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SIMULATION OF CHECK-IN QUEUE MODEL AT SUPADIO PONTIANAK AIRPORT DURING COVID-19 PANDEMIC TIME

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Abstract: The Covid-19 pandemic has changed the order of human life in the world, including Indonesia. In order to avoid the transmission of the Covid-19 virus, a health protocol in the form of maintaining a distance between humans must be 1 meter apart. The check-in area at the airport is one of the places that must receive attention in implementing this health protocol. With the health protocol and the addition of checking flight documents at the check-in counter, it causes additional time in the passenger departure process. Therefore, if it is not managed properly, it can become a problem that creates long queues and creates inconvenience to the passengers. In this study using field observations to describe the conditions and time required for each passenger in the queue system at the airport and provide the best queuing simulation that can be used at the airport. This study uses R studio to examine the dynamic behavior of the observed data. Exploration of the dynamic behavior of the data is done by entering the observed data into the Simmer simulation model. The model will be in a more stressful condition as the value of q increases. The simulation uses the Baseline model which is applied to the stress test (Extrapolation-n model), where it can be concluded that the current check-in system is quite resilient to changes in passenger load. In other words, with the current service time and check-in counters that are always open three times, the passenger arrival speed of 100 times from the pandemic period can still be served without the system experiencing a break down.

Keywords: *Airport, Check-in, Queue*

1. Introduction

The airports managed by PT Angkasa Pura II consist of 19 (nineteen) airports and are divided into several airport classes which are divided based on commercial or income at each airport, production which is determined by airport runway length, terminal area, apron area, number of parking stands, airport area, and electrical power, Operations and services based on the number of passengers, aircraft movements and airport operating hours and Support consisting of the number of human resource needs, productivity, and the number of business partners. Based on these 4 (four) criteria, the airports managed by PT Angkasa Pura II are divided into 6 classes. Namely class A, B, C, D, E and F. In class C which consists of 6 (six) airports, namely Halim Perdanakusuma (Jakarta), Sultan Mahmud Badaruddin (Palembang), Sultan Syarif Kasim II (Pekanbaru),Minangkabau(Padang). Husein Sastranegara (Bandung), Supadio (Pontianak). These airports are airports that are expected to contribute more in increasing revenue and improving better services. Services to passengers based on the Regulation of the Minister of

Transportation Number PM 178 of 2015 concerning service standards for airport service users, namely, facilities used in the process of departure and arrival of passengers, facilities that provide comfort to passengers, facilities that provide added value and the capacity of airport terminals to accommodate passengers. passengers during peak hours. Of the 4 (four) service standards, the facilities used in the departure and arrival of passengers include passenger and baggage inspection, check-in services , departure immigration, arrival immigration, customs services, departure waiting rooms and baggage services. And often a concern is the check-in service at each airport. Every passenger who will make a departure is required to report and show identity and documents. Check-in is the process of confirming a prospective passenger on an airline just before boarding an airplane. Standard check-in has 2 criteria, namely waiting time and processing time in check-in . According to the regulation of the Minister of Transportation of the Republic of Indonesia Number PM 178 of 2015 concerning service standards for airport service users, it is stated that the waiting time for check-in per passenger is calculated from waiting to go to the check-in counter is less than 30 minutes. And the service processing time per passenger is less than 2 minutes 30 seconds.Of the 6 (six) airports that are in class C, there are different levels of service based on e-service reports made by each airport. Supadio Airport has the highest percentage of non-compliance in check-in services among other airports in the same airport class, which is 16% of the total number of service days from September to December 2020 even though the number of domestic passengers has decreased significantly. around 54.13% from the previous year due to the Covid-19 outbreak in the world, and especially in Indonesia which caused many bad impacts for the business sector.

The Minister of Transportation of the Republic of Indonesia has issued Regulation of the Minister of Transportation of the Republic of Indonesia Number PM 18 of 2020 concerning Transportation Control in the context of preventing Corona Virus Disease 2019 (covid -19). The Ministerial Regulation regulates air transportation activities, one of which is that the distance between humans (physical distancing) must be 1 meter apart, to anticipate the transmission of the Covid-19 virus. Area Check-in is one place that should be running health protocols. Thus this area needs attention, if not managed properly it will become a bottleneck that can create long queues that can disrupt the flow of passenger movement and create inconvenience to passengers at Supadio Pontianak Airport. In the video, there are several passengers who do not follow the health protocol, which requires maintaining a distance of 1 meter from other passengers in the queue. During field observations, it was also found that during long queues there was no action from the airline to immediately open additional check-in counters in order to reduce queues and speed up the check-in process for passengers. And this causes disruption to the flow of passengers in the check-in area. This long queue also occurs because at the time of examination at the counter, the check-in counter officer has to do additional checking of documents which previously were only Identity Cards and Flight Tickets, now have to check the doctor's certificate free of COVID-19 results of the rapid test or swab. This needs to be corrected with a provision for the number of passengers in the queue in one check-in counter queue system in each airline.

