APPOINTMENT-BASED QUEUE MANAGEMENT SYSTEM USING GEOLOCATION INFORMATION

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DECLARATION

This thesis is a presentation of my original research work. Wherever contributions of others are involved, every effort is made to indicate this clearly, with due reference to the literature, and acknowledgement of collaborative research and discussions. The work was done under the guidance of Ir. Dr. Yen Kin Sam, at the Universiti Sains Malaysia, Engineering Campus.

Tee Kah Hui

Date: 5th June 2017

In my capacity as supervisor of the candidate's work, I certify that the above statements are true to the best of my knowledge.

Ir. Dr. Yen Kin Sam

Date: 5th June 2017

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Thank you,

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TABLE OF CONTENTS

Declaration i

Acknowledgement ii

List of Tables iv

List of Figures iv

Abstract v

Abstrak vi

Introduction 1

Queue Modelling 2

Model Validation 6

GeoQueue Algorithm 7

A. Information collection 8

B. ETA calculation 10

C. Time slot arrangement 11

Result & Discussion 12

Conclusion 19

References 20

Appendix 22

LIST OF TABLES

Table 1: Statistics of waiting time and service time in OPD

Table 2: Result of two-tailed t-test

Table 3: Patients' information with their ETA and arranged time slot

Table 4: Simulation result for different number of doctors in service

LIST OF FIGURES

Fig. 1. Total daily patient for August, September, and October 2016

Fig. 2. Process flow of OPD

Fig. 3. M/G/c queue model in Simulink

Fig. 4. GeoQueue algorithm flowchart

Fig. 5. Screen shot of MATLAB mobile sensors

Fig. 6. Available time slot

Fig. 7. Sample result of Google Distance Matrix API

Fig. 8. Comparison between arrival pattern of patient before and after GeoQueue.

Fig. 9. Waiting time distribution before GeoQueue

Fig. 10. Waiting time distribution after GeoQueue

Fig. 11. Waiting time comparison (5 doctors)

Fig. 12. Waiting time comparison (4 doctors)

Fig. 13. Waiting time comparison (3 doctors)

Fig. 14. Waiting time comparison (2 doctors)

Fig. 15. Waiting time comparison (1 doctor)

ABSTRACT

Queues are often seen in hospitals across Malaysia. Majority of outpatient departments (OPD) receive patients by unscheduled walk-in which results in an uncontrollable and unpredictable arrival rate. When the arrival rate exceeds the service capacity of OPD, a queue is formed. Patients are required to queue for more than two hours at OPD in Malaysia government hospital. Hence, reduction of waiting time is one of the major issues that need to be tackled. Previous works have never consider reducing the waiting time by controlling the arrival rate of OPD patient. This work aims to develop an appointment-based queue management system using geolocation information (GeoQueue) to tackle long queues. A current OPD queue model was simulated with discrete-event simulation (DES) method. Average waiting time of a queue was obtained as the performance index. GeoQueue was developed to provide the patients a time slot to arrive at OPD based on their geolocation information. Result from that, the arrival rate of patient is controllable and predictable. A uniform arrival rate of 16 patients per hour was achieved with GeoQueue. Simulation model reveals that the GeoQueue realizes a shorter waiting time for patients. Average waiting time of patients had been reduced by 62%.

Index Terms— Discrete-event simulation, Geolocation information, Queue management system

ABSTRAK

Barisan panjang sering berlaku di Jabatan Pesakit Luar (OPD) seluruh Malaysia. Majoriti OPD menerima pesakit luar tanpa temu janji. Keadaan ini menyebabkan kadar ketibaan pesakit ke OPD tidak terkawal dan tidak dapat diramalkan. Apabila kadar ketibaan melebihi kapasiti perkhidmatan OPD, barisan terbentuk. Pesakit perlu beratur lebih daripada dua jam di OPD dalam hospital kerajaan Malaysia. Oleh itu, pengurangan masa menunggu adalah salah satu isu utama yang perlu diselesaikan. Penyelidikan terdahulu tidak pernah menimbang kaedah untuk mengurangkan masa menunggu dengan kawalan atas kadar ketibaan pesakit. Penyelidikan ini bertujuan untuk membangunkan satu sistem pengurusan giliran berdasarkan maklumat geolokasi (GeoQueue) untuk menangani isu barisan panjang. Model barisan di OPD telah disimulasikan dengan mengunakan kaedah Discrete-event simulation (DES). Indeks prestasi merupakan purata masa untuk menunggu giliran. GeoQueue telah dibangunkan untuk menyediakan pesakit slot masa untuk tiba di OPD berdasarkan maklumat geolokasi mereka. Justerunya, kadar ketibaan pesakit dapat dikawal dan diramal. Kadar ketibaan yang seragam sebanyak16 pesakit bagi setiap jam telah dicapai oleh GeoQueue. Model simulasi juga mendedahkan bahawa GeoQueue menyedari masa menunggu yang lebih pendek untuk pesakit. Purata masa menunggu pesakit telah dikurangkan sebanyak 62%.

INTRODUCTION

Queuing or waiting in line has become a common situation that occurs in everyday life. Queues are seen at hospitals, car service centers, restaurants and financial institutes. Queue usually formed when there is large amount of demand with a limited amount of supply according to Levent (2007). In Malaysia, outpatient department (OPD) of government hospital is one of the places that often suffers from long waiting line. A study conducted by Pillay *et al.* (2011) in a total of 21 government hospitals across Malaysia found that patients wait for more than two hours in average to receive their treatment while the contact time with doctors is only on average 15 minutes. Suki *et al.* (2011) also reported that patients must queue for more than an hour in hospitals around Klang Valley area, Malaysia.

Consequences of long waiting time is that it reduces the satisfaction level of patients towards the service provided. Uehira & Kay (2009) documented that waiting time in OPD has been the source of dissatisfaction among patients. Negative impacts are imposed on the reputation of hospital caused by ineffectiveness in handling long queue as suggested by Barlow (2002).Besides patients' satisfaction, there is also physical loss due to excessive queuing. Kembe *et al.* (2012) found that excessive queue is one of the major problems that incurred cost to the operation of hospital. A study conducted by Sullivan (2016) shown that Malaysia healthcare expenditure could rise up to USD 20 billion by year 2020. To maximize the usage of these expenditure, it is crucial to optimize the hospitals resources effectively and reduce unnecessary operational cost

Some solutions had been proposed to tackle the excessive waiting time issue. Virtual queueing and appointment scheduling are found to be able to reduce waiting time of patient. Lange *et al.* (2013) claimed that virtual queueing can reduce the chances of arrival peak with no negative effects on queue. A whitepaper published by QMatic (2013) reported a 70% decrease in actual waiting time by implementing virtual queue. Beside virtual queue system, Cayirli *et al.* (2006) concluded that patient sequencing is an important factor that affects the waiting time. Wijewickrama & Takakuwa (2005) also identified some effective appointment scheduling rules that can reduce the patients' waiting time while maximizing the utilization of doctors without any additional resources.

As discussed earlier, long queue consumes hospital resource. Many studies had been conducted on the use of queueing theory and modelling technique in optimizing resources of healthcare services. Vass & Szabo (2015) proposed a queue model based on M/M/3 queue theory to monitor the patient flow. The model was used for decision making and optimization of waiting time for patients. Belciug & Gorunescu (2014) further employed genetic algorithm (GA) along with queuing model to optimize the resource allocation of a hospital.

To our knowledge, there are no study conducted on arrival control to reduce patients' waiting time. Lee *et al.* (2013) compared the performance of open access and overbooking in appointment scheduling but did not consider arrival control.

Bhattacharjee & Ray (2016) examined the appointment system with respect to patients' mean service time and determined the best performance among multiple classes of patients. However, they considered only the classification of patients to determine inter-appointment time. Other solutions such as proposed by Hassan *et al.* (2015) to involved sub-retailers has not considered the use of technological advantage to reduce the waiting time of patients.

In this study, discrete-event simulation (DES) method was used to model the condition in OPD. Giachetti *et al.* (2005) proposed the use DES to address the three main problems in outpatient department. Ben-Tovim *et al.* (2016) used DES to simulate the patient flow of a teaching hospital with mathematical and statistical modelling technique. An extensive review of application of DES in healthcare can be found in Günal & Pidd (2010).

Current system in OPD receives walk-in patients with an uncontrollable arrival rate. Enabling appointment system in advance to the outpatients is one of the ways to reduce long queue. Appointment-based queue management system using geolocation information (GeoQueue) is developed to allocate a specific date and time for arriving client to a service facility. To develop an appropriate GeoQueue, several factors need to be taken into consideration such as the arrival pattern of patients, service duration of doctors, patient's location and mode of travel.

