A Systematic Methodology for the Generation of Lift Passengers under a Poisson Batch Arrival Process

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Abstract. It is generally accepted that passenger arrivals for lift service follow a Poisson arrival process. Moreover, recent research has also shown that the arrivals take place in batches rather than single passenger arrivals. For these reasons, lift traffic simulation software may use the Poisson batch arrival process to generate the time of each batch arrivals and the size of each batch (i.e., the number of passengers arriving in each batch). This provides a better representation of real life conditions and produces a more realistic simulation. Alternative models for generating passengers for lift traffic simulation packages are considered. A methodology for generating batch arrival times and the size of each batch is presented.

1 INTRODUCTION

An important part of any lift traffic simulator is the passenger arrival process. The passenger arrivals represent the demand to which the lift system is subjected. The passenger arrival model should reflect the actual characteristics of the arrival process. This ensures that the output of the simulation is more representative of reality. In this paper, alternative arrival models are presented and discussed. A new methodology for generating passenger arrivals is proposed.

2 POSSIBLE PASSENGER ARRIVAL GENERATION MODELS

This section examines possible models with which passengers can be generated for lift traffic simulation. All examples in this section assume a passenger arrival rate, λ of 0.2 passengers per second.

2.1 Constant inter-arrival time

This is a simplification of the passenger arrival process. It is assumed that the time between the arrivals of consecutive passengers is constant (i.e., deterministic rather than random). The time in seconds between the arrivals of consecutive passengers or inter-arrival time Δt can be calculated:

$$\Delta t = 1/\lambda \tag{1}$$

A diagrammatic representation of passenger arrivals against time is shown in Figure 1. As the arrival rate is 0.2 passengers per second, then the inter-arrival time is 5 seconds.



Figure 1 Passenger arrivals with constant inter-arrival time

2.2 Random inter-arrival time with uniform probability density function

This model assumes that the inter-arrival time is random. However, it contains a simplification of the passenger arrival process by assuming that the distribution of the inter-arrival time is a uniform probability distribution function (pdf). The value of the inter-arrival time has an average value of $1/\lambda$ and varies between 0 seconds and the twice the average value $2/\lambda$.

The value of an inter-arrival sample time can be evaluated using the equation 2 where *Rand* is a function that generates a uniformly distributed random number between 0 and 1. This yields the representation of passenger arrivals given in Figure 2.



Figure 2 Passenger arrivals under a rectangular pdf process

Although this model offers a better representation of the passenger arrival process by introducing random passenger arrivals, it assumes that a passenger must arrive in the time period of $2/\lambda$ which is not necessarily true. A much longer period of time might pass without a passenger arriving. Moreover, the model gives equal probability to all possible values of the inter-arrival time, which is not an accurate reflection of reality.

2.3 Random passenger arrivals applying Poisson probability density function

The most widely accepted passenger arrival model is the Poisson process [1, 3, 4]. This assumes that the number of passengers arriving in a period of time follows a Poisson distribution, see Equation 3.

$$P(n) = \frac{(\lambda \cdot T)^n \cdot e^{-\lambda \cdot T}}{n!}$$
(3)

Where P(n) is the probability that the number of passengers arriving in the period of time *T* is equal to *n*. Using a period, *T* of 10 seconds, the Poisson probability density function has been generated and shown in Figure 3. Figure 4 shows a representation of passenger arrivals.







The passengers are assumed to arrive in the middle of the period of time T (10 seconds) as the actual arrival time of each passenger is not defined. For this reason, this basic application of the Poisson process is unrealistic, even with a smaller T.

A further disadvantage of this approach is that the number of passengers generated in the time period does not necessarily correspond to the arrival rate. This inconsistency between user input and passengers generated can cause confusion to users of traffic simulation software.

2.4 Random inter-arrival time with exponential probability density function

The random variable in the previous Poisson passenger arrival model is the number of passengers arriving in a time period, T. A better approach is to use the inter-arrival time as the random variable. This can be achieved by considering the time after which one or more passengers are expected, 1-P(0). Substituting Equation 3 yields Equation 4. Figure 5 shows a representation of passenger arrivals.



Figure 5 Passenger arrivals assuming random inter-arrival time with exponential pdf

As for the original Poisson approach, the number of passengers generated in the time period does not necessarily correspond to the arrival rate.

2.5 Random arrival time in a given time period

To address the inconsistency in passenger numbers, some traffic simulators create the exactly the number of passengers required by the arrival rate for the time period T. As only whole passengers can be generated, rounding up or down is determined using a random number. Random numbers are used to place the passengers on the time line. This achieves a similar result to the previous model with an exponential probability density function, see Figure 6.



Figure 6 Passenger arrivals assuming random arrival in a given time period

A consequence of this approach is that the longer the time period T, the more variation there is in the demand during that period. For example, if T is 5 minutes, 60 passengers would be generated. If T is one hour, 720 passengers would be generated; however in the first five minutes, there may be 58 passengers, and in the second five minutes there may be 64 passengers.

