DESIGN OF NEURAL PREDICTORS FOR PREDICTING AND ANALYSING COVID-19 CASES IN DIFFERENT REGIONS

S. Yildirim[*], *A. Durmusoglu*[†], *C. Sevim*[‡], *M.S. Bingol*[*], *M. Kalkat*[‡]

Abstract: Nowadays, some unexpected viruses are affecting people with many troubles. COVID-19 virus is spread in the world very rapidly. However, it seems that predicting cases and death fatalities is not easy. Artificial neural networks are employed in many areas for predicting the system's parameters in simulation or real-time approaches. This paper presents the design of neural predictors for analysing the cases of COVID-19 in three countries. Three countries were selected because of their different regions. Especially, these major countries' cases were selected for predicting future effects. Furthermore, three types of neural network predictors were employed to analyse COVID-19 cases. NAR-NN is one of the proposed neural networks that have three layers with one input layer neurons, hidden layer neurons and an output layer with fifteen neurons. Each neuron consisted of the activation functions of the tan-sigmoid. The other proposed neural network, ANFIS, consists of five layers with two inputs and one output and ARIMA uses four iterative steps to predict. The proposed neural network types have been selected from many other types of neural network types. These neural network structures are feed-forward types rather than recurrent neural networks. Learning time is better and faster than other types of networks. Finally, three types of neural predictors were used to predict the cases. The R^2 and MSE results improved that three types of neural networks have good performance to predict and analyse three region cases of countries.

Key words: *COVID-19, NAR-NN, ANFIS, ARIMA, prediction, modelling of the pandemic*

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1. Introduction

Viruses that are part of nature have threatened human health throughout history. Patients can be infectious for as long as symptoms last or without symptoms. Some

[*]Sahin Yildirim – Corresponding author; Mehmet Safa Bingol; Erciyes University, Faculty of Engineering, Turkey, E-mail: sahiny@erciyes.edu.tr, msbingol@erciyes.edu.tr

[†]Asli Durmusoglu; Hakkari University, Faculty of Engineering, Turkey, E-mail: aslidurmusoglu@hakkari.edu.tr

[‡]Caglar Sevim; Menderes Kalkat; Nigde Ömer Halisdemir University, Faculty of Engineering, Turkey, E-mail: caglar.sevim@ohu.edu.tr, mkalkat@ohu.edu.tr

people may act as super spreaders. Super spreaders are infected people who infect susceptible individuals with an infectious disease agent much more than expected. They are usually asymptomatic. So they can spread the disease quickly. Viruses adversely affect not only human health but also the health of plants and animals. The virus means poison in Latin. Viruses are microscopic structures with only one of the DNA or RNA packaged in a sheath of protein structure. The lack of reproductive mechanisms and genetic information from viruses does not allow them to reproduce alone in the inanimate environment. Therefore, viruses need a living cell which is called the host to reproduce. Viruses disrupt the internal structure of the host cell. It infects and produces their copies. This condition is called infection [1]. Coronaviruses, a large family of viruses, cause respiratory infections in humans and animals [2]. Before the emergence of the severe acute respiratory syndrome (SARS) in 2002 in China's Guangdong Province, coronaviruses were not considered a threat to humans [3]. Another member of the coronavirus family appeared as the Middle East respiratory syndrome (MERS-CoV) in Arabia in 2012 [4].

The disease has a highly variable nature and is spreading rapidly. The number of confirmed cases worldwide varies depending on the differences in the detection capacities of the countries. For health services to continue effectively, the rate of disease spread must be controlled. Therefore, modelling the daily number of cases and deaths and predicting possible future cases is of vital importance in terms of managing and directing the health system. Using artificial intelligence and statistical modelling tools, short- and the long-term case can be estimated to make the necessary resource planning for dealing with the epidemic. Thus, by estimating the expected disease burden, medical resources can be managed effectively. It can also direct measures to be taken to alleviate the epidemic.

Ceylan [5] used auto-regressive integrated moving average (ARIMA) models to predict the epidemic for Italy, Spain and France. Various models of ARIMA were formulated with different parameters, and it is seen that ARIMA models can be used to predict the prevalence of COVID-19. Furthermore, artificial intelligence modelling techniques have been used frequently to predict the spread and mortality rates of the epidemic. Pathak et al. [6] used deep transfer learning (DTL) to build a classification model for a patient infected by COVID-19. Hasan [7] improved a hybrid model which includes ensemble empirical mode decomposition (EEMD) and artificial neural network (ANN) to predict COVID-19 epidemic. Mandal et al. [8] to reduce the spread of disease, a mathematical model was improved, which included quarantine class and government intervention. They also study the dynamical behaviour of the model of reproduction number. Tomar et al. [9] used long short-term memory (LSTM) and curve fitting to predict COVID-19 cases in India and they investigated the effect of social isolation and secluded. Wu et al. [10] predicted the rage of COVID-19 for the national and global size to assess the effect of the metropolitan-wide quarantine of Wuhan and its neighbours. Al-qaness et al. [11] enhanced the adaptive neuro-fuzzy inference system (ANFIS) by utilizing an enhanced flower pollination algorithm (FPA) by using the salp swarm algorithm (SSA) to predict the number of confirmed COVID-19 cases in China.

In this study, unlike other studies, the number of COVID-19 cases and death numbers were modeled with ARIMA, NAR-NN and ANFIS approaches and the model performances of the classical time series method and neural predictors were compared. COVID-19 cases and deaths numbers were collected from the web. These data include the number of daily cases, daily deaths, total cases and deaths from COVID-19. The dataset, which is obtained from World Health Organization's website, was analysed during this work period between 10 March 2020 and 22 December 2020. [12] The proposed model can forecast the number of new COVID-19 cases and deaths. For the next 30 days, forecasts were made with specific accuracy rates. The conclusion of this study may be used to improve the precaution for the pandemic.

2. Materials and methods

2.1 COVID-19 pandemic dataset

At all the world under COVID-19 pandemic, the first case in Turkey was seen on March 10, 2020. The first death due to the COVID-19 pandemic in Turkey took place on March 15, 2020 [13]. This study used a dataset of the 287 days Ministry of Health data between the dates 10.03.2020-22.12.2020 in Turkey [13]. Following the positive test of two Chinese tourists in Rome on January 31, 2020, the first two coronavirus cases were reported in Italy. The first death from COVID-19 pandemic in Italy occurred on February 21, 2020. In this study, 287 days of data of WHO between 10.03.2020-22.12.2020 was used while creating the dataset in Italy [12]. The first case of COVID-19 in India was reported on January 30, 2020. In this study, 287 days of data of WHO between 10.03.2020-22.12.2020 was used while creating the dataset in India [12]. Fig. 1 shows the graph of the daily number of cases in Turkey, Italy, and India. On the other hand, Fig. 2 shows the graph of the daily number of death in Turkey, Italy, and India. As can be depicted from the Fig. 1, the cases of death in Turkey are stable and the others are not stable.