In this work, the main objective is to reduce the overall waiting time of OPD by controlling the arrival rate of patient. A model will be created to simulate the queue condition in OPD. Then, GeoQueue algorithm will be developed to control the arrival of patients according to their geolocation information. Finally, simulation model will be used to verify and validate GeoQueue effectiveness.

QUEUE MODELLING

There are two groups of data involved in this study: treatment-related data and queue-related data. Treatment-related data includes type of sickness and length of service time whereas queue-related data are patient arrival rate and waiting time. These data were gathered over a period of 5 months. Fig. 1 indicates the total daily patient for August, September and October 2016

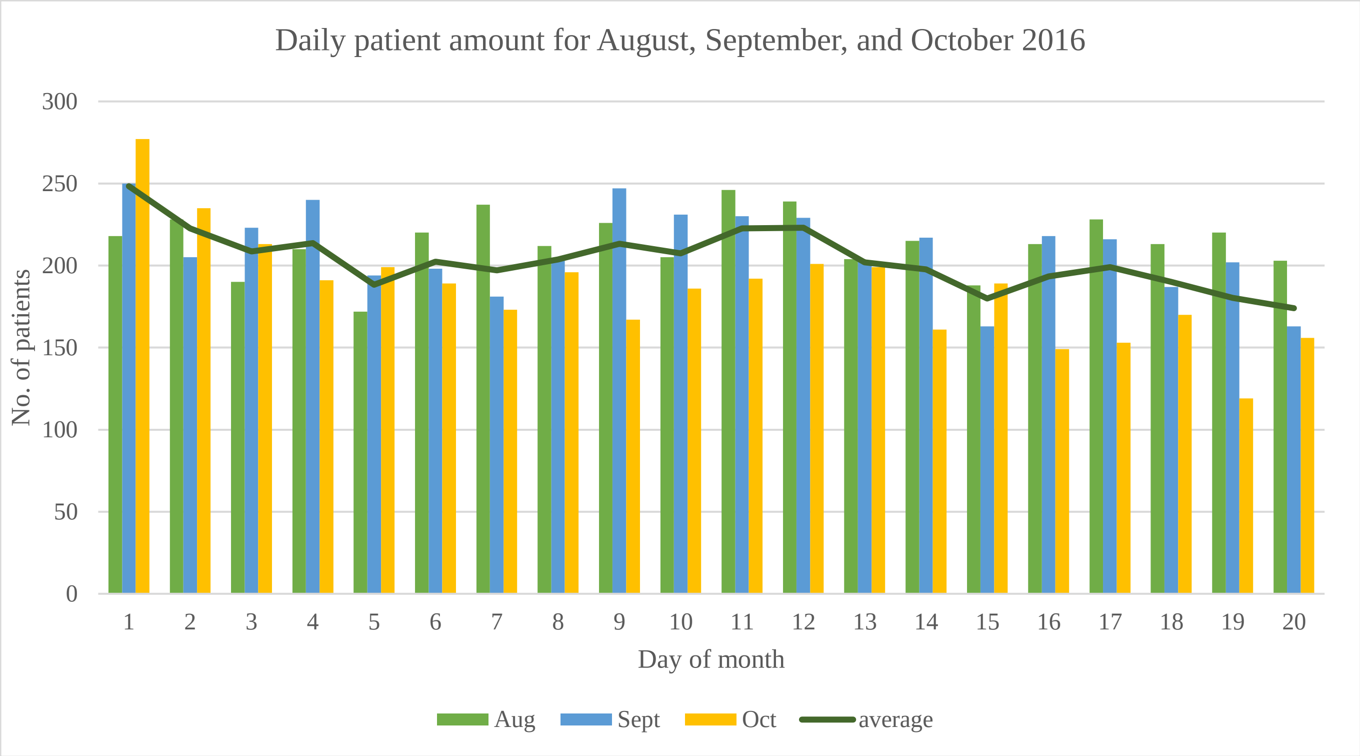

Fig. 1. Total daily patient for August, September, and October 2016

These OPD arrival data were collected using simple random sampling method. Each patient has the same probability to be selected as a sample. Time study from work measurement techniques was used to measure the length waiting time and service time. Besides that, interviews were conducted with medical personnel to obtain information about the daily operation and process flow of OPD.

The raw data was filtered to removed outliers and incomplete data points (i.e. no show.) Slovin's formula from Altares (2003) was used to determine required sample size for a representative data as shown in (1).

$$n = \frac{N}{1 + Ne^2} \tag{1}$$

where

n = sample size

N = population

e = margin of error

With a margin of error of 10%, the sample size required is 67 patients. 70 patients were sampled during morning session of OPD where congestion often happened. In this study, waiting time is defined as the total time elapsed from the end of registration to the start of consultation. Table 1 shows the statistics of waiting time and service time for a morning session in OPD. The statistics shows that

- Patients had long waiting time despite the consultation time only a few minutes. Around 80% to 95% of patients' time spent in OPD were recorded as waiting time.
- Average waiting time for both type of patients is 75.70 minutes with a standard deviation of 18.86 minutes.

Table 1: Statistics of waiting time and service time in OPD

Patient type	**Waiting time (minutes)**		**Service time (minutes)**		
	Average	**% of patients exceeds 90 minutes of waiting time**	**Minimum**	**Maximum**	**Average**
Normal	86.73	31.5%	2	6	4.63
Priority	65.72	9.52%	2	7	7.73

Queue condition in OPD was modelled with discrete-event simulation (DES) method. The primary performance measure for the queue condition in OPD is the average waiting time of patient. The simulation model was built based on the fundamental of queue theory. According to queue theory, the current queue model in OPD is M/G/c queue, where M denotes the exponential time between arrivals to the queue, G refers to independent service time and *c* is the number of servers. When the arrival rate is greater than service rate, the queue model will be unstable and result in formation of queue. Fig. 2 indicates the process flow of OPD and Fig. 3 shows the developed M/G/c queue model in Simulink. In this model, patients were assumed that they only visit the doctor once to simplify the simulation process. Several conditions were set to resemble to actual condition in OPD:

- Patients were distributed randomly to doctors. No specific doctor is assigned to patient.
- Only one queue is formed. Patient randomly departs to one of the doctors when the turn is up.
- Consultation starts 45 minutes after registration begins.

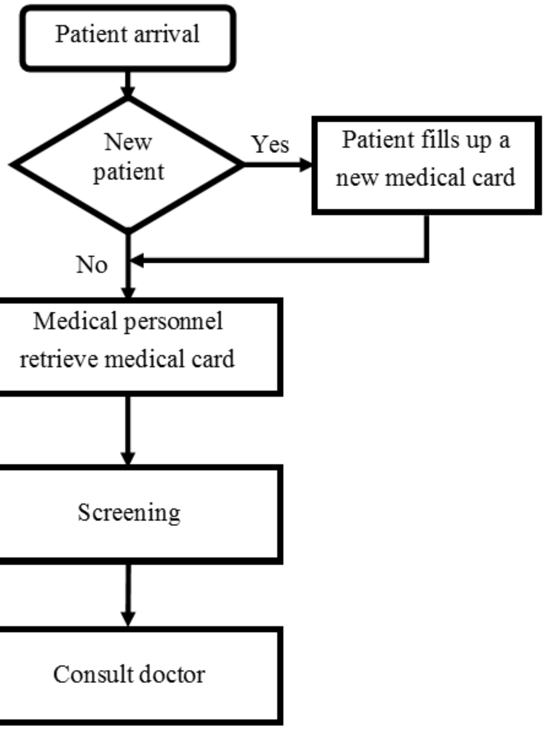

Fig. 2. Process flow of OPD

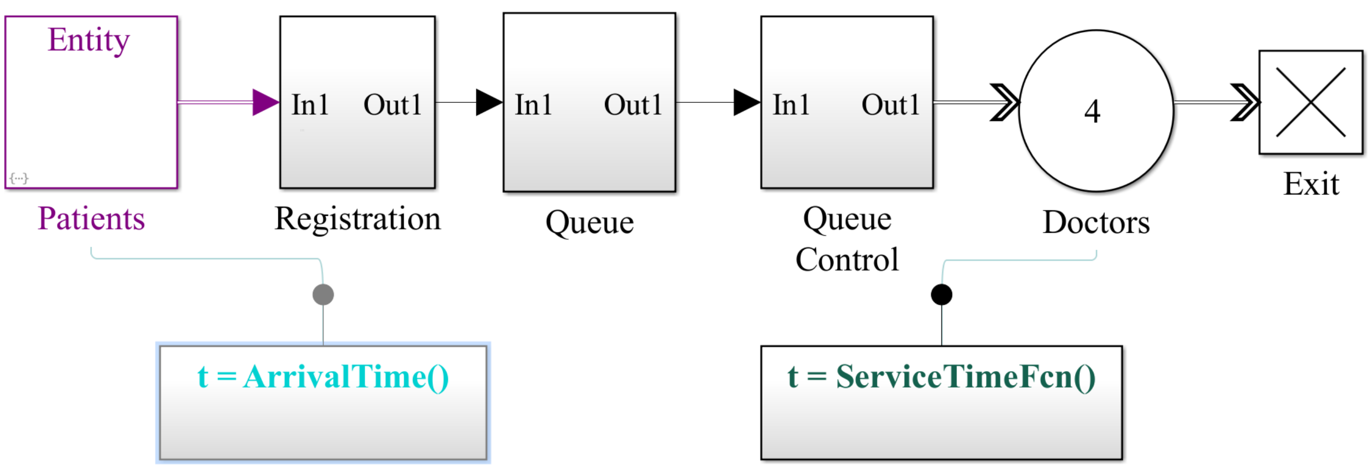

Fig. 3. M/G/c queue model in Simulink

The M/G/c queue model was divided into 5 sections which are entity generator (patient), registration, queue, queue control, and server (doctor).