2.6 Further considerations

It has been shown that passengers arrive in batches [5], also referred to as bulk arrivals [2]. The probability density function of the batch sizes depends on the nature of the building and the time of the day. Thus for every batch arrival, there are two parameters to generate: the time at which it occurs and the size of the batch.

3 A METHODOLOGY FOR GENERATING PASSENGERS FOR SIMULATION

3.1 Steps of the methodology

The passenger generation methodology presented in this paper combines the most useful features of the methods discussed in section 2: (i) the methodology assumes a random inter-arrival time with exponential probability density function; (ii) the total number of passengers is consistent with the expected number of passengers; (iii) the batch size may be building and time specific.

3.2 Procedure

For each floor where passengers arrive, consider the total number of passengers generated, p_{gen} during the workspace, WS. The WS is the time over which passengers are being generated in seconds. λ may be determined from the passenger demand which in turn is calculated according to population and building type.

$$p_{gen} = \lambda \cdot WS \tag{5}$$

To generate passengers for the WS:

- 1. Calculate the required number of passengers to be generated as shown in equation 5. Assign the first passenger's arrival time to zero seconds.
- 2. Using Equation 4 generate the inter-arrival times between all the consecutive passengers.
- 3. Repeat step 2 until the number of passengers generated is one more than the required number of passengers, $p_{gen} + 1$.
- 4. Discard the last passenger generated, but retain his or her arrival time. This arrival time will be referred to as WS'.
- 5. It is likely that the value of WS' is different from the desired workspace time, WS. Thus apply a shrink or stretch correction factor, SF = WS/WS' to the whole set of arrival times. This will ensure that the total passenger generation time is equal to WS.

3.3 Example without batch arrivals

A building has a population, U of 1000 persons and arrival rate, AR% of 12% of the population per five minutes at the floor being considered. The value of the workspace is 60 seconds.

$$\lambda = \frac{AR\% \cdot U}{300} = \frac{12\% \cdot 1000}{300} = 0.4 \text{ passengers/second}$$
(6)

The expected number of passengers to be generated in the workspace can be calculated:

$$p_{gen} = \lambda \cdot WS = 0.4 \cdot 60 = 24 \tag{7}$$

The arrival times of each passenger are shown in Table 1, column 2. As the target number of passengers is 24, the number of passengers that are initially generated is 25. The 25th passenger will be discarded, but his or her arrival time retained. Table 1, column 2 needs to be shrunk or stretched such that exactly 24 passengers arrive within 60 sec. The correction factor is found by dividing the desired workspace by the actual workspace.

$$SF = \frac{WS}{WS'} = \frac{60}{63.6529} = 0.9426 \tag{8}$$

The arrival times are thus adjusted by multiplying them by SF, as shown in Table 1, column 3. The original and adjusted arrival times for the 24 passengers are shown in Figure 7 with each passenger arrival shown as an inverted triangle.

Passenger (#)	Arrival time (s)	Adjusted arrival time (s)
1	0	0
2	5.5392	5.2214
3	6.556	6.1798
4	9.5555	9.0071
5	10.1065	9.5265
6	10.1841	9.5996
7	13.5913	12.8113
8	15.3242	14.4448
9	16.9587	15.9855
10	22.8361	21.5256
11	25.1892	23.7437
12	27.5929	26.0094
13	32.4982	30.6332
14	36.5914	34.4915
15	38.7407	36.5175
16	39.2458	36.9935
17	39.9316	37.64
18	45.3718	42.768
19	45.4445	42.8365
20	47.1274	44.4228
21	47.587	44.8561
22	57.2073	53.9243
23	60.3254	56.8634
24	62.0606	58.499
	63.6529	60

 Table 1: Passenger arrival times



Figure 7 Initial and adjusted passenger arrivals

3.4 Example with batch arrivals

A building has a population, U of 300 persons and an arrival rate of 4% of the population per five minutes at the floor being considered. The value of the workspace is 15 minutes.

$$\lambda = \frac{AR\% \cdot U}{300} = \frac{4\% \cdot 300}{300} = 0.04 \text{ passengers/second}$$
(9)

Using the value of the arrival rate above, the expected number of passengers to be generated in the workspace can be found as shown below:

$$p_{gen} = \lambda \cdot WS = 0.04 \cdot 900 = 36 \tag{10}$$

The probability density function that is to be used for the generation of the batch sizes, based on reference [5], is given in Table 2.

Batch size	1	2	3	4	5
Probability	37/58	13/58	6/58	2/58	0

 Table 2 Probability density function for the batch sizes

The average batch size can be calculated from the pdf as shown below:

$$\overline{b} = \frac{1 \cdot 37 + 2 \cdot 13 + 3 \cdot 6 + 4 \cdot 2}{58} = 1.5345 \ passengers/batch \tag{11}$$

In order to account for the average batch sizes, calculate the batch arrival rate, λ_b in batches per second.

$$\lambda_b = \frac{\lambda}{\overline{b}} = \frac{0.04}{1.5345} = 0.0261 \ batches/second \tag{12}$$

Using the arrival rate for the batches found in equation (12) the batch arrival times can be generated. These are shown in Table 3 together with the batch sizes. The batch sizes are randomly generated using the batch size pdf shown in Table 2.

