Simulation and Analysis of LRT 2 Hourly Passengers

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Abstract - **Transportation has an impact on practically every element of Filipinos' everyday lives. Trail railways provide the creation of a fast and reliable transit system which directly connects to hubs of social and economic interest and has boosted entrepreneurship and the growth of Small-to-Medium Enterprises. In this study, we focus on modeling and analysis of the hourly passengers of Light Rail Transit (LRT), as their way of transportation. The dataset was collected from the FOI website. The main objective of this study is to propose a comprehensive discrete-event simulation (DES) model that can be used for evaluating the railway transport capacity of a specific corridor and also conduct a hypothetical what-if scenario to test the efficiency and reliability of the model. [1] The pedestrian simulation was done using the simulation software Anylogic to assess the passenger capacity of LRT 2. This study depicts the current condition within the railway station while also anticipating the behavior of queued pedestrians and calculating the volume-to-capacity ratio of people entering the station.**

Keywords - Simulation modeling, train queue, passenger queue, time interval

I. Introduction

The railway system is one of the easiest and most convenient ways of traveling from one place to another. For this reason, many people prefer trains as their mode of transportation. Since trains provide comfort, uninterrupted movement, and high speed while generating low pollution and low energy consumption, which are essential attributes of sustainable transport, a high rail-based travel demand is expected. [2]

High economic and population expansion in the recent decade were not supported by equivalent and timely infrastructure investment, resulting in considerable traffic congestion in Metro Manila and other major cities. In 2015, a number of public-private partnership (PPP) projects were also delayed at various stages from planning to implementation. In particular, the much-needed LRT-MRT common station has been delayed for five years now since inception as the two operators have yet to agree on where to build it. [3]

As the Philippines' capital city, Metro Manila seems to be eternally on the move—and consequently, so are its people. However, there still exists a struggle to keep up with the fast-paced lifestyle that Manila demands. Most notably, the public transport system is one of these infrastructures that are unable to catch up, and quite literally at that. At present, it has become the norm for commuters to wait for hours for their transportation, if it will be available at all [4]. In addition to the wait time for their commute, many have grown accustomed to spending hours on the road due to traffic, making their total time spent on travel much longer [5].

II. Case Study Background

The LRT (light rail transit) Line 2 was constructed between 1996 and 2003. Phase One covered the stations of Santolan, Katipunan, Anonas and Araneta Center-Cubao and began its operations on 5 April 2003 while Phase Two from Betty Go-Belmonte to Legarda was inaugurated on 5 April 2004 [6]. In 2021 President Rodrigo Roa Duterte led the inauguration of the 3.79-kilometer elevated LRT-2 East Extension Marikina-Pasig and Antipolo stations on 01 July 2021. Marikina-Pasig station is located in front of Robinsons Metro East near Mayor Gil Fernando Avenue in Marikina City while the Antipolo station is situated in front of SM Masinag, adjacent to the Masinag junction near Sumulong Highway in Antipolo City, Rizal. [7]. The line is designed and was forecasted to carry 570,000 passengers daily [8]. However, the line operates under its designed capacity. Before the pandemic, the line had a ridership of 200,000 passengers, but the ridership soon decreased in 2019 due to lack of trains and a power trip that closed three stations in October 2019 that was reopened in January 2021. The line served 33,267 passengers daily on average in 2021 [9], with eight trains available for revenue service running at an operating speed of 60 to 70 kilometers per hour (37 to 43 mph) in 10-minute intervals.

A. Poisson distribution

The Poisson distribution is popular for modeling the number of times an event occurs in an interval of time or space. It is a discrete probability distribution that expresses the probability of a given number of events occurring in a fixed interval of time and/or space if these events occur with a known average rate and independently of the time since the last event. The Poisson probability distribution gives the probability of a number of events occurring in a fixed interval of time or space if these events happen with a known average rate and independently of the time since the last event. [17]

B. Problem Statement

The planning process in public transportation, according to Liebchen (2008), consists of the following steps: 1) network design 2) line planning 3) timetabling 4) vehicle scheduling 5) duty scheduling 6) crew rostering Liebchen (2008). The outcome of a previous planning stage is used as input for the tasks that follow. Headway optimization is one of three techniques for constructing a timetable and is part of task timetabling (Ceder 2001). Passengers tend to ignore the schedule since a rapid transportation system like a subway system normally has a headway of less than 10 minutes (particularly during peak hours) (Mandl 1980).

Origin-destination matrices are required to model such a complex service system. Related contributions, to the best of our knowledge, usage count data (Ceder 1984), smart card data (Pelletier et al. 2009), and mobile phone data (Friedrich et al. 2010). Another challenge is predicting passenger behavior, particularly how they choose which route to travel (Agard et al. 2007). Regional variances are also evident, according to Raveau et al. (2014). Bauer et al. published a study on the various technologies utilized in pedestrian counting and tracking (2009) [14].

Line 2 Ridership CY 2020 vs 2021					
Particulars	Target 2021	Actual 2021	Actual 2020	Variance from Target (%)	Variance from 2020 (%)
Ridership (In Millions)	12.68	11.84	12.50	-6.62%	-5.28%
Daily Average	35,606	33,267	45,463	-6.57%	-26.83%
Highest Daily Ridership for the Year		72,872	148,444		-50.91%
Date		December 20 (Monday)	January 9 (Thursday)		

Figure 1. Line 2 Ridership CY 2020 vs 2021

A. Objective

The objectives of this case study are to acquire insight into the system's boundaries: first, whether there is room to improve the current system's performance by altering headways, and what the consequences are in terms of vehicle count, mileage, and passenger satisfaction (passenger times). Second, there are concerns about the future instances, such as how many more passengers can be accommodated with the existing headway setting. It's critical to look at how certain key performance metrics (such as passenger times) interact in both scenarios. However there are of course conflicting goals such as passengers prefer tight headways, which result in reduced waiting and, as a result, lower passenger journey time as well as poor utilization.

Instead of using only a reference sheet to determine train data, the solution will be able to "learn" how each specific train (and passengers) behaves in the network. This means even more accurate plans and improves decision-making at the operations center. Therefore, this study can give more efficiency to railroad operation for the LRT 2.