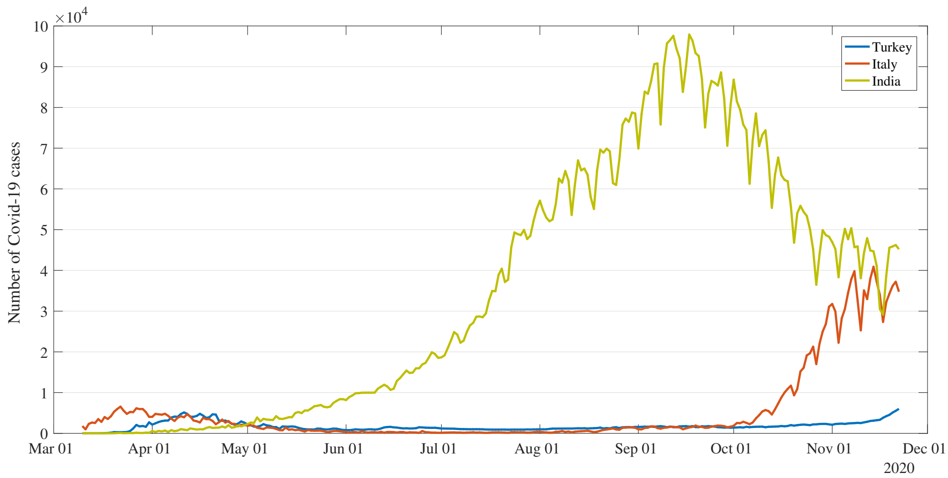

Fig. 1 *Daily number of cases in three countries.*

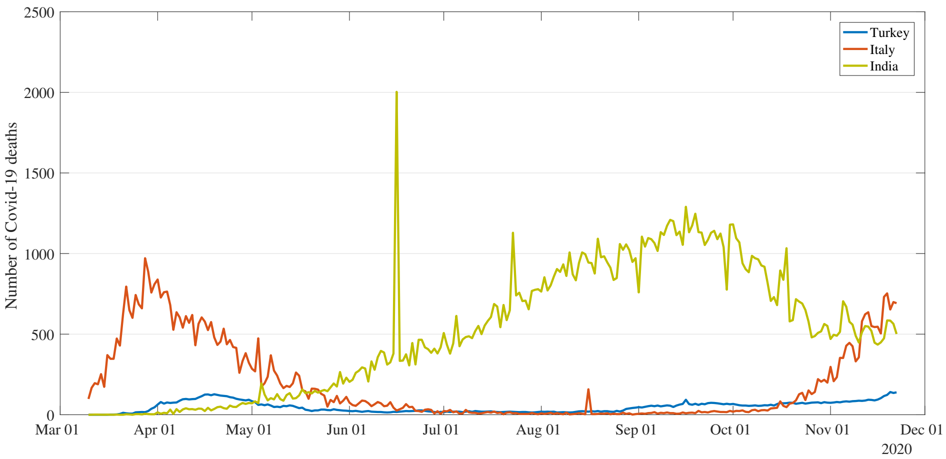

Fig. 2 *Daily number of deaths in three countries.*

As outlined in Fig. 1 and Fig. 2, the cases of viruses are indicated that Turkey and Italy have stable cases because of the correct information of cases. However, the cases in India are not estimated with correct information by conventional methods. As shown in Fig. 1, the cases on May 1 in India are unpredictable because of the sudden increase of cases. On the other hand, as can be seen in Fig. 2, there are very peak death cases in the mid of June for India, approximately 2000 death reports. The case is depicted that some cases have some unexpected situations for viruses. Nevertheless, these graphs show that these kinds of viruses (such as COVID-19) can not be controlled with standard approaches. It needs to be modeled by intelligent solving and modelling methods.

Fig. 3 and Fig. 4 show the total number of cases and deaths for three countries. As expected, a continuous increase is in total numbers. However, neural predictors can be used to predict these cases.

In this study, inputs for neural network models are daily number of positive cases, daily number of deaths, total number of positive cases, total number of deaths, respectively. Days are also inputs with cases for every neural network models. Outputs of the models are the estimates of the cases mentioned above for next 30 days.

2.2 Non-linear autoregressive neural networks

An artificial neural network (ANN) can model non-linear systems. In this way, it is a system that can be successfully used to estimate non-linear time series. NAR-NN is a particular ANN type used for the prediction of time series. NAR-NN also uses previous data when training with training data [14]. COVID-19 cases have a non-linear structure and dynamic time series. Therefore, the NAR-NN model is considered to predict the number of COVID-19 cases.

NAR-NN model computes the output $y(t)$ using n past values of $y(t)$ as feedback delays, as shown in Eq. 1. f is a non-linear function, and $e(t)$ is the model

