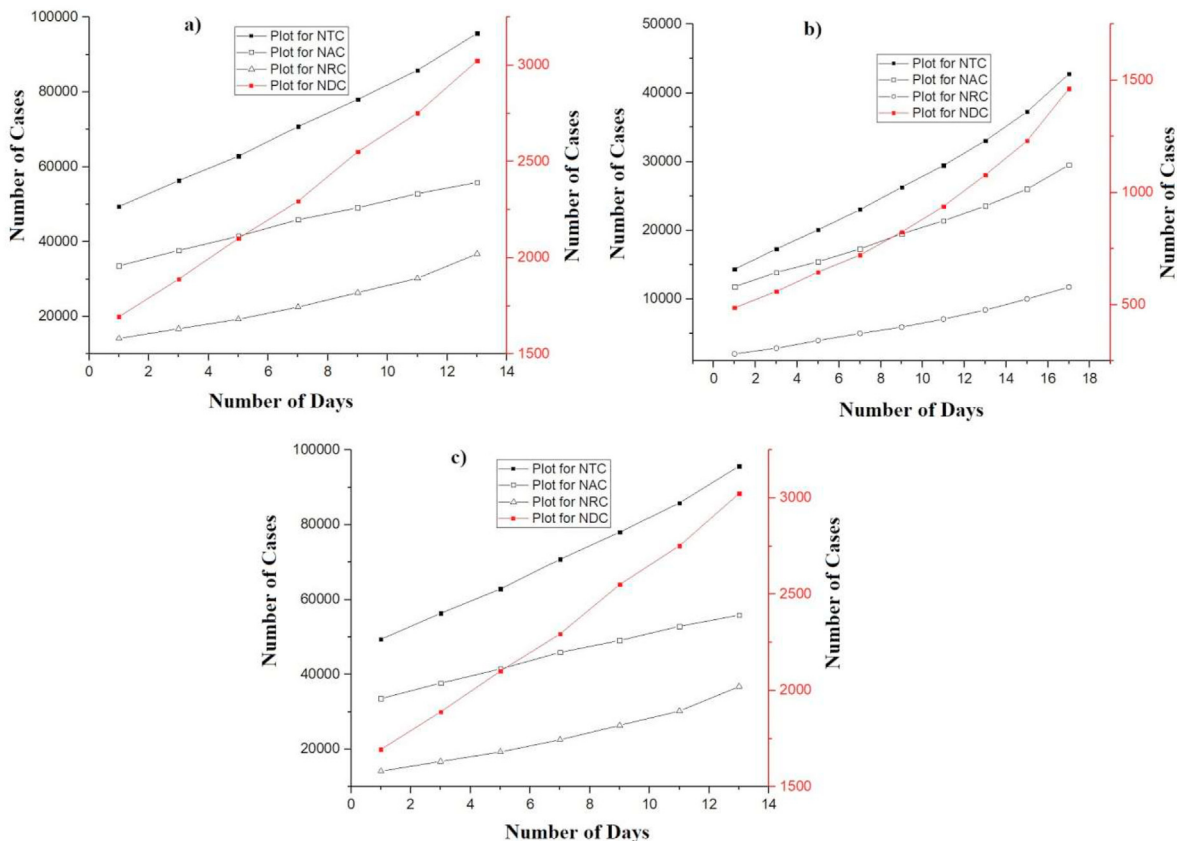
Fig. 4. Effects of (a) lockdown 1, (b) lockdown 2 and (c) lockdown 3 on various numbers of cases.

Fig. 5. Best FFNN architecture for prediction and forecasting of COVID-19 spreading rate.