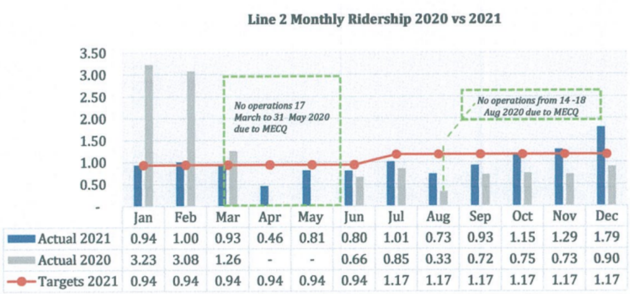

Figure 2. Line Monthly Ridership 2020 vs 2021

B. Project timeline

As shown in Figure 3, the proponents created the gantt chart to show the timeline or process that will follow. Data Gathering spanned for the entire month of March since it was difficult to find data from private companies, and there is no data available on the internet even in FOI websites of each government department. Model building is difficult and time consuming, that is why it spanned for almost two months. It was also under verification and validation in the last part of May. For the documentation, the proponents started in April until the whole simulation finished.

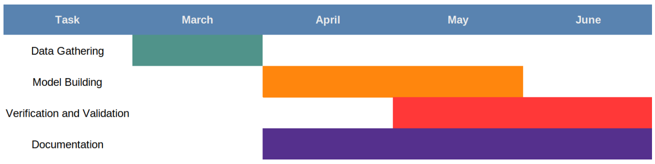

Figure 3: Gantt Chart For Simulation Building

C. Key Performance Indicators (KPI)

A KPI, or key performance indicator, is a quantitative value used to assess a person's or organization's progress in meeting a goal. You can have high-level KPIs that look at the overall performance of your company, as well as KPIs that drill down into individual or departmental activities. [18].

- Passenger Traffic: this indicator shows the total income per passenger.. Together with the total income indicator, these two can also be used to analyze the ability of the train station in obtaining income from each journey [19].
- Gross Revenue Collection: is calculated by dividing the LRT's gross profit (which is calculated by subtracting total operating expenses from total revenue) over a specific period of time, and dividing that by the total number of passengers during that period [19].
- Peak-Hour Trainsets Running: the busiest hours, as during rush hour [19].
- Peak Hour Load Factor: load factor is defined as the ratio of the average load over a given period to the maximum demand (peak load) occurring in that period. In other words, the load factor is the ratio of energy consumed in a given period of the times of hours to the peak load which has occurred during that particular period [19].
- Fare Box Ratio: the farebox recovery ratio of a passenger transportation system is the fraction of operating expenses which are met by the fares paid by passengers. It is computed by dividing the system's total fare revenue by its total operating expenses [19].

III. Discrete Event Simulation Model

Discrete-event in a simulation occurs at a predetermined point in time and changes the state of the system. Continuous simulation is another option. It is activity-based rather than event-based, which means that a state is changed/updated at a certain time slice. Entities, activities and events, resources, global variables, a random number generator, and a 9 2. A discrete-event simulation typically comprises the following components, theory collectors, system state variables, and theory calendar[10].

A. Anylogic simulation software

The AnyLogic Company (former XJ Technologies) created AnyLogic, a multimethod simulation modeling tool. Agent-based, discrete event, and system dynamics simulation approaches are all supported. AnyLogic is a cross-platform simulation software that runs on Windows, macOS, and Linux. It's used to simulate things like markets and competition, healthcare, manufacturing, supply chains and logistics, retail, business processes, social and ecosystem dynamics, defense, project and asset management, pedestrian dynamics and road traffic, IT, and aerospace. Simulation modeling is a safe and efficient way to solve real-world problems. It offers a significant way of analysis that is simple to verify, communicate, and comprehend. Simulation modeling delivers valuable solutions across sectors and disciplines by providing clear insights into complicated systems[11].

Bits not atoms. Simulation allows you to explore with a system's digital representation. Simulation modeling, unlike physical modeling, such as producing a scale model of a building, is computer-based and uses algorithms and mathematics. Simulation software creates a dynamic environment for analyzing computer models while they're operating, with the option of seeing them in 2D or 3D[12].

B. Main Elements Considered in the Simulation Model (States, Entities)

Discrete event simulation (DES) is a strategy used to replicate real-world systems that can be turned into a set of discrete processes that emerge logically and autonomously by time. Each event occurs on a specific process and is assigned a reasonable time (a timestamp). The result of this event can be passed to one or more other processes. The content of the result can generate new events that are generated to be handled at a specific, reasonable future [16].

The simulation model represents the entity, which is the train's flow through the different ways (depending on its state) as it passes through the cycle. We considered the train as an entity since we are currently finding the delay of the train in a specific station and the time interval it gets to the next station. Also, the containers on the trains will have an attribute that tells us where it came from, and where it is heading. The passenger is considered as an entity, since it has its own different time interval/s. And last, the loading Area, in which we considered it as a resource since this is the platform where the passengers wait for the arrival of the train. This is also used for the selection of passengers that could go-in and out from/to the train.

Therefore, three state variables are needed: the train, the passenger, and the loading area/platforms. There are three events related to the simulation of the system.

C. Modeling the Passenger Flow

A passenger can access the light rail transit in a very simple way. Usually, when a person needs to get from point A to point B they just need to first buy a single journey ticket and in some cases people who already have a beep card will just load them in the nearest beep card machine. After possessing a loaded card, they will pass through a turnstile then wait for the train to arrive at the loading area. Then enter the train which makes them in an active state. Being on the journey holds the passengers in a dead state. After arriving at the desired station the passengers will exit the train then exit the station. Being outside the station makes them in the position of being in a dead state. Lastly entering the station leaves them in the position of being in an active state.

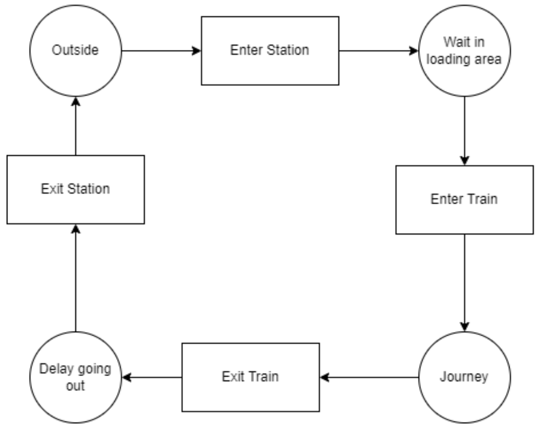

Figure 4. Passenger Flow

D. Modeling the Train Flow (Flowchart Pic)

The shapes on the figure 5, signifies that while the process is in the dead state, the shape will be in a circle. On the other hand, the rectangle shape signifies the process of being in an active state.