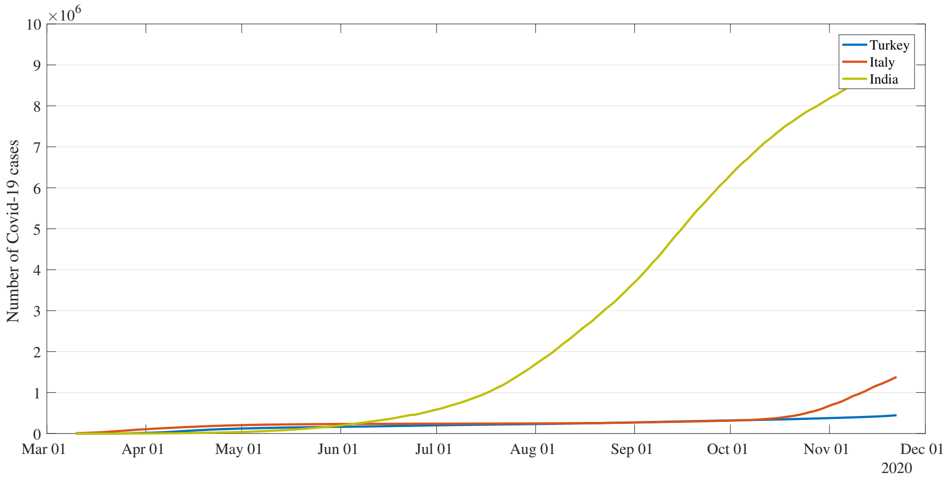

Fig. 3 *Total number of cases in three countries.*

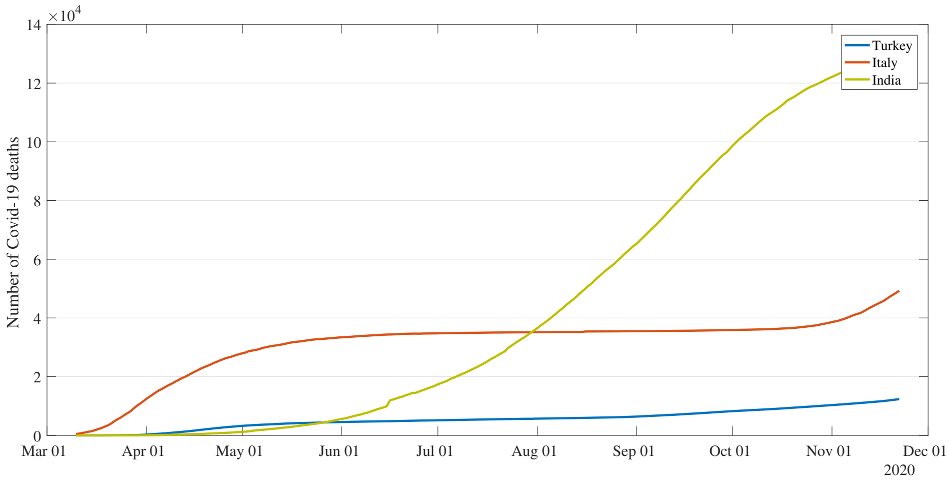

Fig. 4 *Total number of deaths in three countries.*

approximation error at the time t [15].

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-n)) + e(t). \tag{1}$$

Neurons in the NAR-NN model make computations with the help of Eq. 2. Where h activation function, w weight, n past value and b bias are given.

$$out_i = h_i \left(\sum_j w_{i,j} \cdot n_{i,j} + b_i \right), \tag{2}$$

where i is neuron number and j represents each input connection.

The tan-sigmoid activation function, which can take values between −1 and 1, was used as the h activation function. The bias and n values are chosen 0 and 15, respectively. These parameters have been obtained by trial and error. w (weights) are started randomly and updated according to the Levenberg-Marquardt backpropagation training algorithm in each iteration. By considering the t value of the time series and n previous values, the function relation is tried to be found according to Eq. 1. The structure of NAR-NN is given in Fig. 5.

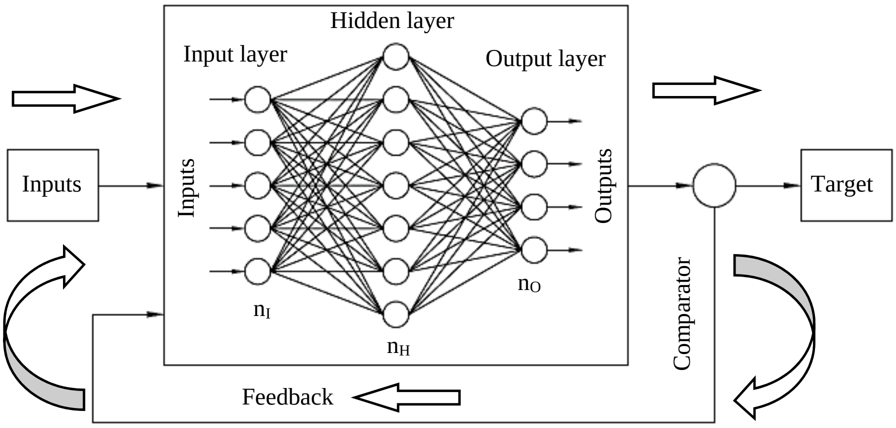

Fig. 5 *The structure of NAR-NN [22].*

2.3 MA (q) models

In the MA (q) model, the Y_t value is the linear function of the series' backward q period past error terms and their mean. MA (q) models are generally shown as follows.

$$Y_t = \mu + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q}. \tag{3}$$

Here a_t, a_{t-1}, $a_{t-2}, \ldots, a_{t-q}$ error terms, $\theta_1, \theta_2, \ldots, \theta_q$ error term related coefficients, μ indicates the average of a constant process.

2.3.1 ARMA (p, q) models

ARMA models, a combination of AR and MA models, are a linear function of past observations and past error terms. ARMA (p, q) models can be generally shown as follows.

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + \delta + a_t + \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q}. \tag{4}$$

In the equation, $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p}$ represent past observation values, $\Phi_1, \Phi_2, \ldots, \Phi_p$ represent coefficients for past observation values, δ is a constant value,

$a_t, a_{t-1}, a_{t-2}, \ldots, a_{t-q}$ represent error terms, $\theta_1, \theta_2, \ldots, \theta_q$ represent coefficients for error terms [5].

2.3.2 ARIMA (p, d, q) models

In cases where the time series is stationary, that is, as the average, variance and covariance of the process do not change depending on time. ARMA (p, q) or one of the models AR (p) or MA (q), which is the particular version of ARMA (p, q), can be used. However, there is a change in the mean and variance of time series depending on time. This state is called a non-stationary state. When such time series are converted to stationary, the ARMA (p, q) models mentioned above can be used for estimation. Stationarizing of the time series is done by making a difference. The first difference series becomes stationary if the time series has a linear trend. If the time series has a curvilinear trend, the difference is retaken and the second difference series becomes stationary. In this case, the model is expressed as ARIMA (p, d, q). Here, d is the stabilization (difference) parameter of the series.

2.4 Adaptive-network based fuzzy inference systems

Adaptive-network based fuzzy inference systems (ANFIS) is a hybrid artificial intelligence method that uses the inference feature of fuzzy logic with the ability to calculate parallel and learn artificial neural networks. Adaptive (compatible) networks consist of directly connected nodes. Links between nodes show a relation (weight) in which the value is not entirely clear. Fig. 6 shows the typical ANFIS architecture. There are five layers in a Sugeno-type ANFIS structure with two inputs and one output and two rules.

