Self-Similar Characteristics of COVID-19 Patient arrival at Healthcare Centre – A Study Using Queuing Models

AM Girija[a],*D.Mallikarjuna Reddy[b], Pushpalatha Sarla[c]

[b]Assistant Professor, Department of Mathematics, GITAM University, Hyderabad
[a]Research Scholar, Department of Mathematics, GITAM University, Hyderabad
[c]Assistant Professor, Dept. of Mathematics, SRITW, Warangal.
*mallik.reddyd@gmail.com

Article History: Received: 10 November 2020; Revised 12 January 2021 Accepted: 27 January 2021; Published online: 5 April 2021

Abstract: The entire world is spreading of coronavirus-COVID-19 has increased exponentially across the globe, and still, no vaccine is available for the treatment of patients. The crowd has grown tremendously in the hospitals where the facilities are minimal. The queue theory is applied for the Single-server system and its self-similarity existence in a queue used to identify the queue time, waiting time, and Hurst parameter by different patient arrivals methods Health care center in our local area located in Hosapete, Ballari district, Karnataka. Due to more arrivals to the health care center for the identification and confirmation of disease covid-19. This study paper presents a sequential queuing model for estimating infections' detection and identification in severe loading conditions. The goal is to offer a simplified probabilistic model to determine the general behavior to predict how long the treatment cycle will diagnose and classify people already tested and get negative or positive results. For this type of Method, there are some graphical representations of the various measurement criteria. The modelling results showed that the patient's waiting period in the course of inquiries, detections, detecting, or treating COVID-19 in the event of imbalances in the system as a whole rise following the logarithm rule.

Keywords: Queuing model, Self-Similarity, Hurst parameter, Probabilistic model, COVID-19

1. Background

1.1 History of COVID-19(Coronavirus-2019)

The COVID-19(coronavirus-2019) was formally declared as disease identified by the World Health Organization (WHO) on 11th February 2020. After the outbreak of COVID 19, over 200 countries and regions worldwide have been affected and faced significant challenges. A Probabilistic Model for the Assessment of Queuing Time of Coronavirus Disease (COVID-19) Patients using Queuing Model To date, more than 19 million cases worldwide have been confirmed, with total deaths over 700,000 (WHO, 2020). However, around 12 million patients have also recovered from the disease. The cases in India have also increased exponentially from June'2020. The daily infection rate is growing at a rapid pace. The 1.9 million cases were reported in India by the end of July 2020, with fatalities of around 40,000. Most of the COVID-19 patients are found asymptomatic but may spread the virus to others. The asymptomatic infections lead to positive nuclear acid detection by reverse transcriptase-polymerase chain reaction (RT-PCR) samples. They are still not distinguished by a classic clinical symptom or sign or by apparent anomalies in medical transcription, like lung-computed tomography (C.T.) (Gao, W.J., Zheng, K., Ke, J., and Li, L.M., 2020). The sufficient identification of an infected individual and the elimination of the transmission path are the main points for COVID-19 surveillance (Brockwell, J. P., & Davis, A. R.1996); However, because of the lack of visible clinical signs and inadequate knowledge of prevention that leads to COVID-19's rapid spread, most asymptomatic infections do not seek medical attention (Gao, W.J., Zheng, K., Ke, J., and Li, L.M., 2020). Hospitals should provide a robust preparedness plan for COVID patients to cope with the increase in healthcare demand. The balance of request (e.g., patients) and supply (e.g., resources) is an important principle that should be integrated with the preoperational plans(Ali, I., and Omar M L A., 2020). The allocation of resources within the minimum time is a vital part of any preparedness plant. Queuing theory provides full application in assessing the time spent by the user in the system and time elapsed in waiting to avail of the service.

The computer networks field has been found to exhibit self-similarity, and it plays a prominent role in the design of such networks (M. Gospodinov and E. Gospodinova,2005). Unlike the other models to represent network traffic, self-similarity-based models are best suited to represent real network properties such as burst network traffic, etc... To accommodate the history of contacts in the intelligent decision making of future routing protocols, we identify the opportunistic networking system to possess two high-level properties of predictability and connectedness, which determine the connectivity of the network. For the nodes participating in the opportunistic data exchanges to estimate their predictability and connectedness of contacts with their neighbors, they can utilize the self-similarity present in the network connectivity.

1.2 Fundamentals of Self-similarity and Hurst Index Parameter:

Day today's mathematics usually addresses that a **self-similar** thing is precisely or roughlysimilar to a part of itself (i.e., the entire has the same shape as one or more details). Numerous objects in the real globe, such as coastlines, are statistically self-similar: parts of them show the same statistical properties at multiple scales. Self-similarity is a typical characteristic of fractals. Also, Scale invariance is an exact form of self-similarity, where at any magnification, there is a smaller piece of the object that is similar to the whole. Take an example like, a side of the Koch snowflake is both symmetrical and scale-invariant; however, by not changing shape, it can be continually magnified 3x. Hence, non-trivial resemblance manifest in fractals is illustrated by their acceptable arrangement or detail on logically small scales. Because of counterexample, while any portion of a straight line may look like the whole, further detail is not revealed. Hence, the time just beginning phenomenon is said to show self-similarity if the numerical value of certainly visible quantity $f(x,t)$ calculated at diverse times, are different, but the dimensionless matching size at a known value of x/t^2 stay invariant. However, if the quantity $f(x,t)$ exhibits dynamic scaling, then it will happen. Basic information is just an additionto the idea of the resemblance of two triangles. Also, two triangles are alike if the numerical values of their sides are different. Hence the equivalent dimensionless quantities, such as their angles, agree.

1.2.1 Mathematical Definition of self-similarity:

Definition (1): A stochastic process {x (t), t≥ 0} is known as self-similar if whichever

a> 0, there subsists b > 0 such that

$$X(at) = d\{bX(t)\} \tag{1}$$

Let d denotes the parity of finite-dimensional distributions.

