Virus Graph and COVID-19 Pandemic: A Graph Theory Approach

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Abstract In the field of science and technology, the graph theory has offered several approaches to articulate any situation or concept. The use of graph theory enables the users to understand and visualize the situations like COVID-19. Looking at this pandemic disease, its impact and the preventing measures, the graph theory would be the most appropriate way to exercise the graph models with theoretical as well as practical aspects to control this epidemic. In the context of COVID-19, this chapter defines the variable set, variable graphs, and their types considering the variations in the vertex sets and edge sets. The virus graph and their type are discussed in this chapter that states that the Virus graph type I and III are not so perilous for all living beings, but virus graph type III and IV are extremely hazardous for the harmony of the world. Initially, the COVID-19 was in Virus graph-I type, but presently it is in Virus graph-II type. Given different aspects for expansion of pandemic, this chapter presents growth types of virus graphs and their variation as 1-1, 1-P, and 1-all growth types. This chapter provide the number of infected people after ‘n’ number of days concerning different values of P and growth rates with I0 = 100. At the end of this chapter, the country-wise starting dates of stages of the virus graph-I and II are specified. The concept of cut sets is applicable for the prevention of COVID-19 and the whole world is using the same analogy.
Keywords Virus graphs · COVID-19 · Pandemic · Epidemic

1 Introduction

COVID-19 is the transferrable disease caused by the recent coronavirus recently started in Wuhan, China. This virus and subsequently the disease were shadowy to the world before its outbreak. Considering the recent COVID-19 virus and its spread across the globe, it is important to understand and visualize the virus spread and impact. The disease caused by this virus has become pandemic and many countries are affected badly. Using the graph theory approach, this chapter helps users to understand and visualize this disease, impact and spread. The different graph method presented in this chapter shows a virus, its growth type is presented using graph theory. The number of persons who are affected and prevention is also presented in this chapter. This chapter concludes that there is an infinite scope of mathematics for the research as well as resolving social problems like COVID-19 and technical problems.

The reader will refer [1–4] for the absolute dealing with the subject matter. All Graphs considered in this chapter are simple as well as connected. The neighbor of the vertex v in graph H is the set of all the vertices adjacent to the vertex v in H. A graph with n vertices and without any edges is called the Null graph and it is denoted by Nn [1, 5–9].

A simple connected graph, in which the degree of each vertex is 2, is called a cycle graph. Cn is the cycle graph on n vertices [4]. A graph, in which one vertex is adjacent to n pendant vertices, is called the star graph. It is symbolized by K1, n. Here, | V(K1, n) | = n + 1 along with | E (K1, n) | = n [10].

The chapter is organized as follows. Basic terms of graph are presented in Sect. 1. Motivation and related work is presented in Sect. 2 and 3 respectively. Graphical theoretical model that emphasizes on Virus Graph I, II, III and IV is presented in Sect. 4. Sections 5 and 6 discusses on growth rate and its types. Country wise stages of Virus graph I and II is presented in Sect. 7. Growth rate of COVID-19 is predicted and presented in Sect. 8. This chapter is summarized with future outlook in Sect. 9 [10].

2 Motivation

Almost 2.5 million cases of COVID-19 (corona virus) and more than 160,000 deaths have now been reported worldwide [4]. The largest part of the epidemic in the world comes into sight to be steady or declining [3]. A good number countries are immobile in the early stages of their epidemics and few of them were affected early in the pandemic are now starting to see an improvement in cases. Hence, it is the most important and essential to prevent the spread of such types of epidemic [10]. As we
know, mathematical modelling award different astonishing inspiration and tools to study different communal as well as technical problems and interpret solutions. This will lead to find the practical solutions of a variety of problems and helps to continue the harmony of the mankind.

3 Related Work

Let us consider following terminologies.

- **Partite Graphs**

  A graph $H$ is an $n$-partite graph if $V(H) = V_1 \cup V_2 \cup \ldots \cup V_n$, where all $V_i$ are disjoint and every edge of $H$ joins a vertex of $V_i$ and $V_j$ for $i \neq j$. If $n = 2, 3, 4$ then graphs are called Bipartite, Tripartite and four partite respectively [1].

- **Cut Sets**

  A set of edges of a connected graph $H$, whose removal disconnects $H$, is called the disconnecting set of $H$. The smallest disconnecting set is called the cut set of $H$ [2, 4].

- **Corona Product of Graphs**

  The corona product of $H$ and $K$ is denoted by $H \circ K$ and obtained from a copy of $H$ and $|V(H)|$ copies of $K$, joining each vertex of $H$ to all vertices of the graph $K$. This graph product was initiated by mathematicians Frucht and Harary in 1970 [11, 12].

  Giulia Giordano et al. [2] proposed an innovative epidemic model which distinguishes between infected people depending on whether they have been confirmed by considering their symptoms. Non diagnosed peoples can spread virus rapidly than diagnosed people. Therefore the divergence between diagnosed and non-diagnosed plays an important role for the deterrence of a pandemic. A fuzzy theory and deep learning networks help to enhance for acquiring superior stochastic insights concerning the epidemic growth is experimented [3]. A deep learning based Composite Monte-Carlo (CMC) showed better results than simple Monte Carlo (MC) which will be obliged for decision makers for greater ranges of the future promises of epidemic and pandemic [13]. In [14], it is studied that due less and incorrect information about COVID-19, there is no any exact model which can predict spread of the pandemic. Every model has different levels of predictive efficiency.