Arrival rate in OPD follows a Poisson distribution with a mean of 0.38 and variance of 0.0014. Hence, the interarrival rate is exponentially distributed with a mean interarrival time of 3.5 minutes per patient. In the entity generation section, inverse transform sampling technique was employed to define the interarrival time of patient. The MATLAB function defining the interarrival time is represented by (2).

$$F^{-1}(x) = \frac{\ln(1-x)}{\lambda} \tag{2}$$

where

x = random variable

λ = arrival rate of patient

Registration section served as a gate to control the amount of patient entering the system. In the context of OPD, registration counter generally closes at 12:00 p.m. when the nurses realize the waiting zone is crowded. This is to ensure that the queue can be cleared before session ends. Hence, this gate will stop patient being deployed into the queue when it receives a step input from 0 to 1 at pre-defined time.

In queue section, the queue principle was defined as First-In-First-Out (FIFO). Patient was discharge to doctor according to the sequence of arrival. Before arriving to server (doctor), patients were passed through a queue control section. The main function of queue control is to prevent the patient from entering the server before it is online. In the context of OPD, there is a buffer time of 45 minutes between the starts of registration and beginning of consultation. Hence, the queue control block simulates the scenario of buffering.

Service time of doctor is normally distributed which denoted by $N(1200,\ 300^2)$. Parameter *c* represents the number of doctors. It varies between one to five as it resembles the capacity of doctors of OPD under this study. All servers operate in parallel with each other.

MODEL VALIDATION

The model was verified so that it can accurately reflect the real system model. The current system in OPD provides queue number to walk-in patients. To validate the queue model and algorithm, several sets of hospital outpatient data were collected and served as the reference. Two approaches were used to validate the model: internal validation and external validation.

First, the parameters of OPD condition such as number of doctors in service, arrival rate of patient, and service time were imported into Simulink's model. The model was used to simulate the average waiting time with those parameters. From that, the average waiting time was then compared with the average waiting time from historical data.

Next, the number of doctors was varied to compute a new average waiting time for different scenarios. The average waiting time was compared with actual data for external validation. Two-tailed t-test with 95% confidence level was used to validate the result. Two hypotheses were made in two-tailed t-test.

a) H_0: model waiting time = average waiting time
b) H_1: model waiting time ≠ average waiting time

Table 2 indicates the result of t-test for different number of doctors and outpatient session. A total of five sets of random historical data were selected to validate the queue model. As shown in last row of table, the absolute t-values calculated were smaller than the critical t-values. Hence, the null hypothesis (H_0) is not rejected. The model is adequate in representing the actual OPD queue condition.

Table 2: Result of two-tailed t-test

Number of doctors	2	3	4	4	4
Sample Size	11	31	37	27	40
Critical t-value	2.201	2.040	2.026	2.052	2.023
|t-value|	1.653	1.898	1.665	1.888	0.419

GEOQUEUE ALGORITHM

The GeoQueue algorithm was developed using MATLAB. It was divided into three major parts which are information collection, ETA calculation and time slot arrangement. Fig. 4 shows the flowchart of GeoQueue algorithm.

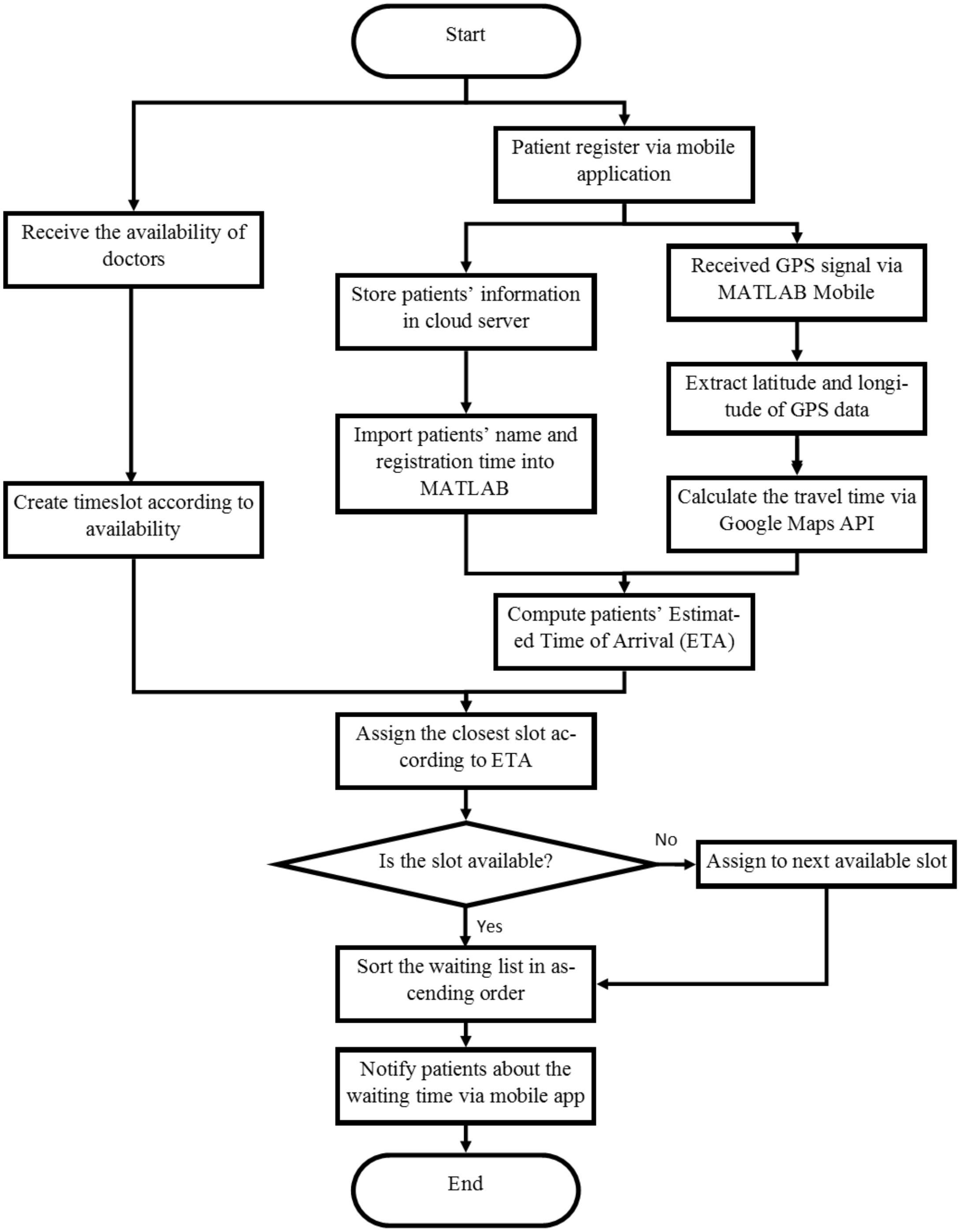

Fig. 4. GeoQueue algorithm flowchart

A. Information collection

During registration, patients were required to enter their basic personal information for their service request. Upon the completion of registration process, patients were prompted to allow the application to read the location information of their mobile computing devices. Once the request is approved, GPS sensor of the mobile device will be turned on by the system. Latitude and longitude information were extracted from the GPS sensor.

MATLAB Support Package for Android Sensors was used to acquire GPS signal data from mobile device. This process was demonstrated with MATLAB Mobile as shown in Fig. 5. At the same time, patients' registration time was read and saved automatically from their mobile system.