The process in Figure 5, begins when the operating hours of the train within the day starts. At the beginning, the first process that will happen is the waiting time for the train to depart on the next station. After arriving at the platform on the station, an allotted time will be provided for the train to garner all the possible passengers that it may carry upon to the next succeding station/s. While the train is finished carrying passengers on the platform, the state of the train will be in the active state, since the train will depart from one station going to the other. For instance, when the train from the succeeding station is currently loading or unloading passenger/s, that's the time when the status of the train is in a dead state. Specifying what state that the train is at, using the shapes are much more enlightening to see, since we can clearly visualize the simulation in just a form of diagrams.

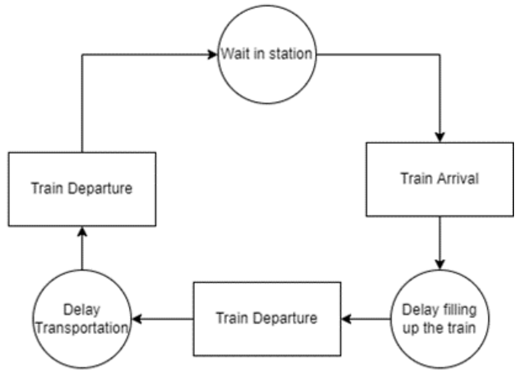

Figure 5. Train Flow

IV. The Simulation

A. Input and Output Data Requirements

The LRT-2 Hourly Ridership 2017 dataset, was extracted by the electronic freedom of information's (FOI) website, from the LRT-Authority agency. It contains the total tally per hour, which consists of the daily entry/exit traffic per station within each hour, for the month of December, year 2017. The expected output for the simulation is the hourly ridership of every station. Hence, the model should create a file where each of the stations has the hourly ridership. The output data will be used for validation.

B. Poisson Distribution

The table 1 shows the gathered data using Poisson Distribution, which consists of; the timestamp starting from 4:00 am in the morning, up to 22:00 or 10:00 pm in the evening; the Mean; the Min; and Max in each succeeding hour/s of the station within the day. The value of the variable *mean* came from the total average time of the hourly ridership of LRT-2 passengers, from 4am to 4:59 am, and so on. While, the value of the variables *min* and *max*, came from the total average of the hourly entry ridership of LRT-2 passengers from 4am to 4:59 am, and so on.

The researchers used the default setting from the Anylogic software of Shift which is 0, and Stretch – which is 1.

Time	Mean	Min	Max
4	16.03225806	4	33
5	80.35483871	20	123
6	159.4516129	49	260
7	255.1290323	44	425
8	262.6451613	51	454
9	300.7741935	96	425
10	369.3225806	142	619
11	482.6129032	133	783
12	643.5806452	134	1329
13	753.7096774	128	1344
14	762.6129032	126	1358
15	929.2580645	150	1721
16	1131.709677	135	2299
17	1274.193548	124	2608
18	1120.032258	144	2131
19	929.8064516	34	2077
20	665.3	27	1700
21	496.9310345	48	1170
22	110.2068966	18	620

Table 1. Sample Poisson Distribution Table Calculated From Legarda Station Only

C. Project Boundaries and Limitation

The dataset includes all the 11 station; such as Recto, Legarda, Pureza, V.Mapa, J.Ruiz, Gilmore, Betty Go, Cubao, Anonas, Katipunan, and Santolan. Specifically, the dataset contains the timestamp from 04:00-24:00 hours within each day of December, year 2017. We had an agreement to exclude the newly added station, which is the Marikina and Antipolo station, due to the inconvenience in tallying the total number of the hourly passenger within the specific month.

D. System Assumptions

Structural assumptions and data assumptions were made in this simulation model as shown in the following:

1. Passengers
   a. Passengers do not know the actual arrival time of trains at stations.
   b. Passengers would enter the trains after passengers who are inside the trains step out from the train.
   c. Principle of "first in, first out" was applied.
   d. If an event of missing the trains due to reaching the maximum passenger capacity of trains occurred, those passengers would not leave the station for alternative transportation. v. Passengers would step out from trains at desired destinations only, in other words, passengers would not travel beyond the destination.
   e. All the passengers waiting at the platform would be able to enter the trains within the dwell time.
   f. Passengers would not arrive at stations in groups
2. Trains and tracks
   a. Trains arrive at stations punctually as scheduled.
   b. Train failure would not occur.
   c. Total number of passengers idle on the platform will automatically enter once the train arrives.
3. Arrival pattern of passenger at stations
   a. Number of arrivals of passengers at a station within a certain interval of time could be modeled as Poisson distribution.
   b. Arrival rates of passengers would not be changed within a certain interval of time.
   c. The arrival process of passengers on one day is independent of the arrival process of passengers on another day.
   d. The arrival rates of passengers in a day are different from the arrival rate of passengers in another day within the same interval of time.
   e. Inter arrival times of passengers are assumed to be an independent and identically distributed exponential random variable.
4. Proportion of passengers to certain destinations
   a. Proportions of passengers to certain destinations are assumed to be constant.
5. Dwell time at stations
   a. Dwell times are assumed to be uniformly distributed.
   b. Distributions of dwell time would not be varied with time and with day.

Developed simulation model was verified from the aspects of its function and its model logic with a debugging tool provided in the Anylogic software.

E. Animation requirements

Figure 6, shows a partial snapshot of a DES model developed for a LRT-2 Platforms, using Anylogic simulation software.

