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# MATHEMATICAL MODELLING OF FIGHTING CURRENT PANDEMIC-USING FINITE SOURCE RETRIAL QUEUES

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**Abstract:** In this paper, we prefer to implement a retrial queueing contraption with a finite number of homogeneous sources for covid-19 patients, orbital requests for the care, and unstable orbit, driven by the wish for overall output models suitable for modelling and study of covid-19 patients. Day by day pandemic situation in India is more critical, patients are facing the unavailable of treatment resources so they are automatically switched into the orbit mode. Data is taken from the ICMR website, Dated: Sep 21, 2020. It is believed that all random patients who are concerned with seeking care are impartial and exponentially distributed. Regular-state analysis of the underlying continuous-time Markov process is performed victimization Time NET package constant state performance measurements are computed by providing a generalized pandemic random Petri net model. The implementation of an unstable orbit and its use in a pandemic situation is the main novelty. Numerical derivation to explain the death/ recovery time effect.

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## 1. INTRODUCTION

The global has experienced several epidemics posing a serious risk to international public health, together with the 2002 extreme acute breathing syndrome (SARS) epidemic, the 2009 H1N1 pandemic, the 2012 Middle East respiration syndrome (MERS) epidemic, the 2014 Ebola, and the cutting-edge corona-virus disease (COVID-19) pandemic [1,2]. Emerging infectious diseases maintain to infect and reduce human populations. The COVID-19 pandemic has spread to more than 114 countries before it was officially declared as a plague utilization the WHO on the $11^{th}$ March 2020. Here, the primary set of index cases in Africa and the variations among SARS-CoV-2 and different corona viruses further to the preventive strategies on the emergence of COVID-19 had been reviewed [3].

In this paper, we suggest a version that lets in discussing the trade-off the strange than deficiency and effective usage of a hospital by using displaying the positive and negative effects of services they provide for the duration of the COVID-19 state of affairs. Our most significant contribution is to present the beginning and unfolding of the worldwide pandemic shown in figure 1 and to discuss the Covid-19 pandemic in India via a generalized model of unreliable orbit finite-source retrial queues that jointly take into account unreliable hospitals[8,10,15,16] and orbit search[5,9,17-19].

The version is based on retrial queueing systems [20], now a critical day scenario in India in which regular arrivals of patients with corona inflammation who notice that all hospitals are inaccessible do not line up in a queue but are part of an orbit. An orbit is a buffer from which patients continue to get remedies before they do not recover. The hospital(s) could be passive in contrast to daily queueing systems, even though the buffer carries workers. Due to their extensive realistic applicability, e.g. on this pandemic situation, and because of their non-triviality, retrial queues had been receiving huge hobby with inside the clinical community.

Here, we are becoming aware of retrial queues for finite-supply. Therefore, the arrival of patients is non-Poisson and depends on the progress of patients already in the system. Though trial work has studied varied variants of finite-source retrial queues [5, 8-10, 12-14], the authors aren't longer turned into any dialogue concerning the irresponsibleness of the orbit, even within the limitless supply scenario.

TimeNET (version 4) software package, a graphical and interactive stochastic petri net (SPN), and stochastic colored Petri net (SCPN) modelling toolkit [24]. Queueing Petri Nets combine the power and power of modelling both queueing Petri nets and generalized GSPNs are articulate in a special class of Petri net with various advantages over regular SPNs compared to the qualitative and quantitative study of systems [25].

As follows, the paper is structured. In Section 2, we present the investigation of the generalized queueing model. In section 3, the complete model definition in the form of generalized stochastic Petri net is described, the underlying Markov continuous-time chain is discussed and the key performance measures are described. Numerical findings are presented and their effects on retrial queueing are discussed in Sect 4, conveniently extracting using the TimeNET method. Through summarizing the paper in Sect 5, we conclude.