Definition (2): Arrival patterns are modelled as a point process. Assume that $X = \{X_t /\ t = 1, 2\ldots\}$ are the arrivals in *t*he interval, segregate the time axis into disjoint intervals of unit length. Let X be a second-order stationary process with autocorrelation function $\gamma(k)$; $k\geq 0$ and variance σ^2 is given by

$$\gamma(k) = \frac{Cov(X_t, X_{t+k})}{Var(X_t)} \tag{2}$$

The process $'X'$ is known to be precisely second-order self-similar with the Hurst index H and variance σ^2 if

$$\gamma(k) = \frac{\sigma^2}{2}[(k+1)^{2H} - 2k^{2H} + (k-1)^{2H}], \forall\, \mathrm{k} \geq 1 \tag{3}$$

Definition (3): For each m = 1, 2, 3,…assume a new time series as $X^{(m)}=\{X_t^{(m)} /\ t = 1,2,\ldots\}$

is determined averaging the unique time series process X over non-overlapping

blocks of size m. i.e.

$$X_t^{(m)} = \frac{1}{m}\sum_{i=1}^{m} \mathrm{x}_{(\mathrm{t}-1)\mathrm{m}+\mathrm{i}}, \mathrm{t} = 1, 2, \ldots\ldots \tag{4}$$

For each m, this new series $X_t^{(m)}$, is also a second-order stationary process with ACF of $\gamma^{(m)}(k)$. Hurst index H and variance if the process $'X'$ is said to be asymptotically second-order self-similar with in terms of variance of the averaged process, we describe the similar method as

$$\gamma^{(m)}(k) = \frac{\sigma^2}{2}[(k+1)^{2H} - 2k^{2H} + (K-1)^{2H}], \forall k \geq 1 \qquad (5)$$

Explaining and interpreting are very difficult for quantifying the self-similarity in mathematics, considering its complexity. But Hurst's (Hurst, 1951) constraint is enchanting because it addresses a lot of mathematics areas: autocorrelation, fractals, wavelets, etc. Hence Hurst catalog proposes a widespread calculation, whether a time series has LRD or not. This has been useful in the examination of system traffic study and modeling. But Hurst index H was employed to approximate the self-similarity. The Hurst exponent H was named later than the hydrologist, who depleted so many years to examine the difficulty of storage of the water concludes the altitude forms of the Nile River. Here, the range of Hurst exponent is $0.5 \leq H < 1$. Also, quantifying exponent$H$ is a difficult task. Genuinely, many techniques for quantifying Hurst exponent show significantly diverse consequences& other methods were rescaled accustomed range method and correlogram method. Despite very theoretical foundations, the practical application of these methods depends on the reviewed case's nature. The calculation is expensive in terms of computational power and time.

1.2.2 Methods for computing Hurst Index:

Hurst exponent (H) is the classical parameter of measuring the intensity of self-similarity. The development of Hurst is traced before in 1951. The hydrologist H.E (Hurst H 2005) with his team investigates the optimum dam sizing of water storage and determines the Nile River's drought conditions. The Hurst parameter is used in the Financial market to make decisions about trading securities. It can also be applied in ecology to increase and decrease populations. The parameter has a range of $0.5 < H < 1$ is a measure of self-similarity. There are several methods for Hurst index evaluation in a time-series (Roughness 2003). There are various methods for estimating Hurst exponent which provides the measurement of self-similar characteristic are as follows:

(i) Method of Rescaled adjusted range statistics, (Hurst, 1978).

(ii) Variance time method, (Cox and smith,1953)

(iii) Periodogram method, (Daniell, 1948)

(iv) Correlogram method (Licklider, 1951

(v) Higuchi's method, (Higuchi, 1988)

1.3 Description of M/M/1 model:

Waiting in line to get the appointment, check-up, and treatment is the typical scenario in India. The delay in getting treatment is the most crucial time for any patient. Nearly all of us waited for days or weeks before we had a medical appointment or scheduled treatment, and we hoped for something more when we arrived. In the hospital, patients waiting for beds are not uncommon in India, and there are frequent delays in surgery or medical tests. This delay has become more longer to the spreading of Corona disease and declared a pandemic by WHO. The basic principle of queue models gives a different type of resources to make sure that the patient procedure in a hospital or another health care facility is planned practically (Nosek Jr, R. A., and Wilson, J. P, 2001).Also, due to these models' orientation to maximize or reduce, is the time spent in queues waiting for treatment, thus escalating the efficiency of the whole care method. The problems of such queuing models are that: (1) these models are typically non-linear, which makes it challenging to create an empirical model for a wide variety of stochastic simulations of the patient arrival and treatment procedures, thus requiring simulation to validate and apply this model to actual patient therapy processes; (2) These models are based on a system stationary stage, i.e., on the stabilization of the design features over time.

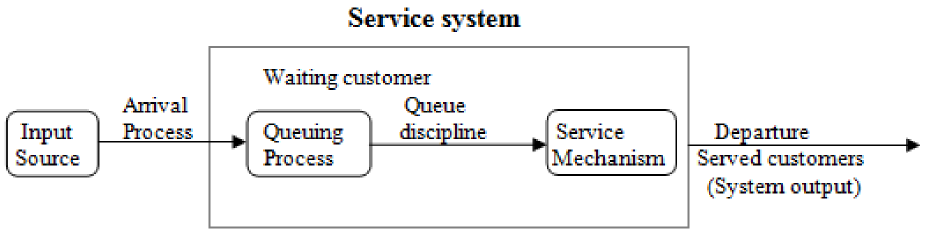

Fig-1: Service Model M/M/1

The structure of the queuing model is defined as

- input or arrival distribution,
- service distribution,
- service channels,
- maximum number of customers/objects in the system,
- population size or calling source,
- service discipline
- Input or arrival distribution: This corresponds to the pattern in which the patrons or things arrive at a service center. Arrivals are signified by the inter-arrival time, which means the time epoch among two consecutive appearances.

2. Materials and methods

In this situation, the Government of India introduced a rapid test to know the results of COVID-19 patients; under this our local area, government hospitals started rapid testing with help of Healthcare organizations where more COVID-19 expected people could test and get results within a day.

The concept of self-similarity was pioneered and is used to support modeling Geological and Hydrological problems. Self-similarity is a word where an entity's convinced property is kept concerning scale in time and space. If an entity is self-similar to its parts, a magnified bear a resemblance to the whole shape. (Meng, Q., Khoo, H.L.,2009) examined the patient's arrival to the health care center and observed that the patients waiting in queue to test COVID-19 and patients who tested confirmed results showed self-similarity characteristics.

These findings, from motivation, conclude that the arrival pattern of the testing center can be characterized as a self-similar process. Also, this study's very purpose is the quantifying Hurst exponent, addressing the intensity of self-similarity. The primary purpose of this research checked the behavior of real-life data pattern, is self-similar (Meng, Q., Khoo, H.L,2009), which is an addition to examine the presentation metrics, as mean waiting time and mean queue length against the traffic intensity. Hence research efforts, to arrive at a balance mean size of the queue and waiting time distribution for M/M/1 Queuing systems. However, the queuing system structure is cleared as input or arrival distribution, service distribution, checking channels, the severe number of patrons in the scheme, people size or calling source, service obedience.

2.1 Data of Covid-19 patients Collected from Primary Health Center

Data is collected from the Health care center of Hospital for three months, July-2020 to September-2020, i.e., 92 days, Table-1.Using this data checking how the queuing theory is working with a single server, with patients' waiting time. We calculated patients waiting time, traffic intensity and tested that the self-similarity is existing to that data. And calculated Hurst parameter using different methods like rescaled adjusted range method and correlogram method. Collected data and sorted out as day wise as Table-2.