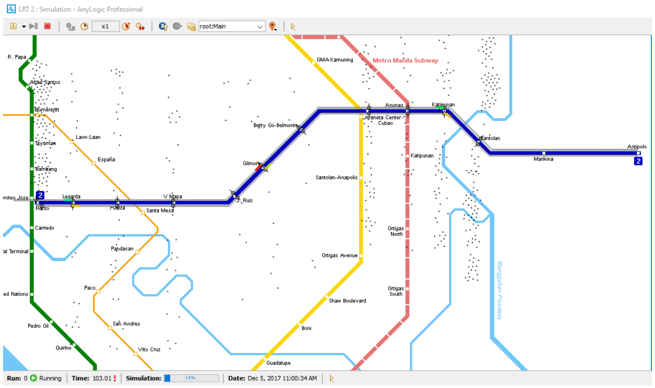

Figure 6: DES model for the LRT-2 Platforms

As shown in Figure 7, the simulation uses railway trains and passengers to put the entities into action. There are 11 stations which have the "position in track" space markup to determine the origin and destination of the passenger. As for the passenger, it was scaled down to 1:20 ratio since the proponents cannot place all actual data in the visualization part because it might cause lags in graphics.

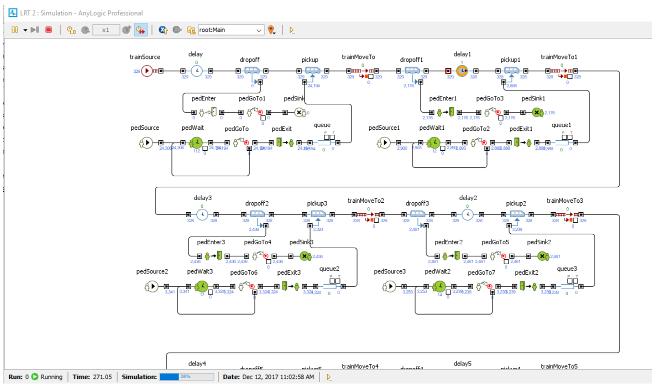

Figure 7: Lane Process

As shown in Figure 7, the simulation has processes or flowchart used since that's where the proponents interact with the passengers and trains. At this process, it also runs the poisson distribution to generate a sample per hour. It has two processes, one for lane 1 and one for lane 2. Both are the same, it differs from where the train should start since it has eastbound and westbound.

Figure 8: Time Plot Chart

As shown in Figure 8, when the simulation runs, every hour it generates samples of passengers in every station, and the system adds it in a dataset block which the time plot chart consumes. This is to keep track and visualize at the same time the number of passengers every hour. It is helpful to know what time has the most ridership and what stations have the least and high ridership.

F. "What-if?" scenarios to be evaluated

The proponents will be testing two outputs when certain variables are changed, here are the following:

- Passengers waiting in loading area
- Average passengers' waiting time

In figure 9, both outputs will change when the train max capacity and train delay are adjusted. The default train max capacity is 1600, and train delay is 7 minutes.

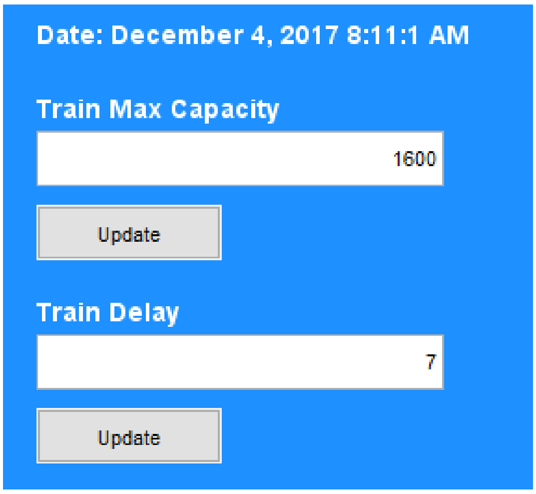

Figure 9: Train max capacity and train delay inputs

When the two variables are not adjusted, figure 10 will be the output. Based on the figure, the lowest average waiting time is 11.69 minutes which is on Lane 2 of Katipunan, while the highest is 55.62 minutes which is on Lane 1 of Santolan. On the other hand, the passengers waiting in loading are mostly 0 since the max train capacity can handle the number of passengers going in.

Month Income	People Waiting In Loading Area			Passenger Average Waiting Time	
174,900	Station	Lane 1	Lane 2	Lane 1	Lane 2
	Recto	0	0	11.727	0
	Legarda	0	0	18.869	12.593
	Pureza	0	0	26.123	33.97
	VMapa	0	0	33.408	26.685
	JRuiz	0	0	12.03	19.37
	Gilmore	0	0	19.268	12.132
	Betty Go	0	0	26.547	33.484
	Araneta	0	0	33.885	26.156
	Anonas	0	0	12.441	18.919
	Katipunan	0	0	19.67	11.69
	Santolan	0	15	55.618	33.156

Figure 10: Passengers waiting in loading are and average waiting time

When the train max capacity is changed to 800, the behavior of the outputs will change also. Based on figure 11, the average waiting time increases, and the passengers waiting in the loading area increases also.

Month Income	People Waiting In Loading Area			Passenger Average Waiting Time	
673,800	Station	Lane 1	Lane 2	Lane 1	Lane 2
	Recto	43	0	35.135	0
	Legarda	0	0	13.596	7.118
	Pureza	0	0	20.85	57.126
	VMapa	21	0	116.817	49.841
	JRuiz	1	0	35.438	13.895
	Gilmore	0	0	13.995	35.288
	Betty Go	0	0	21.274	28.009
	Araneta	1	42	57.294	109.312
	Anonas	0	30	7.168	102.075
	Katipunan	23	88	43.078	94.846
	Santolan	201	94	110.345	56.312

Figure 11: Train max capacity changed outputs

When the train delay to arrive changes to 10 minutes, and the train max capacity is the default (1600). Based on figure 12, there are stations that can accommodate passengers in least amount of time, while there are stations also that can accommodate for about an hour. The passengers waiting in the loading area can still get into the train since it has a lot of space, but it took them a while to get in.

