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Forecasting of COVID-19 Confirmed Cases in Vietnam Using Fuzzy Time Series Model Combined with Particle Swarm Optimization

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Keywords

COVID-19,
Forecasting,
Fuzzy time series,
Fuzzy relationship groups,
Particles warm optimization.

Abstract

Since December past year, a novel coronavirus has named COVID-19, which was discovered in Wuhan, China, and has spread to different cities in China as well as to 208 other countries and becomes as a global threat. The spread of virus COVID-19 can put all countries in situation of incapacity of how manage and face. In order to help people to make decisions in dealing this epidemic issue. This study proposes a forecasting model based on fuzzy time series (FTS) and Particle swarm optimization (PSO) for forecasting the number of confirmed cases of COVID-19 in Vietnam. First, the fuzzy relationship groups are utilized to overcome drawbacks of fuzzy relationship matrix in building of fuzzy forecasting model. Second, the PSO algorithm is used to find and adjust the proper number and length of intervals with an intent to achieve the best forecasting accuracy. To verify the effectiveness of the proposed model, a numerical COVID-19 dataset is selected for forecasting process. These forecasting results could be helpful in forecasting future confirmed cases if the spread of the virus did not change very strangely.

1. Introduction

COVID-19 has greatly affected over the world after first being reported in Wuhan, China in December-2019. Since then, there has been an exponential growth in the number of such cases around the globe. As of 7th April 2020, the total confirmed cases of 1.345.653 out of which 74.644 have died. It can very well be observed that most countries have reported cases of new Coronavirus. As of now, it has affected 209 countries with COVID-19, including Vietnam.

Considering Vietnam, after first emerging in late January 2020, the number remained constant until the beginning of March, when the 17th case returned from London, England, it grew exponentially. As of 7th April, the number of total cases has reached 245 cases. Given the current rate of growth, where can the cases expect to reach in the next 15 days, if no specific precaution is taken. In this context we are really worry of the coming days, and months, everybody now over world, and especially in Vietnam country, ask the question: what's the trend of this virus? under this serious question ,we will trying to give a response by using the forecasting model based on Fuzzy Time Series.

The fuzzy time series forecasting models based on fuzzy set theory [1] have been widely applied to diverse fields such as enrolments forecasting [2] - [9], crop productions prediction [10], stock markets [11] and temperature prediction [12]. The fuzzy time series and the corresponding forecast model was introduced by Song and Chissom in 1993. They introduced both the time-invariant fuzzy time series [2] and the time-variant time series [3] model which use the max–min operations to forecast the enrolments of the University of Alabama. Unfortunately, their method has many drawbacks such as huge computation when the fuzzy rule matrix is large and lack of persuasiveness in determining the universe of discourse and the length of intervals. Therefore, Ref. [5] proposed the first-order fuzzy time series model by using simple arithmetic calculations instead of max-min composition operations [3] for better forecasting accuracy. Thereafter, the fuzzy time series methods received increasing attention in many forecasting applications. To achieve better forecasting accuracy, Ref. [6] presented an effective approach which can properly adjust the lengths of intervals. Chen in [7] presented a new forecasting model based on the high-order fuzzy logical relationship groups to forecast the enrolments of the University of Alabama. Singh [9] developed a simplified and robust computational method for the forecasting rules based on one and various parameters as fuzzy logical relationships. Lee et al. in [12] presented a method for forecasting the temperature and the TAIFEX based on the high-order fuzzy logical relation groups and genetic algorithm. They also used genetic algorithm and simulated annealing in it. Recently, Particle swarm optimization technique has been successfully applied in many applications. Based on Chen's model [5] , Kuo et