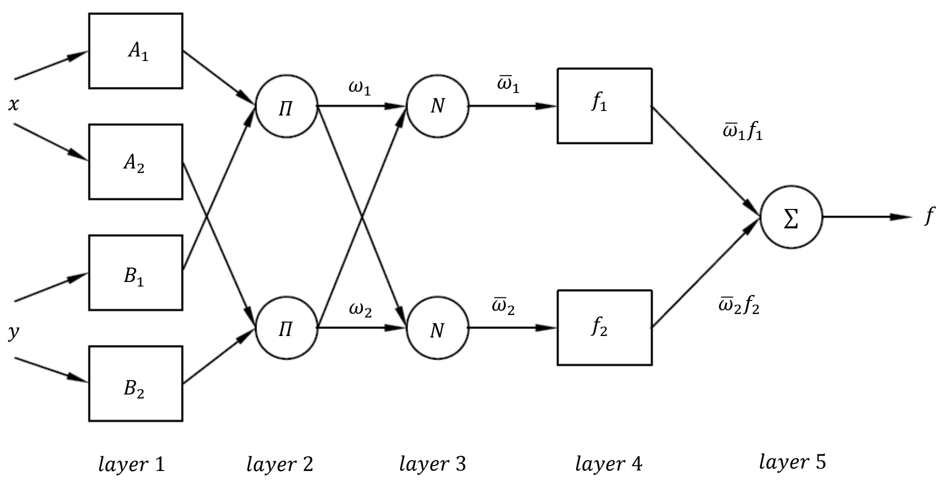

Fig. 6 *ANFIS Structure [16].*

Rule 1: if x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$
Rule 2: if x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$

Here x and y are inputs and f is output. A and B are fuzzy membership sets, p and q are the number of membership equations, r is the design parameter that is defined during the train process.

In Fig. 6, there are five layers in a Sugeno-type ANFIS structure with two inputs, one output, and two rules. The node functions in the same layer are identical and are defined as follows.

Layer 1: This is the input layer that defines actual data and desired data. Each i node in this layer is a square node. In ANFIS structure, round nodes are static and square nodes are adaptable. So model parameters at square nodes change during training. The output of the node is the membership function given in Eq. 5.

$$O_i^1 = \mu_{A_i}(x) \quad i = 1, 2, \tag{5}$$

where x is the input variable of the node; A_i shows the fuzzy cluster represented by this node. Fuzzy logic is based on fuzzy clusters. It is defined by fuzzy cluster membership. In the classical cluster, an element is a member of the cluster or not. In fuzzy logic, the degree of belonging ranges from 0 to 1. $\mu_{A_i}(x)$ is usually selected as a Gaussian curve type with a maximum of 1 and a minimum of 0. Fig. 7 shows the shape and parameter definitions of the membership function.

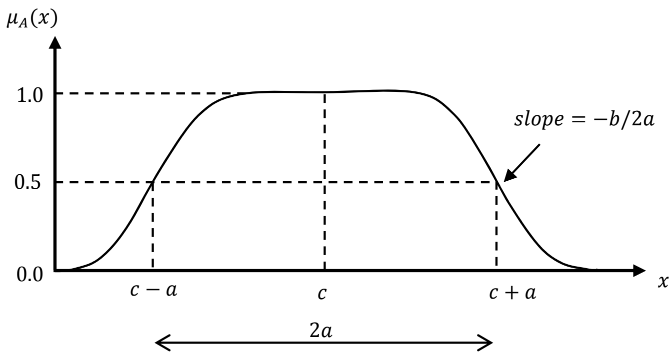

Fig. 7 *Gauss curve type membership function and parameter definitions [16].*

Accordingly, depending on the value of the parameters a_i, b_i, c_i, the node outputs, $\mu_{A_i}(x)$ and $\mu_{B_i}(y)$ can be calculated according to one of the expressions given below. [16]

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{bi}}, \tag{6}$$

$$\mu_{B_i}(y) = \frac{1}{1 + \left[\left(\frac{y-c_i}{a_i}\right)^2\right]^{bi}}. \tag{7}$$

Layer 2: Each node in this layer refers to the rules and number created according to the Sugeno fuzzy logic inference system. Obtaining the μ_i values is calculated as follows: $(i = 1, \ldots, n)$.

$$\omega_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y), \; i = 1, 2. \tag{8}$$

Layer 3: Each node in this layer accepts all nodes from the rule layer as the input value and calculates the normalized value of each rule.

$$\overline{\omega} = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1, 2. \tag{9}$$

Layer 4: In this layer, each node i is a square node. The output of the node is the output membership function.

$$o_i^4 = \overline{\omega} f_i = \omega_i(p_i x + q_i y + r_i). \tag{10}$$

Layer 5: In the total layer, there is only one node which labelled with Σ and it computes all signals with resulting in the real value of the ANFIS system.

$$o_i^5 = \sum_i \overline{\omega_i} f_i = \frac{\sum_i \overline{\omega_i} f_i}{\sum_i \overline{\omega_i}}. \tag{11}$$

2.5 Model performance

The success (performance) of a modelling process is determined by various definitions based on the difference (error) between the output produced by the existing system represented by the developed model in response to a particular input sign and the output produced by the model against the same input.

Accordingly, the first measurement used to measure model performance is the sum of squares of the difference between the actual system output and the model output.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} \varepsilon_i^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2. \tag{12}$$

A second measure is R square is a statistical measure that represents the proportion of the variance for a dependent variable that's explained by an independent variable in a regression model. R square error is given with the Eq. 13.

$$R^2 = \frac{1 - \sum_{i=1}^{N}(x_i - y_i)^2}{\sum_{i=1}^{N}\left({x_i}^2\right)}. \tag{13}$$

For the optimization of the model parameters, one of the error definitions given with the above equations is generally used. Estimating the model parameters is determined with algorithms based on minimizing the error size used.

3. Simulation results

There are many studies in the literature on the estimation of epidemic diseases. Time series data sets are often predicted using auto-regressive integrated moving average (ARIMA). Saba et al., autoregressive integrated moving average (ARIMA) and non-linear autoregressive artificial neural networks (NAR-NN) approaches which are based on statical and artificial intelligence approaches are used to model and forecast of the epidemic in Egypt [17]. In this study, the number of the daily and total confirmed COVID-19 cases and deaths in Turkey, Italy and India for 287 days (10 March 2020-22 December 2020) have been used for all forecasting models. Mortality and prevalence of the COVID-19 are estimated for the next 30 days with NAR-NN, ARIMA and ANFIS models, as shown in Fig. 8.