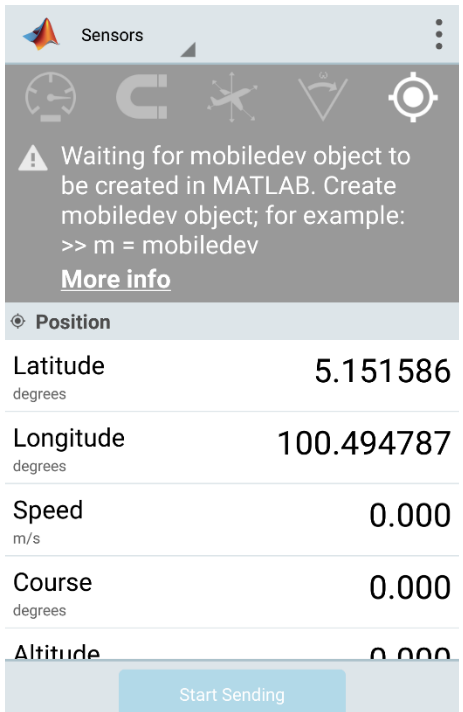

Fig. 5. Screen shot of MATLAB mobile sensors

Besides that, hospital service capacity was taken into consideration. Number of doctors in service greatly affects the service rate. Total number of time slots available were determined from doctors' availability. An example of time slot creation is shown in Fig. 6 below.

```
Table =
```

	Time	Doctor1
1	27-Mar-2017 08:00:00	{1×1 cell}
2	27-Mar-2017 08:30:00	{1×1 cell}
3	27-Mar-2017 09:00:00	{1×1 cell}
4	27-Mar-2017 09:30:00	{1×1 cell}
5	27-Mar-2017 10:00:00	{1×1 cell}
6	27-Mar-2017 10:30:00	{1×1 cell}
7	27-Mar-2017 11:00:00	{1×1 cell}
8	27-Mar-2017 11:30:00	{1×1 cell}
9	27-Mar-2017 12:00:00	{1×1 cell}
10	27-Mar-2017 12:30:00	{1×1 cell}
11	27-Mar-2017 13:00:00	{1×1 cell}
12	27-Mar-2017 13:30:00	{1×1 cell}
13	27-Mar-2017 14:00:00	{1×1 cell}
14	27-Mar-2017 14:30:00	{1×1 cell}
15	27-Mar-2017 15:00:00	{1×1 cell}
16	27-Mar-2017 15:30:00	{1×1 cell}
17	27-Mar-2017 16:00:00	{1×1 cell}
18	27-Mar-2017 16:30:00	{1×1 cell}
19	27-Mar-2017 17:00:00	{1×1 cell}

Fig. 6. Available time slot

B. ETA calculation

Google Distance Matrix Application Program Interface (API) was used to determine the travel time required based on latitude and longitude. Latitude and longitude of patients' locations was the origin address. A coordinate of the hospital was pre-defined as destination address. The output result from API includes distance and travel time. Patients' ETA was calculated based on (3).

$$ETA = RT + TT \tag{3}$$

where

ETA = Estimated Time of Arrival

RT = Registration time

TT = Travel time

Fig. 7 shows the sample response of Google Distance Matrix API for distance and travel time between Universiti Sains Malaysia and the nearest hospital.

```
{
  "destination_addresses" : [
    "Hospital"
  ],
  "origin_addresses" : [
    "Universiti Sains Malaysia"
  ],
  "rows" : [
    {
      "elements" : [
        {
          "distance" : {
            "text" : "4.5 km",
            "value" : 4543
          },
          "duration" : {
            "text" : "10 mins",
            "value" : 610
          },
        }
      ]
    }
  ],
}
```


Fig. 7. Sample result of Google Distance Matrix API

C. Time slot arrangement

By referring to the ETA calculated, patients were assigned to a time slot that is closest, but not earlier than their time of arrival. For example, a patient that registered on 8:45 a.m. requires an hour of travelling time. He/she was arranged into 10:00 a.m. slot which is closest, but not earlier than his/her arrival time (9:45 a.m.). After all patients had been assigned with a time slot, they were sorted in ascending order to determine the arrival name list.

As observed from current situation of OPD, the service capacity is 8 patients in every half an hour. Based on the sorted patient list, there are 2 possible conditions:

1. Less than or equal to 8 patients in a slot.
2. More than 8 patients in a slot.

For condition 1, all patients in the specific time slot will be assigned to the computed time slot. For condition 2, the number of patients exceeded the service capacity of doctors. Hence, the remaining patients were assigned to the next available time slot to reduce their waiting time. Table 3 shows the sample of 12 patients' ETA computed by algorithm. Notice that patient "Aide" had been assigned to 9:00 AM slot as the 8:30 AM slot was full.

Table 3: Patients' information with their ETA and arranged time slot

No.	Name	Location	Registration Time	Estimated Time Arrival (ETA)	Arranged time slot
1	Jina	Jawi	7:50:00 AM	8:06:00 AM	8:30:00 AM
2	Ashli	Bagan Serai	7:50:00 AM	8:14:00 AM	8:30:00 AM
3	Dayle	Bagan Serai	7:52:00 AM	8:16:00 AM	8:30:00 AM
4	Vicenta	Pekaka	7:54:00 AM	8:03:00 AM	8:30:00 AM
5	Hyo	Nibong Tebal	7:56:00 AM	8:04:00 AM	8:30:00 AM
6	Marie	Nibong Tebal	7:59:00 AM	8:07:00 AM	8:30:00 AM
7	Tova	Bukit Panchor	8:10:00 AM	8:23:00 AM	8:30:00 AM
8	Toby	Pekaka	8:13:00 AM	8:22:00 AM	8:30:00 AM
9	Arielle	Bagan Samak	8:18:00 AM	8:38:00 AM	9:00:00 AM
10	Denese	Sungai Bakap	8:18:00 AM	8:38:00 AM	9:00:00 AM
11	Aide	Sentosa	8:18:00 AM	8:30:00 AM	9:00:00 AM
12	Leanora	Simpang Ampat	8:19:00 AM	8:49:00 AM	9:00:00 AM

RESULT & DISCUSSION

Patient arrival pattern in OPD has a Lognormal distribution. After the implementation of GeoQueue, a uniform arrival pattern was achieved with an average arrival rate of 16 patients per hour.

A comparison between current arrival pattern and new arrival pattern is shown in Fig. 8. The arrival rate of patient is predictable and controllable after implementation of GeoQueue. Hospital can set the arrival rate of patient according to the capacity of service daily. In this study, the hospital service capacity is 16 patients per hour.