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al.[13] introduced a new hybrid forecasting model which combined fuzzy time series with PSO algorithm to find the proper length of each interval. Afterward, to improve previous model in [13]. They continued to present a new forecast method to solve the TAIFEX forecasting problem based on fuzzy time series and PSO [14]. Huang et al. in [15] proposed a new hybrid forecasting model based on two computational methods, fuzzy time series and PSO for forecasting enrolments by considering more local information of latest fuzzy logical relationship in current state of fuzzy logical relationship group to find the forecasting value in FTS. Some other authors, proposed some methods for the temperature prediction and the TAIFEX forecasting, based on two-factor fuzzy logical relationships and PSO as shown in [16], [17]. Other approach for interval process is found in [18], They proposed a new data partition based on based on rough-fuzzy for the high order fuzzy time series model. In Addition, other hybrid techniques such as: Chen and Kao [19] proposed a new method for forecasting the TAIEX, based on fuzzy time series, particle swarm optimization techniques and support vector machines. Pritpal and Bhogeswar [20] presented a new model based on hybridization of fuzzy time series theory with artificial neural network (ANN). Cheng and Li [21] proposed an enhanced HMM-based forecasting model by developing a novel fuzzy smoothing method to overcome the problem of rule redundancy and achieve better results. Efendi et al.[22] introduce stock market forecasting by using auto-regression time series model and produce more accurate forecasted value. Gautam et al.[23], [24] proposed a solution to the decision-making problems in intuitionistic fuzzy environment. Ref.[25] presented a forecasting model based on combining adaptive neuro-fuzzy inference system and the chaotic bat swarm optimization algorithm for forecasting wind energy generation.

The above-mentioned researches showed that the lengths of intervals and fuzzy logical relationship are two important issues considered to be serious influencing the forecasting accuracy and applied to different problems. However, most of the models were implemented for forecasting of other historical data and not the number of confirmed cases of COVID-19. In this paper, a forecasting model based on Fuzzy time series and PSO is presented to forecast the confirmed cases of the COVID-19 in Vietnam from on 4 march 2020 to 7 April 2020. Firstly, the historical data of the COVID-19 is fuzzified into fuzzy sets to create the first-order and the high – order fuzzy logical relationship groups. Secondly, the PSO algorithm for the optimal lengths of intervals is developed by searching the space of the universe of discourse. The experimental results bring a significant meaning for the future and is a reference that can help people make decisions in term of disease outbreaks.

The rest of the paper is structured as follows. Basic definitions of fuzzy time series and PSO algorithm are given in the succeeding section. The model to forecast the confirmed cases of the COVID-19 in Vietnam based on the FTS and PSO are presented in Section 3. The results obtained from the implementation of the proposed method are presented in Section 4. Finally, the last section provides brief discussion and concludes the paper.

2. Basic FTS Definitions and Algorithms

2.1. Definitions

Fuzzy time series was firstly put forward by Song and Chissom [2],[3], [4]. Fuzzy time series can be shortly defined as time series whose observations are fuzzy sets. Let $U = \{u_1, u_2, \ldots, u_n\}$ be an universal set; a fuzzy set A_i of U is defined as $A_i = \{ f_A(u_1)/u_1 +, f_A(u_2)/u_2 \ldots + f_A(u_n)/u_n \}$, where f_A is a membership function of a given set A, $f_A : U \rightarrow [0,1]$, $f_A(u_i)$ indicates the grade of membership of u_i in the fuzzy set A, $f_A(u_i) \in [0, 1]$, and $1 \leq i \leq n$. General definitions of FTS are given as follows:

Definition 1: Fuzzy time series

Let Y(t) $(t = .., 0, 1, 2 ..)$, a subset of R, be the universe of discourse on which fuzzy sets $f_i(t)$ $(i = 1,2 \ldots)$ are defined and if F(t) is a collection of $f_1(t), f_2(t), \ldots$, then F(t) is called a fuzzy time series on Y(t) (t . . ., 0, 1,2 . ..). Here, F(t) is viewed as a linguistic variable and $f_i(t)$ represents possible linguistic values of F(t).