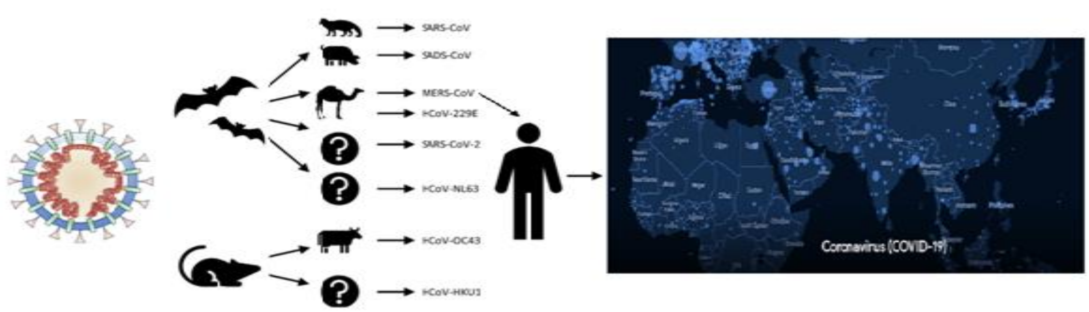


**Figure 1: Pandemic spread**

## 2. GENERALIZED RETRIAL QUEUEING MODEL

The situation is more critical every day, Covid19 patients are more than the available beds in hospitals. Now the situation is that the serious patients can get the hospital's facility others are taking a home assessment. Figure 2 describes how the patient suffers nowadays. First of all patient search in any covid19 hospitals bed are available or not if not then somehow actually needed the hospitalized facility like who have breathing problem are waiting for bed availability and some have a fever and any normal symptoms they take self-assessment or home quarantine and trying to search bed availability in the hospital. Some critical patients can't wait and they leave the queue and go to the orbit and search again in all the hospitals.

Whenever the bed is available and the critical patient gets the priority and getting the treatment. Every covid19 patient needs to be hospitalized for a minimum of 14 days, which means after that one bed free for the next patient. In this pandemic situation, the other patients suffer for their routine treatment and other patients are not taken from any other hospitals. Sometimes that patients are also trying to treatment at somehow so the queue is increased in the orbit.

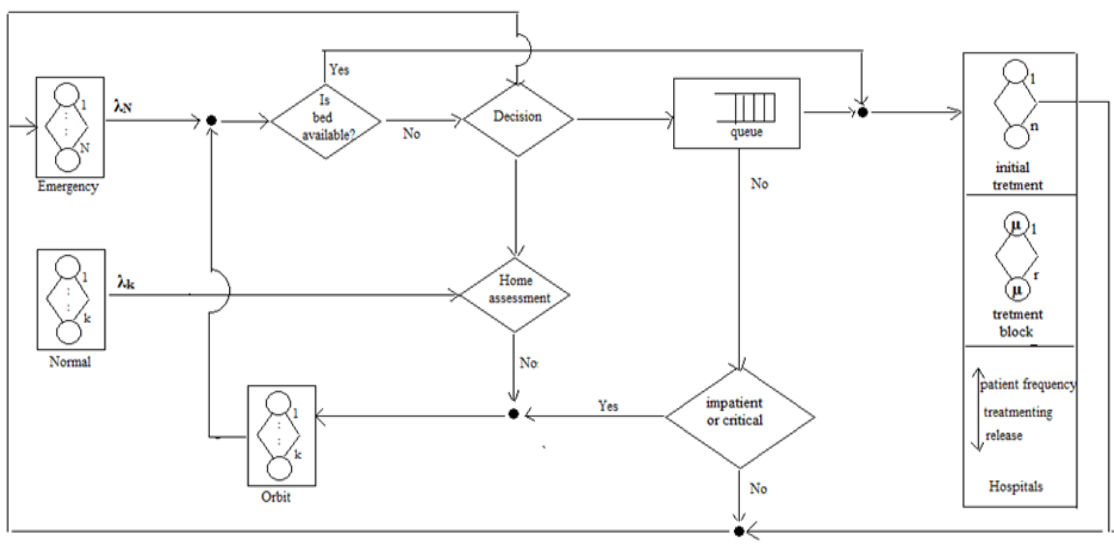


**Figure 2: Retrial queue with the components of the Covid-19 patient's situation**

## 3. MODEL AND PERFORMANCE MEASURES

In this segment, we present a Retrial queue version with the components of the Covid-19 patient's state of affairs, and this situation representing the sort of institution of nodes. Performance metrics are derived based entirely on the steady-state probabilities of the model after consulting the version in the form of a Generalized Stochastic Petri net version [6, 7 page 64] and discussing the underlying Continuous-time Markov Chain [6, 7 page 96].