  By analyzing data in few countries, it is noted that an infection reached to peak around 10 days after the controlling measures are initiated. The growth rate of infected people was slowly decreasing during this period. But, especially the growth rate in Italy remains exponential. Hence, quarantine is insufficient and need strict measures [15]. In [16], the authors have made a mathematical model for the epidemic by applying linear differential equations. By identifying patterns and analyzing desired data, it is concluded that the growth rate is dynamic or exponential depending upon precautions taken by people. Shinde Gitanjali et al. [17], presented and meticulously
discussed different predictive analytic models as well as algorithms for the number infected cases in the near future. Moreover, the Prophet predictive analytics algorithm is implemented on the Kaggle dataset and its predictions are studied in their research work. The following new terms are defined for constructing the pedestal of mathematical modelling of any types of pandemic or COVID-19.

Critical decision making is difficult due to uncertainty caused by novel coronavirus epidemic. Fong et al. [10] presented deep learning and fuzzy based prediction method for the future possibilities of coronavirus and its impact. The present events and its future behavior is presented using Composite Monte Carlo simulation method. The difficult task is accurate forecasting of destiny of an epidemic is presented by Fong et al. [18] using augmentation of existing data, panel design for selection of best forecasting model and its fine tuning of parameters of each model. Deep learning method was presented by Hu et al. [19] for forecasting of COVID-19.

Based on the lung CT scan images, Rajinikanth [20] presented a system for detection of COVID-19. This proposed method is based on Otsu and a meta-heuristic Harmony search algorithm. Using graph theory, data classification was proposed by Kamal [21] which is based on De-Bruijn graph with MapReduce framework.

After evaluation of related work, there is a need for the mathematical modelling and visualization of COVID-19 using graph theory is essential to spread awareness among many stakeholders.

3.1 Variable Set

A set $S$ is said to be Variable set if elements of the set $S$ changes with respect to time or some rule. That is, the set $S$ is not constant set. Its cardinality changes with respect to time. $S_v$ is the notation of variable set. In the variable sets, time units depend upon its nature. According to the scenery of the cardinality of the set $S$, there are three types of sets.

- Increasing Variable Set: A variable set $S_v$ is said to be increasing variable set if $|S_v(x)| < |S_v(y)|$, whenever $x < y$, where $x$ and $y$ are different times.
- Decreasing Variable Set: A variable set $S_v$ is said to be decreasing variable set if $|S_v(x)| > |S_v(y)|$, whenever $x < y$.
- Non Decreasing Variable Set: A variable set $S_v$ is said to be non-decreasing variable set if $|S_v(x)| \leq |S_v(y)|$, whenever $x \leq y$.
- Non Increasing Variable Set: A variable set $S_v$ is said to be non-increasing variable set if $|S_v(x)| \geq |S_v(y)|$, whenever $x \leq y$.
- Stable Variable Set: A variable set $S_v$ is said to be stable variable set if $|S_v(t)|$ is constant, for any time $t$. However, the set is a variable set. Elements of the set $S$ vary according to time, but the $|S_v(t)|$ is steady, for any time $t$. 
3.2 Variable Graph

A graph $H$ is said to be a vertex variable graph if $V(H)$ or $E(H)$ is variable sets. Variable graphs are also known as V-graphs. Big network graphs are variable graph. There are two types of variable graphs.

3.3 Edge V-Graph

A variable graph $H$ is said to be edge V-graph if $E(H)$ is a variable set and $V(H)$ is the stable variable set.

3.4 Vertex V-Graph

A variable graph $H$ is said to be vertex V-graph if $V(H)$ is a variable set and $E(H)$ is the constant variable set.

3.5 N-Partite V-Graphs

A variable graph $H$ is said to be $n$-partite V-Graph if

1. $V(H) = V_1 \cup V_2 \cup V_3 \ldots \cup V_n$ where $V_1, V_2, V_3, \ldots, V_n$ disjoint variable sets having different characteristics.
2. There exists a bond on the link or edge between vertices of $V_i$ & $V_j$, for $i, j$ and $i \neq j$.

3.6 Bipartite V-Graph

A variable graph $H$ is said to be Bipartite V-Graph if

1. $V(H) = V_1 \cup V_2$, where $V_1$ and $V_2$ are disjoint variable sets with different characteristics.
2. There exists a bond on the link or edge between vertices of $V_1$ and vertices of $V_2$
3. There is no any bond among the vertices of $V_1$ only or $V_2$ only.

These types of graphs are denoted by BV$_2$. In BV$_2$, a vertex $x$ of $V_1$ is said to be Active Vertex or element if there exists a bond between $x$ and at least one vertex of $V_2$ or $x$ is trying to build a bond or edges to the vertices of $V_2$. Moreover, $x$ is ready for the sharing some characteristics. Other vertices of $V_1$ are known as the Passive
Vertices. A vertex $y$ of $V_2$ is said to be Active Vertex or element if there exists a bond between $y$ and at least one vertex of $V_1$ or $y$ is aiming to build a bond or edges to the vertices of $V_1$. Other vertices of $V_2$ are known as the Passive Vertices.