2. Literature Review

2.1 Airport Operation and Management

Operations management is the company's main activity which includes the systematic design, direction and control of processes that produce value in the form of goods and services by converting inputs into outputs. (Wijayanto, 2017). Through production and operation activities, all input resources of the company are integrated to produce outputs that have added value. Operations management is a continuous and effective process of using management functions to efficiently integrate various resources in order to achieve goals.

2.2 Check-in

Check-in is the process of confirming prospective passengers on the airline immediately before boarding the aircraft. According to (Waris et al, 2018) or the passenger flow paths inside the terminal can be determined based on the concept of *check-in* which is applied at an airport terminal, where there are three types of concepts, namely: *Check-in* centralized (*centralized check-in*), *check- in* Separate (*split check-in*), *Check-in* door (*gate check-in*).

2.3 Queue Theory

Queueing theory *(* Queueing *Theory)* was first proposed and developed by Agner Kraup Erlang (1 January 1878 – 3 February 1929) who first published a paper on *Queueing Theory* in 1909. Queue system is a consequence of the relative and limited service facilities and services. can occur in various places and times (Waris et al, 2018). Queuing theory is the mathematical study of congestion. This theory explores the relationship between demand on a service system and the delays suffered by users or passengers of that system, because all airports as a whole or broken down into their individual elements can be seen as a network of queuing systems. Queuing theory often plays a central role in the study and management of airport operations and in the planning and design of airport facilities and services. (de Neufville et al. 2013). Queues basically occur because there is a process of human movement that is disrupted by a service activity that must be passed, for example: a passenger queue that forms in front of the *Check-in Counter* at the airport due to the activity of checking the flight requirements document, resulting in a queue. Usually for passengers, the thing that is at issue is the waiting time during the queuing process. As for airport managers, queues that are too long can cause disruption to passenger movement in the *Check-in area* .

2.4 Queue Component

There are 3 (three) main components in queuing theory that must be properly known and understood, namely: Arrival rate, the number of people moving to one or several places of service in one unit moving to one or several places of service in a certain time unit, can be expressed in units of people/minute. Then the level of service, namely the number of passengers that can be served by one service place in a certain time unit, usually expressed in units of people/minute. And queue discipline Queuing discipline has an understanding of how passengers queue. Several types of queues are often used are: (Arsyad, 2012)

a. First in first out (FIFO) or First come first served (FCFS). In the field of transportation where the first person or vehicle to arrive will be served first.

b. First in last out (FILO) or First come last served (FCLS). In the FILO or FCLS queue, the vehicle or person who arrives first will be served last. This queue is common in ferry services, where the first vehicle to enter will be the last to leave.

c. First Vacant First Served (FVFS). This FVFS queuing discipline means that the first vehicle or person who arrives will be served by the first empty service place. In this FVFS usually only 1 (one) single queue will be formed, but the number of service places can be more than 1 (one).

d. Last In First Out (LIFO). This LIFO queue discipline is the first to enter last in and the first to leave.

2.5 Queue Model

The queuing model is a line or flow of consumers who are waiting to get service from the company. Here are some queuing models, namely: Model M/M/1 This model means that arrivals and service times are exponentially distributed (Poisson process). In this situation, arrivals form a single line to be served by a single station.

λ : Average passenger arrival rate

µ: Average level of service

Utilization factor : $\rho = \frac{\lambda}{\mu}$

a. Zero probability of customer in system $Po = 1 - \rho$

b. Probability of n customers in the system $P_n = P_0 p^n$

c. Average number of customers in the system

$L_S = \frac{\rho}{1-p} = \frac{\lambda}{\mu-\lambda}$

d. Average number of customers in queue

$L_Q = L\ x\ p = \frac{p^2}{1-p} = \frac{P\lambda}{\mu-\lambda}$

e. Average time in queue W_Q

$$w_Q = \frac{L_Q}{\lambda} = \frac{p}{\mu - \lambda}$$

f. Average waiting time spent in the system, including waiting time W_S

$$W_S = \frac{L}{\lambda} = \frac{1}{\mu - \lambda}$$

2.6 Simulation

Simulation is a decision-making model by imitating or using the actual picture of a real-world living system without having to experience it in real situations. (Prihati, 2012). In a systems view, simulation or modeling can be used for the following purposes: Studying the behavior of complex systems, i.e. systems in which an analytical solution cannot be performed, Comparing alternative designs for systems that do not or do not yet exist, Studying the effect of changes on existing systems without changing system and strengthen or verify unit analytical solutions.

2.7 Total Quality Management

Quality is generally the focal point of every company. Various things are done to improve the quality applied to products, services and company management. In the development of science, an innovation known as TQM was born. Total quality management is an approach to running a business that tries to maximize a company's competitiveness through continuous improvement of products, services, people, processes and the environment. (Juharni, 2017). Air transportation services are growing rapidly along with the existing globalization, everyone wants faster, more efficient and smoother results, including developing service companies. The implementation of *Total Quality Management (* TQM) is a very appropriate thing in order to improve the ability of these elements on an ongoing basis. (Yudianto, 2019).