Table-1: Data collected to test sample of COVID-19 from Healthcare center

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	W
1	Laboratory Name	Patient ID	Patient Name	Age	G	Contact Number Belongs To	State of Residence	District of Residence	Village Town	Was the patient quarantined	Date of Sample Collection	Date of Sample Received	Sample Type	Hospitalized	Hospitalization Date	Symptoms Status	symptoms	Testing Kit Used	Repeat Sample	Date of Sample Tested	Final Result Sample	
2	H B Halli Gh	2.95E+12	MOHAN	3 years	M	relative	KARNA	BAL	HB H	No	01-08-2020 10:23	01-08-2020 14:17	Thro	No	N/A	Sy	fever	Ag-SI	No	01-08-2020 14:17	Antigen Negative	
3	H B Halli Gh	2.95E+12	HANUM	50 years	M	patient	KARNA	BAL	HB H	No	01-08-2020 10:30	01-08-2020 14:18	Thro	No	N/A	Sy	fever	Ag-SI	No	01-08-2020 14:18	Antigen Positive	
4	H B Halli Gh	2.95E+12	SARAS	35 years	F	relative	KARNA	BAL	HB H	No	01-08-2020 10:33	01-08-2020 14:18	Thro	No	N/A	Sy	fever	Ag-SI	No	01-08-2020 14:18	Antigen Negative	
5	H B Halli Gh	2.95E+12	GANES	30 years	M	patient	KARNA	BAL	HB H	No	01-08-2020 10:38	01-08-2020 14:19	Thro	No	N/A	Sy	fever	Ag-SI	No	01-08-2020 14:19	Antigen Negative	
6	H B Halli Gh	2.95E+12	BASAV	41 years	M	patient	KARNA	BAL	HB H	No	01-08-2020 10:42	01-08-2020 14:20	Thro	No	N/A	Sy	fever	Ag-SI	No	01-08-2020 14:20	Antigen Negative	
7	H B Halli Gh	2.95E+12	HALAM	35 years	F	relative	KARNA	BAL	HB H	No	01-08-2020 10:47	01-08-2020 14:21	Thro	No	N/A	As		Ag-SI	No	01-08-2020 14:21	Antigen Negative	
8	H B Halli Gh	2.95E+12	JYOTHI	24 years	F	patient	KARNA	BAL	HB H	No	01-08-2020 10:51	01-08-2020 14:22	Thro	No	N/A	As		Ag-SI	No	01-08-2020 14:22	Antigen Negative	
9	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	
10	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	....	

Table-2: Day-wise sample Arrivals of COVID-19 positive cases to analyze Self Similarity and Hurst Parameter

S.No	Date	Hours	Time	No.of patients sample collected	Sample type Throat swab	Sample type Nasopharyngeal swab	confirmed cases	Negative Cases
1	01-07-2020	3Hours	10AM -2PM	30	30	0	2	28
2	02-07-2020	3 Hours	11PM-4PM	21	21	0	3	19
3	03-07-2020	4 Hours	10PM-2PM	42	42	0	2	40
4	04-07-2020	1 Hour	2Pm-3PM	16	16	0	0	16
5	05-07-2020	2Hours	1 PM-3 PM	28	28	0	1	27
6	06-07-2020	2 Hours	10 PM-12 PM	15	15	0	0	15
7	07-07-2020	3Hours	11 PM-3 PM	34	34	0	2	32
8	08-07-2020	2 Hours	10AM-12PM	20	20	0	1	19
9	09-07-2020	2 Hours	10AM-12PM	15	15	0	1	14
10	10-07-2020	2 Hours	10AM -12PM	17	17	0	1	16
11	11-07-2020	3 Hours	1PM-3PM	31	31	0	2	29
12	12-07-2020	1 Hour	1PM-2PM	14	14	0	0	14
13	13-07-2020	1 Hour	2PM-3PM	26	26	0	2	24
14	14-07-2020	1 Hour	1PM-2PM	18	18	0	1	17
15	15-07-2020	2 Hours	2PM-4PM	22	22	0	1	21
16	16-07-2020	3 Hours	12PM-4PM	35	35	0	3	32
17	17-07-2020	3Hours	10AM-3PM	25	25	0	2	23
18	18-07-2020	3 Hours	1PM-4PM	36	26	10	6	30
19	19-07-2020	2Hours	2AM-4PM	18	16	2	1	17
20	20-07-2020	4 Hours	10AM-4PM	60	60	0	0	60
....	....	....	....	....	....	....	....	....
....	....	....	....	....	....	....	....	....
....	....	....	....	....	....	....	....	....
....	....	....	....	....	....	....	....	....
92	30-09-2020	3Hours	10AM-1PM	41	0	41	7	34

Table-3: Hurst index measure for patients' arrivals by R/S Method

Day of Test	Day wise No.of Arrivals	Log (Time)	Log(R/S)	Day of Test	Day wise No.of Arrivals	Log(Time)	Log(R/S)
1	30	0.47712125	0.13114085	46	13	1.68124124	1.08550072
2	21	0.60205999	0.22135452	47	15	1.69019608	1.09173373
3	42	0.69897	0.28367455	48	41	1.69897	1.09875498
4	16	0.77815125	0.3326208	49	31	1.70757018	1.10602652
5	28	0.84509804	0.38773778	50	27	1.71600334	1.11261314
6	15	0.90308999	0.43256918	51	40	1.72427587	1.11989167
7	34	0.95424251	0.47365787	52	31	1.73239376	1.12704759
8	20	1	0.50948845	53	15	1.74036269	1.133535
9	15	1.04139269	0.54303708	54	12	1.74818803	1.14017333
10	17	1.07918125	0.57415166	55	37	1.75587486	1.147807
11	31	1.11394335	0.6005414	56	38	1.76342799	1.15529214
12	14	1.14612804	0.62610735	57	40	1.77085201	1.16324136
13	26	1.17609126	0.64925406	58	38	1.77815125	1.17133642
14	18	1.20411998	0.67007913	5960	45	1.78532984	1.18010859
15	22	1.23044892	0.68912623	61	40	1.79239169	1.18800983
16	35	1.25527251	0.70694939	62	26	1.79934055	1.19598055
17	25	1.2787536	0.72234925	63	59	1.80617997	1.20430306
18	36	1.30103	0.73863366	64	52	1.81291336	1.21208432
19	18	1.32221929	0.7534145	65	46	1.81954394	1.21918183
20	60	1.34242268	0.7708074	67	55	1.8260748	1.22773749
21	11	1.36172784	0.78797258	68	54	1.83250891	1.23664502
22	11	1.38021124	0.806093	69	42	1.83884909	1.24572148
23	6	1.39794001	0.82415429	70	21	1.84509804	1.25523595
24	8	1.41497335	0.8423439	71	75	1.85125835	1.26452441
25	13	1.43136376	0.86016132	72	80	1.8573325	1.27316119
26	54	1.44715803	0.87790441	73	54	1.86332286	1.2804125
27	29	1.462398	0.89481683	74	78	1.86923172	1.28831851
28	96	1.47712125	0.91118905	75	75	1.87506126	1.29568404
29	32	1.49136169	0.92613078	76	47	1.88081359	1.30314977
30	44	1.50514998	0.94056538	77	15	1.88649073	1.31077449
31	39	1.51851394	0.95355241	78	54	1.8920946	1.31843252
32	36	1.53147892	0.96649657	79	75	1.89762709	1.32515071
33	18	1.54406804	0.97778441	80	65	1.90308999	1.33183375
34	54	1.5563025	0.98921775	81	21	1.90848502	1.33853622
35	27	1.56820172	0.99937899	82	89	1.91381385	1.34453728
36	35	1.5797836	1.00902942	83	69	1.91907809	1.35043427
37	30	1.59106461	1.01861399	84	43	1.92427929	1.35532636
38	33	1.60205999	1.02726765	85	82	1.92941893	1.35883631