4 Graph Theoretical Model

4.1 Virus Graph I

A Bipartite V-graph $H$ is said to be Virus Graph I (VRG-I) if

1. $V(H) = I \cup N$, where, $I$ be the variable set of vertices have some special properties or infected by virus and $N$ be the variable set of vertices not having a virus.
2. If $x \in I$, creates a bond or an edge with the vertex $y \in N$ or vice versa, then $y$ is shifted to $I$ and $N = N - \{y\}$.
3. If $x \in I$, is recovered by treatment or lost properties of virus then, $x$ is shifted to $N$ and $N = N \cup \{x\}$. The diagrammatic representation of VRG-I is shown in Fig. 1.

4.2 Virus Graph II

A Tripartite V-graph $H$ is said to be Virus Graph II (VRG-II) if

1. $V(H) = I \cup N \cup F$, where, $I$ be the variable set of vertices having the virus, $N$ be the variable set of vertices not having virus and $F$ be the set of vertices which can never be shifted to $I$ or $N$.
2. If $x \in I$, creates a bond or an edge with the vertex $y \in N$ or vice versa, then $y$ is shifted to $I$ and $N = N - \{y\}$.
3. If $x \in I$, is recovered by treatment or vanished properties of virus then, $x$ is shifted to $N$ and $N = N \cup \{x\}$.
4. Vertices of $I$ are shifted to $F$ if the vertices are infected forever. Therefore, $S$ is the non-decreasing variable set. This is represented in Fig. 2.
4.3 Virus Graph III

A Tripartite V-graph $H$ is said to be Virus Graph III (VRG-III) if

1. $V(H) = I \cup N \cup S$, where, $S$ be the set of vertices which is never infected by the virus.
2. If $x \in I$ creates a bond or an edge with the vertex $y \in N$ or vice versa, then $y$ is shifted to \in I and $N = N - \{y\}$.
3. If $x \in I$ is recovered by treatment or lost properties of virus then, $x$ is shifted to $N$ and $N = N \cup \{x\}$.
4. Vertices of $N$, with some additional features, can be shifted to variable set $S$. Furthermore, the vertices of $S$ are protected by a shield of antivirus or some special vaccines. The vertices of $V$ can’t be directly transformed into $S$, but transformed to $N$ and $N$ to $S$. Consequently, $S$ is the non-decreasing variable set. This occurrence is shown in Fig. 3.

![Fig. 2 Virus Graph II](image)

![Fig. 3 Virus Graph III](image)


4.4 Virus Graph IV

A four partite V-graph $H$ is said to be Virus Graph IV (VRG-IV) if

1. $V(H) = I \cup N \cup S \cup F$, where, $F$ be the set of vertices which can never be shifted to $I$ or $N$ or $S$.
2. If $x \in I$, creates a bond or an edge with the vertex $y \in N$ or vice versa, then $y$ is shifted to $I$ and $N = N - \{y\}$.
3. If $x \in I$, is recovered by treatment or lost properties of virus then, $x$ is shifted to $N$ and $N = N \cup \{x\}$.
4. Vertices of $N$, with some additional features, can be shifted to variable set $S$. Furthermore, the vertices of $S$ are protected by a shield of antivirus or some special vaccines.

Vertices of $F$ can be never shifted to any other set. The elements of $F$ are having philosophy “infected once is infected forever”. It is shown in Fig. 4.

**Virus Graph**: A variable graph is said to be a Virus graph if it belongs to class of either Virus graph-I or Virus graph-II or Virus graph-III or Virus graph-IV.

5 Growth Rate

The growth rate of any V-graph is the rate of increase of active elements minus the rate of increase of passive elements.

6 Types of Growth

There are three types of growth of any virus, according to graph theory. Each type of growth is discussed as below.

![Fig. 4 Virus Graph IV](image-url)
6.1 One–One Growth

A growth is said to be one–one or 1–1 growth if one active element of the variable set infects only one active element of another set at that instant. This growth is articulated as the corona product of cycle graph with $K_1$. Here $C_m$ is the cycle graph having $r$ active elements, which are elements of the variable set $I$. Additionally, $K_1$ is an individual active element of the variable set $N$. It is shown in Fig. 5.

- Growth rate is constant

Without loss of generality, assume that there are 30% active elements in each set. Also assume that the number of infected people is extremely less than the total population. In this growth type, every day 30% new patients are increased in the set $I$. Let $I_0$ be the number of people infected by the virus at initial stage. Let $I_n$ be the number of people will be infected after $n$ days. As a result,

$$I_1 = I_0 + (0.30) I_0 = 1.3 I_0,$$

$$I_2 = I_1 + (0.30) I_1 = 1.30 I_1 = 1.3 I_1 = 1.3(1.3 I_0) = (1.3)^2 I_0$$

In general, $I_n = (1.3)^n I_0$.

Let $R$ be the rate of the virus per unit time and $I_0$ be an initial number of infected people. Therefore,

$$I_1 = I_0 + R I_0 = (1 + R) I_0,$$

$$I_2 = I_1 + (0.30) I_1 = 1.30 I_1 = 1.3 I_1 = 1.3(1.3 I_0) = (1.3)^2 I_0$$

In general, $I_n = (1.3)^n I_0$.