Month Income	People Waiting In Loading Area			Passenger Average Waiting Time	
1,127,100	Station	Lane 1	Lane 2	Lane 1	Lane 2
	Recto	0	0	55.18	0
	Legarda	0	0	65.322	15.012
	Pureza	28	0	34.895	45.389
	VMapa	8	16	45.18	35.104
	JRuiz	0	0	14.802	24.789
	Gilmore	0	0	25.04	14.55
	Betty Go	4	0	35.319	44.903
	Araneta	0	133	45.657	214.575
	Anonas	0	18	15.213	124.969
	Katipunan	0	39	25.441	114.74
	Santolan	203	0	95.708	44.575

Figure 12: Train delay changed outputs

The last test is when the train max capacity changes to 2000 and the train delay changes to 4 minutes. In figure 13, the passengers' average waiting time decreases to less than 30 minutes, and the passengers waiting in the loading area can still be accommodated since it has a lot of space in the train.

Month Income	People Waiting In Loading Area			Passenger Average Waiting Time	
680,800	Station	Lane 1	Lane 2	Lane 1	Lane 2
	Recto	0	0	18.817	0
	Legarda	0	0	6.277	19.38
	Pureza	0	16	10.532	15.126
	VMapa	17	0	14.817	10.841
	JRuiz	0	0	19.12	6.526
	Gilmore	0	0	6.677	18.919
	Betty Go	0	4	10.956	14.64
	Araneta	30	0	15.294	10.312
	Anonas	0	0	19.531	6.075
	Katipunan	0	0	7.078	35.109
	Santolan	0	95	28.026	30.944

Figure 13: Train max capacity and delay changed outputs

V. *Verification and Validation*

The process of validating the accuracy and quality of data is known as data validation. It is implemented by incorporating various checks into a system or report to ensure that input and stored data are logically consistent. Data is entered into automated systems with little or no human intervention. As a result, it's critical to make sure that the data that goes into the system is correct and fulfills the quality requirements that have been set.

A. *Verification*

In figure 14, the passengers enter the station, and wait in the loading area, waiting until the train arrives. It will then go to the destination, exit from the train, and leave the station. This repeats the cycle every hour until 11PM. On the other hand, the train flows, arrives in the station and waits for filling up the train for about 10 minutes, and it will go to the next station, and will wait again. This repeats the process every hour until 11PM. As shown in Figure 8, passengers and trains work simultaneously with each other to process the output.

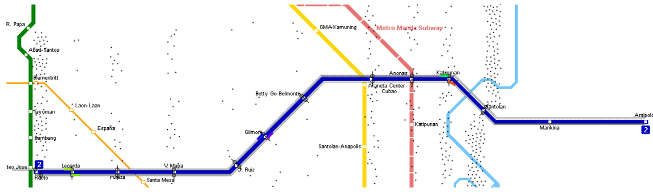

Figure 14: Passengers and Train Flow

B. *Validation*

The simulation model creates a file that contains the hourly data of each station as shown in figure 15. That is only for day 1 of December.

Time	Recto	Legarda	Pureza	VMapa	Jruiz	Gilmore	BettyGo	Araneta	Anonas	Katipunan	Santolan
12/1/2017 4:0:0 AM	77	15	30	23	8	11	2	53	39	100	279
12/1/2017 5:0:0 AM	498	75	153	147	30	40	27	265	208	619	1499
12/1/2017 6:0:0 AM	1016	173	465	463	146	160	140	821	550	1553	3831
12/1/2017 7:0:0 AM	1624	289	800	830	249	270	239	1102	802	1920	4941
12/1/2017 8:0:0 AM	1693	248	823	842	215	233	184	1236	761	2015	4332
12/1/2017 9:0:0 AM	1883	292	704	666	192	235	204	1126	738	1703	3714
12/1/2017 10:0:0 AM	1963	348	666	594	186	210	145	1132	634	1472	3136
12/1/2017 11:0:0 AM	2252	443	717	555	172	226	143	1243	607	1399	2801
12/1/2017 0:0:0 PM	2444	621	681	672	187	266	164	1352	607	1289	2618
12/1/2017 1:0:0 PM	2819	765	861	709	163	272	157	1518	586	1207	2156
12/1/2017 2:0:0 PM	3138	778	868	771	162	315	143	1673	591	1108	2043
12/1/2017 3:0:0 PM	3434	914	854	761	203	395	135	1804	600	968	1744
12/1/2017 4:0:0 PM	3774	1046	933	858	230	451	186	1937	588	881	1592
12/1/2017 5:0:0 PM	4498	1308	1074	1064	326	660	231	2135	699	1018	1597
12/1/2017 6:0:0 PM	4549	1153	899	1023	276	596	162	2493	642	884	1341
12/1/2017 7:0:0 PM	3375	910	685	817	137	480	116	2193	473	641	1115
12/1/2017 8:0:0 PM	2243	630	585	584	105	230	58	1808	288	477	756
12/1/2017 9:0:0 PM	1477	515	353	408	52	176	42	1432	193	299	470
12/1/2017 10:0:0 PM	258	113	65	124	18	31	11	293	19	9	1

Figure 15: Hourly Ridership of Every Station Output

As shown in Figure 15, the proponents get the output of the simulation which is hourly based for each of the stations. The figure only shows the first day of December 2017.