$$\text{Final ouput} = W_{ho}\, O_{hl} + T_o \tag{3}$$

FFNN was executed in combination of training, testing and validation stages. In the present study, MATLAB R2015a software was used for the execution of FFNN modeling. In combination of one neuron for both th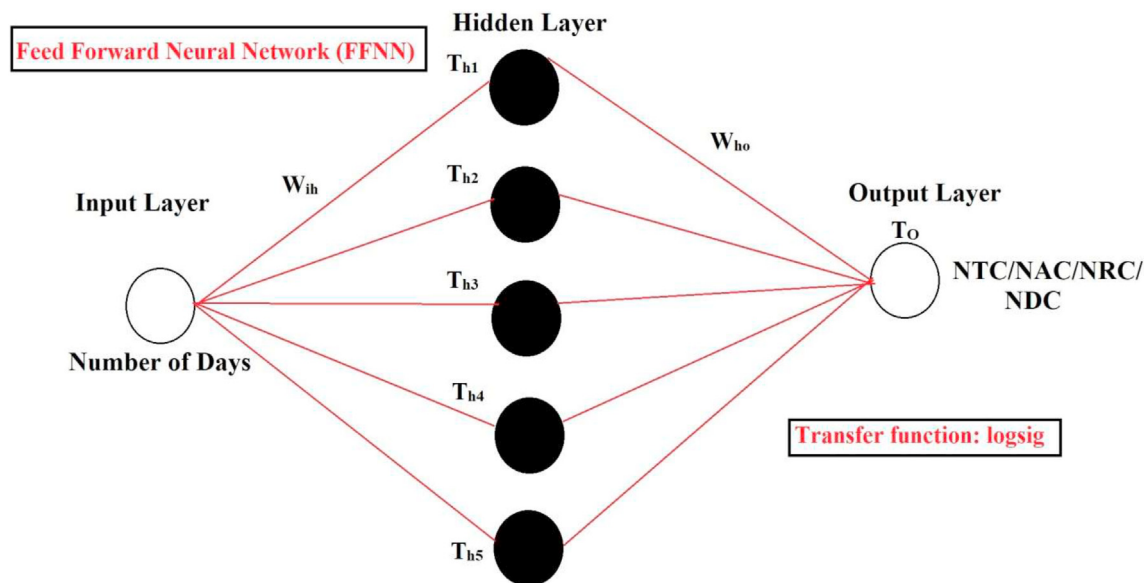e input and layers in each cases (NTC, NAC, NRC and NDC) FFNN was formulated. The neurons of the hidden layer were decided on the basis of coefficient of determination (R^2) and mean square error (MSE) values.

3.3. Mathematical modeling for estimation of the COVID-19 spreading rate

Mathematical modeling approach was applied for the mapping of COVID-19 spreading rate. Number of cases in terms of NTC, NAC, NRC and NDC and spreading rate for each case (No. of cases/day) was modeled as a function of number of days. The mathematical expression used for the modeling of number of cases (NTC, NAC, NRC and NDC) is given as follows:

$$NC = \exp(m \times NC^n) \tag{4}$$

Here, NC stands for number of cases (NTC, NAC, NRC and NDC), m and n are model constants and ND stands for number of days.

To enumerate the effect of lockdown on the number of cases, first order reaction kinetics equation was used. The mathematical expression for the first order reaction kinetics equation is given as follows:

$$NC = NC_0 \exp(k \times ND) \tag{5}$$

Here, NC_0 refers to number of cases at initial point of each lockdown and k is reaction rate constant.

The value of reaction rate constant was observed for all the cases. Adequacy of the model fitting was checked by considering coefficient of determination (R^2) values. Model fitting was done by using MATLAB R2015 a.

3.4. Estimation of recovery percentage (RP)

Recovery percentage (RP) for the COVID-19 affected social environment was calculated by multiplying the ratio of NRC and NTC with 100. The mathematical expression for the estimation of RP is given as follows:

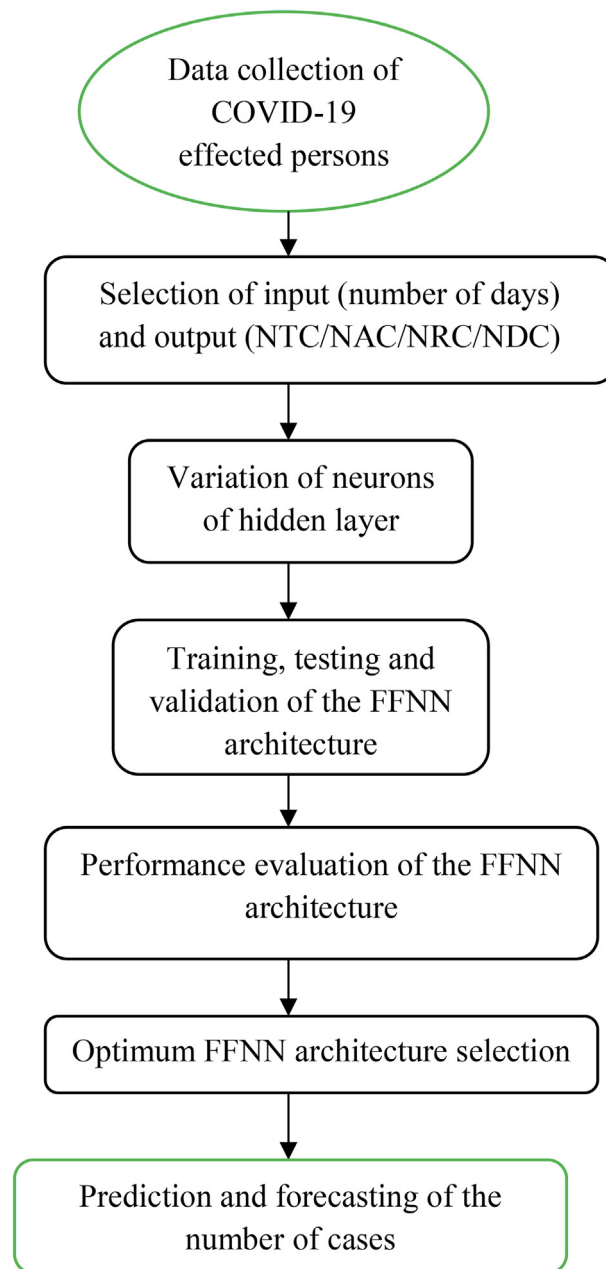$$RP\ (\%) = \frac{NRC}{NTC} \times 100 \tag{6}$$

Data collection of
COVID-19
effected persons

↓

Selection of input (number of days)
and output (NTC/NAC/NRC/NDC)

↓

Variation of neurons
of hidden layer

↓

Training, testing and
validation of the FFNN
architecture

↓

Performance evaluation of the FFNN
architecture

↓

Optimum FFNN architecture selection

↓

Prediction and forecasting of the
number of cases

Fig. 6. FFNN methodology for the prediction and forecasting of COVID-19 spreading rate.

4. Results and discussions

4.1. Effect of lockdown on the COVID-19 spreading rate in India

For controlling the pandemic situation of COVID-19 in the social environment, Indian government followed consecutive lockdown stages namely lockdown 1 (25th March to 14th April 2020), lockdown 2 (15th April-3rd May 2020), lockdown 3 (4th May-17th may, 2020) and lockdown 4 (18th May-31st May 2020). In this study, the effects of lockdown 1, 2 and 3 were studied. Fig. 1 illustrates the scenario for the transformation of COVID-19 in the social environment.

First order kinetic model as shown in equation (5) was used for comparing the effect of various lockdown stages. The reaction rate constant values (k value) obtained for three lockdown stages were compared. The behaviors of NTC, NAC, NRC and NDC for 115 days (from 1st Feb-23rd May 2020) are demonstrated in Fig. 2. From the figure, increasing trends for all the

Table 2
wt and bias values of the best ANN architectures for different cases.