Definition 2: Fuzzy logic relationship(FLR**)** [2, 3]

If F(t) is caused by F(t-1) only, the relationship between F(t) and F(t-1) can be expressed by $F(t-1) \rightarrow F(t)$. Song and Chissom [3] suggested that when the maximum degree of membership of F(t) belongs to A_i, F(t) is considered A_j. Hence, the relationship between F(t) and F(t -1) is denoted by fuzzy logical relationship $A_i \rightarrow A_j$ where Ai and Aj refer to the current state or the left - hand side and the next state or the right-hand side of fuzzy time series.

Definition 3: m - order fuzzy logical relationship [7]

Let $F(t)$ be a fuzzy time series. If $F(t)$ is caused by $F(t-1), F(t-2), \ldots, F(t-m+1) F(t-m)$ then this fuzzy relationship is represented by by $F(t-m), \ldots, F(t-2), F(t-1) \rightarrow F(t)$ and is called an m - order fuzzy time series.

Definition 4: Fuzzy Logical Relationship Group (FLRG) [5]

Fuzzy logical relationships, which have the same left-hand sides, can be grouped together into fuzzy logical relationship groups. Suppose there are relationships such that

$A_i \rightarrow A_{k1}$, $A_i \rightarrow A_{k2}$, …,$A_i \rightarrow A_{kn}$

So, based on [5], these fuzzy logical relationship can be grouped into the same FLRG as : $A_i \rightarrow A_{k1}, A_{k2}, \ldots, A_{kn}$

2.2. PSO Algorithm

PSO was first introduced by Eberhart and Kannedy [26] . It belongs to a population-based evolutionary algorithm that can efficiently search a nearly optimal or optimal solution of any complex problems. In the PSO, a set of potential solutions is represented by a swarm of particles and each particle is moved through the search space for search the optimal solution. When particles moving, the position of the best particle among all particles found so far is recorded and each particle keeps its personal best position which has passed previously. The particles change its state according to the three principles: weight inertia i.e. ω , it's most optimist position i.e. P_{best_id} , swarm's most optimist position i.e. G_{best}; and converges to the most optimal position in the entire solution space by continuous change in the personal best and global best position. Each element v_{id}^k in the velocity vector $V_{id}^k = [v_{id}^1, v_{id}^2, \ldots, v_{id}^n]$ and each element

x_{id}^{k} in the position vetor $X_{id}^{k} = [x_{id}^{1}, x_{id}^{2}, \ldots, x_{id}^{n}]$ of particle id are calculated as follows:

$$V_{id,j}^{k+1} = \omega^{k} * V_{id}^{k} + C_1 * Rand() * (P_{best\_id} - x_{id}^{k}) + C_2 * Rand() * (G_{best} - x_{id}^{k}) \quad (1)$$

$$x_{id}^{k+1} = x_{id}^{k} + x_{id}^{k+1} \quad (2)$$

$$\omega^{k} = \omega_{max} - \frac{k*(\omega_{max} - \omega_{min})}{iter\_max} \quad (3)$$

The G_{best} at k^{th} iteration is computed as $G_{best} = \min(P_{best_{id}}^{k})$;

where,

- X_{id}^{k} is the current position of a particle id in k^{th} iteration;
- V_{id}^{k} is the velocity of the particle id in k^{th} iteration, and is limited to $[-V_{max}, V_{max}]$ where V_{max} is a constant pre-defined by user.
- P_{best_id} is the position of the particle id that experiences the best fitness value.
- G_{best} is the best one of all personal best positions of all particles within the swarm.
- Rand() is the function can generate a random real number between 0 and 1 under normal distribution.
- C_1 and C_2 are acceleration values which represent the selfcondence coefficient and the social coefficient, respectively.
- ω is the inertia weight factor accoding to Eq. (3).
- iter_max is maximum number of iterations

3. A Forecasting Model Based on FTS and PSO

In this section, a forecasting model based on article [13] by combining the fuzzy logical relationship group with PSO algorithm is introduced. First, the original historical COVID-19 dataset are used instead of the variations of historical data in the proposed model. Second, the FLRGs are derived from the fuzzified data and calculate the forecasting output based on the fuzzy sets on the right-hand side of the FLRGs. Third, the PSO algorithm is applied to adjust the interval lengths to increase forecasting accuracy. A detailed explanation of the proposed model is expressed in Section 3.1 and 3.2 as below:

3.1 Forecasting Model Based on the FTS.

The daily confirmed cases of COVID-2019 from March 4th, 2020 to April 7th, 2020 are used to illustrate the first - order fuzzy time series forecasting process. It was collected from the WHO website (https: //www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports/) or https://ncov.moh.gov.vn and which listed in Table 1. The step-wise procedure of the proposed model is detailed as follows:

Step 1**:** Define the universe of discourse U

Assume Y(t) be the historical data of Covid-19 on day t. The universe of discourse is defined as $U = [D_{min}, D_{max}]$. In order to ensure the forecasting values bounded in the universe of discourse U, we set $D_{min} = I_{min} - N_1$ and $D_{max} = I_{max} + N_2$; where I_{min}, I_{max} are the minimum and maximum data of Y(t); N_1 and N_2 are two proper positive to tune the lower bound and upper bound of the U. From the historical data are shown in Table 1, we obtain $I_{min} = 16$ và $I_{max} = 245$. Thus, the universe of discourse is defined as U= $[I_{min} - N_1, I_{max} + N_2]$= [16, 245] with $N_1 = 0$ and $N_2 = 0$.

Table 1: The original historical COVID-19 dataset in Vietnam

Stt	Date(D/M/Y)	Confirmed Cases
1	4/3/2020	16
2	5/3/2020	17
3	6/3/2020	17
4	7/3/2020	20
5	8/3/2020	21
6	9/3/2020	30
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29	31/3/2020	207
30	01/04/2020	218
31	02/04/2020	227
32	03/04/2020	233
33	04/04/2020	239
34	05/04/2020	241
35	06/04/2020	245
36	07/04/2020	245

Step 2**:** Partition U into equal length intervals

We divide U into initial seven intervals with equal length, $u_1, u_2, \ldots, u_7$, respectively. The length of each interval is $L = \frac{D_{max} - D_{min}}{7} = \frac{245-16}{7} = 32.71$. Thus, the seven intervals are defined as follows:

$u_i = (D_{min} + (i-1)*L,\ D_{min} + i*L]$, with $(1 \le i \le 7)$ gets seven intervals as:

u_1 = [16, 48.71], u_2 = (48.71, 81.4], …, u_6 = (179.6, 212.3], u_7 = (212.3, 245].

Step 3**:** Define the fuzzy sets for observation of COVID-19

Each interval in Step 2 represents a linguistic variable of "COVID-19". For seven intervals, there are seven linguistic values [13] which are A_1 = "not many", A_2="not too many", A_3 =" many", A_4 = "many many", A_5 = "very many", A_6 = "too many", and A_7=" too many many" to represent different regions in the universe of discourse on U, respectively. Each linguistic variable represents a fuzzy set A_i and its definitions is described according to Eqs.(4) & (5)

$$A_i = {}^{a_{i1}}/_{u_1} + {}^{a_{i2}}/_{u_2} + \ldots + {}^{a_{ij}}/_{u_j} + \cdots + {}^{a_{i7}}/_{u_7} \quad (4)$$

$$a_{ij} = \begin{cases} 1 & j = i \\ 0.5 & j = i-1 \text{ or } j = i+1 \\ 0 & otherwise \end{cases} \quad (5)$$

Here, the symbol '+' denotes the set union operator, $a_{ij} \in [0,1]$ $(1 \le i \le 7, 1 \le j \le 7)$, u_j is the jth interval of U. The value of a_{ij} indicates the grade of membership of u_j in the fuzzy set A_i. For simplicity, the different membership values of fuzzy set A_i are selected by according to Eq.(5). According to Eqs.(4) and (5), a fuzzy set contains 7 intervals. Contrarily, an interval belongs to all fuzzy sets with different membership degrees. For example, u_1 belongs to A1 and A2 with membership degrees of 1 and 0.5 respectively, and other fuzzy sets with membership degree is 0.