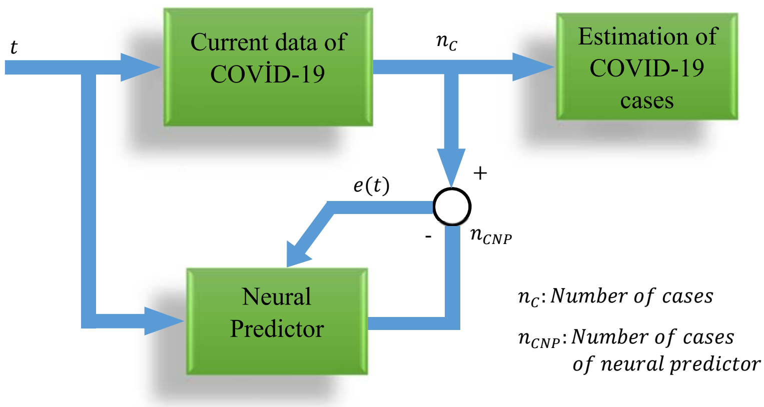

Fig. 8 *The block diagram of learning and predicting stage of simulation study.*

In Fig. 9, 10, 11 and 12 prevalence and mortality of COVID-19 was submitted with three forecasting model for Turkey. All figures show that all forecasting models successfully predict the prevalence and mortality of the COVID-19 pandemic. However, ANFIS showed a better performance compared with NAR-NN and ARIMA depending on different model performance criteria.

In Fig. 13, 14, 15 and 16, estimation of daily and total confirmed cases and deaths was presented with three predictors for Italy. All figures show that ANFIS and NAR-NN predictors are more successful than the ARIMA due to the fluctuating number of cases.

In Fig. 17, 18, 19 and 20 prediction of daily and total confirmed cases and deceased was indicated for India. All figures show that the number of cases and deaths is rising rapidly. So, the forecasting of prevalence is not easy. However, intelligent neural predictors gave good results for predicting the prevalence and

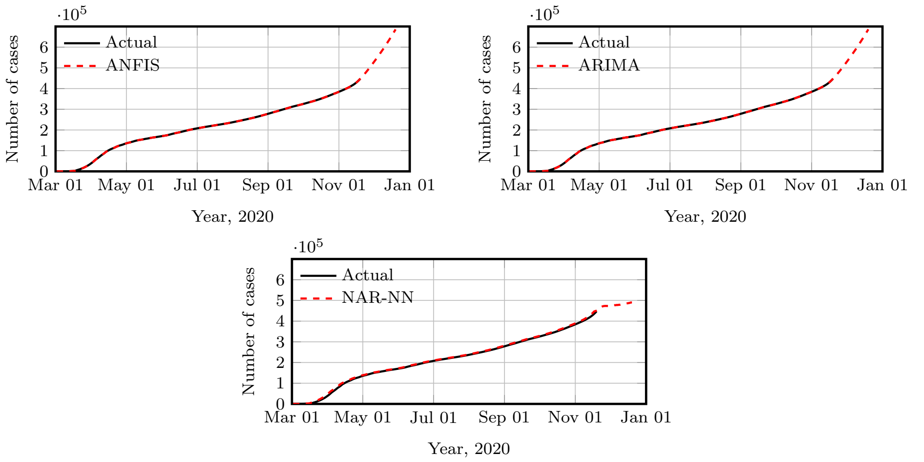

Fig. 9 *Prediction of total confirmed cases and forecasting for the next 30 days for Turkey.*

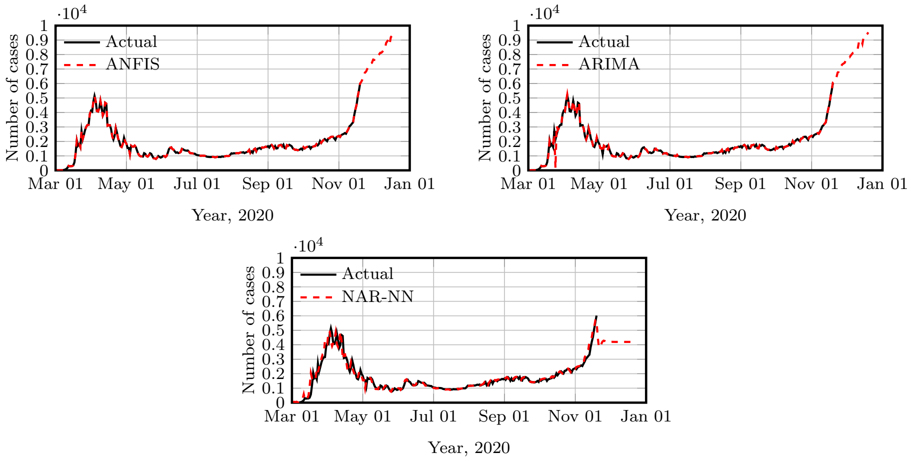

Fig. 10 *Prediction of daily positive cases and forecasting for the next 30 days for Turkey.*

mortality of COVID-19 pandemic in India. The graphs were generated with the testing dataset.

In ANFIS and NAR-NN forecasting models, the data has been used from 10 March 2020 to 22 December 2020. 60 % of total data is used for training, 30 % for testing and 10 % for validation. Test and validation data were chosen randomly to improve the model's predictability. The training subset is used to adjust the network operation according to the calculated error. The validation subset is used to evaluate the network's generalization capacity. Test subset is used to measure the last performance of the network. In this study, different NAR-NN network structures were tried. It was decided to use 15 hidden neurons that give the best

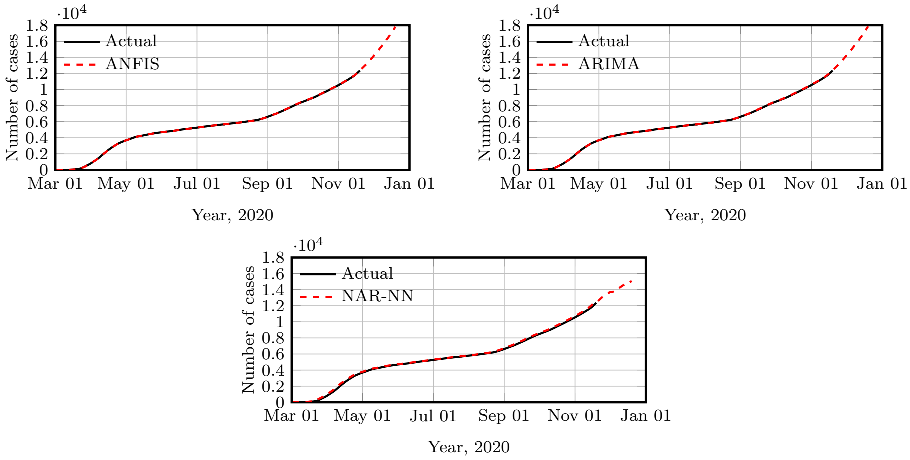

Fig. 11 *Prediction of total deaths and forecasting for the next 30 days for Turkey.*