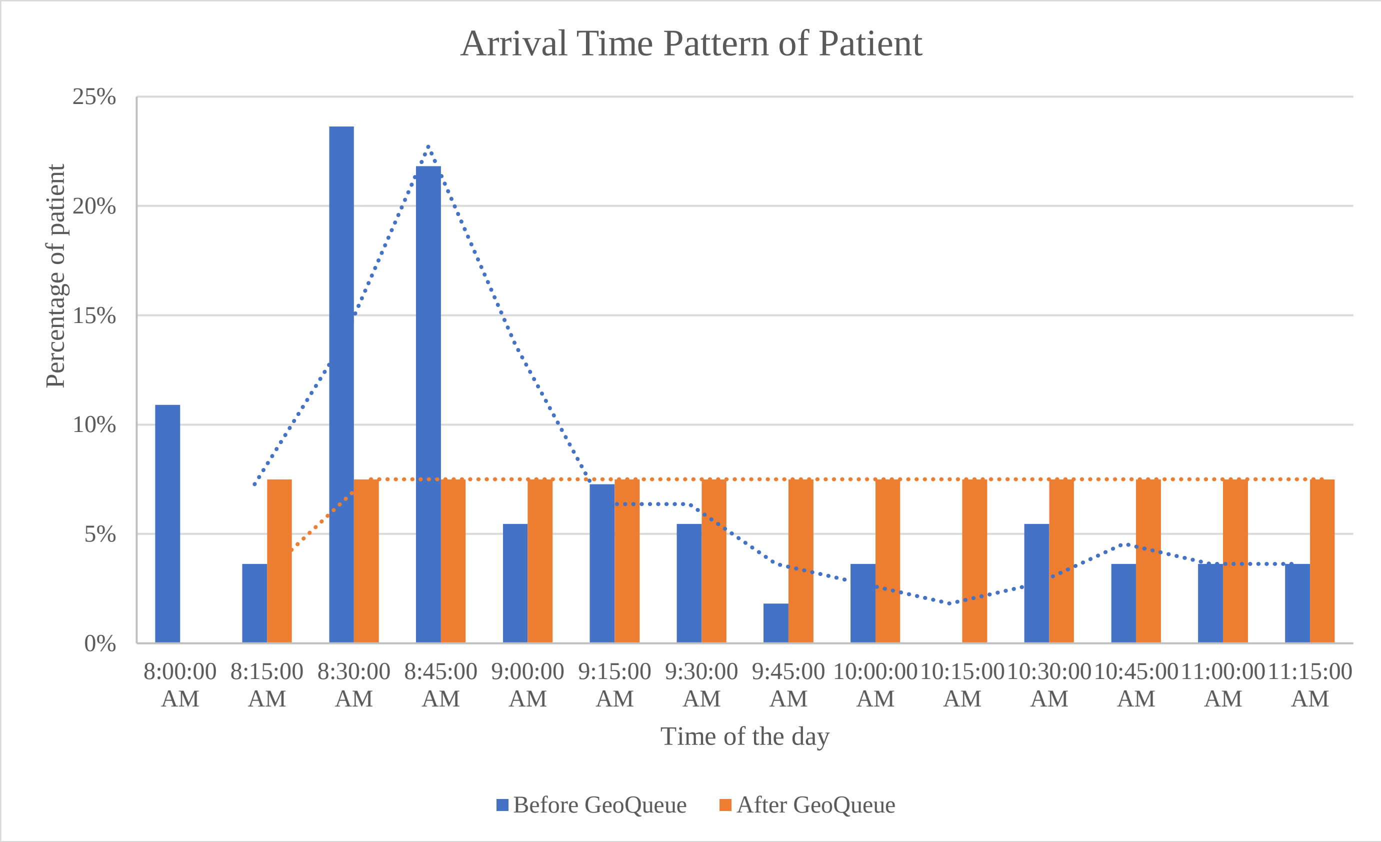

Fig. 8. Comparison between arrival pattern of patient before and after GeoQueue.

In term of waiting time reduction, a total of five different cases were simulated based on the new arrival pattern of patient. Table 4 shows the waiting time of patients before and after the implementation of GeoQueue.

The average waiting time before GeoQueue implementation for each case ranging from five doctors to one doctor are 51.50 minutes, 67.25 minutes, 81.70 minutes, 93.82 minutes, and 105.93 minutes respectively. The maximum waiting time are 56.30 minutes, 82.08 minutes, 112.48 minutes, 137.27 minutes, and 158.33 minutes respectively. The minimum waiting time for all cases are quite constant with 44.48 minutes, 48.23 minutes, 49.35 minutes, 49.55 minutes and 50 minutes respectively.

The average waiting time shows a significant reduction after the implementation of GeoQueue. 5-doctor case shows the highest percentage of reduction which is 93.65% with a new average waiting time of 3.27 minutes. Following that is 76.68% reduction for 4-doctor case, 58.84% reduction for 3-doctor case, 50.01% reduction for 2-doctor case and 41.28% reduction for 1-doctor case.

From the result, the percentage of reduction in average waiting time shows a increasing trend when the number of doctors increases. Hence, the performance for GeoQueue in waiting time reduction is directly proportional to the number of doctors in service.

Table 4: Simulation result for different number of doctors in service

No. of doctors	Duration (hours)	Waiting time before GeoQueue (minutes)			Waiting time after GeoQueue (minutes)			% of reduction in average waiting time
		Average	Maximum	Minimum	Average	Maximum	Minimum	
5	5	51.50	56.30	44.48	3.27	6.29	0	93.65%
4	5	67.25	82.08	48.23	15.68	30.53	0	76.68%
3	5	81.70	112.48	49.35	33.63	66.50	0	58.84%
2	5	93.82	137.27	49.55	46.90	92.01	0	50.01%
1	5	105.93	158.33	50.00	62.20	121.98	0	41.28%

The model was simulated for 10 iterations in each case. Fig. 9 indicates the maximum, minimum, standard deviation, and average waiting time of current condition in OPD via simulation. The range between simulated maximum and minimum waiting time for the case of 4, 2, and 1 doctors are relatively large in current OPD situation. This is mainly due to multitude of variation in arrival pattern in which number of patients peaked at certain hours in the morning. The maximum waiting time for 4-doctor case is 86.04 minutes while the minimum waiting time is 20.50 minutes, representing a difference of 65 minutes.

For 2-doctor case, the maximum and minimum waiting time are 101.80 minutes and 47.30 minutes respectively, representing 54.50 minutes in difference. In 1-doctor case, the maximum waiting time is 107.55 minutes, which is 40.22 minutes greater than minimum waiting time of 67.33 minutes. On the other hand, 5-doctor and 3-doctor case show a consistent waiting time distribution with a maximum of 72.77 minutes and 86.02 minutes and minimum of 49.78 minutes and 74.73 minutes respectively.

Overall, the average waiting time ranges from 62.66 minutes for 5-doctor case to 95.23 minutes in 1-doctor case. Hence, the waiting time is inversely proportional to the number of doctors in service as expected.

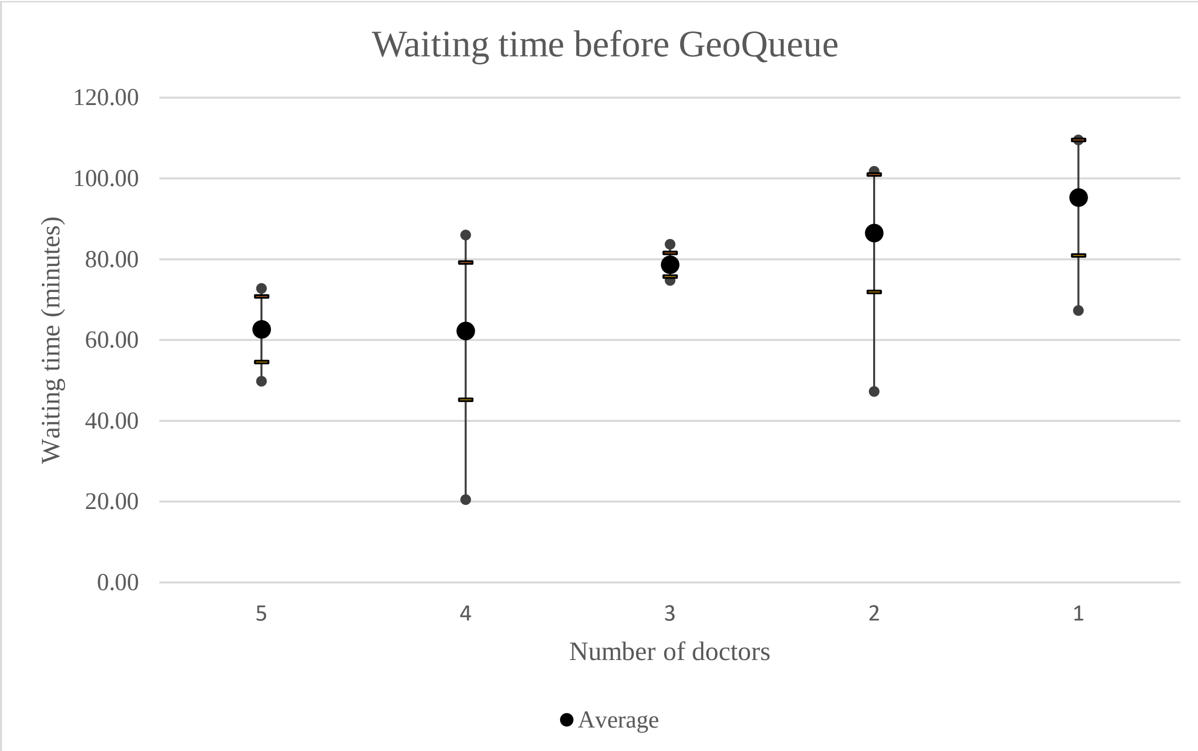

Fig. 9. Waiting time distribution before GeoQueue

Fig 10 shows the improved waiting time of OPD after implementation of GeoQueue. In general, the graph indicates an evenly distributed waiting time for all cases in compare with current waiting time.

For 4-doctor case, the maximum waiting time is 20 minutes whereas the minimum waiting time is 9.50 minutes, representing a difference of 10.15 minutes. The differences between maximum and minimum waiting time are similar for the remaining case, which are 11.13 minutes for 3-dcotor case, 13.80 minutes for 2-doctor case and 15.17 minutes for 1-doctor case.

In term of average waiting time, 4-doctor case has a waiting time of 14.25 minutes in average whereas 3-dcotor case achieved an average waiting time of 31.18 minutes. As observed from the graph, the average waiting time shows a linear increment with the reduction in number of doctors. Hence, the average waiting time for 2-doctor and 1-doctor cases are 44.36 minutes and 59.60 minutes respectively.