The application of TQM in a company can provide several main benefits which ultimately increase the company's competitiveness, with continuous quality improvement, a company can increase its profits. In the application of TQM, there are tools used to facilitate the application of the methods and techniques used in TQM. According to (Heizer et al, 2017) there are 7 tools or *tools* to implement the TQM method which are divided into 3 functions, namely:

a. Tools for generating ideas
   In the function of generating ideas, you can use *check sheets* , *Scatter diagrams* and *Cause and effect diagrams.*
b. Tools for organizing data
   In the function of managing data, you can use *Pareto* charts and *flowcharts.*
c. Tool to identify Problems
   The function of identifying problems can use *histograms* and *statistical process control charts.*

2.8 R Studio

R is an open source programming language that deals with computing and data processing for statistics related to graphical display using the tools provided by its packages which are very useful in research and industry. The R studio application can be used to process linear and nonlinear data for model identification, classification, statistical testing, analysis and visualization. Another advantage of R is the quality graph plot, the appearance of the simulation can be in the form of bar chart plots, graphs, curves, wordclounds and others, including mathematical symbols and formulas (Budiarto w and Rachmawati RN, 2013).

I. Result and Discussion

This study was conducted with the aim of knowing the condition of the queue model implemented at Check-in at Supadio Pontianak Airport during the Covid-19 pandemic and to find out the condition of the best Check-in area queuing model to be implemented at Supadio Airport during the covid-19 pandemic.

Table 1 Types of Research

No	Rating Characteristics	Type	Explanation
1	By Method	Quantitative	The method used in this study is a quantitative research method, namely a research method that tries to make accurate measurements of behavior, knowledge, opinions or attitudes (Indrawati, 2015).
2	By Purpose	Descriptive	This research is categorized as descriptive research. Descriptive research itself aims to describe current problem solving based on existing data (Darmawan, 2013).
3	Based on Researcher Involvement	Not Interfering with Data	This research is included in research where there is no researcher intervention on the data, namely there is no data manipulation by researchers, in Indrawati (2015)
4	Based on Unit of Analysis	Check-in Queue	Research conducted for a particular company or organization in this case is PT Angkasa Pura II (Persero).
5	Based on Execution	*Cross Section*	Indrawati (2015) states that cross-sectional research is research conducted in one period, then the data is

No	Rating Characteristics	Type	Explanation
	Time		processed, analyzed, and then conclusions are drawn.

The definition of a variable is anything that has a value, and its value can vary and can change (Indrawati, 2015). Operationalization of variables is a process of reducing the variables contained in the research problem into the smallest parts so that the size classification can be known, and it is easier to obtain the data needed in the assessment of research problems (Indrawati, 2015). Indicators of the variables that will be operated in this study can be seen in Table 2 below.

Tabel 2 Operational Variables

Variable	Operational definition	Scale
λ	Averagepassenger arrival rate	Numerical
μ	Average Service Level	Numerical
W_Q	Average time in queue $w_Q = \frac{L_Q}{\lambda} = \frac{p}{\mu-\lambda}$	Numerical
W_S	Average waiting time spent in the system including waiting time $W_S = \frac{L}{\lambda} = \frac{1}{\mu-\lambda}$	Numerical
L_Q	Average number of customers in queue $L_Q = L\,x\,p = \frac{p^2}{1-p} = \frac{P\lambda}{\mu-\lambda}$	Numerical
L_S	Average number of customers in the system $L_S = \frac{\rho}{1-p} = \frac{\lambda}{\mu-\lambda}$	Numerical

In this study, to see the queuing model that occurred at the Pontianak Supadio Airport, observations were made by taking videos of the queues that occurred at the Lion Air *check-in* counter at the Pontianak Supadio Airport. To see the arrival distribution, service distribution and inter-arrival distribution from observation data, and get the waiting time for passengers in the queue and the average waiting time in the system. In research by (Ahsan et al, 2018) the queuing model can be characterized by the following factors: arrival time distribution which has a Poisson distribution pattern, deterministic distribution or general distribution. The distribution of service time can be in the form of constant, exponential, and general distributions. From the explanation of the theory carried out, in assessing the queue there are several factors that will affect the length of a queue. In a study conducted by (Al-Sultan, A. T, 2018) said that the process of passenger *check-in* is stochastic, and the number of *check-in* counters required varies depending on the number of passengers, type of aircraft and destination. After getting the data from the observations, then an exploration of the dynamic behavior of the data is carried out by entering the data from the observations into the Simmer simulation model. Simmer is a Discreet Event Simulation (DES) simulation package from the R community (CRAN). Modeling uses Kendall's (1953) notation to be used as baseline data in the use of loop and extrapolation simulations from the Lion Air *check-in* counter queue system used at Supadio Pontianak airport.