After second time interval,
\[ I_2 = I_1 + R_1 I_1 = (1 + R) I_1 = (1 + R)^2 I_0. \] (4)

After n time intervals, the number of infected people will be

\[ I_n = (1 + R)^n I_0 \] (5)

**Growth rate is not constant**

Now, assume that the growth rate is different in each time interval as given Table 1

After the second time interval,

\[ I_2 = I_1 + R_2 I_1 = (1 + R_2) I_1 = (1 + R_2)(1 + R_1) I_0, \] (6)

\[ I_3 = (1 + R_3)(1 + R_2)(1 + R_1) I_0. \] (7)

After n time intervals, the number of infected people is

\[ I_n = (1 + R_n) \ldots (1 + R_2)(1 + R_1) I_0. \] (8)

Moreover, at time \( t_i \), growth rate is \( R_i \) and \( R_i \) is repeated \( m_i \) times in the given interval. Hence,

\[ I_n = (1 + R_1)^{m_1}(1 + R_2)^{m_2} \ldots (1 + R_j)^{m_j} \]

where \( 1 \leq j \leq n \) and \( m_1 + m_2 + \cdots + m_j = n \). (9)

Thus, the growth of the infected people is exponential. Consider the Table 2 for the number of elements in I after nth days corresponding to various percentages of active elements with \( I_0 = 100 \).

In this growth type, by Table 2, it seems that if growth rate is 30%, then the number of infected people will reach to 1060 after 9th day, 19,005 after the 20th day, 262,000 after the 30th day and 24,793,351,109,660 after 100th day. But if growth rates are 1%, 2%, 3%, 4% and 5%, then the number of infected people will be 245, 594, 1430, 3412 and 8073 respectively after 100th days. Therefore, the growth rate of any pandemic must be very less for the welfare of mankind.
Table 2  Number of elements in I after nth days with respect to active elements

| No. of days | \( I_n \) (Growth 30%) | \( I_n \) (Growth 1%) | \( I_n \) (Growth 2%) | \( I_n \) (Growth 3%) | \( I_n \) (Growth 4%) | \( I_n \) (Growth 5%) | \( I_n \) (Growth 7%) | \( I_n \) (Growth 10%) | \( I_n \) (Growth 15%) | \( I_n \) (Growth 20%) |
|-------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| 1           | 130             | 101             | 102             | 103             | 104             | 105             | 107             | 110             | 115             | 120             |
| 2           | 169             | 102             | 104             | 106             | 108             | 110             | 114             | 121             | 132             | 144             |
| 3           | 220             | 103             | 106             | 109             | 112             | 116             | 123             | 133             | 152             | 173             |
| 4           | 286             | 104             | 108             | 113             | 117             | 122             | 131             | 146             | 175             | 207             |
| 5           | 371             | 105             | 110             | 116             | 122             | 128             | 140             | 161             | 201             | 249             |
| 6           | 483             | 106             | 113             | 119             | 127             | 134             | 150             | 177             | 231             | 299             |
| 7           | 627             | 107             | 115             | 123             | 132             | 141             | 161             | 195             | 266             | 358             |
| 8           | 816             | 108             | 117             | 127             | 137             | 148             | 172             | 214             | 306             | 430             |
| 9           | 1060            | 109             | 120             | 130             | 142             | 155             | 184             | 236             | 352             | 516             |
| 10          | 1379            | 110             | 122             | 134             | 148             | 163             | 197             | 259             | 405             | 619             |
| 15          | 5119            | 116             | 135             | 156             | 180             | 208             | 276             | 418             | 814             | 1541            |
| 20          | 19,005          | 122             | 149             | 181             | 219             | 265             | 387             | 673             | 1637            | 3834            |
| 25          | 70,564          | 128             | 164             | 209             | 267             | 339             | 543             | 1083            | 3292            | 9540            |
| 30          | 262,000         | 135             | 181             | 243             | 324             | 432             | 761             | 1745            | 6621            | 23,738          |
| 35          | 972,786         | 142             | 200             | 281             | 395             | 552             | 1068            | 2810            | 13,318          | 59,067          |
| 40          | 3,611,886       | 149             | 221             | 326             | 480             | 704             | 1497            | 4526            | 26,786          | 146,977         |
| 50          | 49,792,922      | 164             | 269             | 438             | 711             | 1147            | 2946            | 11,739          | 108,366         | 910,044         |
| 60          | 686,437,717     | 182             | 328             | 589             | 1052            | 1868            | 5795            | 30,448          | 438,400         | 5,634,751       |
| 70          | 9,463,126,845   | 201             | 400             | 792             | 1557            | 3043            | 11,399          | 78,975          | 1,773,572       | 34,888,896      |
| 80          | 130,457,239,505 | 222             | 488             | 1064            | 2305            | 4956            | 22,423          | 204,840         | 7,175,088       | 216,022,846     |

(continued)
### Table 2 (continued)

| No. of days | $I_n$ (Growth 30%) | $I_n$ (Growth 1%) | $I_n$ (Growth 2%) | $I_n$ (Growth 3%) | $I_n$ (Growth 4%) | $I_n$ (Growth 5%) | $I_n$ (Growth 7%) | $I_n$ (Growth 10%) | $I_n$ (Growth 15%) | $I_n$ (Growth 20%) |
|-------------|--------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| 90          | 1,798,463,828,896  | 245              | 594              | 1430             | 3412             | 8073             | 44,110           | 521,302          | 29,027,233       | 1,337,556,525     |
| 100         | 24,793,351,109,660 | 270              | 724              | 1922             | 5050             | 13,150           | 86,772           | 1,378,061        | 117,431,345       | 8,281,797,452     |
| 120         | 4,711,967,396,969,860 | 330              | 1077             | 3471             | 11,066           | 34,891           | 335,779          | 9,270,907        | 1,921,944,500     | 317,504,237,378   |
6.2 One-P Growth

If one active element of the variable set (I) infects at most -p active elements of another set (N) together at that instant, is called One-P growth or 1-P growth. In this case, Cm is the cycle graph having r active elements of variable set I and there is a group of P individual active elements of variable set N. Therefore, it is the corona product of the Cm with null graph having n vertices, which is shown in Fig. 6.