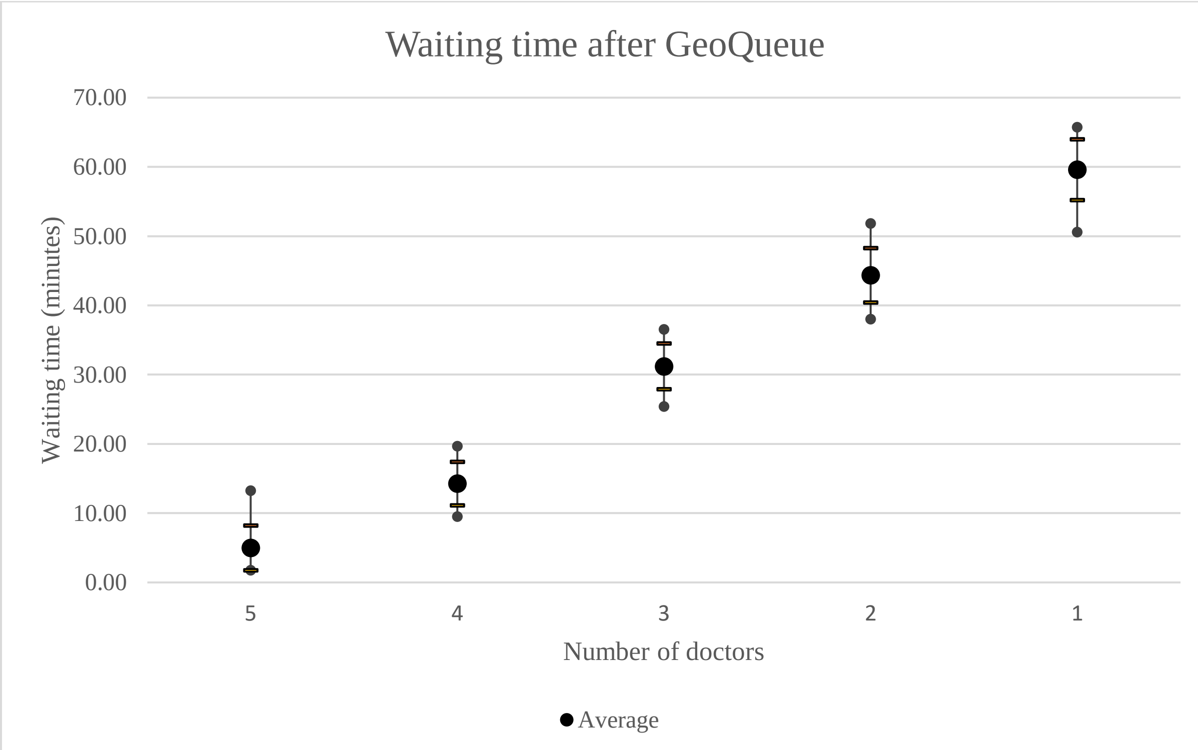

Fig. 10. Waiting time distribution after GeoQueue

Fig. 11, 12, 13, 14, and 15 show the comparison between waiting time before and after the implementation of GeoQueue. The average waiting time reduction for the condition of 5 doctors to 1 doctor are 92%, 74%, 60%, 47% and 36% respectively. Hence, it concludes that the GeoQueue has a greater effect when the number of doctors is higher.

Besides that, it can be noticed that in some iterations such as iteration eight in 4-doctor case, the current waiting time is relatively low compared to the others. This was affected by the scenario of OPD whereby the arrival rate of patient is lower than the service rate of doctors. It results in shorter queue length and waiting time. Same situations are also shown in 2-doctor case and 1-doctor case. Dotted line indicates the upper and lower standard deviation of the result.

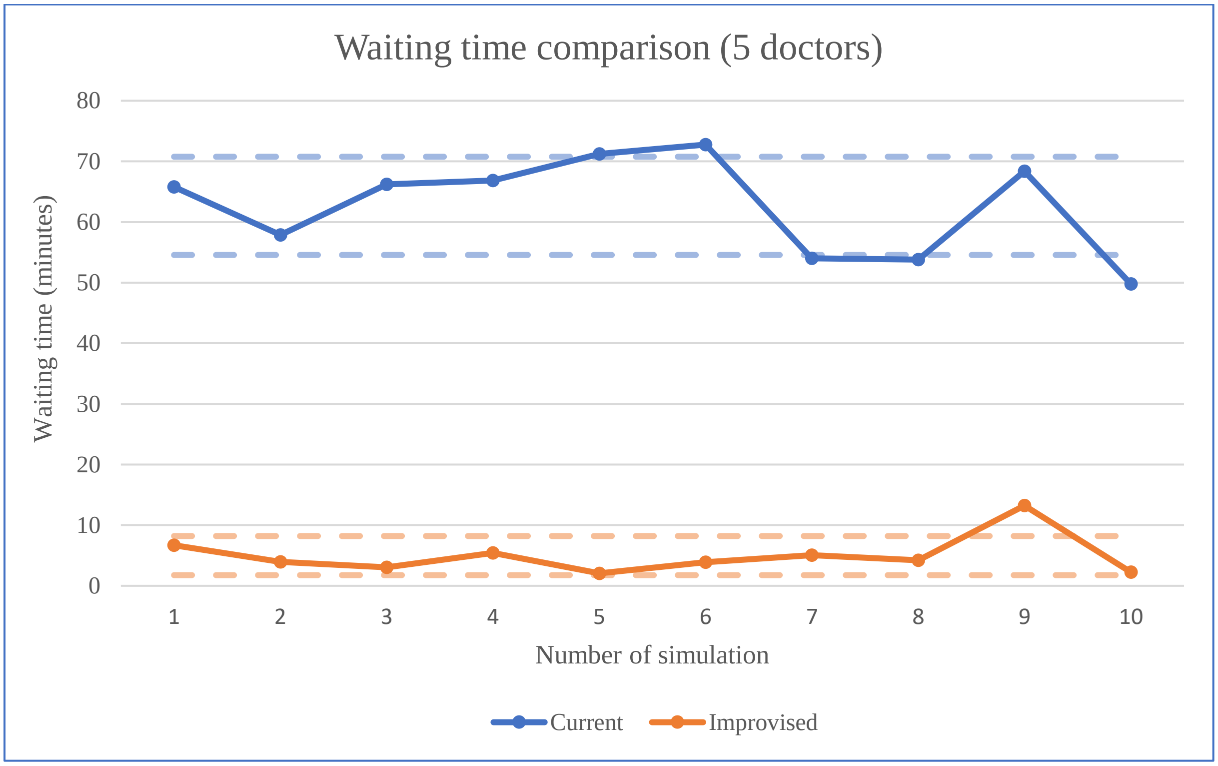

Fig. 11. Waiting time comparison (5 doctors)