Types of Cases	Weight and bias values							
	W_{ih}	W_{ho}					T_h	T_o
NTC	22.702	0.601	−10.492	−2.356	2.664	3.432	−31.348	5.780
	−25.305						27.401	
	−5.263						4.369	
	6.902						−0.276	
	15.385						11.964	
NAC	26.458	4.444	−2.990	1.425	0.685	0.551	−27.728	−1.764
	−6.417						0.288	
	8.345						−6.353	
	14.312						7.013	
	17.125						15.876	
NRC	14.960	9.332	−0.275	22.200	0.849	−15.669	−16.845	−14.165
	−40.315						15.066	
	0.541						−0.065	
	39.436						2.227	
	−110.159						−88.554	
NDC	15.899	8.356	−1.178	−2.448	−1.199	−0.489	−17.277	0.818
	−10.241						6.613	
	−9.399						0.931	
	−14.103						−6.667	
	14.103						13.914	
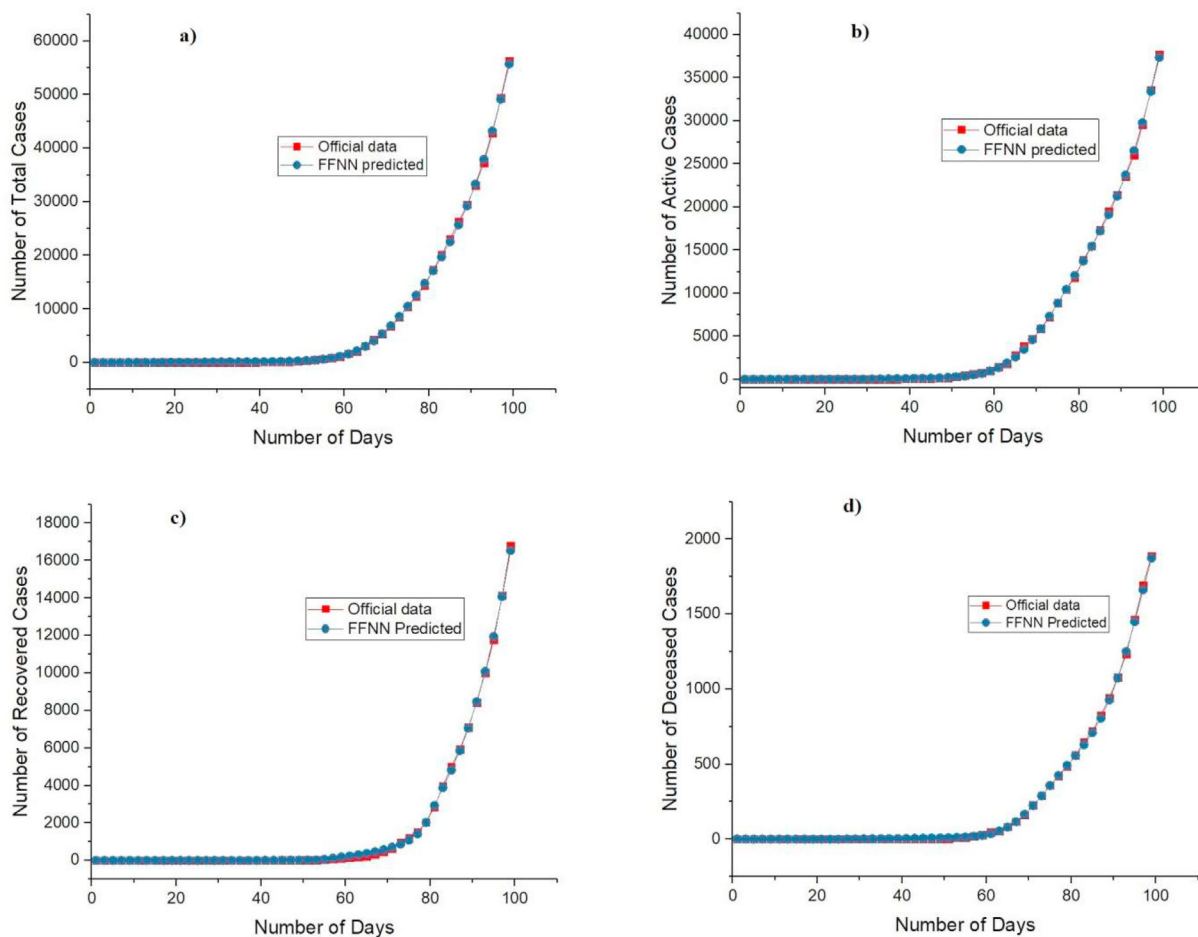
Fig. 7. Plots between experimental and FFNN predicted values for (a) NTC, (b) NAC, (c) NRC and d) NDC.
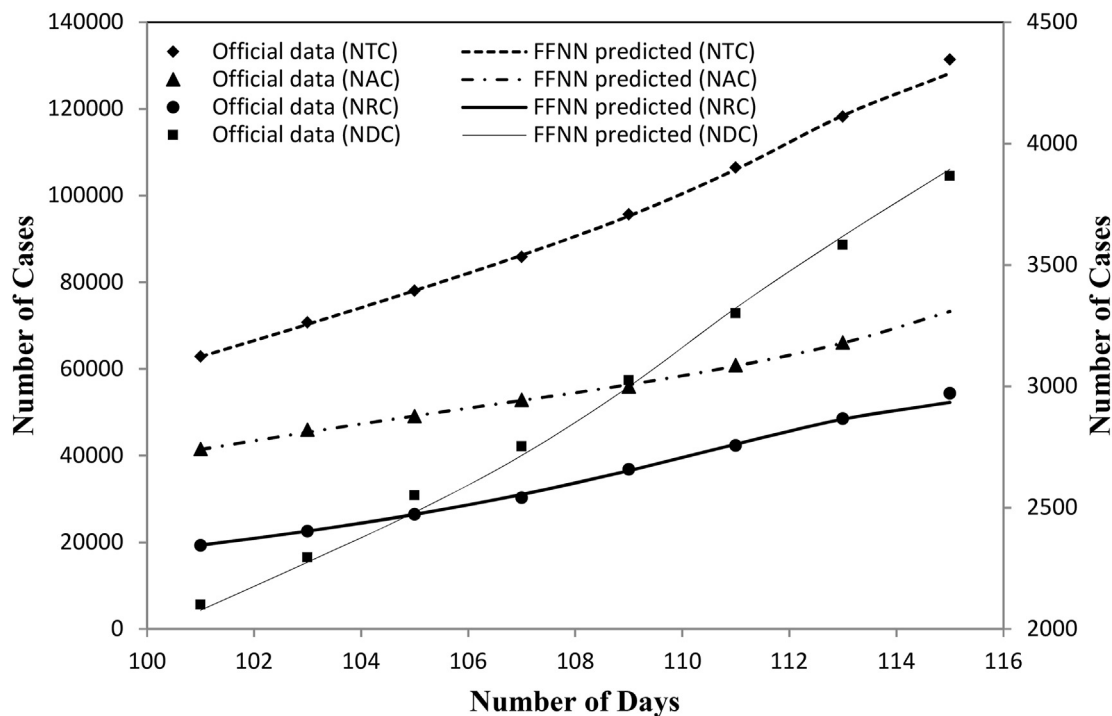
Fig. 8. Forecasting of different number of cases for 14 days based on best FFNN architecture.