In the early stages of this research, what will be done is to make observations to be able to clearly see the field conditions that occur at the *check-in* area at Supadio Pontianak Airport. Observations are observations made directly by coming directly and recording or recording all the things that are considered necessary and carried out by the object of the study. From these observations, the researchers saw and revealed the phenomena that occurred at the *check-in* area of the Pontianak Supadio airport. The formulation of the problem is the focus of the researchers' attention in carrying out the research process (Indrawati, 2015). Researchers want to know how long it takes passengers to complete the *check-in* process at Pontianak Supadio Airport. The researcher then conducted a literature study related to the standard length of a *check-in* queue at the airport and conducted a literature study related to queuing theory. Researchers collected data by taking video recordings in the Lion Air *check-in* area at Supadio Pontianak airport, then processing data on the video recordings. Then perform a simulation of the observation data to draw conclusions on the research to be carried out.

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Whole group of people, events, objects that interest researchers to study (Indrawati, 2015). The population used in this study is video recording at *Check-in* Supadio airport which will be taken for 6 (six) days with a duration of 90 minutes per day. Samples are members of the population selected to be involved in the study, either to be observed, given treatment, or asked for opinions about what is being studied (Indrawati, 2015). The sample in this study uses video recordings at the *check-in* counter on Lion Air flights with flight number JT 712. Flight JT 712 is

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a flight with departure hours at 08.20 WIB, video recordings were made on March 18, March 19, March 22, March 23 , March 24 and March 27, 2021.

The population in this study were all passengers who came and entered the *check-in* queue system at the LION counter at Supadio Pontianak airport. Check-in activities only take place for one flight per day, namely flights by Lion Air. The sample in this study is the passenger who comes in line or enters the queue system and the flight *check-in service is* based on a certain day and time. The sampling technique used in this study is a two-stage quasi-random sampling. The first stage is to choose the day on which the observations will be made. The criteria for the selected day is a day that represents a certain event which is expected to bring up a large number of passengers for sampling. The second stage is to select the peak of the queue on that day and conduct sampling for a certain duration, not sampling the entire *check-in* process . From this sampling technique, data on the number of passengers on that day will be obtained for the duration of the sampling. Observations were made by recording check-in activities. Based on the video recording, data on arrival-time, time in queue, service time and queue completion time can be obtained. Observations (video recordings of activities) were carried out on the following dates: March 18, 2021 for 90 minutes, March 19 for 30 minutes, March 22 for 35 minutes, March 23 for 43 minutes, March 24 for 54 minutes, and March 27 for 51 minutes.

4. Result and Discussion

From the observation data, statistical data using visualization techniques using several distributions. Arrival time can use an exponential or Erlang distributed random simulation. For service time can use random simulation with exponential and Poisson distribution. And the time between arrivals can use random simulations with normal distribution and or Poisson.

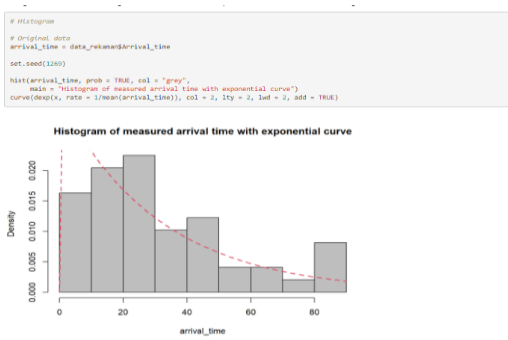


Figure 2 Arrival time histogram with exponential distribution smoothing line with rate= 1/mean(arrival_time).

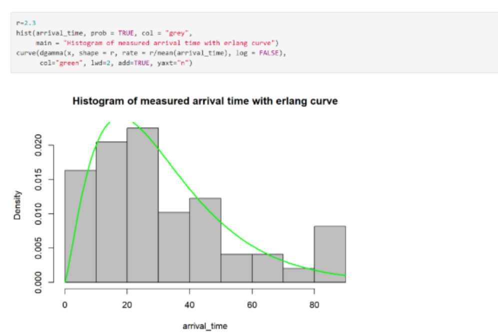
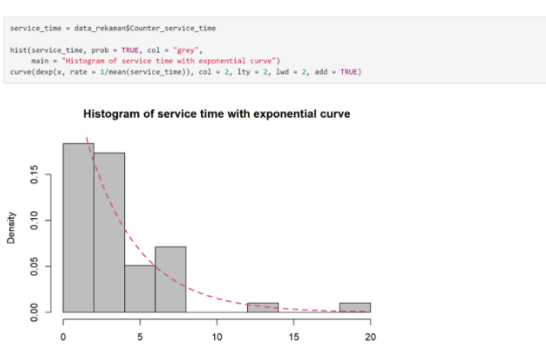


Figure 3 Arrival time histogram with smoothing line of erlang distribution withshape= r, rate=r/mean(arrival_time), dan r=3.5.