Without loss of generality, assume that there are R active elements in each set. R % new patients are increased every day in the set I. Let I0 be the number of people infected by the virus at initial stage. Let In be the number of people will be infected after n days.

As a result,

\[ I_1 = I_0 + (R \times P) \times I_0 = (1 + R \times P) \times I_0, \]

\[ I_2 = I_1 + (R \times P) \times I_1 = (1 + R \times P)^2 \times I_0 = (1.3)^2 I_0 \]

In general,

\[ I_n = (1 + R \times P)^n \times I_0. \]

The number of infected people will be doubled in at most P number of days which will assist for confirming the greatest value of P.

Fig. 6 One—P Growth
If $R = 0.01$ and $n = 2$, then the greatest value of $P$ is the value where $I_0$ will become doubled. Therefore, The greatest value of $P$ is $(e^{0.34657} - 1) \times 100 \approx 42$. Hence, growth is $1-P$ type if the value of $P \leq 42$. For the greater values of $P$, the growth type is $1$-all growth.

### 6.3 One—All Growth

If one active element of the variable set infects all or more than 42 active elements of another set together at that instant, is called $1$—all growth. Such types of growth occur through water or air only. This is extremely perilous for living beings. $C_m$ is the cycle graph having $r$ active elements of variable set $I$ and the group of the active elements of the variable set $N$. This is the corona product of $C_m$ with all individual elements of null graph having more than 42 vertices. Its graph is given in Fig. 7.

### 7 COVID-19

COVID-19 is a virus graph. At the initial stage, it was in the type virus graph-I. Let $V(C)$ and $E(C)$ are the variable vertex set (the set of people) and variable edge set of the COVID-19 graph $C$. Therefore, $V(C) = I \cup N$, where $I$ be the variable set of people infected by the virus COVID-19 and $N$ be the variable set of people not infected by the COVID-19. Some corona viruses can be transmitted from person to person, generally after close contact with an infected patient, for example, in a household workplace, or health care center.

The continuity of the graph $C$ can be disconnected by the disconnecting set. So, keep all vertices of either set in the disconnecting set.

That is

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Fig. 7 One—All Growth
\[ D = \{ \text{set of all edges adjacent to active vertices of I} \} \] or
\[ D = \{ \text{set of all edges adjacent to active vertices of N} \} \]  \hspace{1cm} (13)

Moreover, the cut set of C is \{I\} if \(|I| \leq |N|\), otherwise, the cut set is \{N\}. At present, every country of the world is doing the same for controlling the effect of COVID-19. We isolate people of set I as well as N or quarantine the people of set I or N, as per the necessities.

Presently, COVID-19 is in the virus graph-II type. Moreover,
\[ V(C) = I \cup N \cup F \]  \hspace{1cm} (14)

where F be the set of people, who are infected permanently. The people of the set F will not be recovered by any medicine and will die in the near future. The whole world is suffering from the effect of this virus and everyone is fervently waiting for the vaccine of this virus.

Table 3 gives the country wise starting dates of stages of the virus graph-I and II. It is observed that if we take desired precautions, then we can control the spread of the epidemic or pandemic. There are few countries still in virus graph-I and most of the countries rapidly reached to virus graph-II.

After discovering the vaccine on COVID-19, it will be shifted to virus graph-IV type. Therefore,
\[ V(C) = I \cup N \cup F \cup S, \]  \hspace{1cm} (15)

where S be the set of vertices which can never be infected by virus. That is all people in the set S are vaccinated by desired medicines.

In this situation, we need to increase the number of elements of the set S up to the whole population of the universal set. Hence, everyone will be free from the effect of the virus.

Moreover, hope that there should not be such types of pandemic, but if so, that must be Virus graph-III. This will help to preserve excellent harmony of living beings.

8 Growth Rate of COVID -19

The growth type of the COVID-19 is 1-P growth. One person can infect at most \(P \leq 42\) persons at a time. For the superior values of P, this growth is also called Small Community Spread.

Table 4 gives the number of infected people after n days with respect to different values of P and growth rates with \(I_0 = 100\).