Table 3
Validation of the FFNN forecasted data.

| Days	Date	Percent of error (%)			
		NTC	NAC	NRC	NDC
101	**9-May**	0.05	0.09	0.17	1.13
103	**11-May**	0.65	1.12	0.20	0.81
105	**13-May**	0.04	0.17	0.08	2.75
107	**15-May**	0.46	0.23	2.64	1.34
109	**17-May**	0.44	0.90	0.73	0.85
111	**19-May**	0.41	0.30	0.80	0.66
113	**21-May**	0.21	0.14	0.33	0.99
115	**23-May**	2.44	0.14	3.89	0.72

Table 4
Results of the exponential model fitted with the COVID-19 spreading rate in India.

Types	Model parameters		Statistical parameter
	m (day^{-1})	n	R^2
NTC	0.60	0.63	0.99
NAC	0.73	0.58	0.98
NRC	0.08	1.04	0.99
NDC	0.07	1	0.99

cases can be observed. The plot for the NDC shows lowest increasing rate as compared to other cases. The k values obtained for various lockdown stages namely lockdown 1, 2 and 3 are represented in Table 1. Adequate fitting of the first order kinetic model on the basis of coefficient of determination (R^2) value was observed for each lockdown stage.

From the results, it can be also revealed that the k values decrease with the increase of lockdown stages i.e. extension of lockdown stages in the form of lockdown 1, 2 and 3. The decreasing trend of k values with the extension of lockdown stages are also demonstrated in Fig. 3. It means, lockdown implemented by the Indian government was successful for reducing the COVID-19 spreading rate. Further, higher decreasing rate in the k values from lockdown 1 to 2 and lower decreasing rate from lockdown 2 to 3 can also be noticed. Therefore, it can be revealed that lockdown 1 had huge impact in controlling the COVID-
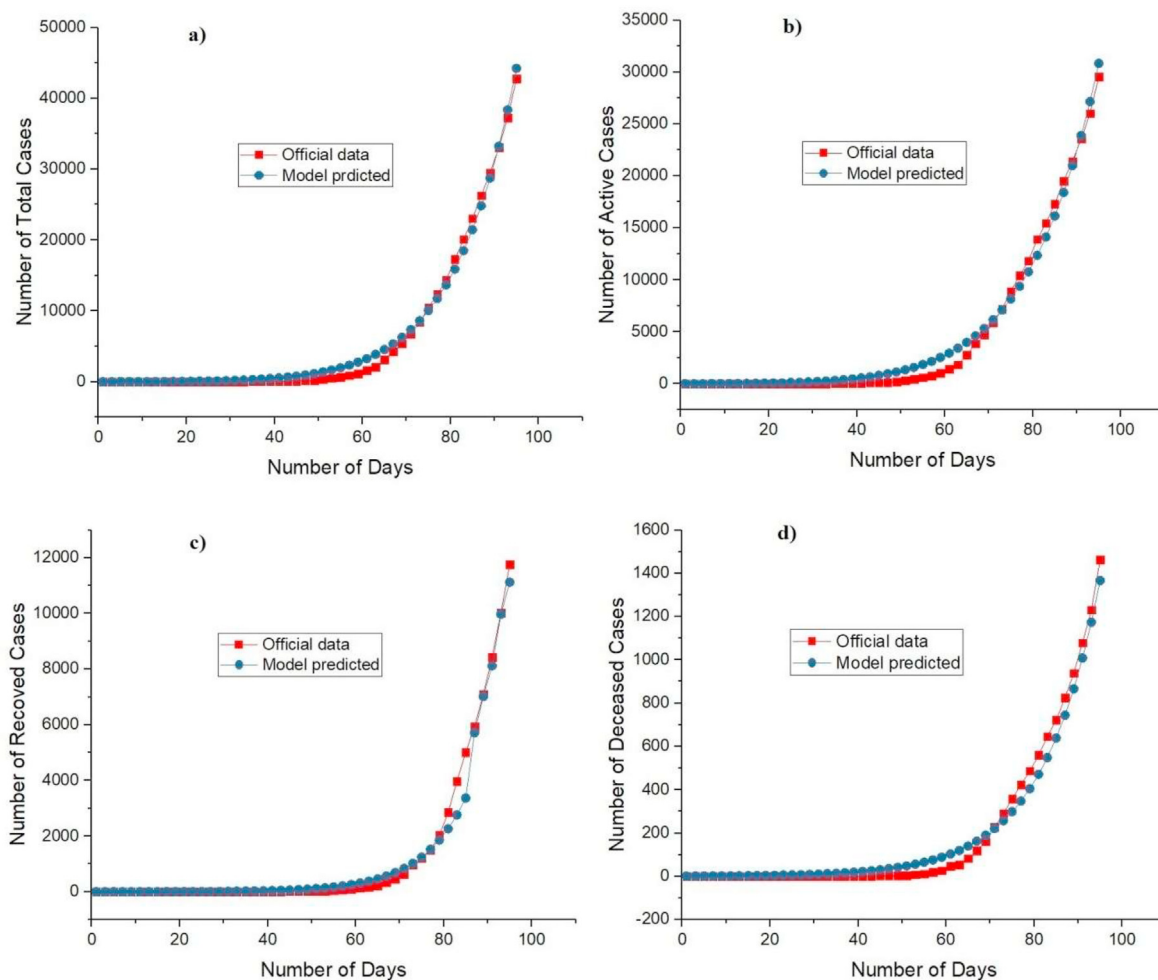
Fig. 9. Plot between experimental and exponential model predicted values for (a) NTC, (b) NAC, (c) NRC and (d) NDC.

19 spreading rate as compared to lockdown 2 and 3. Lockdown 2 and 3 showed almost similar effects on the spreading rate. Higher decrease in the k values was not observed between these two stages. Hence, continuation of the exponential increase in the number of COVID-19 cases has been faced by the social environment of India. The effect of lockdown stages on the increasing trend of number of cases can also be observed from Fig. 4.