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```
hist(service_time, prob = TRUE, col = "grey",
     main = "Histogram of service time with poisson curve")
curve(dpois(x, lambda = 3),
      col="green", lwd=2, add=TRUE, yaxt="n")
```

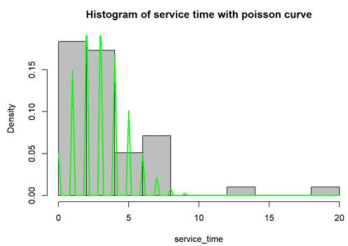

Figure 4 Histogram of service time with smoothing line of exponential distribution with rate= 1/mean(service_time)

```
hist(antar_kedatangan, prob = TRUE, col = "grey",
     main = "Histogram of inter arrival time with normal curve")
curve(dnorm(x, mean=mean(antar_kedatangan), sd=sd(antar_kedatangan)),
      col="green", lwd=2, add=TRUE, yaxt="n")
```

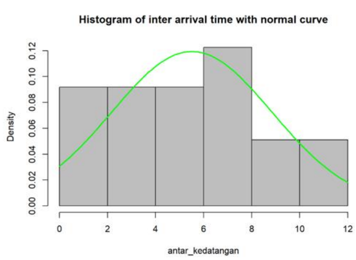

Figure 6 Inter-arrival histogram with normal distribution smoothing line withmean= mean(antar kedatangan) and Standard deviation= sd(inter_arrival).

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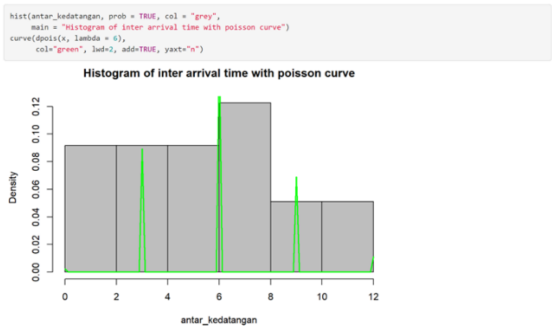

Figure 7 Inter-arrival histogram with smoothing line of Poisson distribution with lambda= 6

The next stage of data exploration is to examine the dynamic behavior of the observed data. Exploration of the dynamic behavior of the data is done by entering the observed data into the Simmer simulation model. In this research report, the exploration of the dynamic behavior of the observed data is named Scenario 1. Scenario 1 consists of three sub-scenarios, namely 1a, 1b, and 1c. Sub-scenario 1a or for convenience, just called Scenario 1a examines data dated March 18, 2021; Scenario 1b uses data on March 24, 2021 and Scenario 1c uses data on March 27, 2021. Observation data on March 19,22 and 23 are not reported on this occasion because there is too little queue data even though in aggregate it is needed to provide a statistical picture. Scenario 1 uses the loop() function to input data (arrival time and service time) into the queue system.

a. Scenario 1a
Scenario 1a uses the R programming language which uses Model G/G/1; G=General or independent with infinite number of queues using data from observations on March 18, 2021. Arrival time is original, original service time, uses 1 server and queue length is not limited. The results obtained are the average resource counter only reached 52%, did not work optimally and for 14 prospective passengers (passengers) spent a total queue time of 89 minutes. It means that the average queue time during counter service per passenger is 89/14 = 6.3 minutes. The average waiting time is 1.87142857142857minutes.

b. Scenario 1b
The simulation of scenario 1b uses Model G/G/1; G=General or independent with infinite number of queue using data from observation on March 24, 2021. Arrival time is original, original service time, uses 1 server and queue length is not limited. utilization from the counter (resource utilization) only reached 50% for 9 passengers spending a total queue time of 54 minutes. The average queuing time during counter service per passenger is 54/9 = 6 minutes. The average waiting time is 0 minutes (-1.97372982155583e-16).

c. Scenario 1c
This 1c scenario simulation uses Model G/G/1; G=General or independent with infinite number of queue using data from observation on 27 March 2021. Arrival time is original, original service time, uses 1 server and queue length is not limited, utilization of the counter only reaches 58% for 12 passengers spending time total queue for 51 minutes. The average queue time during counter service per passenger is 51/12 = 4.25 minutes. The average waiting time is 0.221666666666667 minutes.

From Scenario 1, it can be concluded that although the similarity in the utilization of counter resources, which ranges from 52-58%, basically each queue is unique. Queue dynamics reinforce the assumption that is often used in modeling queues, namely the randomness of events. To be able to get a model that is flexible and can be used as an extrapolation to the normal period, the observed data will be used as the baseline model. The baseline model uses a Markovian model with stochasticity represented by exponential, Poisson, erlang and normal distributions for arrival time, inter-arrival and service. Various M/M/c models will be tested and the best one will be selected as the baseline model. The criteria for selecting the best model is a model based on parameters obtained from observation data which gives the best total time and waiting time. the average arrival of prospective passengers per minute (rate) is as follows: March 18: 0.157091562, March 19: 0.167280027, March 22: 0.167280027, March 23: 0.094517958, March 24: 0.166112957, March 27: 0.235710077. From the six queues, the aggregate average from March 18 to 27 is 0.164665435 with a standard deviation of 0.04481326. Rate = 0.164665435 will be used in the baseline model. Mean(arrival) =1/Rate = 6.07292 minutes .

a. Baseline Simulation (Loop-1)
   Loop-1 uses the M/M/1/Inf model: Exp/Exp/1/Inf. In this simulation, the loop() function is used as used in the examination of the dynamic behavior of the observed data above. The arrival time input is generated by creating 100 random numbers using an exponential distribution with rate = 0.164665435 through the equation Sim_arr = sort(rexp(100, 0.164665435), decreasing = FALSE). A random number of 100 simulates the arrival of 100 prospective passengers. The 100 prospective passengers are in reality equal to approximately 67% to 77% of the load on the Boeing 737-300 aircraft which are widely used by domestic airlines. The service time at *the check-in counter is* expressed through the equation: Sim_service = rexp(100, 1/mean(service_time)). From the Loop-1 simulation, it was found that 100 passengers spent a total queue time of 366 minutes. It means that the average queue time during counter service per passenger is 366/100 = 3.66 minutes. The average waiting time is 160.055852158307 minutes. The average waiting time of 160 minutes, which is more than two hours, is problematic. counter/server utilization that reaches 100%.