Forecasted Value Mean											
Time	Recto	Legarda	Pureza	VMapa	Jruiz	Gilmore	BettyGo	Araneta	Anonas	Katipunan	Santolan
04:00:00 AM	90.74	15.45	28.16	23.68	6.65	5.68	4.00	46.81	31.45	101.55	280.52
05:00:00 AM	478.97	80.55	154.13	150.71	38.87	41.19	33.06	296.61	189.52	638.55	1,541.97
06:00:00 AM	1,011.42	164.10	422.68	440.45	150.35	166.81	133.77	789.23	560.87	1,509.52	3,844.39
07:00:00 AM	1,639.13	253.94	821.71	857.71	249.16	240.94	225.00	1,188.65	821.97	1,973.35	4,905.23
08:00:00 AM	1,721.52	267.42	820.35	806.97	242.90	235.61	215.23	1,180.19	779.74	1,984.61	4,402.71
09:00:00 AM	1,877.52	301.19	672.74	647.23	207.65	212.61	186.39	1,166.58	715.29	1,677.52	3,755.03
10:00:00 AM	2,016.35	367.06	652.81	602.26	180.35	210.10	168.52	1,170.84	650.52	1,517.26	3,082.35
11:00:00 AM	2,260.84	490.35	684.42	605.58	164.32	234.19	153.45	1,258.90	607.06	1,409.55	2,756.65
12:00:00 PM	2,524.00	644.81	728.90	657.97	172.35	271.61	164.81	1,401.45	617.45	1,369.42	2,615.19
01:00:00 PM	2,828.23	748.29	848.45	706.23	173.97	277.58	153.42	1,561.52	619.61	1,227.61	2,252.58
02:00:00 PM	3,155.29	762.71	896.90	736.39	171.16	336.84	154.74	1,668.23	615.52	1,067.48	2,018.29
03:00:00 PM	3,418.32	928.90	853.16	774.23	197.87	403.58	152.61	1,789.03	547.03	935.00	1,745.45
04:00:00 PM	3,879.52	1,129.03	895.16	878.45	230.29	485.29	175.97	1,991.39	570.74	907.23	1,587.87
05:00:00 PM	4,535.61	1,270.55	997.58	1,048.61	325.71	657.71	247.39	2,205.42	721.87	1,028.90	1,588.58
06:00:00 PM	4,524.74	1,116.81	927.97	1,018.16	263.45	599.61	175.26	2,455.23	677.48	885.61	1,393.87
07:00:00 PM	3,434.74	933.32	699.87	791.71	159.90	473.81	126.19	2,215.81	444.84	619.97	1,079.26
08:00:00 PM	2,230.27	664.80	577.37	588.53	99.03	238.73	69.70	1,850.20	315.87	467.07	769.73
09:00:00 PM	1,457.03	497.23	355.63	411.47	56.53	169.33	41.47	1,445.83	190.43	306.53	484.33
10:00:00 PM	263.27	109.07	71.57	129.37	15.73	35.17	9.27	274.13	12.27	6.97	0.37

Actual Data											
Time	Recto	Legarda	Pureza	VMapa	Jruiz	Gilmore	BettyGo	Araneta	Anonas	Katipunan	Santolan
04:00:00 AM	91.52	16.03	27.42	23.06	6.58	6.06	4.06	46.87	29.10	104.58	274.58
05:00:00 AM	477.39	80.35	155.74	149.61	38.10	41.71	33.29	297.32	185.13	638.00	1,539.42
06:00:00 AM	1,002.61	159.45	422.58	447.19	151.68	169.84	133.77	799.68	562.52	1,508.42	3,844.97
07:00:00 AM	1,622.97	255.13	821.45	850.00	254.39	240.29	227.48	1,193.23	817.87	1,975.71	4,894.03
08:00:00 AM	1,731.23	262.65	816.52	813.06	242.19	237.71	220.87	1,185.19	783.29	1,988.39	4,412.81
09:00:00 AM	1,870.87	300.77	674.68	648.42	203.55	217.13	187.94	1,160.71	710.06	1,678.68	3,753.19
10:00:00 AM	2,013.00	369.32	660.19	602.19	181.16	212.16	169.87	1,167.81	649.74	1,520.71	3,089.77
11:00:00 AM	2,262.94	482.61	684.39	600.16	165.97	230.03	155.68	1,262.68	612.00	1,408.90	2,773.42
12:00:00 PM	2,516.00	643.58	723.29	662.45	170.81	273.52	160.48	1,417.65	617.55	1,367.61	2,610.19
01:00:00 PM	2,824.87	753.71	841.10	702.19	172.45	276.90	153.16	1,564.06	617.00	1,223.16	2,242.16
02:00:00 PM	3,151.00	762.61	895.52	734.97	170.26	340.58	153.03	1,663.48	612.32	1,073.84	2,021.65
03:00:00 PM	3,416.32	929.26	850.52	767.39	191.94	402.94	152.06	1,788.61	554.48	933.81	1,736.77
04:00:00 PM	3,882.81	1,131.71	890.42	881.61	227.23	483.48	177.19	1,992.94	572.23	906.94	1,588.19
05:00:00 PM	4,545.52	1,274.19	994.35	1,054.26	325.97	659.84	243.29	2,206.74	722.35	1,029.55	1,581.32
06:00:00 PM	4,525.29	1,120.03	924.58	1,009.68	265.48	601.55	178.39	2,444.06	667.90	888.26	1,388.48
07:00:00 PM	3,439.45	929.81	707.55	776.55	160.71	473.52	125.35	2,209.10	450.39	614.87	1,072.74
08:00:00 PM	2,253.53	665.30	583.77	587.97	98.53	242.73	69.07	1,830.20	309.40	471.43	770.27
09:00:00 PM	1,467.24	496.93	358.48	420.86	59.48	167.97	42.48	1,444.62	190.14	308.52	477.45
10:00:00 PM	263.21	110.21	72.83	130.21	14.50	34.83	8.64	273.90	11.76	6.97	0.31

Figure 16: Hourly Average Ridership of Every Station
Simulation and Actual Data

In figure 16, the hourly average ridership of every station and the actual data are compared. Based on the figure, it seems that the data are almost the same or close enough.