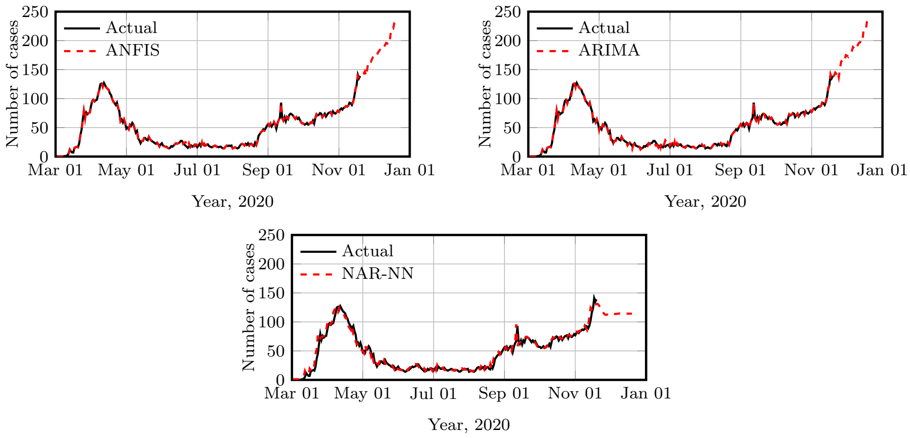

Fig. 12 *Prediction of daily deceased and forecasting for the next 30 days for Turkey.*

results and a network structure with two delay values. The structure of ANFIS consists of five layers and has two inputs and one output. One of the other forecasting models, the procedure of ARIMA modelling consists of four iterative steps; model, parameters prediction, diagnostic control and estimation. The first step of ARIMA model is to check whether the time series are stationary and seasonal. Statistical properties such as mean, variance, and autocorrelation are fixed over time. When a time series observation is stationary, it will make it easier to get accurate predictions. When the ARIMA models were developed, various models were also produced. ARIMA models with the minimum R^2 and MSE values were chosen as the optimal model. Among the tested models, ARIMA $(0, 2, 1)$ model was selected as the optimal model for Turkey, Italy and India.

In this paper, three computing models are used to investigate the forthcoming tendency of COVID-19 in Turkey, Italy and India by verifying with performance

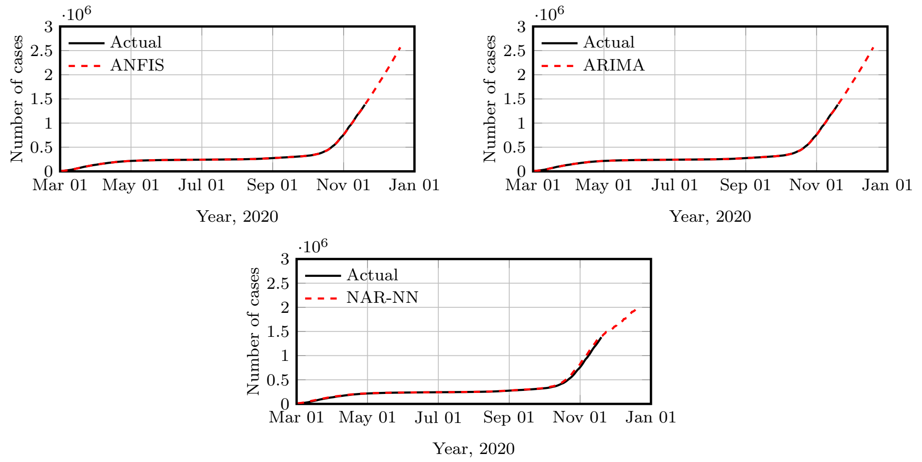

Fig. 13 *Prediction of total confirmed cases and forecasting for the next 30 days for Italy.*

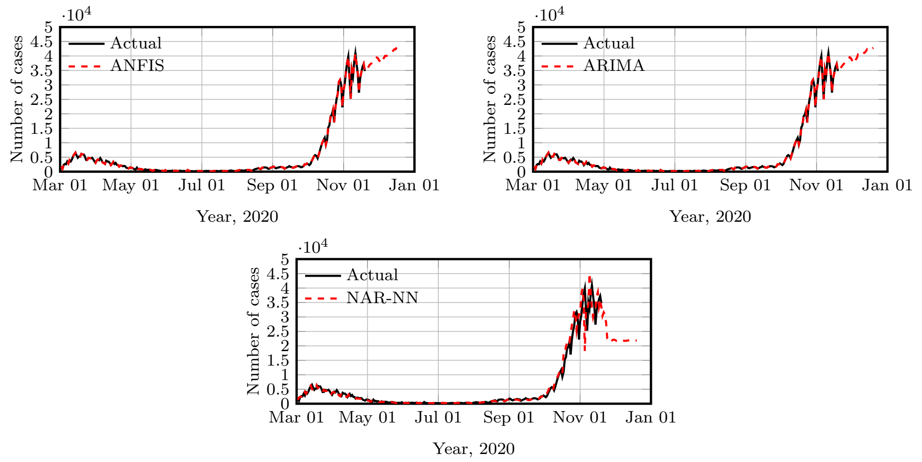

Fig. 14 *Prediction of daily positive cases and forecasting for the next 30 days for Italy.*

criteria and lastly, forecasting the total confirmed cases, daily positive cases and total deaths for the next 30 days. We measure the analytical results of computing models using two popular forecasting parameters, i.e. MSE (mean square error) and R^2 (R square) in Tab. I. In Tab. I, the results of Turkey's total confirmed cases, daily positive cases and total death show that the performance of ANFIS with regards to MSE and R^2 is better than the ARIMA and NAR-NN. The results of Italy's total confirmed cases, daily positive cases and total deaths demonstrate the values of MSE and R^2 of ANFIS are superior to ARIMA and NAR-NN. Consequently, ANFIS is the best choice for predicting the number of cases of COVID-19 in Italy as compared to the two methods. Finally, the results of India's total confirmed