b. Baseline Simulation (Loop-2)
   Loop-2 simulation. In the Loop-2 simulation, the principle is similar to Loop-1, which is still using the M/M/1/Inf model. The difference is the arrival time simulation equation that uses the erlang distribution. The second simulation or Loop-2 uses the M/M/1/Inf model: Erl/Exp/1/Inf. Note that this simulation uses the loop() function as used in the dynamic behavior check of the observed data above. The arrival time input is generated by creating 100 random numbers using the Erlang distribution with shape=3.5, rate=3.5*0.164665435 through the equation: Sim_arr = sort(rgamma(100, shape = 3.5, rate = 3.5*0.164665435), decreasing = FALSE). A random number of 100 simulates the arrival of 100 prospective passengers. The 100 prospective passengers are in reality equal to approximately 77% to 67% of the load on the Boeing 737-300 aircraft which are widely used by domestic airlines. The service time at *the check-in counter is* expressed through the equation: Sim_service = rexp(100, 1/mean(service_time)). From this Loop-2 simulation, it was found that 100 passengers spent a total queue time of 343 minutes. It means that the average queue time during counter service per passenger is 343/100=3.43 minutes. The average waiting time was (Average waiting time for 100 completions was) 174.587558044034 minutes. The average waiting time of 174 minutes, which is almost 3 hours, is problematic. For server services reach 100% utilization.

c. Baseline Simulation (Loop-3)
The Loop-3 simulation uses the same random model as the Loop-2 model but with an increase in the number of servers to 2 with a fixed queue line 1. The third simulation or Loop-3 uses the M/M/2/Inf model: Erl/Exp/2/Inf. In this simulation using the loop() function as used in the dynamic behavior check of the observed data above. The arrival time input is generated by creating 100 random numbers using the Erlang distribution with shape=3.5, rate=3.5*0.164665435 through the equation: Sim_arr = sort (rgamma(100, shape = 3.5, rate = 3.5*0.164665435), decreasing = FALSE). A random number of 100 simulates the arrival of 100 prospective passengers. The 100 prospective passengers are in reality the same as approximately 67%-77% of the load on the Boeing 737-300 aircraft which are widely used by domestic airlines. The service time at *the check-in counter is* expressed through the equation: Sim_service = rexp(100, 1/mean(service_time)). From this Loop-3 simulation, it was found that 100 passengers spent a total queue time of 172 minutes. It means that the average queue time during counter service per passenger is 172/100 = 1.72 minutes. The average waiting time was (Average waiting time for 100 completions was) 82.0911023081484 minutes. The average waiting time of 82 minutes, which is almost 1.5 hours, seems normal. For service counter/server utilization, 2 servers reach 100% utilization.

d. Baseline Simulation (Loop-4)
The Loop-4 model will be simulated using the same random model as the Loop-3 model with 2 servers but with individual lines. Servers 1 and 2 each have their own queue. In this Loop-4 model, prospective passengers who come will choose to enter the shorter queue line. The fourth or Loop-4 simulation uses the M/M/2/Inf Individual Line model: Erl/Exp/2/Inf Individual Line. Note that this simulation uses the loop() function as used in the dynamic behavior check of the observed data above. The arrival time input is generated by creating 100 random numbers using the Erlang distribution with shape=3.5, rate=3.5*0.164665435 through the equation: Sim_arr = sort(rgamma(100, shape = 3.5, rate = 3.5*0.164665435), decreasing = FALSE). A random number of 100 simulates the arrival of 100 prospective passengers. The 100 prospective passengers are in reality equal to approximately 67% to 77% of the load on the Boeing 737-300 aircraft which are widely used by domestic airlines. The service time at *the check-in counter is* expressed through the equation: Sim_service = rexp(100, 1/mean(service_time)). From this Loop-4 simulation, it was found that 100 passengers spent a total queue time of 199 minutes. It means that the average queue time during counter service per passenger is 199/100 = 1.99 minutes. The average waiting time was (Average waiting time for 100 completions was) 84.4235014024592 minutes. The average waiting time of 84 minutes, which is almost 1.5 hours, seems normal and the 2 server service counter/server utilization reaches 100% utilization.

e. Baseline Simulation (Loop-5)
To test the effect of the seed number on the simulation results, a Loop-5 model simulation was carried out. Loop-5 uses the Loop-3 model but is run using five different seed numbers: 393, 1005, 79955, 39772, 234999 with the coding: mclapply(c(393, 1005, 79955, 39772, 234999), function(the_seed){ set .seed(the_seed) …} The results of the Loop-5 simulation show five different average waiting time values as follows:

```
## [1] "Average wait for 100 completions was 71.9243549087582 minutes."
## [2] "Average wait for 100 completions was 76.3203064470353 minutes."
## [3] "Average wait for 100 completions was 83.4450095628096 minutes."
## [4] "Average wait for 100 completions was 76.488973421936 minutes."
```

[5] "Average wait for 100 completions was 67.4129208722451 minutes."

When run 100x produces an average waiting time of 79.31764 minutes and a standard deviation of 11.8707642. Based on the discussion above, it was decided that the baseline model is loop-3 with the M/M/2/Inf Single Line model with M=Exponential Arrivals/ M=Exponential Services/c: capacity=2 counters/Unlimited number of queues=Inf and one queue line serving 2 counters. Rate (for arrival time)= 0.164665435 prospective passengers per minute, rate (for service time)=1/mean(service_time) is the best simulation because the processing time is shorter than loop-1, loop-2 and loop-4. The exponential distribution for arrival time was deliberately chosen considering that the Erlang distribution which is a special case of the gamma distribution tends to approach the normal curve with increasing shape values.

The baseline model is based on the assumption of pandemic conditions, which occur at *the check-in counter* . This condition provides relatively more relaxed pressure compared to conditions before the pandemic. To see the behavior of the model under normal conditions, it is necessary to do stress analysis. Stress analysis of the baseline model is carried out by introducing the q factor. The q factor serves as a rate multiplicator. The baseline model is identical to q=1. The model will be in a more stressful condition as the value of q increases.

a. Extrapolation Simulation 1
The Extrapolation 1 simulation uses the same random model as the Baseline loop-3 model with the M/M/2/Inf Single Line Model with M = Exponential Arrivals / M = Exponential Services/ c, capacity = 2 counters / Unlimited number of queues = Inf and one line queue serving 2 counters. Rate (for arrival time) = 0.164665435 prospective passengers per minute, rate (for service time) = 1/mean(service_time). In the Extrapolation-1 model, the multiplication factor is q=10. The Extrapolation-1 model can handle stress well. Its performance is no different from that of the Baseline model. The average processing time for Extrapolation-1 is 1.89 minutes. This time is longer than the Baseline model which is 1.61 minutes. The average waiting time for Extrapolation-1 is 95 minutes. This time is longer than the Baseline model which is 68.87 minutes. The Extrapolation-1 simulation results in maximum loading (100%) on both *check-in counters* .

b. Extrapolation 2 . Simulation
Extrapolation-2 simulation is the same as Extrapolation-1 except the value of q changes from 10 to 100. Extrapolation-2 model can handle stress well. Its performance is no different from that of the Baseline model. The average processing time for Extrapolation-2 is 1.89 minutes. This time is longer than the Baseline model which is 1.61 minutes. The average waiting time for Extrapolation-2 is 95 minutes. This time is longer than the Baseline model, which is 68.87 minutes and results in maximum loading (100%) on both *check-in counters* .

c. Simulation Extrapolation 3
Extrapolation-3 model, increased service capacity from 2 counters to 3 counters. The Extrapolation-3 simulation uses the M/M/3/Inf single Line model: Exp/Exp/3/Inf Single Line. The dynamic behavior of Extrapolation-3 is similar to the previous extrapolation simulation. The improvement obtained in the Extrapolation-3 simulation compared to the previous extrapolation simulation is its ability to improve the average processing time to 1.27 minutes and waiting time to 62.7 minutes to serve 100 passengers. Processing time of 127 minutes to serve 100 passengers shows a very good queue performance.

d. Extrapolation Simulation 4
   To see the effect of randomness on the Extrapolation-3 model, a test was conducted using the same technique used in the Loop-4 simulation. Extrapolation 4 introduces 100 different seed numbers. As a result, the average waiting time is 54.58732306 minutes with a standard deviation of 6.525936958. The waiting time was 62.7 minutes close to the right limit of one standard deviation (σ).
e. Extrapolation Simulation 5