A. Mean Absolute Percentage Error - MAPE

MAPE – Mean Absolute Percentage Error											
Time	Recto	Legarda	Pureza	VMapa	Jruiz	Gilmore	BettyGo	Araneta	Anonas	Katipunan	Santolan
04:00:00 AM	0.85	3.62	2.71	2.66	0.98	6.38	1.59	0.14	8.09	2.90	2.16
05:00:00 AM	0.33	0.24	1.04	0.73	2.03	1.24	0.68	0.24	2.37	0.09	0.17
06:00:00 AM	0.88	2.91	0.02	1.51	0.87	1.79	0.00	1.31	0.29	0.07	0.02
07:00:00 AM	1.00	0.47	0.03	0.91	2.05	0.27	1.09	0.38	0.50	0.12	0.23
08:00:00 AM	0.56	1.82	0.47	0.75	0.29	0.88	2.56	0.42	0.45	0.19	0.23
09:00:00 AM	0.36	0.14	0.29	0.18	2.01	2.08	0.82	0.51	0.74	0.07	0.05
10:00:00 AM	0.17	0.61	1.12	0.01	0.45	0.97	0.80	0.26	0.12	0.23	0.24
11:00:00 AM	0.09	1.60	0.00	0.90	0.99	1.81	1.43	0.30	0.81	0.05	0.60
12:00:00 PM	0.32	0.19	0.78	0.68	0.91	0.70	2.69	1.14	0.02	0.13	0.19
01:00:00 PM	0.12	0.72	0.87	0.57	0.88	0.24	0.17	0.16	0.42	0.36	0.46
02:00:00 PM	0.14	0.01	0.15	0.19	0.53	1.10	1.12	0.29	0.52	0.59	0.17
03:00:00 PM	0.06	0.04	0.31	0.89	3.09	0.16	0.36	0.02	1.34	0.13	0.50
04:00:00 PM	0.08	0.24	0.53	0.36	1.35	0.37	0.69	0.08	0.26	0.03	0.02
05:00:00 PM	0.22	0.29	0.32	0.54	0.08	0.32	1.68	0.06	0.07	0.06	0.46
06:00:00 PM	0.01	0.29	0.37	0.84	0.77	0.32	1.75	0.46	1.43	0.30	0.39
07:00:00 PM	0.14	0.38	1.09	1.95	0.50	0.06	0.67	0.30	1.23	0.83	0.61
08:00:00 PM	1.03	0.08	1.10	0.10	0.51	1.65	0.92	1.09	2.09	0.93	0.07
09:00:00 PM	0.70	0.06	0.79	2.23	4.96	0.81	2.39	0.08	0.16	0.64	1.44
10:00:00 PM	0.02	1.03	1.73	0.65	8.51	0.97	7.22	0.09	4.32	0.02	18.15

Figure 17: Mean Absolute Percentage Error - MAPE

In order for the proponents to know the distance of the simulated data from the actual data, it was submitted to MAPE to validate the error. As shown in figure 17, the errors are between 11 to 0 which is close enough.

Mean Percentage Similarity											
Time	Recto	Legarda	Pureza	VMapa	Jruiz	Gilmore	BettyGo	Araneta	Anonas	Katipunan	Santolan
04:00:00 AM	99.15	96.38	97.29	97.34	99.02	93.62	98.41	99.86	91.91	97.10	97.84
05:00:00 AM	99.67	99.76	98.96	99.27	97.97	98.76	99.32	99.76	97.63	99.91	99.83
06:00:00 AM	99.12	97.09	99.98	98.49	99.13	98.21	100.00	98.69	99.71	99.93	99.98
07:00:00 AM	99.00	99.53	99.97	99.09	97.95	99.73	98.91	99.62	99.50	99.88	99.77
08:00:00 AM	99.44	98.18	99.53	99.25	99.71	99.12	97.44	99.58	99.55	99.81	99.77
09:00:00 AM	99.64	99.86	99.71	99.82	97.99	97.92	99.18	99.49	99.26	99.93	99.95
10:00:00 AM	99.83	99.39	98.88	99.99	99.55	99.03	99.20	99.74	99.88	99.77	99.76
11:00:00 AM	99.91	98.40	100.00	99.10	99.01	98.19	98.57	99.70	99.19	99.95	99.40
12:00:00 PM	99.68	99.81	99.22	99.32	99.09	99.30	97.31	98.86	99.98	99.87	99.81
01:00:00 PM	99.88	99.28	99.13	99.43	99.12	99.76	99.83	99.84	99.58	99.64	99.54
02:00:00 PM	99.86	99.99	99.85	99.81	99.47	98.90	98.88	99.71	99.48	99.41	99.83
03:00:00 PM	99.94	99.96	99.69	99.11	96.91	99.84	99.64	99.98	98.66	99.87	99.50
04:00:00 PM	99.92	99.76	99.47	99.64	98.65	99.63	99.31	99.92	99.74	99.97	99.98
05:00:00 PM	99.78	99.71	99.68	99.46	99.92	99.68	98.32	99.94	99.93	99.94	99.54
06:00:00 PM	99.99	99.71	99.63	99.16	99.23	99.68	98.25	99.54	98.57	99.70	99.61
07:00:00 PM	99.86	99.62	98.91	98.05	99.50	99.94	99.33	99.70	98.77	99.17	99.39
08:00:00 PM	98.97	99.92	98.90	99.90	99.49	98.35	99.08	98.91	97.91	99.07	99.93
09:00:00 PM	99.30	99.94	99.21	97.77	95.04	99.19	97.61	99.92	99.84	99.36	98.56
10:00:00 PM	99.98	98.97	98.27	99.35	91.49	99.03	92.78	99.91	95.68	99.98	81.85

Figure 18: Percentage of Similarity From Model Output To Actual Data

To get the opposite of the MAPE which is the accuracy, the proponents just subtracted the 100% from each hour average ridership of each station. As shown in figure 18, the accuracies are from 81% to 100% which is close enough.

B. Paired T-Test

In order to test if there's a significant difference between the simulation result and actual data, the proponents ran a t-test. The two hypotheses are null and alternative, null means that there are no significant differences between the actual data and simulation result, and the other one is alternative hypothesis which means that there is significant difference between the two data.