The 20th batch is discarded, but its arrival time is retained. Table 3 column needs to be shrunk or stretched such that exactly 36 passengers arrive within 15 minutes. The correction factor is found by dividing the desired workspace by the actual workspace.

$$SF = \frac{WS}{WS'} = \frac{15}{16.2531} = 0.9229 \tag{13}$$

The arrival times are adjusted by multiplying them by SF as shown in Table 3, column 3. It is worth noting that the initial batch sizes are not changed. The sum of the passengers arriving in 15 minutes is 36 passengers as required.

Batch (#)	Arrival time (minutes)	Adjusted arrival time (minutes)	Batch size (passengers)
1	0	0	1
2	0.9921	0.9156	3
3	1.9611	1.8099	2
4	2.667	2.4614	1
5	2.7586	2.546	2
6	2.7726	2.5588	1
7	3.2973	3.043	4
8	3.526	3.2542	4
9	5.3186	4.9085	3
10	7.8494	7.2442	1
11	8.0653	7.4435	1
12	9.097	8.3956	1
13	10.5448	9.7318	2
14	11.1267	10.2688	3
15	12.5041	11.54	3
16	14.3439	13.238	1
17	14.8533	13.7081	1
18	15.6866	14.4772	1
19	16.2364	14.9845	3
20	16.2531	15	N/A
		Total passengers	36

 Table 3 Adjusted batch arrival times.

The original and adjusted arrival times for the batches are shown in Figure 8.



Figure 8 Initial and adjusted batch arrivals

4 CONCLUSIONS

Alternative models for generating passengers for lift traffic simulation packages have been presented.

The first model assumes a constant passenger arrival rate, where the time between passenger arrivals is deterministic and constant. This model is not representative of reality as it is known that passengers arrive randomly. However, it can be used for the verification of the value of the round trip time found using calculation. The second model assumes a uniform (rectangular) probability density function, where the inter-arrival time of the passengers randomly varies between 0 s and $2/\lambda$ seconds (λ is the passenger arrival rate in passenger per second). It assumes that a passenger must arrive at most every $2/\lambda$ seconds and gives equal probability to all values of inter-arrival time between 0 and $2/\lambda$ seconds; neither of these assumptions reflect reality.

The third model assumes that the number of passenger, n, arriving in a period of time T follows a Poisson process. The passengers are assumed to arrive in the middle of the period of time T as the actual arrival time of each passenger is not defined; this is unrealistic, even with a smaller T. The fourth model modifies Poisson to allow for exact arrival times to be defined; this is more realistic, however, the random nature of arrivals means that the passengers generated in the time period does not necessarily correspond to the arrival rate.

Another approach creates a Poisson-like arrival process, but generates the exact number of passengers expected. Further consideration is given to research that proposes that people arrive in batches.

The passenger generation methodology proposed combines the most useful features of the methods discussed. (i) the methodology assumes a random inter-arrival time with exponential probability density function; (ii) the total number of passengers is consistent with the expected number of passengers; (iii) the batch size may be building and time specific. Two examples are then given, the first assuming single passenger arrivals, and the second assuming batch arrivals with one or more passengers in each batch. The methodology also shows how to ensure consistency between the actual number of passengers generated in the workspace and the actual number of expected passengers, by using a correction factor, SF.

5 FURTHER WORK

A Kolmogorov-Smirnov goodness of fit test has been carried out on a real life survey data to confirm that the model assuming random inter-arrival time with exponential probability density function cannot be rejected. A discussion of determining the destinations of passengers will be provided. Alternative methods of passenger generation will be included in traffic simulation software, and an assessment made on the impact on example designs. This work will be published in a future paper or papers. The implication of turnstiles at the entry to the building or lift lobby also needs to be considered.

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BIOGRAPHICAL DETAILS

Richard Peters has a degree in Electrical Engineering and a Doctorate for research in Vertical Transportation. He is a director of Peters Research Ltd and a Visiting Professor at the University of Northampton. He has been awarded Fellowship of the Institution of Engineering and Technology, and of the Chartered Institution of Building Services Engineers. Dr Peters is the author of Elevate, elevator traffic analysis and simulation software.

Lutfi Al-Sharif received his Ph.D. in lift traffic analysis in 1992 from the University of Manchester. He worked for 9 years for London Underground, London, United Kingdom in the area of lifts and escalators. In 2002, he formed Al-Sharif VTC Ltd, a vertical transportation consultancy based in London, United Kingdom. He has 19 published papers in peer reviewed journals, is co-inventor of four patents, co-author of a book chapter on LVDT design and co-author of a book on lift traffic engineering. He is currently Associate Professor in the Department of Mechatronic Engineering at The University of Jordan, Amman, Jordan.

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