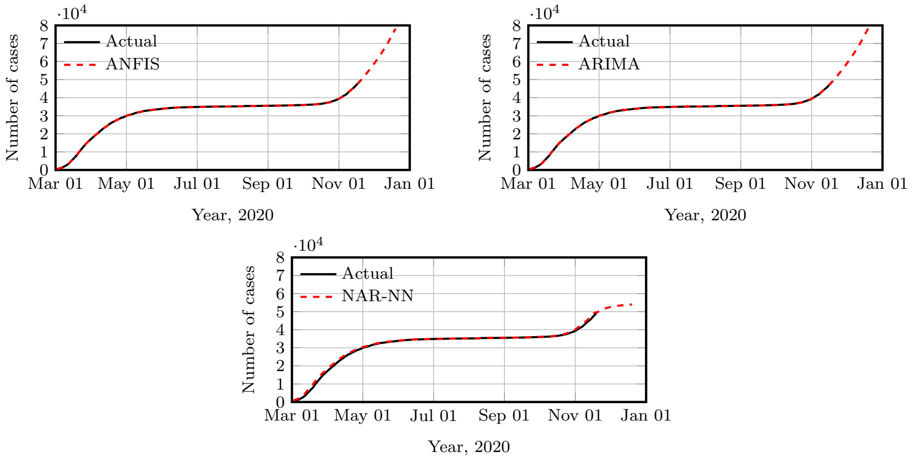

Fig. 15 *Prediction of total deaths and forecasting for the next 30 days for Italy.*

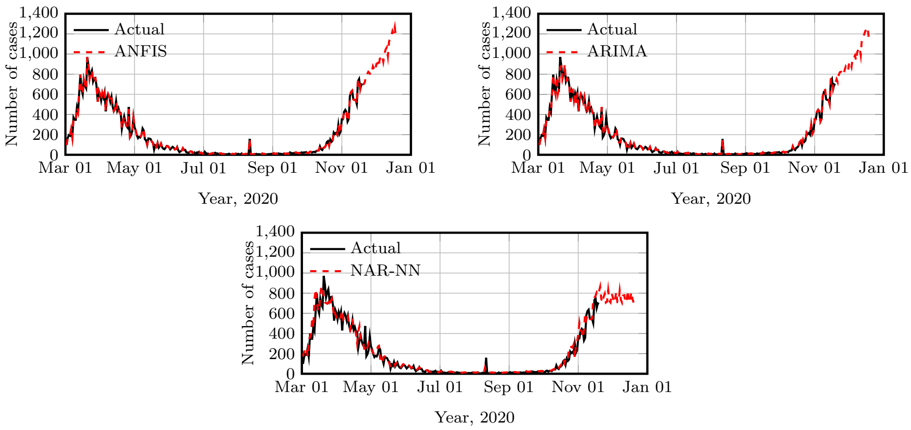

Fig. 16 *Prediction of daily deceased and forecasting for the next 30 days for Italy.*

cases, daily positive cases and total deaths indicates the values of MSE and R^2 of ANFIS is better in term of low error rate among the ARIMA and NAR-NN. This indicates that ANFIS performs better in terms of high accuracy and sensitivity rate than the other computing models. Moreover, ANFIS is a better choice for forecasting the number of recovered cases of COVID-19 in Turkey, Italy and India.

The proposed model confirmed by the aforesaid conversation to forecast COVID-19 cases and death in Turkey, Italy and India may help the short-term plans for this pandemic's prevalence. Essentially, it is difficult to predict the course of such outbreaks. Because protective measures affect the increase in the number of cases, by developing different forecasting models prevalence of pandemics can be estimated. This is used as a prognostic system in the hospitals and can help the governments with emergency economic plans.

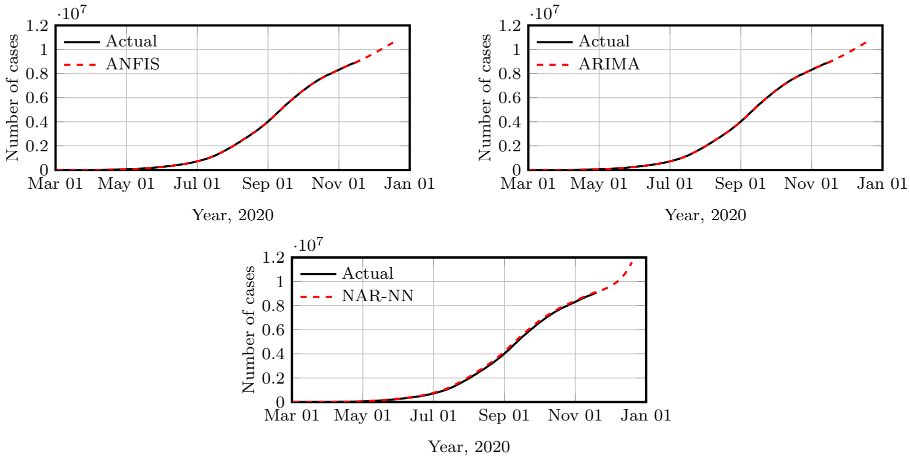

Fig. 17 *Prediction of total confirmed cases and forecasting for the next 30 days for India.*

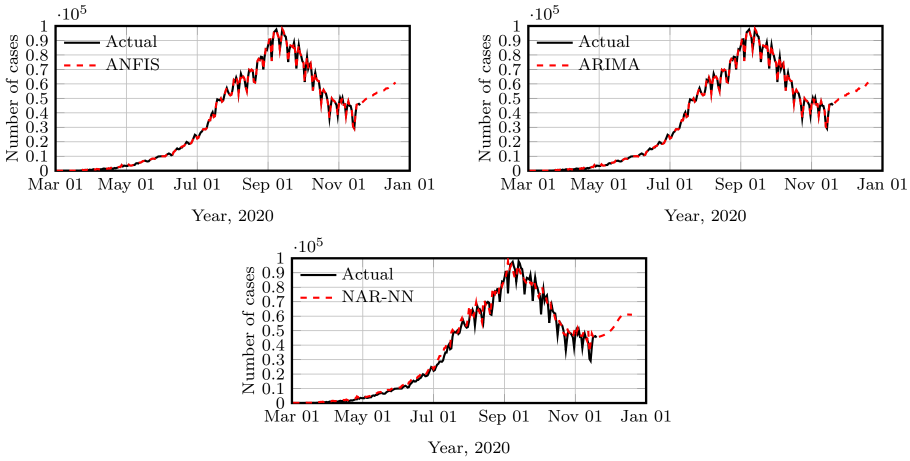

Fig. 18 *Prediction of daily positive cases and forecasting for the next 30 days for India.*

As can be depicted from the results and approaches, it is not easy to predict the cases of India, because of standard life level and region. The prediction of the cases is depended on obeying rules and some broad information about viruses. There is also a very important expanding speed and distance of viruses. Initially, some rules were applied without exact information about the virus. When some exact information has been changed the other rules, this situation has affected people's concentrations and living styles. Intelligent systems will be employed in real-time to solve unpredictable situations like viruses.