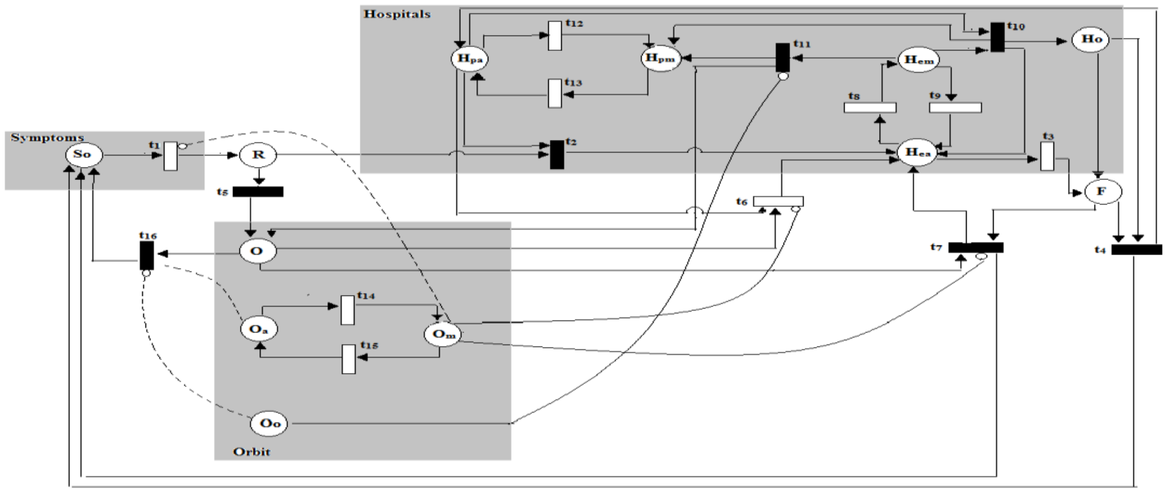


**Figure 3: The finite- resource retrial queue situation of COVID-19 patients with unreliable servers, unreliable orbit, orbital search, and outbreak situation**

### 3.1 GENERALIZED STOCHASTIC PETRI NET MODEL (GSPN)

The model is depicted graphically in the form of a GSPN in figure 3. The model is a generalization of retrial queues of finite-source with unreliable hospitals [8, 11] and retrial queue finite-source with orbital search [9,10] by adding doctors to an unstable orbit, hopping hospitals, and hospital number variable.

In Table, the main model parameters, descriptions of the positions, and the functions of the transitions are summarized. Table 3 Using charts Case parameters for the default values used as the configuration parameters.

Note that the graphical GSPN can not be mapped to all the model properties Pleasant display. For example, additional guard functions apply to the dashed inhibitor arcs. The model consists of three main parts (in Fig. 3, the grey boxes): a finite Source set, a finite server, and a part orbit. In our finite-source model, described by K Petri net tokens residing initially on location, there are k sources. Thus, all tokens in place represent events that the node under investigation does not currently, detect, register, or remember. New incidents arrive unreported at the rate of arrival (transition t1). Notice that accident reports are obtained that the node is already being processed does not suggest new activities motivating the implementation of a finite-source platform.

Tokens arriving from where they immediately attempt to join the hospitals join the place. Patients try to get the medication immediately (Represented by tokens in position R) to one of the nearest hospitals, identified by the H hospital party, defined by tokens in place R. Every hospital may be passive and ascending (tokens at $H_{pa}$), engage and ascend ($H_{ea}$), passive and miserable ($H_{pm}$), or engage and miserable ($H_{em}$). Filled hospitals reflect next-hop nodes that cannot receive incident treatment at present since they process former treatment (t3) at the same place as previous patients. A server is taken as when the corresponding next-hop node sleeps down, i.e. in energy-saving node Wear. Also, ascend and passive hospitals can collect tokens. If none the hospitals (next hops) are passive and ascend (awake), tokens arriving (incident messages) moving to orbit O through $t_5$.