39	19	1.61278386	1.03554449	86	75	1.93449845	1.36162661
40	12	1.62324929	1.04256949	87	52	1.93951925	1.36325591
41	32	1.63346846	1.05048767	88	113	1.94448267	1.37353417
42	14	1.64345268	1.0578121	89	270	1.94939001	1.38305951
43	27	1.65321251	1.06491877	90	149	1.95424251	1.39181331
44	36	1.66275783	1.07168145	91	93	1.95904139	1.39983598
45	28	1.67209786	1.07942745	92	104	1.96378783	1.40334725

Table-4 Hurst parameter for No.of patient Arrivals per day Using Correlogram Method

Lag	Autocor relation	Std. Error	Box-Ljung Statistic			Log SNO	Log Sample ACF
			Value	df	Sig.b		
1	.575	.103	31.437	1	.000	0	-0.240219397
2	.407	.102	47.364	2	.000	0.30103	-0.390263454
3	.453	.101	67.304	3	.000	0.477121	-0.343896443
4	.473	.101	89.305	4	.000	0.60206	-0.32500331
5	.188	.100	92.815	5	.000	0.69897	-0.726046949
6	.218	.100	97.607	6	.000	0.778151	-0.660951346
7	.278	.099	105.481	7	.000	0.845098	-0.555642978
8	.196	.099	109.447	8	.000	0.90309	-0.707144128
9	.132	.098	111.257	9	.000	0.954243	-0.880036932
10	.222	.097	116.473	10	.000	1	-0.652875715
11	.182	.097	120.017	11	.000	1.041393	-0.739487192
12	.035	.096	120.147	12	.000	1.079181	-1.459146496
13	.115	.096	121.595	13	.000	1.113943	-0.93938446
14	.199	.095	126.003	14	.000	1.146128	-0.700251622
15	.170	.094	129.235	15	.000	1.176091	-0.770499055
16	.088	.094	130.122	16	.000	1.20412	-1.054003291

Table-5: Average Queue Length for various Hurst parameters

Day of Test	Patients Arrival λ	Patients testing (Service) μ	Traffic Intensity $P = \lambda/\mu$	Queue Length	H = 0.88 $\bar{L} = \frac{\rho^{0.5/(1-H)}}{(1-\rho)^{H/(1-H)}}$	H = 0.82 $\bar{L} = \frac{\rho^{0.5/(1-H)}}{(1-\rho)^{H/(1-H)}}$
1	30	45	0.6667	1.3333	26.178	15.516
2	21	38	0.5526	0.6827	21.694	12.945
3	42	78	0.5385	0.6282	21.316	12.723
4	16	19	0.8421	4.4912	46.291	26.565
5	28	39	0.7179	1.8275	29.489	17.376
6	15	30	0.5000	0.5000	20.433	12.201
7	34	45	0.7556	2.3354	32.811	19.222
8	20	23	0.8696	5.7971	54.123	30.750
9	14	17	0.8235	3.8431	42.323	24.424
10	17	19	0.8947	7.6053	64.686	36.325

11	31	80	0.3875	0.2452	18.832	11.208
12	14	22	0.6364	1.1136	24.679	14.665
13	26	43	0.6047	0.9248	23.376	13.919
14	18	23	0.7826	2.8174	35.902	20.925
15	22	25	0.8800	6.4533	57.990	32.800
16	35	77	0.4545	0.3788	19.625	11.713
17	25	40	0.6250	1.0417	24.184	14.382
18	36	47	0.7660	2.5068	33.916	19.833
19	18	21	0.8571	5.1429	50.224	28.673
20	60	68	0.8824	6.6176	58.952	33.308
21	52	64	0.8125	3.5208	40.326	23.340
22	12	16	0.7500	2.2500	32.257	18.916
23	6	7	0.8571	5.1429	50.224	28.673
24	8	11	0.7273	1.9394	30.227	17.788
25	13	17	0.7647	2.4853	33.778	19.757
26	54	73	0.7397	2.1024	31.296	18.383
27	29	44	0.6591	1.2742	25.777	15.289
28	96	112	0.8571	5.1429	50.224	28.673
29	32	44	0.7273	1.9394	30.227	17.788
30	44	52	0.8462	4.6538	47.277	27.095
31	39	47	0.8298	4.0452	43.566	25.097
32	36	46	0.7826	2.8174	35.902	20.925
33	18	33	0.5455	0.6545	21.499	12.831
34	54	110	0.4909	0.4734	20.252	12.093
35	27	33	0.8182	3.6818	41.325	23.883
36	35	44	0.7955	3.0934	37.649	21.882
37	30	43	0.6977	1.6100	28.042	16.566
38	33	82	0.4024	0.2710	18.970	11.300
39	19	22	0.8636	5.4697	52.177	29.715
40	12	20	0.6000	0.9000	23.204	13.820
41	32	48	0.6667	1.3333	26.178	15.516
42	18	26	0.6923	1.5577	27.692	16.370
43	27	50	0.5400	0.6339	21.355	12.747
44	36	58	0.6207	1.0157	24.004	14.280
45	28	58	0.4828	0.4506	20.099	12.001
46	13	30	0.4333	0.3314	19.326	11.527