If the growth rate is 1% and \(P = 5\), then the number of infected people will be doubled after 15 days, whereas, \(R = 5\) and \(P = 5\), then the number of infected people will be 244 after the 4th day, 1164 after 11th day, 10,842 after the 20th day and
| Sr. No. | Name of country | Virus Graph-I from | Virus Graph-II from |
|---------|-----------------|--------------------|--------------------|
| 1       | Afghanistan     | 25-Feb-20          | 24-Mar-20          |
| 2       | Africa          | 15-Feb-20          | 9-Mar-20           |
| 3       | Australia       | 25-Jan-20          | 1-Mar-20           |
| 4       | Bermuda         | 20-Mar-20          | 9-Apr-20           |
| 5       | Bhutan          | 6-Mar-20           | –                  |
| 6       | Bolivia         | 12-Mar-20          | 1-Apr-20           |
| 7       | Brazil          | 26-Feb-20          | 18-Mar-20          |
| 8       | Bulgaria        | 8-Mar-20           | 12-Mar-20          |
| 9       | Cambodia        | 28-Jan-20          | –                  |
| 10      | Canada          | 26-Jan-20          | 10-Mar-20          |
| 11      | China           | 31-Dec-19          | 11-Jan-20          |
| 12      | Colombia        | 7-Mar-20           | 22-Mar-20          |
| 13      | Denmark         | 27-Feb-20          | 16-Mar-20          |
| 14      | Egypt           | 15-Feb-20          | 9-Mar-20           |
| 15      | Europe          | 25-Jan-20          | 15-Feb-20          |
| 16      | Finland         | 30-Jan-20          | 22-Mar-20          |
| 17      | France          | 25-Jan-20          | 15-Feb-20          |
| 18      | Germany         | 28-Jan-20          | 12-Mar-20          |
| 19      | Ghana           | 13-Mar-20          | 22-Mar-20          |
| 20      | Greece          | 27-Feb-20          | 12-Mar-20          |
| 21      | Greenland       | 20-Mar-20          | –                  |
| 22      | Hungary         | 5-Mar-20           | 16-Mar-20          |
| 23      | India           | 30-Jan-20          | 13-Mar-20          |
| 24      | Indonesia       | 2-Mar-20           | 12-Mar-20          |
| 25      | Iran            | 20-Feb-20          | 23-Feb-20          |
| 26      | Iraq            | 25-Feb-20          | 14-Mar-20          |
| 27      | Ireland         | 1-Mar-20           | 12-Mar-20          |
| 28      | Israel          | 22-Feb-20          | 21-Mar-20          |
| 29      | Italy           | 31-Jan-20          | 27-Feb-20          |
| 30      | Japan           | 15-Jan-20          | 13-Feb-20          |
| 31      | Kenya           | 14-Mar-20          | 27-Mar-20          |
| 32      | Kuwait          | 24-Feb-20          | 5-Apr-20           |
| 33      | Malaysia        | 25-Jan-20          | 25-Mar-20          |
| 34      | Nepal           | 25-Jan-20          | –                  |
| 35      | Netherlands     | 28-Feb-20          | 7-Mar-20           |
| 36      | New Zealand     | 28-Feb-20          | 29-Mar-20          |
1,00,974 after 31st day. Thus the growth rate as well as the P value play a vital role in prevention of any types of epidemics.

| Sr. No. | Name of country     | Virus Graph-I from | Virus Graph-II from |
|---------|---------------------|--------------------|---------------------|
| 37      | North America       | 21-Jan-20          | 1-Mar-20            |
| 38      | Oman                | 25-Feb-20          | 1-Apr-20            |
| 39      | Pakistan            | 27-Feb-20          | 21-Mar-20           |
| 40      | Peru                | 7-Mar-20           | 21-Mar-20           |
| 41      | Poland              | 4-Mar-20           | 13-Mar-20           |
| 42      | Russia              | 1-Feb-20           | 29-Mar-20           |
| 43      | Rwanda              | 15-Mar-20          | –                   |
| 44      | Singapore           | 24-Jan-20          | 29-Mar-20           |
| 45      | South Africa        | 6-Mar-20           | 31-Mar-20           |
| 46      | South America       | 26-Feb-20          | 8-Mar-20            |
| 47      | South Korea         | 20-Jan-20          | 21-Feb-20           |
| 48      | South Sudan         | 6-Apr-20           | –                   |
| 49      | Spain               | 1-Feb-20           | 5-Mar-20            |
| 50      | Sri Lanka           | 28-Jan-20          | 29-Mar-20           |
| 51      | Sudan               | 14-Mar-20          | 15-Mar-20           |
| 52      | Swaziland           | 15-Mar-20          | 18-Apr-20           |
| 53      | Sweden              | 1-Feb-20           | 12-Mar-20           |
| 54      | Switzerland         | 26-Feb-20          | 6-Mar-20            |
| 55      | Taiwan              | 21-Jan-20          | 17-Feb-20           |
| 56      | Thailand            | 13-Jan-20          | 1-Mar-20            |
| 57      | Turkey              | 12-Mar-20          | 19-Mar-20           |
| 58      | Uganda              | 22-Mar-20          | –                   |
| 59      | United Arab Emirates| 27-Jan-20          | 1-Apr-20            |
| 60      | United Kingdom      | 31-Jan-20          | 6-Mar-20            |
| 61      | United States       | 21-Jan-20          | 1-Mar-20            |
| 62      | Vietnam             | 24-Jan-20          | –                   |
| 63      | Yemen               | 10-Apr-20          | –                   |
| 64      | Zimbabwe            | 21-Mar-20          | 24-Mar-20           |
Table 4  Number of infected people with respect to R and P