Passive hospitals fail (t12), i.e. passive next hops, with a rate$\delta_{Hp}$ fall asleep. It fixes any unsuccessful passive hospital (t13), i.e. passive next-hop wakes up, with a rate of $\tau_{Hp}$ each (if$H_D \geq H$). Similarly, the involvement of hospitals fail (t8) with the rate $\delta_{He}$is repaired (t9) with $\tau_{He}$each (if $H_R$>H). We call the breakdowns independent if $\delta_{Hp} = \delta_{He} > 0$, and if$\delta_{Hp} = 0 < \delta_{He}$, we call them to care given [8]. In the following, we presume that all breakdowns and doctors are independent, respectively, of the rate $\delta \coloneqq \delta_{Hp} = \delta_{He}$ and$\tau \coloneqq \tau_{Hp} = \tau_{He}$. We call $\delta^{-1}$and $\tau^{-1}$the next hops mean, respectively, awake and sleeping time.

We also allow the number of hospital doctors $H_D$ to be lower than the number of hospitals to sustain the overall model and be able to compare the model to similar work. If $0<H_D<H$, the higher priority is given to repairing failed engaged hospitals than passive servers. $H_D$ is thus the maximum number of doctors eligible for failed passive hospitals is max (o, $H_D$-$H_{ea}$). We assume, below that $H_D$=H.

If the parameters $\sigma$ and $\emptyset$ are set to true (i.e., 1), the model permits hospitals to hop (t10) and flushing (t11) on hospital failure the hospital hopping allows the tokens to be stirred directly from a transferred from failing hospitals to the orbit. If each choice is disabled ($\sigma = 0$), hopping has a higher priority patient load at failure in hospitals, and hospital flushing is cited as next-hop dropping as incident patients are born from failing next-hops if $\emptyset = 1$.

Incident patients stored in the node under investigation for the retreat are represented by tokens located in orbit (O). After an exponentially distributed retrial period with a mean $1/\nu$, each patient waiting for treatment in the orbit (O) retries (t6) to join the community of hospitals.

The orbit is subject to failure ($t_{14}$) with a rate $\delta_0$, representing the nodes that can refrain from storing incoming patients and from treating patients for strong immunity reasons. A failed orbit get repaired ($t_{15}$) is repaired at a rate of $\tau_0$. The failed orbit can discard all stored tokens (node dropping, $\omega = 1$) through $t_{16}$ (outbreak) depending on the parameter $\omega$, or retain them for later resumption. We assume$\delta_0 = \delta$, and $\tau_0 = \tau$ in the following. If the orbit fails and it is not feasible for any patient treatment, the outbreak is the time according to the model situation($O_o$).

It is possible to model the parameters $\beta$ and $\gamma$ from unavailable sources (cf [8]) (see guard function). In the inaccessible case, if all hospitals ($\beta = 1$) and/or the orbit ($\gamma = 1$) are miserable, the active case does not generate new cells if the active case does not generate new cells. In the available case ($\beta = \gamma = 0$), neither hospitals nor orbit failures are known.

**Table 1. Parameters of the Principal Variables**

| Parameter | Symbol | Range |
|---|---|---|
| Number of symptoms | K | ℕ |
| Number of available hospitals for COVID patients | **H** | ℕ |
| Number of available doctors | **$H_D$** | ℕ |
| Arrival rate of COVID patients | $\Lambda$ | $\mathbb{R}^+$ |
| Patients service rate | $\mu$ | $\mathbb{R}^+$ |
| Retrial rate | $\nu$ | $\mathbb{R}^+$ |
| Search probability | $p$ | 0,1 |
| Engage hospitals dissolution rate | $\delta_{he}$ | $\mathbb{R}^+$ |
| Engage hospitals repair rate | $\tau_{he}$ | $\mathbb{R}^+$ |
| Passive hospitals dissolution rate | $\delta_{hp}$ | $\mathbb{R}^+$ |
| Passive rate of hospitals doctors | $\tau_{hp}$ | $\mathbb{R}^+$ |
| Orbit dissolution rate | $\delta_o$ | $\mathbb{R}^+$ |
| Orbit repair rate | $\tau_o$ | $\mathbb{R}^+$ |
| Hospitals outbreak | $\xi$ | $\mathbb{R}^+$ |
| Orbit outbreak | $\psi$ | $\mathbb{R}^+$ |
| Hospitals hopping[2] | $\sigma$ | 0,1 |
| Hospitals unavailability[2] | $\beta$ | 0,1 |
| Orbit unavailability[2] | $\gamma$ | 0,1 |
| Hospitals flushing[2] | $\phi$ | 0,1 |
| Orbit flushing[2] | $\omega$ | 0,1 |