Step 4*:* Fuzzy all historical data of COVID-19

In order to fuzzify all historical data in Table 1, it's necessary to assign a corresponding linguistic value to each interval first. The simplest way is to assign the linguistic value with respect to the corresponding fuzzy set that each interval belongs to with the highest membership degree**.** For example, the historical COVID-19 dataset on 4 march, 2020 is 16, and it belongs to interval u_1 = [16, 48.71]. So, we then assign the linguistic value ‘‘not may” (eg. the fuzzy set A_1) corresponding to interval u_1 to it. Consider two time serials data $Y(t)$ and $F(t)$ at day t, where $Y(t)$ is actual data and $F(t)$ is the fuzzy set of $Y(t)$. According to Eqs. (4) and (5), the fuzzy set A_1 has the maximum membership value at the interval u_1. Therefore, the historical data time series on 4 march, 2020 is fuzzified to A_1. The completed fuzzified results of COVID-19 are listed in Table 2.

Table 2. The results of fuzzification for COVID-19 data.

Year	Confirmed Cases	Fuzzy sets
4/3/2020	16	A1
5/3/2020	17	A1
6/3/2020	17	A1
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06/04/2020	245	A7
07/04/2020	245	A7

Step 5. Create all m – order fuzzy relationships.

Based on Definition 3. To establish a m-order fuzzy relationship, we should find out any relationship which has the $\mathrm{F}(\mathrm{t}-m), \mathrm{F}(\mathrm{t}-m+1), \ldots, \mathrm{F}(\mathrm{t}-1) \rightarrow F(t)$, where $\mathrm{F}(\mathrm{t}-m), \mathrm{F}(\mathrm{t}-m+1), \ldots, \mathrm{F}(\mathrm{t}-1)$ and $F(t)$ are called the current state and the next state, respectively. Then a m - order fuzzy relationship is got by replacing the corresponding linguistic values. The same linguistic values (fuzzy set) cannot appear more than once on the right hand side. For example, supposed $m = 1$, a fuzzy relationship $\mathrm{A}_1 \rightarrow \mathrm{A}_1$ is got as $\mathrm{F}(4\ \mathrm{march}, 20) \rightarrow \mathrm{F}(5\ \mathrm{march}, 20)$. So, from Table 2 we get fist - order fuzzy logical relationships are shown in Table 3.

Table 3. The first - order fuzzy logical relationships

Year	Fuzzy relationships	F(t)
1	A1 -> A1	F(4/3/2020)
2	A1 -> A2	F(5/3/2020)
3	A2 -> A2	F(6/3/2020)
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12	A6 -> A7	F(06/04/2020)
13	A7 -> A7	F(07/04/2020)

Step 6: Establish all m – order fuzzy logical relationships groups

Based on [13] all the fuzzy relationships having the same fuzzy set on the left-hand side or the same current state can be put together into one fuzzy relationship group. Thus, from Table 3 and based on Definition 4, we can obtain seven fuzzy logical relationship groups shown in Table 4**.**

Table 4. The complete results for all first – order FLRGs

No	**FLRGs**	**No**	**FLRGs**
1	A1 → A1, A2	5	A5 → A5, A6
2	A2 → A2, A3	6	A6 → A6, A7
3	A3 → A3, A4	7	A7 → A7
4	A4 → A5, A5		

Step 7: Calculate and defuzzify the forecasted outputs

First, we calculate the predicted value for each group of fuzzy relation by the proposed rules [5], then based on the value of each of these groups to defuzzify the forecasted output for year i. For each FLRG in the training phase and the testing phase, we use the principles to compute it as follows.

Rule 1**:** If the fuzzified rice production of year i is A_i, and there is only one fuzzy logical relationship in the fuzzy logical relationship groups, which is shown as $A_i \rightarrow A_k$, the forecasted output of year i+1 is m_k ; where m_k is the midpoint of interval u_k.