   Finally, what will be done for the extrapolation simulation is to examine the Extrapolation-5 model, namely the M/M/3/Inf Individual Line: Exp/Exp/3/Inf Individual Line model and compare it with the Extrapolation-3 simulation model. The Extrapolation-5 simulation uses the M/M/3/Inf Individual Line model: Exp/Exp/3/Inf Individual Line. This simulation uses the loop() function as used in the dynamic behavior check of the observed data above. The arrival time input is generated by creating 100 random numbers using an exponential distribution with rate=q*0.164665435, q=100, through the equation: Sim_arr = sort(rexp(100, rate = q*0.164665435), decreasing = FALSE). A random number of 100 simulates the arrival of 100 prospective passengers. The 100 prospective passengers are in reality the same as approximately 67%-77% of the load on the Boeing 737-300 aircraft which are widely used by domestic airlines. The service time at *the check-in counter is* expressed through the equation: Sim_service = rexp(100, 1/mean(service_time)). utilization for all three counters/servers reaches 100% utilization. From the Extrapolation-5 simulation, it was found that 100 passengers spent a total queue time of 110 minutes. It means that the average queue time during counter service per passenger is 110/100 = 1.1 minutes. The average waiting time was (Average waiting time for 100 completions was) 52.0543397496404 minutes. The average waiting time of 52 minutes, which is almost 1 hour, seems normal.

   The Extrapolation-5 simulation model shows an indication of an improvement in the average processing time and average waiting time. The average processing time per passenger has improved to 1.1 minutes compared to Extrapolation-3's 1.27 minutes. The average waiting time per passenger has improved from 54.58 minutes on Extrapolation-3 to 52 minutes on Extrapolation-5.

   The loop-3 simulation becomes the model that has the lowest average service time and average waiting time or it can be said that the loop simulation is the best compared to other loops because to serve 100 passengers it only takes 82 minutes or 1 hour 22 minutes with an average waiting time 1.72 minutes or 2 minutes 12 seconds. And the Extrapolation 5 Simulation with the M/M/3/Inf model: Exp/Exp/3/Inf individual line with q=100 gets the results of the average queue time during counter service per passenger is 1.1 minutes, the average waiting time 52.05 minutes with counter/server utilization reaching 100%. From the results of the Extrapolation 5 simulation, it was found that to be able to serve 100 passengers with passenger arrival speeds 100x faster than the current pandemic period. the check-in system that has been built at this time is quite resilient to changes in passenger load with the current service time and *the check-in counter* which is always open three counters can still serve without the system experiencing a break down with an average waiting time of only 52 minutes with a waiting time an average of 1.1 minutes.

5. Conclusion and Suggestion

Conclusion

From the research that has been done, several conclusions can be drawn as follows:

a. The behavior of passengers at *the* Lion *check-in counter at* Supadio Pontianak Airport is random, and the results of the loop-3 simulation with the M/M/2/Inf, Erl/Exp/2/Inf single line model, the average queue time for service is 1 ,72 minutes, the average waiting time is 82 minutes with counter/server utilization reaching 100% being the best result compared to the queue time and average waiting time results from other loop simulations.

b. From the results of the Extrapolation simulation that has been carried out in this study, it can be concluded that the current queuing model is good, checking using the Baseline model which is applied to the stress test (Extrapolation-n model), Lion Air check-in system at Supadio Pontianak Airport which has been currently built is quite resilient to changes in passenger load that comes using Extrapolation 5 Simulation with the M/M/3/Inf model: Exp/Exp/3/Inf individual line with q=100 it is found that the average queue time during counter service per passenger is 1.1 minutes, average waiting time is 52.05 minutes with counter/server utilization reaching 100%. This result is the best result compared to the results of the queue time and average waiting time from other Extrapolation simulations.

Suggestion

Based on the results of this study, there are several suggestions that can be given both for further research and for companies, as follows:

a. For further research, it is hoped that the observation data collected can be more varied based on events that occur at other airports, and can calculate efficiency in terms of costs. Because this research was only conducted at Pontianak Supadio airport which has different characteristics of passenger behavior, so that the distribution that occurs is different from other airports and does not calculate cost efficiency in a check-in process;

b. This research is expected to be an input for the *Airport Operation & Service* unit *at* Supadio Pontianak Airport as the manager of the *Check-in Counter, which* can be an aspect that is taken into account in determining the opening time of *the check-in counters* and the number of *check-in counters* to be opened so that service standards are achieved. To get service times that are in accordance with predetermined standards, *the check-in counter* can be opened at least 3 counters at any time of the check-in process at Supadio Pontianak Airport and can be used for airline management in order to maximize the *check-in counter* desk and the required resources. in the check-in process at Supadio Pontianak airport.

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