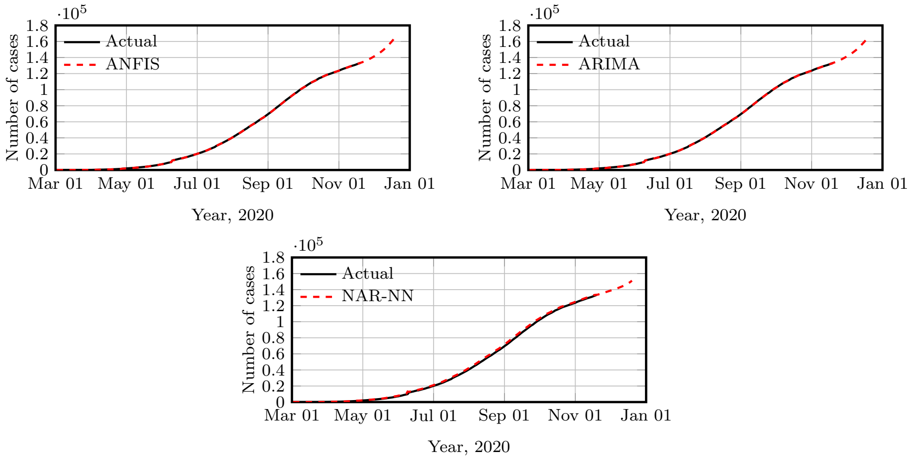

Fig. 19 *Prediction of total deaths and forecasting for the next 30 days for India.*

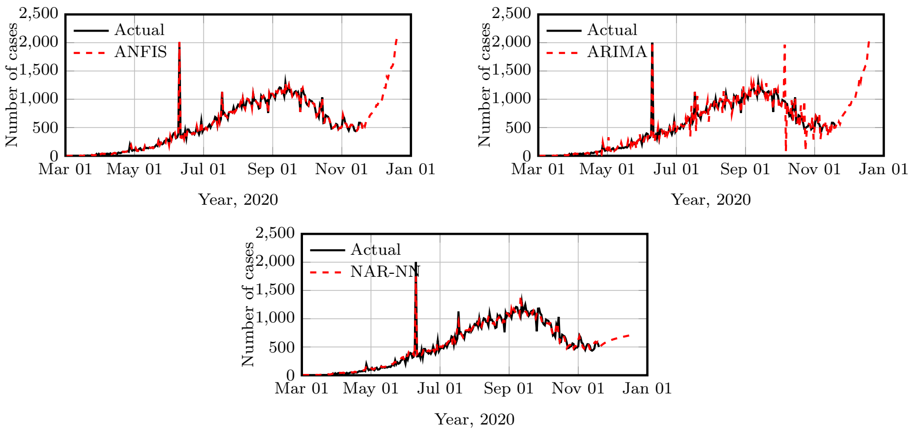

Fig. 20 *Prediction of daily deceased and forecasting for the next 30 days for India.*

4. Conclusion and discussions

The cases have been analysed to use three types of neural network predictors. These are ANFIS, NAR-NN and ARIMA. First of all, ANN predictors have superior performance to predict three regions cases. This means that this kind of ANN techniques can be used in real time applications. Thus, the estimation of the future values of the collected case data includes time values outside the range of training data. More specifically, such applications of ANN could be very suitable for short-term forecasts. However, such short-term forecasts provide an adequate viewpoint of the COVID-19 pandemic for human experts where there is necessary database. Since the spread behaviour of the COVID-19 epidemic in each country has different trends, three different forecasting models were used in this study as well. However, unlike the ANN models proposed in this study, different classical

	ANFIS	NAR-NN	ARIMA	ANFIS	NAR-NN	ARIMA
		R^2			MSE	
Turkey total confirmed	0.99841	0.97325	0.95621	0.0134	0.0172	0.0198
Turkey daily positive	0.99954	0.99892	0.99861	0.0130	0.0135	0.0133
Turkey total death	0.99982	0.98074	0.97935	0.0120	0.0180	0.0210
Turkey daily deceased	0.99843	0.97750	0.96754	0.0132	0.0265	0.0390
Italy total confirmed	0.99921	0.99915	0.99912	0.0100	0.0100	0.0110
Italy daily positive	0.99869	0.99815	0.99622	0.0121	0.0126	0.0134
Italy total deaths	0.99755	0.99620	0.99410	0.0196	0.0199	0.0199
Italy daily deceased	0.99851	0.99689	0.99653	0.0122	0.0170	0.0191
India total confirmed	0.95529	0.95230	0.93541	0.0335	0.0374	0.0421
India daily positive	0.99988	0.99912	0.99447	0.0101	0.0102	0.0198
India total deaths	0.99820	0.99768	0.99654	0.0113	0.0120	0.0129
India daily deceased	0.93254	0.92869	0.91236	0.0612	0.0789	0.0852

Tab. I *ANFIS, NAR-NN and ARIMA model performance (R square and MSE).*

prediction methods such as curve fitting, SEIR/SIR, agent-based [18,19] and different machine learning models such as multi-gene genetic programming are also used in the literature [20, 21]. However, when the literature is reviewed, it is seen that different short time intervals (such as 2 weeks, 2 months) are taken into account for the training data used for COVID-19 and that they do not cover enough time for the database. In this study, a database over 9 months was used for ANN, and thus, as seen in Tab. I, R^2 values were largely above 0.99. This situation shows that the performance of the proposed model, ANN is reliable and can give more accurate results compared to classical methods. In a real-time application, fast prediction of cases and viruses is significant to give results to patients or clients. The graphed results of simulation studies have been improved and showed that these kinds of approaches would be employed in such cases in real-time in hospitals to help nurses and doctors. As outlined in many reference books, the neural network is a kind of black box for analysing many cases in simulations and real-time applications. When an adaptive and robust neural network analyser is programmed to predict real-time applications of virus cases, there will be very practical applications in health science and research. By means of the estimation of the course of the outbreak, measures such as reviewing the curfew periods to reduce social interaction, applying stricter rules with the warming of the weather, extending the closure of schools and universities and building new pandemic hospitals can be taken.

The paper has presented three types of artificial neural networks with different learning algorithms. On the other hand, the cases of COVID-19 were selected from three different regions with obeying rules or without obeying rules. The simulation results improved and showed that three types of neural predictors could be used in real-time applications such as these virus cases predicting. These neural networks have superior performance in predicting some virus cases by assuming all rules and obeying some base specifications. Moreover, the age of people is also very important without an illness. On the other hand, the main structure and affection of viruses should be researched and simulated by medical scientists. This proposed method has been improved than it can be used in real-time applications. Also, the table shows that the performances of the neural predictor will be analysed for such problems in hospitals.

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