Rule 2: If the fuzzified rice production of year i is A_i, and there are more one fuzzy logical relationship in the fuzzy logical relationship groups, which are shown as $A_i \rightarrow A_{k1}$, $A_i \rightarrow A_{k2}$, …,$A_i \rightarrow A_{kp}$; the forecasted output of year i+1 is $\frac{m_{k1}+m_{k2}+\cdots+m_{kp}}{p}$.

where, $m_{k1}, m_{k2}, \ldots, m_{kp}$ is the midpoint if interval $u_1, u_2, \ldots, u_p$, respectively .

Rule 3**:** If the fuzzified rice production of year i is A_i, and there is only one fuzzy logical relationship in which the right - hand side of fuzzy logical relationship group is empty, which is shown as $A_i \rightarrow \neq$; the forecasted output of year i+1 is m_i .

From above rules and based on Table 4, we obtain the forecasted value for the first – order fuzzy logical relationship groups are shown in Table 5.

Table 5. The complete forecasted values for all first –order FLRGs in Table 4.

FLRGs	**Value**	**FLRGs**	**Value**
A1 → A1, A2	43.2	A5 → A5, A6	176.8
A2 → A2, A3	78.7	A6 → A6, A7	212.3
A3 → A3, A4	108.6	A7 → A7	228.7
A4 → A5, A5	144.1		

The forecasting performance can be assessed by comparing the difference between the forecasted values and the actual values. The widely used indicators in time series models comparisons are the mean squared error (MSE), Mean Absolute Percentage Error (MAPE) according to Eqs.(6) and (7)

$$MSE = \frac{1}{n}\sum_{i=m}^{n}(F_i - R_i)^2 \quad (6)$$

$$MAPE = \frac{1}{n}\sum_{i=m}^{n}\frac{|F_i - R_i|}{R_i} * 100\% \quad (7)$$

where, R_i denotes actual value at year i, F_i is forecasted value at year i, n is number of the forecasted data, m is order of the fuzzy logical relationships

3.2. Forecasting Model Based on Combining the FTS and PSO

To improve forecasted accuracy of the proposed, the effective lengths of intervals and fuzzy logical relationship groups which are two main issues presented in this paper. A novel model for forecasting the confirmed cases COVID-19 in Vietnam is developed to adjust the length each of intervals in the universe of discourse without increasing the number of intervals by minimizing the MSE value (6).

In our model, each particle exploits the intervals in the universe of discourse of historical data Y(t). Let the number of the intervals be n, the lower bound and the upper bound of the universe of discourse on historical data Y(t) be p_0 and p_n, respectively. Each particle is a vector consisting of n-1 elements pi where 1≤i≤ n-1 and $p_i \leq p_{i+1}$. Based on these n-1 elements, define the n intervals as $u_1 = [p_0, p_1]$, $u_2 = [p_1, p_2]$,...,$u_i = [p_{i-1}, p_i]$,…,and $u_n = [p_{n-1}, p_n]$, respectively. When a particle moves to a new position, the elements of the corresponding new vector need to be sorted to ensure that each element pi ($1 \leq i \leq n-1$) arranges in an ascending order. The complete steps of the proposed method are presented in Algorithm 1.

Algorithm 1: The FTS-PSO algorithm

1. Initialize all particles' positions X_{id} , velocities V_{id} and parameters of the proposed method. These parameters are:
   - Number of particles is **50**
   - Maximum number of iterations is **150**
   - The value of inertial weigh ω be linearly decreased according to Eq.(3) with $\omega_{max} = \mathbf{0.9}$ and $\omega_{min} = \mathbf{0.4}$
   - The coefficient C1 equal C2 equal to **2**
   - The position of particle i be limited by: $x_{min} + Rand() * (x_{max} - x_{min})$; where x_{min} *and* x_{max} are lower and upper bounds of universal set, respectively.
   - The velocity of particle i be exceeded by $v_{min} + Rand() * (v_{max} - v_{min})$
2. **While** the stop condition (maximum iterations or minimum MSE criteria) is not satisfied **do**