| Patient no. | $I_n$ Growth rate 1% | $I_n$ Growth rate 2% | $I_n$ Growth rate 3% | $I_n$ Growth rate 4% | $I_n$ Growth rate 5% |
|-------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
|             | $P = 3$               | $P = 5$               | $P = 3$               | $P = 5$               | $P = 3$               | $P = 5$               | $P = 3$               | $P = 5$               | $P = 3$               | $P = 5$               |
| 1           | 103                   | 105                   | 106                   | 110                   | 109                   | 115                   | 112                   | 120                   | 115                   | 125                   |
| 2           | 106                   | 110                   | 112                   | 121                   | 119                   | 132                   | 125                   | 144                   | 132                   | 156                   |
| 3           | 109                   | 116                   | 119                   | 133                   | 130                   | 152                   | 140                   | 173                   | 152                   | 195                   |
| 4           | 113                   | 122                   | 126                   | 146                   | 141                   | 175                   | 157                   | 207                   | 175                   | 244                   |
| 5           | 116                   | 128                   | 134                   | 161                   | 154                   | 201                   | 176                   | 249                   | 201                   | 305                   |
| 6           | 119                   | 134                   | 142                   | 177                   | 168                   | 231                   | 197                   | 299                   | 231                   | 381                   |
| 7           | 123                   | 141                   | 150                   | 195                   | 183                   | 266                   | 221                   | 358                   | 266                   | 477                   |
| 8           | 127                   | 148                   | 159                   | 214                   | 199                   | 306                   | 248                   | 430                   | 306                   | 596                   |
| 9           | 130                   | 155                   | 169                   | 236                   | 217                   | 352                   | 277                   | 516                   | 352                   | 745                   |
| 10          | 134                   | 163                   | 179                   | 259                   | 237                   | 405                   | 311                   | 619                   | 405                   | 931                   |
| 11          | 138                   | 171                   | 190                   | 285                   | 258                   | 465                   | 348                   | 743                   | 465                   | 1164                  |
| 12          | 143                   | 180                   | 201                   | 314                   | 281                   | 535                   | 390                   | 892                   | 535                   | 1455                  |
| 13          | 147                   | 189                   | 213                   | 345                   | 307                   | 615                   | 436                   | 1070                  | 615                   | 1819                  |
| 14          | 151                   | 198                   | 226                   | 380                   | 334                   | 708                   | 489                   | 1284                  | 708                   | 2274                  |
| 15          | 156                   | 208                   | 240                   | 418                   | 364                   | 814                   | 547                   | 1541                  | 814                   | 2842                  |
| 16          | 160                   | 218                   | 254                   | 459                   | 397                   | 936                   | 613                   | 1849                  | 936                   | 3553                  |
| 17          | 165                   | 229                   | 269                   | 505                   | 433                   | 1076                  | 687                   | 2219                  | 1076                  | 4441                  |
| 18          | 170                   | 241                   | 285                   | 556                   | 472                   | 1238                  | 769                   | 2662                  | 1238                  | 5551                  |
| 19          | 175                   | 253                   | 303                   | 612                   | 514                   | 1423                  | 861                   | 3195                  | 1423                  | 6939                  |
| 20          | 181                   | 265                   | 321                   | 673                   | 560                   | 1637                  | 965                   | 3834                  | 1637                  | 8674                  |
| 21          | 186                   | 279                   | 340                   | 740                   | 611                   | 1882                  | 1080                  | 4601                  | 1882                  | 10,842                |
| 22          | 192                   | 293                   | 360                   | 814                   | 666                   | 2164                  | 1210                  | 5521                  | 2164                  | 13,553                |
| 23          | 197                   | 307                   | 382                   | 895                   | 726                   | 2489                  | 1355                  | 6625                  | 2489                  | 16,941                |
| 24          | 203                   | 323                   | 405                   | 985                   | 791                   | 2863                  | 1518                  | 7950                  | 2863                  | 21,176                |
| 25          | 209                   | 339                   | 429                   | 1083                  | 862                   | 3292                  | 1700                  | 9540                  | 3292                  | 26,470                |
| 26          | 216                   | 356                   | 455                   | 1192                  | 940                   | 3786                  | 1904                  | 11,448                 | 3786                  | 33,087                |
| 27          | 222                   | 373                   | 482                   | 1311                  | 1025                  | 4354                  | 2132                  | 13,737                 | 4354                  | 41,359                |
| 28          | 229                   | 392                   | 511                   | 1442                  | 1117                  | 5007                  | 2388                  | 16,484                 | 5007                  | 51,699                |
| 29          | 236                   | 412                   | 542                   | 1586                  | 1217                  | 5758                  | 2675                  | 19,781                 | 5758                  | 64,623                |
| 30          | 243                   | 432                   | 574                   | 1745                  | 1327                  | 6621                  | 2996                  | 23,738                 | 6621                  | 80,779                |
| 31          | 250                   | 454                   | 609                   | 1919                  | 1446                  | 7614                  | 3356                  | 28,485                 | 7614                  | 100,974               |
8.1 Complexity

The Virus graph representation includes either adjacency matrix or adjacency list. The adjacency matrix is 2D matrix that has row and column combination. The combination may include growth rate and number of infected people. The complexity of representing this information will have $O(n^2)$. On the other side, if it is implemented using adjacency list, the complexity will be $O(v + e)$, where $v$ is vertices and $e$ is edges connecting those vertices.

8.2 Limitations

In this chapter, the data under consideration is enormous and varying, consequently the size of virus graph is extremely large. The cut sets of the graphs recommended for the prevention of the COVID-19 is large but if handled logically, will award superior results. The growth rate is high, so practically difficult to measure, but mathematically it is simple to analyze.