**Table 2 Places indicated in the Fig. 3 Petri net**

| ID | Description | Capacity | Initial value |
|---|---|---|---|
| $S_0$ | Most common symptoms | K | K |
| R | Incoming request | 1 | 0 |
| $H_{aa}$ | Hospitals, engage & ascend | H | 0 |
| $H_{pa}$ | Hospitals, passive & ascend | H | H |
| $H_{em}$ | Hospitals, engage & miserable | H | 0 |
| $H_{pm}$ | Hospitals, passive & miserable | H | 0 |
| $H_0$ | Hospitals & outbreak | H | H |
| O | Orbit | K | 0 |
| $O_a$ | Orbit ascend | 1 | 1 |
| $O_m$ | Orbit miserable | 1 | 0 |
| $O_0$ | Orbit outbreak | 1 | 1 |
| F | Finished requests | 1 | 0 |

The inaccessible supply case reflects the node's ability to minimize incoming patients as a result of the consecutive hop isn't accessible (next-hop unavailability, $\beta = 1$) or because the node itself is in immunity booster mode (node blocking, $\gamma = 1$). Here, the facility saving of the examined node relates to matters wherever it will still handle patients within the next situation where it can still handle patients in future hops, however, refrains from storing and re-trying new events that can't be managed immediately.

**Table 3:** Normal usage case dependent parameters

| **Parameter** | **Symbols** | **Default** |
|---|---|---|
| Variety of forms of cases | $K$ | 13 |
| Imply inter-arrival time per incident unreported | $\lambda^{-1}$ | 11min |
| Suggest retrial time per incident message saved | $\nu^{-1}$ | 3 ms |
| Variety of probable upcoming hops | S | 2 |
| The processing time at the subsequent hop implies | $\mu^{-1}$ | 0.12 ms |
| The probability that the node is aware of the hop service | $\wp$ | 0.1 |
| Sleep/unsleeping time ratio | $\alpha$ | 10 |
| Wakeful time means all nodes' | $\delta^{-1}$ | 116 |
| All nodes' imply time to sleep | $\tau^{-1}$ | 0.13 |
| A shift of patients from snoozing to next-hop operational | $\sigma$ | 0 |
| Message to drop when falling asleep | $\emptyset . \omega$ | 0 |
| If next-are down or re-forwarding is down, block incoming patients | $\beta, \gamma$ | 0 |

A passive patient rehabilitation hospital (token at location F) informs the (operational) orbit of its coming idleness with likelihood P and, if available, receives direct treatment ($t_7$) with a probability of 1-P the next token from the orbit (orbital search), no orbital search is conducted ($t_4$) and also the hospital situation is therefore crossbred within the situation. For $P \approx 1$, a consistent retrial queue efficiency. It is similar to the performance of a typical first come to the first queue, except only care is conducted on a priority basis when an outbreak situation occurs. In the following, we assume that the node examined becomes aware of the next-hop idleness with a 10% probability, i.e., P = 0.1.

### 3.2 UNDERLYING MARKOV CHAIN .

The defined Generalized Stochastic Petri Net COVID- 19 pandemics can be mapped to the five-dimensional stochastic techniques $X(t) = (H_{ea}(t), H_{em}(t), H_{pa}(t), O(t), O_a(t))$, where $0 \leq$

$\mathrm{H_{ea}}(t) \leq \min(\mathrm{H}, \mathrm{K})$, $0 \leq \mathrm{H_{em}}(t) \leq \min(\mathrm{H}, \mathrm{k})$, $0 \leq \mathrm{H_{pa}}(t) \leq \mathrm{H}$, $0 \leq \mathrm{O}(t) \leq \mathrm{K}$, and $\mathrm{O_a} \in \{0,1\}$ are the number of tokens in locations $\mathrm{H_{ea}}$, $\mathrm{H_{em}}$, $\mathrm{H_{pa}}$, $\mathrm{O}$, $\mathrm{O_a}$ respectively at time $t \geq 0$. Note that $\mathrm{H_{pm}}(t) = \mathrm{H} - (\mathrm{H_{ea}}(t) + \mathrm{H_{em}}(t) + \mathrm{H_{pa}}(t))$, $\mathrm{H_0}(t) = ((\mathrm{H_{ea}}(t) + \mathrm{H_{em}}(t)) < \max(\mathrm{R}))$, $\mathrm{S_0}(t) = \mathrm{K} - (\mathrm{O}(t) + \mathrm{H_{ea}}(t) + \mathrm{H_{em}}(t))$, $\mathrm{O_m}(t) = 1 - \mathrm{O_a}(t)$, $\mathrm{O_o}(t) = 1 - \mathrm{O_m}$. Places R and F cannot currently be thought-about as a result of all states wherever R(t) > 0 or F(t) > 0 have non-existent as a result of the approved care request on the spot.