2.1. **For** particle i, (1≤ i ≤ NumberOfParticles) **do**

   - Define linguistic values according to all intervals defined by the current position of particle i
   - Fuzzify all historical data by Step 4 in Subsection 3.1
   - Define linguistic values according to all intervals defined by the current position of particle i
   - Fuzzify all historical data by Step 4 in Subsection 3.1
   - Create all $m-$order fuzzy relationships by Step 5 in Subsection 3.1
   - Make all $m-$order fuzzy relationship groups by Step 6 in Subsection 3.1
   - Calculate forecasting values by Step 7 in Subsection 3.1
   - Compute the MSE values for particle i based on Eq. (6)
   - Update the personal best position of particle i according to the MSE values mentioned above.

end **for**

2.2. Update the global best position of all particles according to the MSE values mentioned above.

3. **For** particle i, (1≤ i ≤ NumberOfParticles) **do**
   - move particle i to another position according to Eqs. (1) and (2)

end **for**

   - update ω according to Eq.(3)

end **while**

4. Experimental Result

In this paper, the COVID-19 dataset in Vietnam is used to evaluate the effectiveness of the proposed model. It contains the daily confirmed cases in Vietnam from 4 march 2020 to 7 April 2020, as shown in Table 1. The proposed model is executed 15 runs for each order, and the best result of runs at each order is taken to be the final result. During simulation with parameters are expressed in Algorithm 1 and number of intervals is set of 16. The forecasted accuracy of the proposed method is estimated using the MSE function (6). The forecasted results of proposed model under number of interval is 16 and various orders are listed in Table 6.

Table 6. The completed forecasting results the confirmed cases COVID-19 in Viet Nam

Date	Actual data of Covid-19	Forecasted Value				
		1st - order	2nd - order	3rd-order	4th-order	5th-order
4/3/2020	16	-	-	-	-	-
5/3/2020	17	20.5	-	-	-	-
6/3/2020	17	20.5	15.7	-	-	-
7/3/2020	20	20.5	15.7	24.4	-	-
8/3/2020	21	22.9	25.3	24.4	24.5	-
9/3/2020	30	22.9	39.3	24.4	24.5	31.7
10/3/2020	31	22.9	39.3	30.5	30.5	31.7
11/3/2020	34	22.9	39.3	34.7	35	31.7
12/3/2020	34	38.9	39.3	34.7	35	36
13/3/2020	34	38.9	39.3	34.7	35	36
14/3/2020	34	38.9	39.3	46.6	35	36
15/3/2020	34	38.9	39.3	46.6	46.5	36
16/3/2020	56	38.9	39.3	46.6	46.5	55.3
17/3/2020	61	65.5	66	58.5	58	55.3
18/3/2020	66	65.5	66	65.3	63.7	65
19/3//2020	85	88.3	86.7	86.3	87.3	90
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31/3/2020	207	204.2	211.5	204	207.3	207.7
01/04/2020	218	224.5	211.5	221	215.5	215
02/04/2020	227	224.5	227	226.5	223.7	222.3
03/04/2020	233	224.5	238.7	232	236.8	222.3
04/04/2020	239	240.3	238.7	240.3	236.8	241
05/04/2020	241	241.5	238.7	240.3	236.8	241
06/04/2020	245	241.5	238.7	240.3	250	243
07/04/2020	245	241.5	244.7	248.7	250	244.5
08/04/2020	N/A		244.5	250	252.8	246.5
MSE		30	24	22	18	11
MAPE		8.14%	7.5%	5.94%	4.72%	2.85%

The forecasting results of proposed model based on the different orders are also depicted in Figure 1. From Figure 1 shown that the performance of the proposed model is improving a lot with increasing number of orders in the same number of intervals. All of these conclusion have also been shown in Table 6 with the MSE criteria in Eqs. (8) and (9).