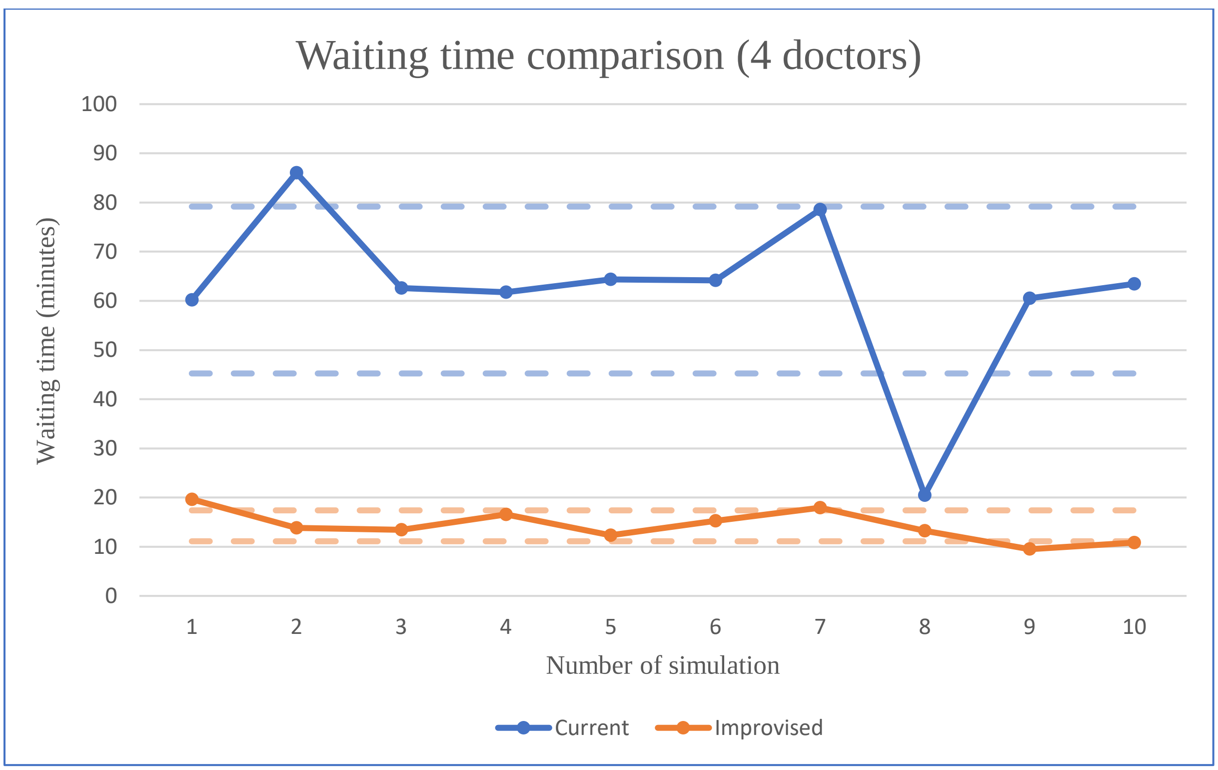

Fig. 12. Waiting time comparison (4 doctors)

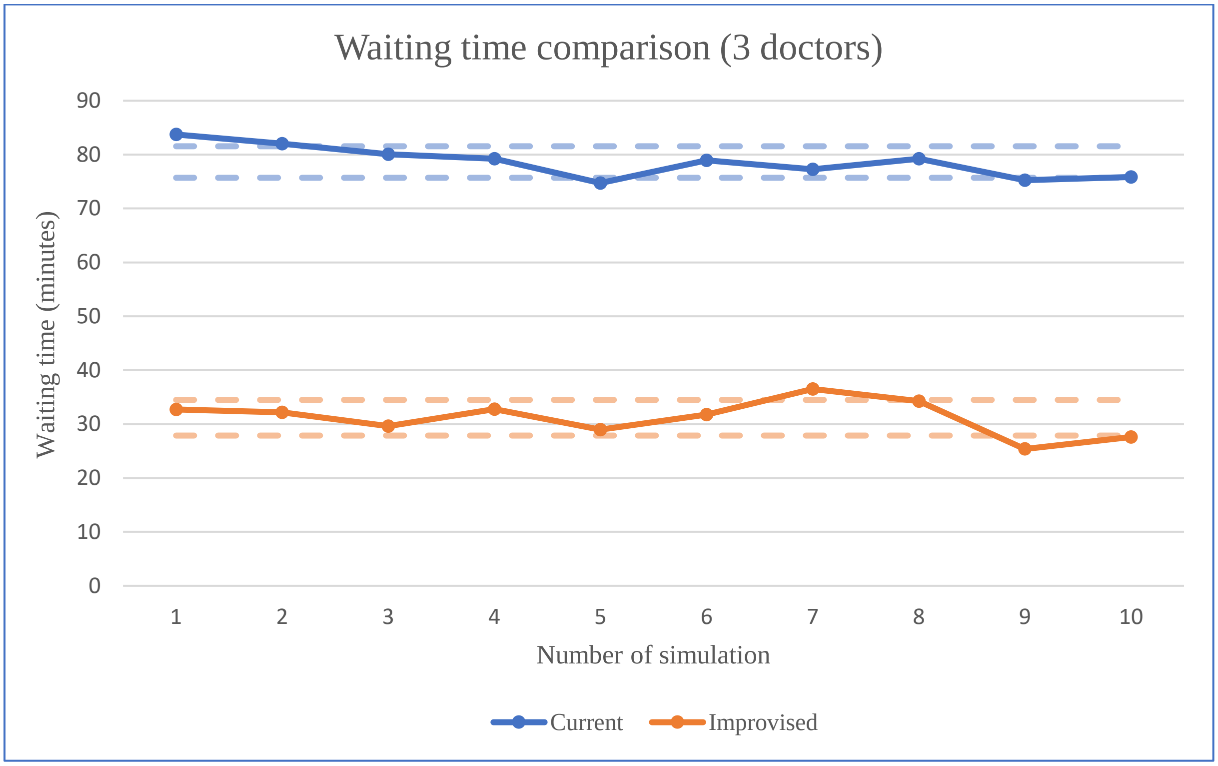

Fig. 13. Waiting time comparison (3 doctors)

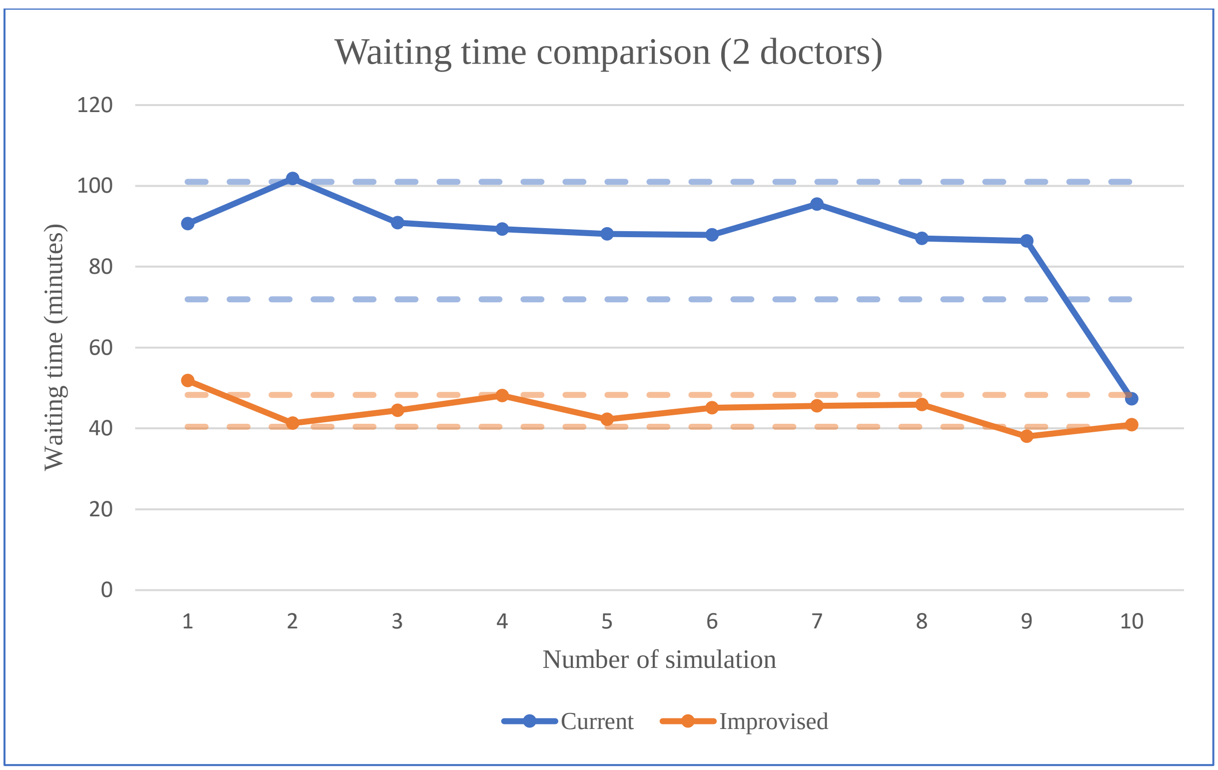

Fig. 14. Waiting time comparison (2 doctors)