Since all concerned random variables are exponentially distributed, X(t) constitutes a Continuous-time Markov Chain. We denote the state space of X(t) with X. As X is both finite and irreducible, for all the enormous values of the arrival rate λ, the continuous-time Markov Chain is periodic. From now on, it is assumed that the system is in a stable, i.e. $t \to \infty$. We refrain from visualizing it here because of space constraints and the high complexity of the underlying Continuous-time Markov Chain. We also choose to give equations based on K and S for the size of X, which is a tedious combination issue. Note that for a model of less complexity [5, 6].

### 3.3 MAIN PERFORMANCE MEASURES

The stationary probability of the Continuous-time Markov Chain discuss in the previous section are $P\left(\mathrm{H_{ea}}(t), \mathrm{H_{em}}(t), \mathrm{H_{pa}}(t), \mathrm{O}(t), \mathrm{O_a}(t)\right)$

$$= \lim_{t\to\infty} P(\mathrm{H_{ea}}(t) = \mathrm{h_{ea}}, \mathrm{H_{em}}(t) = \mathrm{h_{em}}, \mathrm{H_{pa}}(t) = \mathrm{h_{pa}}, \mathrm{O}(t) = \mathrm{o}, \mathrm{O_a}(t) = \mathrm{o_a})$$

Knowing the stationary probabilities, the finite- source retrial queue’s key can be output metrics can be obtained as follows:

- A total number of tokens in hospitals operating:

$$\overline{\mathrm{H_{ea}}} = \sum_{\forall(\mathrm{h_{ea}}, \mathrm{h_{em}}, \mathrm{h_{pa}}, \mathrm{o}, \mathrm{o_a}) \epsilon X} \mathrm{h_{ea}} P(\mathrm{h_{ea}}, \mathrm{h_{em}}, \mathrm{h_{pa}}, \mathrm{o}, \mathrm{o_a})$$

- The total number of collapsed hospitals tokens:

$$\overline{\mathrm{H_{em}}} = \sum_{\forall(\mathrm{h_{ea}}, \mathrm{h_{em}}, \mathrm{h_{pa}}, \mathrm{o}, \mathrm{o_a}) \epsilon X} \mathrm{h_{em}} P(\mathrm{h_{ea}}, \mathrm{h_{em}}, \mathrm{h_{pa}}, \mathrm{o}, \mathrm{o_a})$$

- The total number of orbit tokens:

$$\overline{\mathrm{O}} = \sum_{\forall(\mathrm{h_{ea}}, \mathrm{h_{em}}, \mathrm{h_{pa}}, \mathrm{o}, \mathrm{o_a}) \epsilon X} \mathrm{o} P(\mathrm{h_{ea}}, \mathrm{h_{em}}, \mathrm{h_{pa}}, \mathrm{o}, \mathrm{o_a})$$

- Chances with both hospitals being miserable

$$P_{H_m} = \sum_{\forall(0,\mathrm{h_{em}},0,\mathrm{o},\mathrm{o_a})\epsilon X} P(0, \mathrm{h_{em}}, 0, \mathrm{o}, \mathrm{o_a})$$

- Probability of a miserable orbit:

$$P_{O_m} = \sum_{\forall(\mathrm{h_{ea}},\mathrm{h_{em}},\mathrm{h_{pa}},\mathrm{o},0)\epsilon X} P(\mathrm{h_{ea}}, \mathrm{h_{em}}, \mathrm{h_{pa}}, \mathrm{o}, 0)$$