In addition, from the parameters are expressed in Algorithm 1. The proposed model is also executed 15 runs according to the different number of intervals, and the best result of runs is taken to be the final result. The simulation results according to the intervals of proposed model are presented in Table 7.

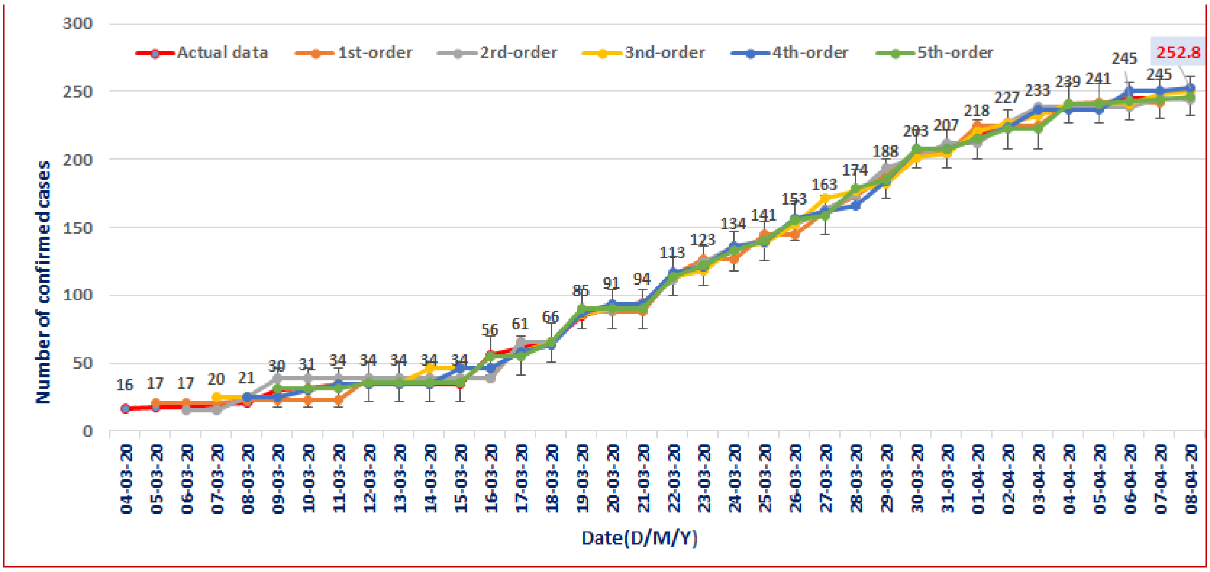

Figure 1. The forecasting trend of proposed model under different number of orders with the same intervals

Table 7. The forecasted results of the proposed model based on the first – order fuzzy time series with different number of intervals

	Number of intervals								
	10	11	12	13	14	15	16	17	Average
MSE	58	49	45	42	35	32	30	31	40.25

In Table 7, it can be seen that the accuracy of the proposed model is improved significantly. Particularly, the proposed model gets the smallest MSE value with number of interval equal to 16 and obtains the average MSE value of ***40.25***. These finding suggest that the proposed model is able to provide effective forecasting capability for the first and high – order FTS model with different number of orders in the same number of interval.

4. Conclusions

In this paper, we have presented a hybrid forecasting model to forecast the daily confirmed cases in Vietnam from 4 march 2020 to 7 April 2020. The main contributions of this paper are illustrated in the following. First, fuzzy logical relationship groups are established from the historical data of COVID-19 after it is fuzzified. Second, the PSO algorithm for the optimized lengths of intervals is developed to adjust the interval lengths by searching the space of the universe. Finally, dataset of the daily influenza confirmed cases in Vietnam were used to evaluate the proposed model, and the evaluation outcomes showed it's the best performance based on 5th - order fuzzy time series with number of interval equal to 16. According to the promising results achieved from the proposed model, it can be applied in different forecasting problems.

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