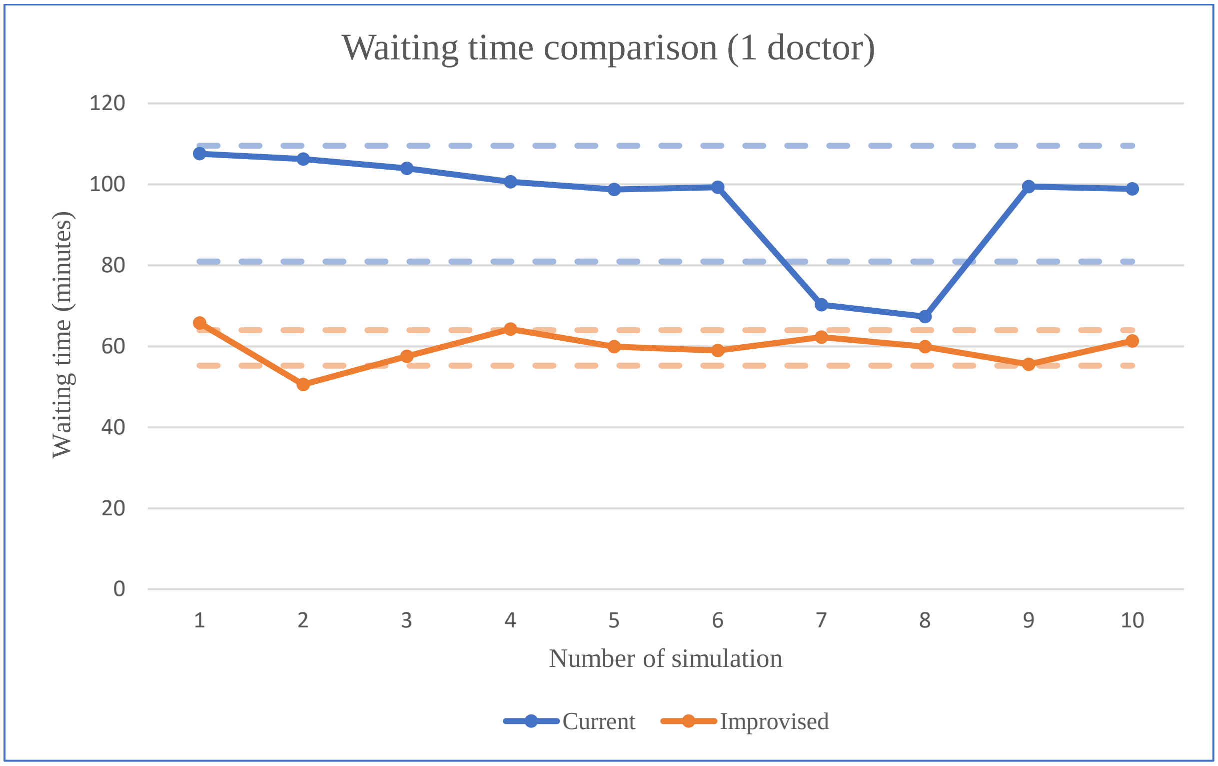

Fig. 15. Waiting time comparison (1 doctor)

In short, GeoQueue is able to control the arrival pattern of patients to OPD. Patient arrival pattern has been transformed from exponential distribution into uniform distribution. An arrival rate of 16 patients per hour is achieved with GeoQueue. On the other hand, GeoQueue also reduces the average waiting time of patient up to 62%. It also shows a significant reduction when the number of doctors in service is higher.

CONCLUSION

In this work, GeoQueue had been developed and the applicability and feasibility were tested via discrete event simulation method. The simulated results indicated that the algorithm developed for the system could calculate patients' ETA based on their location and arrange the patient into most suitable time slot. The average waiting time of patients had been reduced drastically and achieved a reduction of 62%. The algorithm could also produce a uniform arrival rate that maximize the service capacity of doctors and at the same time kept the lowest number of patient possible in waiting line. Hence, the overall performance of the GeoQueue had proven its applicability in the healthcare industry.

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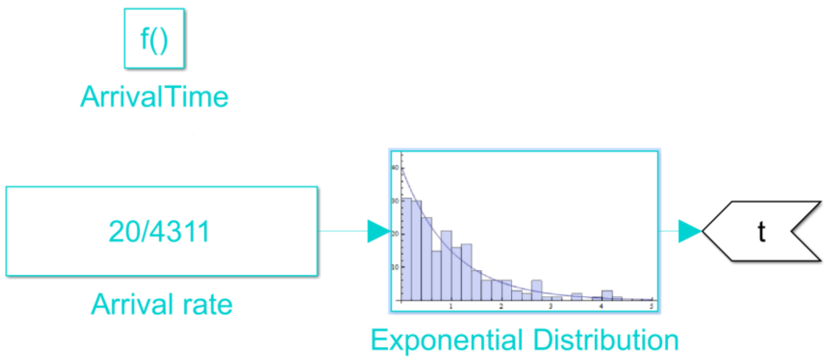
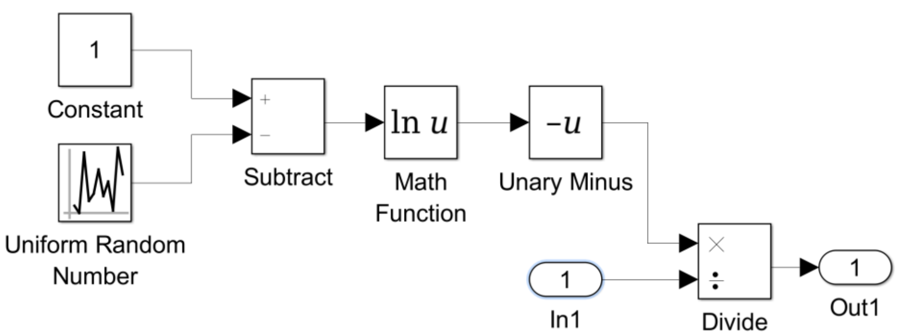
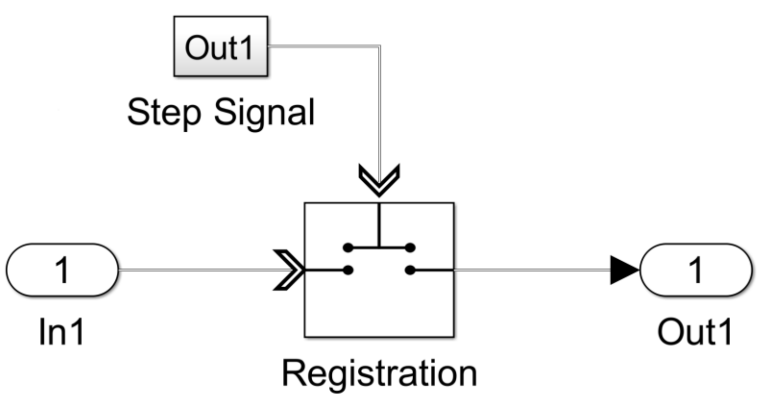
APPENDIX



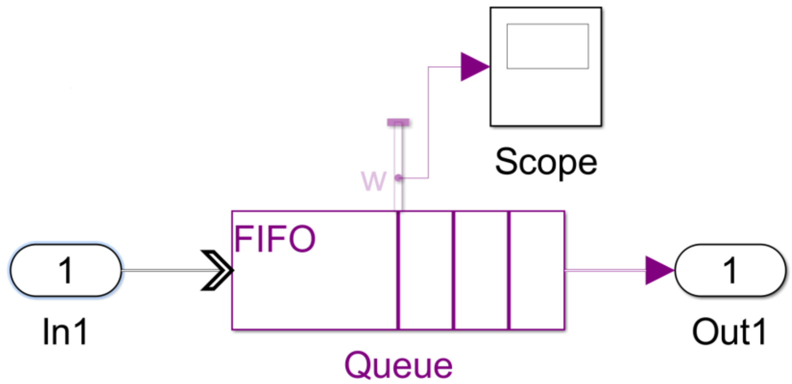
Arrival time function block



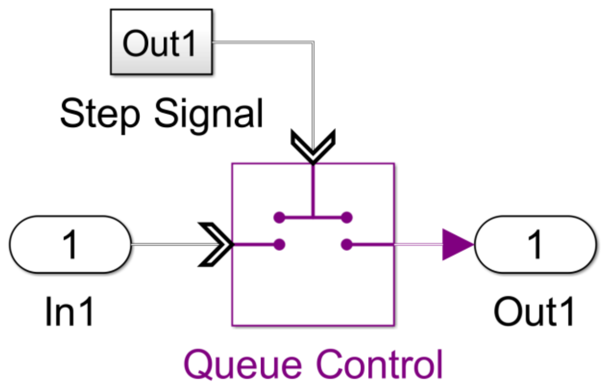
Inverse transform sampling equation



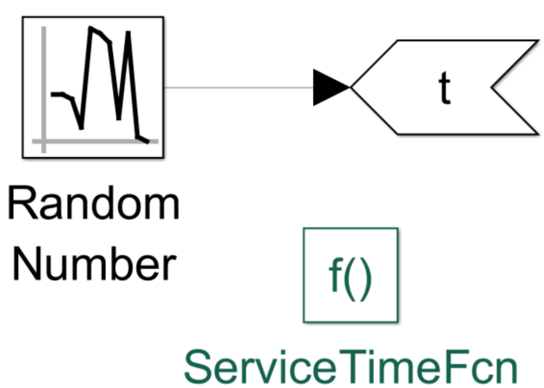
Registration gate control



Queue



Queue control gate



Service time distribution function