47	15	23	0.6522	1.2228	25.426	15.090
48	41	44	0.9318	12.7348	93.431	51.184
49	31	68	0.4559	0.3820	19.646	11.725
50	27	49	0.5510	0.6763	21.649	12.919
51	40	81	0.4938	0.4818	20.309	12.127
52	31	37	0.8378	4.3288	45.302	26.033
53	15	16	0.9375	14.0625	100.653	54.860
54	12	13	0.9231	11.0769	84.300	46.506
55	37	47	0.7872	2.9128	36.507	21.257
56	38	43	0.8837	6.7163	59.528	33.612
57	40	58	0.6897	1.5326	27.523	16.275
58	38	53	0.7170	1.8164	29.415	17.335
59	45	76	0.5921	0.8595	22.923	13.658
60	40	52	0.7692	2.5641	34.284	20.036
61	26	30	0.8667	5.6333	53.151	30.234
62	59	78	0.7564	2.3489	32.898	19.270
63	52	128	0.4063	0.2780	19.009	11.325
64	46	49	0.9388	14.3946	102.448	55.770
65	55	98	0.5612	0.7178	21.939	13.087
66	54	65	0.8308	4.0783	43.770	25.206
67	42	51	0.8235	3.8431	42.323	24.424
68	21	22	0.9545	20.0455	132.395	70.810
69	75	85	0.8824	6.6176	58.952	33.308
70	80	125	0.6400	1.1378	24.844	14.759
71	54	58	0.9310	12.5690	92.523	50.720
72	78	83	0.9398	14.6602	103.881	56.497
73	75	155	0.4839	0.4536	20.119	12.013
74	47	51	0.9216	10.8284	82.920	45.795
75	15	31	0.4839	0.4536	20.119	12.013
76	54	65	0.8308	4.0783	43.770	25.206
77	75	115	0.6522	1.2228	25.426	15.090
78	65	110	0.5909	0.8535	22.882	13.634
79	21	27	0.7778	2.7222	35.296	20.592
80	89	97	0.9175	10.2075	79.456	44.009
81	69	99	0.6970	1.6030	27.995	16.540

82	43	60	0.7167	1.8127	29.391	17.322
83	82	154	0.5325	0.6064	21.165	12.635
84	75	86	0.8721	5.9461	55.004	31.219
85	52	61	0.8525	4.9253	48.916	27.974
86	113	150	0.7533	2.3007	32.586	19.098
87	270	300	0.9000	8.1000	67.529	37.813
88	149	160	0.9313	12.6142	92.771	50.847
89	93	165	0.5636	0.7280	22.009	13.129
90	104	135	0.7704	2.5845	34.415	20.108
91	159	170	0.9353	13.5193	97.707	53.363
92	41	43	0.9535	19.5465	129.791	69.513

2.2 Performance Measures for the Queue model M/M/1

Here we analyze the model with an exponential distribution of inter-arrival times with a mean 1/ ω and an exponential distribution of service times with mean 1/υ of a single server. The exponential distribution permits a straightforward definition position of the system with any time t. The service discipline of First Come First Served (FCFS) is accepted.

Potential utilization of service facility ρ

The potential utilization of service facilities is obtained by dividing the average arrival rate ω (in time) by the average service rate υ.

i.e. $$\rho = \frac{\omega}{\upsilon} \quad (6)$$

Whenever the value of ω is more significant, the arrival of patients will increase, and therefore the system will work harder, and queue length will be longer. Subsequently, whenever the value of ω is lesser, the queue will be shorter, than the use of the system will be low. If a patient's arrival rate within the system is more than the service rate, i.e., ω >υ then ρ> 1, which suggests the system capability lesser, than the incoming patients, Hence the queue length is increased. About queueing system, the average arrival rate is lesser than the average service rate,

i.e., ω< υ.

The average number of patients either waiting in a queue or service:

The mean number of patients either waiting in a queue or service

$p_j = (p)(q)^j$, where j=0,1,2, ….. (7)

Since the patients in the system follows the geometric distribution assume j=0, and

$p_j = (p)(q)^j$ where $p + q = 1$ (8)

Mean Number of Patients waiting in the queue or in service:

The mean number of patients within a system is equal to the mean number of patients within the queue or service. As it can be defined as

$$N = 1/(1-q) \quad (9)$$

Mean Waiting Time in Queue (Wq):

The mean waiting time in the queue (before services are provided)is equal to the meantime in which a patient waits within the queue for getting service. Hence formula is

$$W q = Lq / \omega \tag{10}$$

Mean Time Spent in the System (W_s):

The mean time spent in the system (on queue and getting service) is the same as the total time spent by a patient in a system includes the service time and waiting time. Hence formula is

$$W_s = Wq + 1 / \upsilon \tag{11}$$

2.2.1 Rescaled Adjusted Range Statistics Method

Self-similarity statistically signifies the statistical properties and is designed for the whole data sets. These are identical to each data set's sub-sections, which are relevant to measuring the Hurst parameter, where the Rescaled range statistics are calculated (Gospodinov, M., E. Gospodinova,2005) over divisions of various sizes. Fig-2 describes that the Rescaled range is computed for the whole data set ($RSave_0 = RS_0$). After that, it is calculated for bisects of two data sets, ensuing RS_0 and RS_1. Procedure persists by separating each one of preceding sections in half and manipulative rescaled range of each of the new and averaging each section's Rescaled range values. The subsection ends as the unit acquires very small (as a minimum of eight data points).
The Hurst index H is approximated by measuring the mean of rescaled range over several sections of data. Designed of available observations as a set, $X_1, X_2, ..., X_n$ by the sample mean $\mu = E[X_i]$ be described a series of regulated partial sums:

$$W_j = (X_1 + X_2 + ::: + X_j) - jX(n),\ j = 1, 2, 3......n \tag{12}$$

Where $\overline{X}$ is the average of the first n number of observations.

$R(n)$ is the range described as

$$R(n) = max\ (0, W_1, W_2, ..., W_n) - min\ (0, W_1, W_2, ..., W_n) \tag{13}$$

$S(n)$ is the standard deviation of the observations $X_1, X_2, ..., X_n$ is defined as

$$S(n) = \sqrt{E(X_i - \mu)^2} \tag{14}$$

The Hurst index be accessible through a rescaled adjusted range

$$R/S \text{ statistics} = R(n)/S(n) \tag{15}$$

The predictable value of $R(n)=S(n)$ asymptotically gratify the power-law relation

$$E\left[\frac{R(n)}{S(n)}\right] \to cn^H, \text{ as } n \to \infty, \tag{16}$$

Where a finite constant $c > 0$ and $H > 0.5$ is Hurst index.

Through a power function with an index of 0.5, the predictable value will be described for the short range-model. $E\left[\frac{R(n)}{S(n)}\right] \to dn^{0.5}$, as $n \to \infty$, (17)

Where d is the finite constant. The variation among Equation -15 and Equation-17 is called the Hurst effect.