- The total number of active symptoms unavailable:

$$\overline{\mathrm{S_{ou}}} = \sum_{\substack{\forall(0,\mathrm{h_{em}},0,\mathrm{o},\mathrm{o_a})\epsilon X|\beta=1; \\ \forall(\mathrm{h_{ea}},\mathrm{h_{em}},\mathrm{h_{pa}},\mathrm{o},0)|\gamma=1;}} (K - (\mathrm{h_{ea}} + \mathrm{h_{em}}))P(\mathrm{h_{ea}}, \mathrm{h_{em}}, \mathrm{h_{pa}}, \mathrm{o}, \mathrm{o_a})$$

- Utilization of Hospitals: $\rho = \frac{\mathrm{h_{ea}}}{H}$
- The total number of hospitals engaged: $\overline{\mathrm{H_e}} = \overline{\mathrm{H_{ea}}} + \overline{\mathrm{H_{em}}}$
- The total number of flushed tokens on-orbit failure: $\overline{O_f} = \omega\bar{O}$
- The total number of tokens on-orbit or at service: $\bar{M} = \overline{H_e} + \bar{O}$
- The total number of common symptoms: $\overline{S_O} = K - \bar{M}$
- Chance of a specific symptom not being available: $P_u = \frac{\overline{S_{Ou}}}{\overline{S_O}}$
- A total number of active symptoms available: $\overline{S_{O_a}} = \overline{S_o} - \overline{S_{ou}}$
- Overall patient arrival rate: $\lambda_{in} = \lambda\overline{S_{O_a}}$
- Probability of arrival rate outbreak: $P_{ao} = \frac{\lambda\overline{S_{O_a}}}{\lambda\overline{S_O}}$
- Departure limit for the tokens provided: $\lambda_p = \mu\overline{H_{ea}}$
- Departure threshold for our tokens: $\lambda_t = \lambda_{in} - \lambda_p$
- Probability of being provided service of an incoming token: $P_p = \frac{\lambda_p}{\lambda_{in}}$
- Means time to wait: $\bar{W} = \frac{\bar{O}}{\lambda_{in}}$
- Mean response time: $\bar{T} = \frac{\bar{M}}{\lambda_{in}}$
- Chance of hospitals threshold tokens outbreak: $P_{to} = \frac{\lambda_t}{\lambda_{in}}$.

## 4. Numerical Results

We explicitly formulate the GSPN shown in Figure 3 using the modelling to derive the underlying continuous-time Markov chain and solve the framework of global balance equations manually, GSPN is checked by TimeNET. The TimeNET software package is a general-purpose, graphical, and interactive toolkit designed to model and evaluate multiple stochastic Petri net groups, including instant, exponentially distributed, deterministic, or non-exponentially distributed transition firing delays, as well as stochastic color Petri net models.

According to Tab. 3, model parameters are selected within the following segment.

On the coordinate axis of all result graphs, the parameter alpha (death/ recover ratio) is given. As commenced in Tab. 3, wherever, $\alpha = \frac{\delta}{\tau} = \frac{\tau^{-1}}{\delta^{-1}}$, $\tau^{-1}=\tau_O^{-1} = \tau_{he}^{-1} = \tau_{hp}^{-1}$ is the unit of your time that the nodes (the examined node and its passive or engaging next hops) are recovered. Therefore, α is the quantitative relation of time of the investigated nodes within the energy-saving mode. Compared to the time they're awake, the upper the α, and therefore the less energy they consume over time.

We focus on the response time $\bar{T}$, the probability of source blocking $P_u$, and the likelihood of getting $P_p$ on the y-axis of the result graphs given.

Fig. 4, 5 indicates the effect of death/recover ratio α (x-axis) and death node incident patient $\phi = \omega$ (curves) on the probability of serving $P_p$ (y-axis, bottom).

It is visible at the top of Fig. 4, 5 that dropping incident patients with stored sleeping nodes dramatically decreases the mean response time, well below the reliable scenario. This is because the patients may spend time in the hospital than successfully served treatment at their home.