9 Conclusions and Future Outlook

To describe the different situations in the different contexts across different geolocations, the graph-theory has been useful. By applying different aspects of Mathematics, the world’s universal problems have had been consistently resolved. This chapter presented the graph theory and its variations to understand the outbreak of COVID-19. The concepts of graph theory have provided the mathematical modeling of the COVID-19. The detailed discussion on Virus graph and its Types has revealed that the type I and II are not dangerous as compared with type III and IV. The growth rates are modeled using graphs that show the spread of contagious and active elements are exponential. In the view of COVID-19, the country wise starting dates of stages of the virus graph-I and II is presented and the spread of this pandemic can be reduced by taking necessary precautions.

If the growth rate is 1% and $P = 5$, then the number of infected people will be doubled after 15 days. The growth rate will increase as 1164 after 11th day, 10,842 after the 20th day and 1,00,974 after 31st day. Thus the growth rate as well as the $P$ value play a vital role in the prevention of some types of epidemics. This chapter presents methods to control the spread of some types of a pandemic. The analysis and study presented in this chapter indicate a special need to identify the minutiae of pandemic and apply astonishing theories for maintaining the smooth harmony of mankind. There is an infinite scope of mathematics for the research as well as resolving the social and technical problems of the world.
References

1. West, D.B.: An Introduction to Graph Theory. Prentice-Hall, Pearson Edison India (1995)
2. Giulia Giordano, G., Blanchini, F., Bruno, R., Colaneri, P., Di Filippo, A., Di Matteo, A., Colaneri, M.: A SIDARTHE model of COVID-19 epidemic in Italy. arXiv preprint arXiv: 2003.09861 (2020)
3. Akhtar, I.H.: Understanding the CovID-19 pandemic curve through statistical approach. Cold Spring Harbor Laboratory (2020)
4. WHO: Novel Corona virus (2019-nCoV) Situation Report - 39. 2020 [cited 2020 April 20]; Available from: https://www.who.int/docs/defaultsource/coronaviruse/situationreports/20200228-sitrep-39-covid-19.pdf?sfvrsn=5bb3e7d_2
5. Chung, F.R.K., Lu, L.: Complex graphs and networks, CBMS regional conference series in mathematics. Am. Mathe. Soc. 10 (2006)
6. Bhapkar, H.R., Salunke, J.N.: The geometric dual of HB graph, outerplanar graph and related aspects. Bull. Math. Sci. Appl. 3(3), 114–119 (2014). ISSN 2278-9634
7. Bondy, J.A., Murty, U.S.R.: Graph Theory with Applications. Elsevier, MacMillan, New York - London (1976)
8. Kamal, M.S., Parvin, S., Ashour, A.S., Shi, F., Dey, N.: De-Bruijn graph with MapReduce framework towards metagenomic data classification. Int J Inf Technol 9(1), 59–75 (2017)
9. Deo, N.: Graph Theory with Applications to Engineering and Computer Science, Prentice-Hall of India (2003)
10. Mahalle, P.N., Sable, N.P., Mahalle, N.P., Shinde, G.R.: Predictive analytics of COVID-19 using information. Commun. Technol. Preprints 2020040257 (2020). https://doi.org/10.20944/preprints202004.0257.v1
11. Zmazek, B., Zerovnik, J.: Behzad—vizing conjecture and cartesian product graphs. Elect. Notes in Discrete Math. 17:297–300 (2004)
12. Frucht, R., Harary, F.: On the corona of two graphs. Aequationes Math. 4, 322–325 (1970)
13. DeCapprio, D., Gartner, J., et al.: Building a COVID-19 vulnerability index, medRxiv preprint https://doi.org/10.1101/2020.03.16.20036723
14. Fong, S.J., Li, G., Dey, N., et al.: Composite monte carlo decision making under high uncertainty of novel coronavirus epidemic using hybridized deep learning and fuzzy rule induction. Appl. Soft Comput.
15. Volpert, V., Banerjee, M., Petrovskii, S.: On a quarantine model of coronavirus infection and data analysis. Math Model Nat. Phenom. (2020)
16. Weber, A., Ianelli, F., Goncalves, S.: Trend analysis of the COVID-19 pandemic in China and the rest of the world (2020). arXiv preprint arXiv:2003.09032
17. Shinde, G.R., Kalamkar, A.B., Mahalle, P.N., Dey, N., Chaki, J., Hassanien, A.: Forecasting Models for Coronavirus (COVID-19): A Survey of the State-of-the-Art. TechRxiv. (2020). Preprint. https://doi.org/10.36227/techrxiv.12101547.v1
18. Fong, S.J., Li, G., Dey, N., Crespo, R.G., Herrera-Viedma, E.: Composite Monte Carlo decision making under high uncertainty of novel coronavirus epidemic using hybridized deep learning and fuzzy rule induction. Appl. Soft Comput. 106282 (2020)
19. Fong, S.J., Li, G., Dey, N., Crespo, R.G., Herrera-Viedma, E.: Finding an accurate early forecasting model from small dataset: a case of 2019-ncov novel coronavirus outbreak (2020). arXiv preprint arXiv:2003.10776
20. Hu, S., Liu, M., Fong, S., Song, W., Dey, N., Wong, R.: Forecasting China future MNP by deep learning. In: Behavior engineering and applications, pp. 169–210. Springer, Cham (2018)
21. Rajinikanth, V., Dey, N., Raj, A.N.J., Hassanien, A.E., Santosh, K.C., Raja, N.: Harmony-Search and Otsu based System for Coronavirus Disease (COVID-19) Detection using Lung CT Scan Images (2020). arXiv preprint arXiv:2004.03431