<table>
<tr><td colspan="16">RS₀</td><td>RSave₀</td></tr>
<tr><td colspan="8">RS₀</td><td colspan="8">RS₁</td><td>RSave₁</td></tr>
<tr><td colspan="4">RS₀</td><td colspan="4">RS₁</td><td colspan="4">RS₂</td><td colspan="4">RS₃</td><td>RSave₂</td></tr>
<tr><td colspan="2">RS₀</td><td colspan="2">RS1</td><td colspan="2">RS2</td><td colspan="2">RS3</td><td colspan="2">RS₄</td><td colspan="2">RS₅</td><td colspan="2">RS₆</td><td colspan="2">RS₇</td><td>RSave₃</td></tr>
<tr><td>RS₀</td><td>RS₁</td><td>RS₂</td><td>RS₃</td><td>RS₄</td><td>RS₅</td><td>RS₆</td><td>RS₇</td><td>RS₈</td><td>RS₉</td><td>RS₁₀</td><td>RS₁₁</td><td>RS₁₂</td><td>RS₁₃</td><td>RS₁₄</td><td>RS₁₅</td><td>RSave₄</td></tr>
</table>

Fig-2 R/S method

2.2.2 Correlogram Method

The plot of Autocorrelation Function (ACF) in time series analysis is acknowledged like correlogram, where the approximated correlation can be specified in terms of ACF of $\gamma(k)$ as(Brockwell, J. P., & Davis, A. R.1996)

$$\rho(k) = \frac{\gamma(k)}{\gamma(0)} \qquad (18)$$

It is examined as slow rot of correlation, and proportional to k^{2H-2} for $0.5 < H < 1$ specify Long-memory process. As a result of the sample, ACF is supposed to show this property. An enhanced plot for performing LRD is the plot for Auto Correlation Function within the logarithmic scale. For long memory processes, if an asymptotic decay of correlation is hyperbolic, subsequently the points in the plot supposed to roughly scattered in the order of a line through a -ve slope of $2H$-2, the points must be inclined to diverse of minus infinity on an exponential tempo for short memory process. If the series has LRD, then the log-log correlogram is very helpful. Since a preface heuristic approach of data, it is a realistic one. Some difficulty about sample correlation exists, which is not as much recognized can be establishing (Beran, J., Taqqu, M.S. and Willinger, W, 1995). Although it is neither extensively used nor the striking process of assessment, the self-similarity measuring index H can be approximated with this method. Obtaining the form of an equation is

$$\rho(k) = \hat{H}(2\hat{H} - 1)k^{2\hat{H}-2} \qquad (19)$$

In this segment, we describe some numerical results of mean queue length ($\bar{L}$) against traffic intensity. For that, we use the formula (Gunther 2000) given under

$$\bar{L} = \frac{\rho^{0.5/(1-H)}}{(1-\rho)^{H/(1-H)}} \,. \qquad (20)$$

3. Numerical results and discussion:

Using Table-2 day-wise patients' arrival data of COVID-19 we analysed that the arrival pattern is having self-similarity expressed in Fig-3.And Using Table-2 day-wise COVID-19 cases confirmed patients have self-similarity, which is described in Fig-4.

Hurst index parameter Calculated for patients arrivals by R/S method we get 0.8824by (PushpalathaSarla, Mallikarjuna Reddy, 2020) ρ is the traffic intensity, Results are demonstrated in Table-3 and it’s liner trend in Fig -5. By applying the Correlogram Method, we get 0.8195expressed in Table-4.Its graphical representation trend figure is depicted in Fig-6.