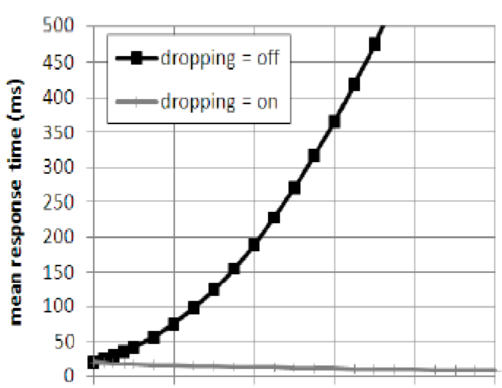


**Figure 4: Mean response time of the Hospitals**

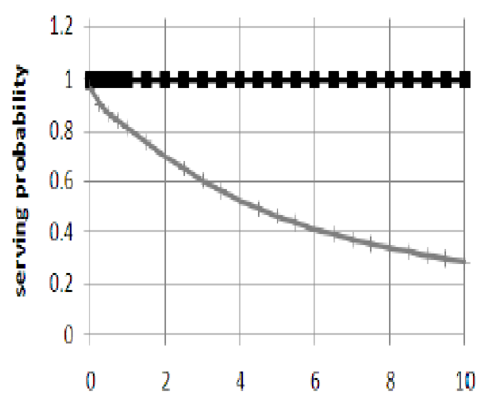


**Figure 5: Service probability**

Therefore, we tend to conjointly get to take a glance at the probability that $P_p$ for associate degree approved incident patient is going to be with success processed. This is illustrated in Fig. 4, 5 to the right. Dropping stored patients means lower probabilities for working. Dropping also only be used by out-of-date patients. However, the age of tokens cannot be regarded by the model presented.

Notice that the likelihood of recover the nodes is close to 1, even for$\alpha \approx 0$, i.e., the likelihood of serving is not necessarily close to 1. Since stored incident patients are reduced after each recovering period (regardless of how short the sleep time is afterward), the probability of serving also depends strongly on the absolute value of the recovery period.

Figure 6 indicates a rapid rise in patients' inter-arrival and an increase in the total waiting period for care and usage of hospitals and an increase in waiting time.

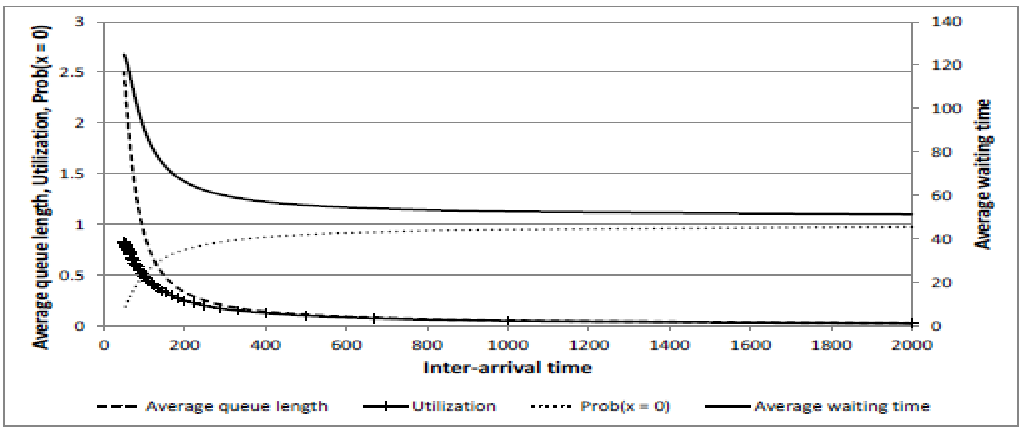


**Figure 6: Patients arrival time, average queue length and utilization**

## 5. MAIN RESULTS

A generalization of retrial queueing systems for finite-source sources is being studied. The model can be used to test the impact of an unstable orbit, in addition to unstable hospitals. In a situation of pandemic usage, the model is used to address the trade-off between immune efficiency and output. Model evaluation is carried out using the TimeNET tools Fig. 3. The GSPN model is verified by a TimeNET. The numerical outcomes are extensively discussed and demonstrate the positive and negative effects of drug treatment. Fig. 6 represents the situation today, which demonstrates how critical the situation is now. The daily arrival of positive patients is increasing, and hospitals are full and patients are in-home quarantine. Some cases have arrived now that individuals have died due to a lack of hospital treatment. Because of the immune system of Indians, the only plus point of Indian's recover rate is higher than the other nation. There is no adequate right now and no vaccine, which is why the condition is serious, so the only option is to strengthen the immune system and stay at home as much as possible.

## CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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