4.2. Prediction and forecasting of number of COVID-19 cases by applying FFNN

In this study, FFNN was applied for the mapping of number of total cases (NTC), number of active cases (NAC), number of recovered cases (NRC) and number of deceased cases (NDC) in India against number of days. Hence, FFNN structure was formulated with one neuron in both the input and output layers for all the cases. Total COVID-19 affected data of 95 days, as mentioned in the methodology section was used for the formation and selection of best FFNN architecture. In the FFNN methodology, logsig transfer function was implemented for prediction of final output. Total 2000 iterations were computed for each run with a learning rate of 0.5–1. The FFNN architecture, 1-5-1 i.e. one neuron in the input layer, five neurons in the hidden layer and one neuron in the output layer was selected as the best architecture for the prediction of all the number of cases against number of days. The coefficients of determination (R^2) values for 1-5-1 architecture of all the cases were greater than 0.99. Fig. 5 demonstrates the best FFNN architecture.

By implementing the methodology shown in Fig. 6, FFNN based predictions and forecasting were preformed. Weight and bias values obtained for the best architectures of NTC, NAC, NRC and NDC were implemented in the methodology. Table 2 represents the weight and bias values of the best FFNN architecture for different cases. The plots between the experimental and FFNN predicted trend curves for different cases are illustrated in Fig. 7. From the plots adequate predicting behavior can be observed. By using the methodology, forecasting was done for next 14 days (101 days–115 days). Forecasting plots for different cases are shown in Fig. 8. The plots show adequate predictive behavior along with the experimental data.

Table 3 represents the validation of the forecasted data. From the table, it can be observed that the percent of error for NTC, NAC, NRC and NDC varies from 0.04 to 2.44%, 0.09—1.12%, 0.08—3.89% and 0.81—2.75% respectively. Similar types of findings were reported by Tomar and Gupta (2020).

4.3. Mathematical modeling approach for the simulation of COVID-19 spreading rate

The exponential model as shown in equation (4) was applied for the simulation of COVID-19 spreading rate based on mathematical modeling approach. The results of the exponential model fitted for various cases are shown in Table 4. Adequate model fitting is observed for all the cases. The model constant m varies from 0.07 to 0.60 day^{-1}, whereas n varies from 0.63 to 1. The plots between the experimental and predicted number of cases are demonstrated in Fig. 9.

4.4. Simulation of recovery percentage by using polynomial fitting

In the pandemic situation of COVID-19, the biggest challenge is to increase the recovery percentage so that the social environment can be stabilized at a faster rate. In this section of the present study, a relationship was developed between the recovery percentage and number of days. A polynomial equation was fitted with the recovery percentage (RP) data by considering RP on the y-axis and number of days on the x-axis. Fig. 10 demonstrates the COVID-19 recovery percentage data fitted with the polynomial equation. From the figure, an increasing trend of the recovery percentage can be observed. Till 23rd May 2020 the COVID-19 recovery percentage for India has increased up to 41.4%. The recovery percentage was modeled as an element of number of days (ND) with the assistance of polynomial fitting. The coefficient of determination (R^2) value of the fitted equation was 0.98. The mathematical equation for the estimation of RP is given as follows:

$$RP = 0.005ND^2 + 0.266ND + 4.731 \qquad (7)$$

Here, RP stands for recovery percentage (%) and ND stands for number of days.
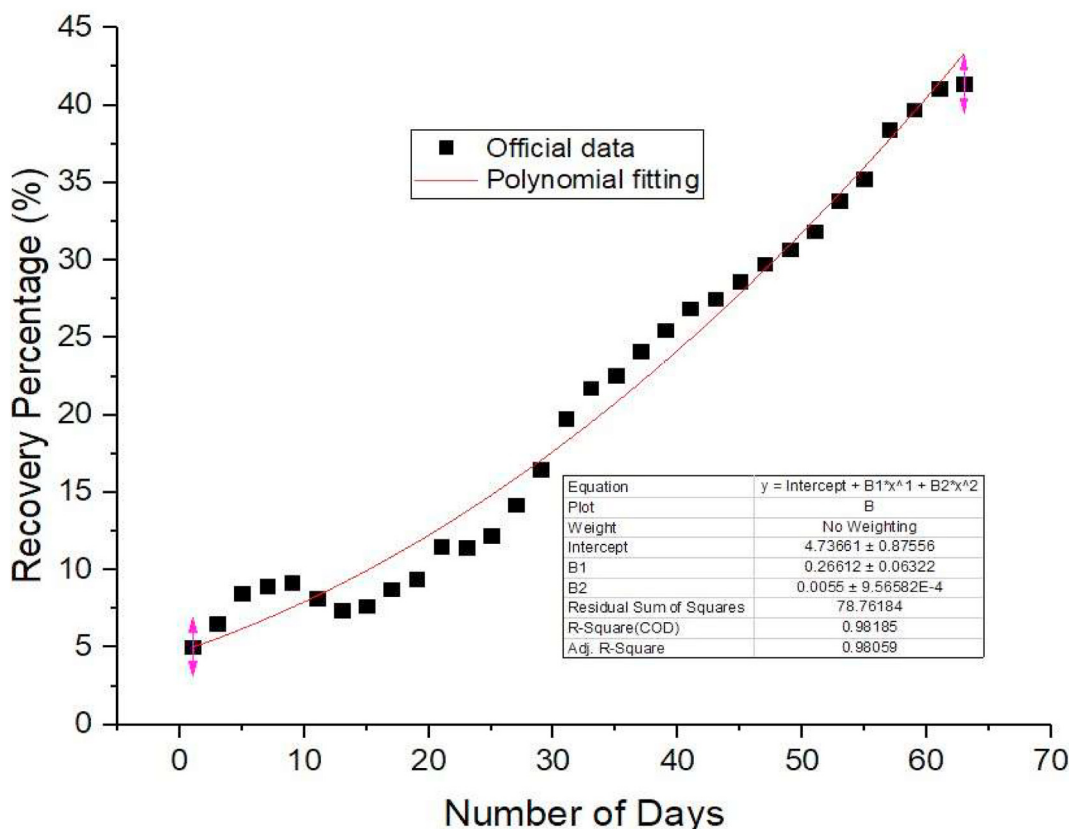

Fig. 10. Polynomial fitting of recovery percentage for the COVID-19 affected social environment.

4.5. Comparison of death rate (DR) of India with the world

Death rate (DR) in the entire world due to COVID-19 is one of the most important concerns in order to control and make strategies against spreading rate. Due to the effect of COVID-19, DR of 4.4 deaths per lakh population is observed in the world as compared to 0.3 deaths per lakh population in India (till 26th May 2020). Based on the available data it can be also revealed that until May 2020, India is at the lowest position among all the countries in terms of DR. Due to lockdown, timely identification and management of COVID-19 cases, this has been possible. Hence, for attaining proper recovery percentage along with death rate, further maintenance of social distancing along with safety measures is suggested.

5. Conclusion

In the present study, simulation of the lockdown effect on the COVID-19 spreading rate in India and its application for the forecasting of recovery percentage were studied. Study of the lockdown effect based on first order reaction kinetics showed higher impact of lockdown 1 on controlling of the COVID-19 spreading rate as compared to lockdown 2 and 3. Although decreasing trend was followed for the reaction rate of different lockdown stages, the differences between the lockdown 2 and 3 were very marginal. Mathematical and feed forward neural network (FFNN) approaches were applied for the prediction of COVID-19 spreading rate. In case of mathematical approach, exponential model showed adequate performance for the prediction of the spreading rate behavior. For the FFNN based modeling, 1-5-1 was selected as the best architecture in order to predict adequate spreading rate for all the cases. The architecture also showed effective performance for the forecasting of number of cases for next 14 days. The recovery percentage was modeled as a function of number of days with the help of polynomial fitting. Therefore, the study suggests proper social distancing and efficient management of corona virus in order to attain higher decreasing trend of k value and required recovery percentage for the stabilization of India.

Credit author contribution statement

Sourav Chakraborty: Conceptualization, neural network modeling aspects, writing. **Arun Kumar Choudhury:** Data listing, justification and mathematical modeling, **Mausumi Sarma**: Figure making and table editing, **Manuj Kumar Hazarika:** Writing and Review of the paper.

Declaration of the competing interest

No known competing financial interests or personal relationships are declared by the authors.

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