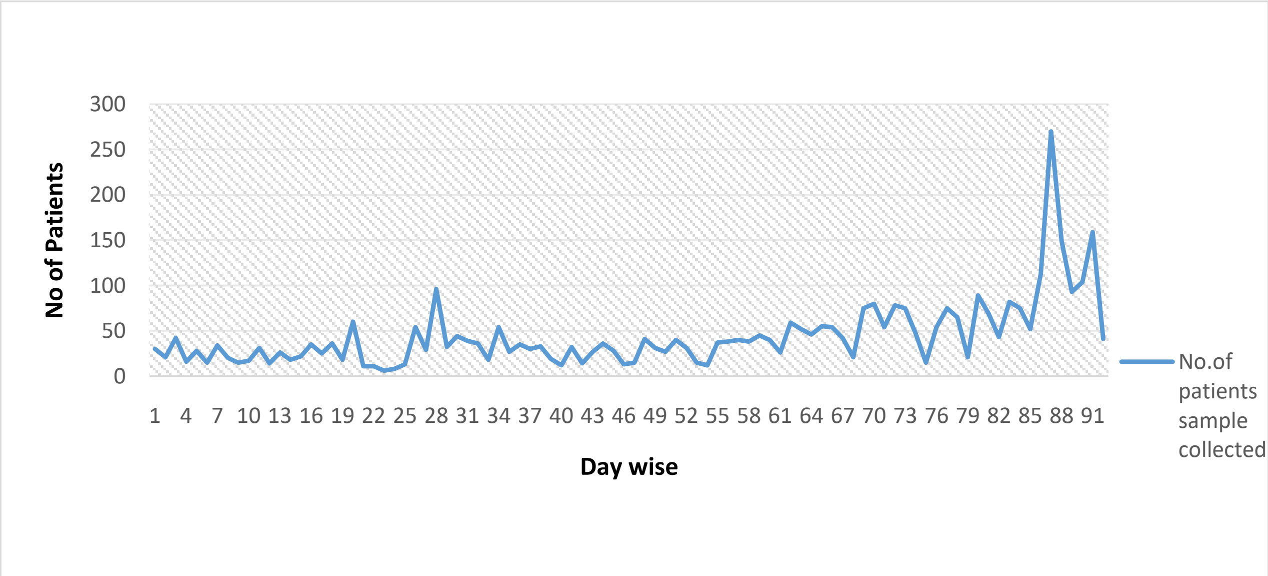

Fig-3: Self-similar Nature of Number of Patients arrival

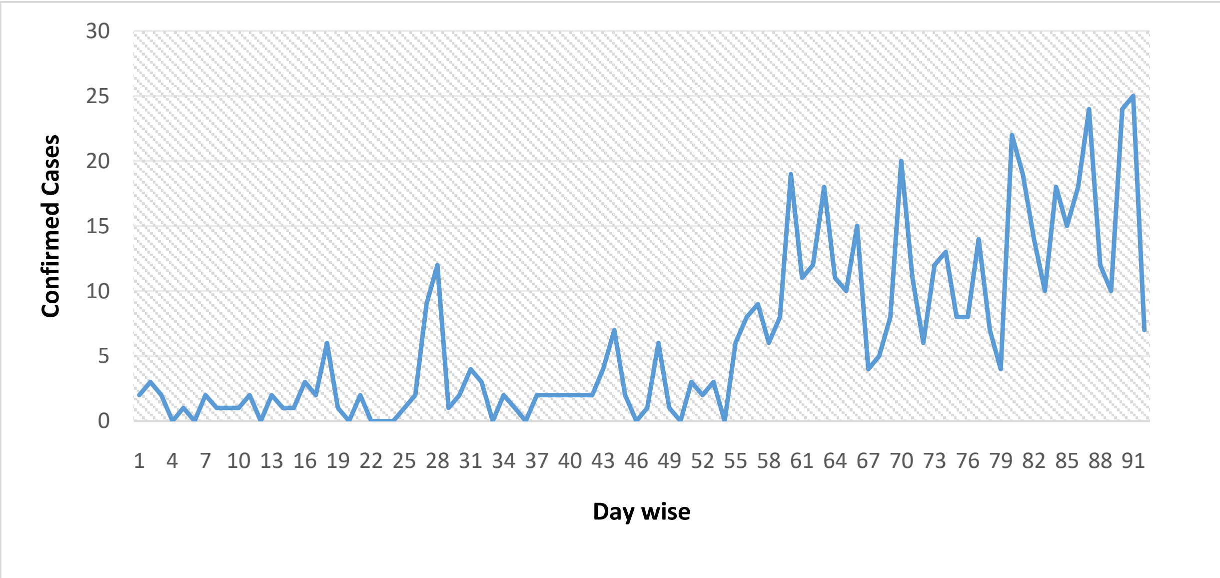

Fig-4: Self-similarity behavior of COVID-19 Confirmed cases

From Fig-3 and Fig-4,we observed that there was a self-similar pattern of the number of patients arrivals to the COVID-19 test. And even COVID-19 confirmed cases also resemble self-similarity. These findings warrant further inquiry. It showed apparent survival of self-similarity in the patient's arrival and their confirmation of positive cases.

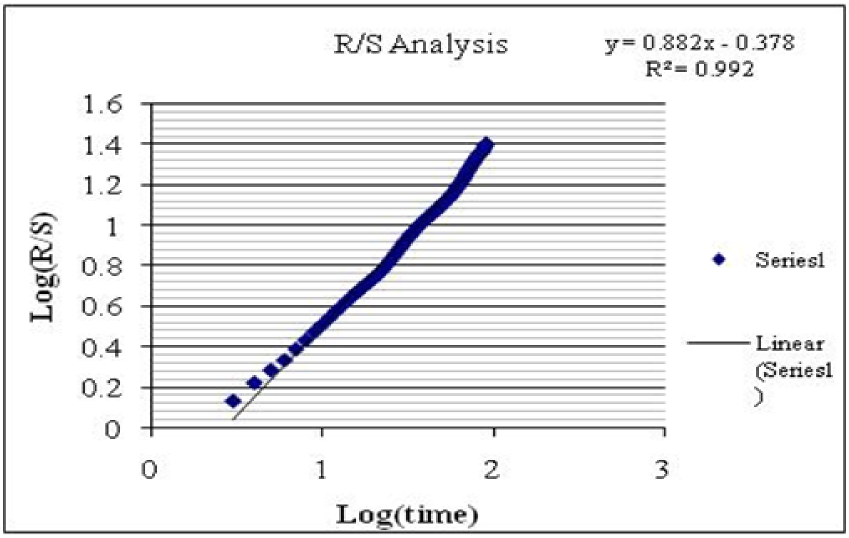

Fig-5 Hurst Index Parameter by R/S Method

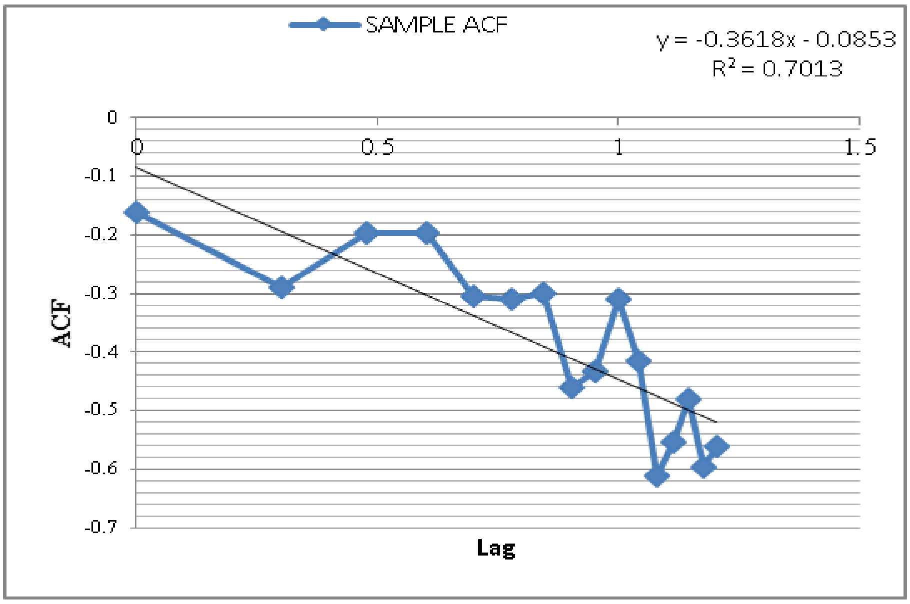

Fig-6 Hurst Index Parameter by Correlogram Method

Calculating queue length($\bar{L}$): $\bar{L} = \frac{\rho^{0.5/(1-H)}}{(1-\rho)^{H/(1-H)}}$

Traffic intensity versus Queue Length using M/M/1 model shows that increase in queue traffic intensity also increases. By Hurst Index parameter by R/S Method is 0.8824, and corresponding queue length is $\bar{L}$ is calculated in Table-5, and by using the Correlogram method is 0.8195. For this, we computed queue length is $\bar{L}$ in the same Traffic intensity versus $\bar{L}$ using Hurst index parameter showed inFig-8. As shown in the figures, we can conclude that as traffic intensity increases, the queues average length increases, which is expected. As well, when *H* increases, the average size of the queue increases resulted in Table-5. This result concurs with our observation.

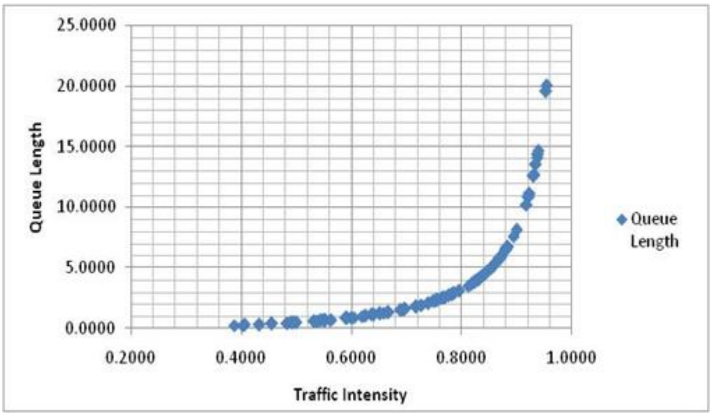

Fig-7 Queue length V/s Traffic intensity of COVID-19 patients M/M/1 model

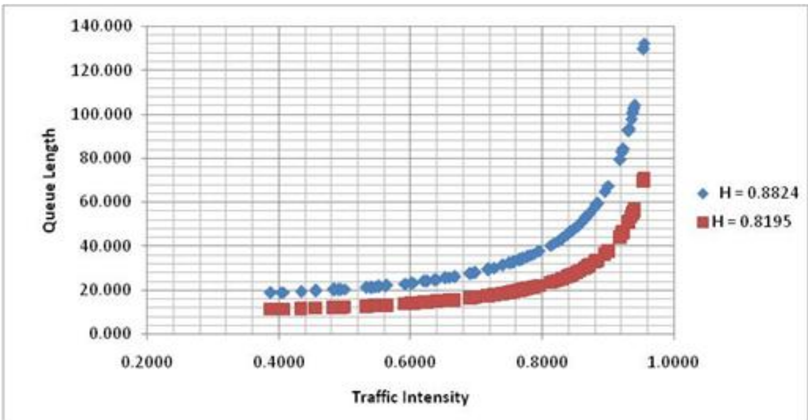

Fig-8 Queue length V/s Traffic intensity of COVID-19 patients' arrival

4. Conclusion:

In this paper's real information related to Covid-19 data from the healthcare, the center shows self-similarity using Hurst index methods. Also, calculate the average queue length using M/M/1 formulae and using the mean size, and we compare results with M/M/1 model and queue length using the Hurst index formula. Based on the concept of self-similarity and finding the intensity of traffic using H is easy to measure the queue length and as the H value increases average queue length also increases This analysis is useful to design the Healthcare centers based on the result of the traffic intensity improve service facilities of the centers in local areas.

5. Acknowledgement:

I sincerely thank Dr.Raghunath and his staff members of Dipali Hospital, Hosapete, Ballari(Dist) who supported me to collect data of covid-19 samples testing information in this pandemic period.

I sincerely thank patients who given their personal details and supporting for my research work.

6. References:

[1] Erlang, A.K., The theory of probabilities and telephone conversations, TidsskriftMathematica, Vol. 20, pp. 33-39,(1909).

[2] Ali, I., and Omar M L A., 2020. COVID-19: Disease, management, treatment, and social impact. The science of the total environment, 728(2020): 138861.

[3] Banerjee, A., Kulcsar, K., Misra, V., Frieman, M., Mossman, K., 2019. Bats and

coronaviruses. Viruses. 11(1): E41.
[4] Cochran, J.K., and Roche, K.T., 2009. A multi-class queuing network analysis methodology for improving hospital emergency department performance. Computers Operations Research,36:1497–512.
[5] Gao, W.J., Zheng, K., Ke, J., and Li, L.M., 2020. Advances on the asymptomatic infection of COVID-19. Chinese Journal of Epidemiology, 41.
[6] Meng, Q., Khoo, H.L. (2009). Self-similar characteristics of vehicle arrival pattern on highways. Journal of Transportation Engineering 135 (11): 864-872.ScholarBank@NUS Repository. https://doi.org/10.1061/(ASCE)0733-947X(2009)135:11(864)
[7] Guo, Y., Cao, Q., and Hong, Z., 2020. The origin, transmission, and clinical therapies on coronavirus disease 2019 (COVID-19) outbreak – an update on the status. Military Medical
[8] Guo, Y., Wang, J., Yue, X., He, S., and Zhang, X., 2010. The Optimization Model of Hospital Sick Beds' Rational Arrangements. In International Conference on Information Computing and Applications, 40-47, Springer, Berlin, Heidelberg.
[9] Harapan, H., Itoh, N., Yufika, A., Winardi, W., Kim, S., Te, H., Megawati, D., Hayati, Z.,Wagner, A.L. and Mudatsir, M., 2020. Coronavirus disease 2019 (COVID-19): A literature review. Journal of Infection and Public Health, 13(5), 667-673
[10]Hu, Z., Song, C., Xu, C., Jin, G., Chen, Y., and Xu, X., 2020. Clinical characteristics of 24 asymptomatic infections with COVID-19 screened among close contacts in Nanjing,China. Science China Life Science, 63(5):706–711.
[11]Gospodinov, M., E. Gospodinova. "Generator of fractional Gaussian noise for modeling self-similar network traffic," CompSysTech'2005.
[12] Brockwell, J. P., & Davis, A. R. (1996). Introduction to Time Series and Forecasting, Springer-Verlag New York Inc.
[13] Beran, J., Taqqu, M.S. and Willinger, W., Long-range dependence in variable bit rate traffic, IEEE Trans. on Communications, Vol. 43, pp. 1566-1579, (1995)
[14] D.Mallikarjuna Reddy, A.M Girija, and PushpalathaSarla. "An Application of Queuing System to patient satisfaction at a selected hospital-A field Study" AIP Conference Proceedings 2246, 020111(2020), https://doi.org/10.1063/5.0014439.
[15] Nosek Jr, R. A., and Wilson, J. P., 2001. Queuing theory and customer satisfaction: A Review of terminology, trends, and applications to pharmacy practice. Hospital pharmacy, 36(3),275-279.
[16] PushpalathaSarla, Mallikarjuna Reddy "Analytical Study of Self-similar Type Traffic Data-Queuing Techniques," AIP Conference Proceedings 2246, 020006(2020), https://doi.org/10.1063/5.0014432
[17] WHO, 2020. Coronavirus disease 2019 (COVID-19) https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports Situation Report-100.
[18] Zhu, N., Zhang, D., Wang, W., Li, X., Yang, B., and Song, J. 2020. A novel coronavirus from patients with pneumonia in China. The New England Journal of Medicine, 382: 727–733.
[19] http://www.iaeme.com/IJARET/index.asp 23 editor@iaeme.com.
[20] Hurst H 2005 Hurst parameter of self-similar network traffic International Conference on Computer Systems and Tech
[21] Roughness 2003 Length Method for Estimation Hurst Exponent and Fractal Dimension of Traces Help Benoit 1.3 version SoftwareTruSoft International Inc.
[22] M.Gospodinov and E. Gospodinova, "The graphical methods for estimating Hurst parameter of self-similar network traffic," in proceedings of ICCST, 2005.
[23] Himanshu Mittal and Naresh Sharmaonline “A probabilistic model for The Assessment of Queuing time of Coronavirusdisease(COVID-19) Patients using Queuing Model” ISSN Print: 0976-6480 http://www.iaeme.com/IJARET/issues.asp?JType=IJARET&VType=11&IType=8.