Paired Samples Test

		Paired Differences							Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
4AM	VAR00004 - VAR00005	-.77419	20.01285	3.59441	-8.11496	6.56658	-.215	30	.415	.831
5AM	VAR00003 - VAR00006	1.80645	105.33927	18.91949	-36.83230	40.44521	.095	30	.462	.925
6AM	VAR00008 - VAR00009	8.80645	308.19263	55.35303	-104.23952	121.85242	.159	30	.437	.875
7AM	VAR00001 - VAR00002	16.16129	512.48409	92.04486	-171.81939	204.14197	.176	30	.431	.862
8AM	VAR00010 - VAR00012	-9.70968	400.42787	71.91897	-156.58781	137.16845	-.135	30	.447	.894
9AM	VAR00013 - VAR00014	6.64516	300.74458	54.01532	-103.66884	116.95916	.123	30	.451	.903
10AM	VAR00015 - VAR00016	3.35484	284.82995	51.15697	-101.12163	107.83131	.066	30	.474	.948
11AM	VAR00017 - VAR00018	-2.09677	301.39889	54.13284	-112.65078	108.45723	-.039	30	.485	.969
12AM	VAR00019 - VAR00020	8.00000	408.27148	73.32772	-141.75519	157.75519	.109	30	.457	.914
1PM	VAR00021 - VAR00022	3.35484	479.75477	86.16650	-172.62063	179.33031	.039	30	.485	.969
2PM	VAR00023 - VAR00024	4.29032	578.20424	103.84855	-207.79671	216.37735	.041	30	.484	.967
3PM	VAR00025 - VAR00026	2.00000	707.73036	127.11213	-257.59759	261.59759	.016	30	.494	.988
4PM	VAR00027 - VAR00029	-3.29032	887.41389	159.38424	-328.79637	322.21572	-.021	30	.492	.984
5PM	VAR00030 - VAR00031	-9.90323	1232.55143	221.37277	-462.00674	442.20029	-.045	30	.482	.965
6PM	VAR00032 - VAR00033	-.54839	1326.21187	238.19468	-487.00683	485.91005	-.002	30	.499	.998
7PM	VAR00034 - VAR00035	-4.70968	1118.75530	200.93438	-415.07243	405.65308	-.023	30	.491	.981
8PM	VAR00036 - VAR00037	-22.51613	602.61856	108.23349	-243.55840	198.52614	-.208	30	.418	.837
9PM	VAR00038 - VAR00039	37.45161	442.85677	79.53942	-124.98956	199.89279	.471	30	.321	.641
10PM	VAR00040 - VAR00041	8.54839	109.90931	19.74029	-31.76667	48.86345	.433	30	.334	.668

Figure 19: Paired T-Test

The proponents used paired t-test since the data being compared are before and after the experiments, and used two-tailed test to know if there is difference between the two data. Each figure in a certain station of LRT-2 and consists of each hour. There are two hypotheses for this test, null and alternative. Null hypothesis means that there are no significant differences between two mean, while the alternative hypothesis means that there are significant difference between two mean. Based on the two-sided p-value, the null hypothesis will keep, hence, there are no significant differences between before and after the experiments.

Paired Samples Test

		Paired Differences							Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
4AM	VAR00004 - VAR00005	-.77419	20.01285	3.59441	-8.11496	6.56658	-.215	30	.415	.831
5AM	VAR00003 - VAR00006	1.80645	105.33927	18.91949	-36.83230	40.44521	.095	30	.462	.925
6AM	VAR00008 - VAR00009	8.80645	308.19263	55.35303	-104.23952	121.85242	.159	30	.437	.875
7AM	VAR00001 - VAR00002	16.16129	512.48409	92.04486	-171.81939	204.14197	.176	30	.431	.862
8AM	VAR00010 - VAR00012	-9.70968	400.42787	71.91897	-156.58781	137.16845	-.135	30	.447	.894
9AM	VAR00013 - VAR00014	6.64516	300.74458	54.01532	-103.66884	116.95916	.123	30	.451	.903
10AM	VAR00015 - VAR00016	3.35484	284.82995	51.15697	-101.12163	107.83131	.066	30	.474	.948
11AM	VAR00017 - VAR00018	-2.09677	301.39889	54.13284	-112.65078	108.45723	-.039	30	.485	.969
12PM	VAR00019 - VAR00020	8.00000	408.27148	73.32772	-141.75519	157.75519	.109	30	.457	.914
1PM	VAR00021 - VAR00022	3.35484	479.75477	86.16650	-172.62063	179.33031	.039	30	.485	.969
2PM	VAR00023 - VAR00024	4.29032	578.20424	103.84855	-207.79671	216.37735	.041	30	.484	.967
3PM	VAR00025 - VAR00026	2.00000	707.73036	127.11213	-257.59759	261.59759	.016	30	.494	.988
4PM	VAR00027 - VAR00029	-3.29032	887.41389	159.38424	-328.79637	322.21572	-.021	30	.492	.984
5PM	VAR00030 - VAR00031	-9.90323	1232.55143	221.37277	-462.00674	442.20029	-.045	30	.482	.965
6PM	VAR00032 - VAR00033	-.54839	1326.21187	238.19468	-487.00683	485.91005	-.002	30	.499	.998
7PM	VAR00034 - VAR00035	-4.70968	1118.75530	200.93438	-415.07243	405.65308	-.023	30	.491	.981
8PM	VAR00036 - VAR00037	-22.51613	602.61856	108.23349	-243.55840	198.52614	-.208	30	.418	.837
9PM	VAR00038 - VAR00039	37.45161	442.85677	79.53942	-124.98956	199.89279	.471	30	.321	.641
10PM	VAR00040 - VAR00041	8.54839	109.90931	19.74029	-31.76667	48.86345	.433	30	.334	.668

Figure 20: Recto Paired T-Test

Paired Samples Test

		Paired Differences							Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
4AM	VAR00001 - VAR00002	-.58065	7.74499	1.39104	-3.42153	2.26024	-.417	30	.340	.679
5AM	VAR00003 - VAR00004	.19355	26.56617	4.77142	-9.55100	9.93810	.041	30	.484	.968
6AM	VAR00005 - VAR00006	4.64516	59.99864	10.77607	-17.36252	26.65284	.431	30	.335	.670
7AM	VAR00007 - VAR00008	-1.19355	113.27148	20.34416	-42.74186	40.35477	-.059	30	.477	.954
8AM	VAR00009 - VAR00010	4.77419	105.01546	18.86133	-33.74579	43.29418	.253	30	.401	.802
9AM	VAR00011 - VAR00012	.41935	95.03535	17.06885	-34.43989	35.27860	.025	30	.490	.981
10AM	VAR00013 - VAR00014	-2.25806	140.24787	25.18926	-53.70140	49.18527	-.090	30	.465	.929
11AM	VAR00015 - VAR00016	7.74194	226.47457	40.67603	-75.32961	90.81348	.190	30	.425	.850
12PM	VAR00017 - VAR00018	1.22581	349.43838	62.76099	-126.94923	129.40084	.020	30	.492	.985
1PM	VAR00019 - VAR00020	-5.41935	420.64068	75.54930	-159.71160	148.87289	-.072	30	.472	.943
2PM	VAR00021 - VAR00022	.09677	438.13380	78.69115	-160.61200	160.80555	.001	30	.500	.999
3PM	VAR00023 - VAR00024	-.35484	575.91872	103.43806	-211.60353	210.89385	-.003	30	.499	.997
4PM	VAR00025 - VAR00026	-2.67742	787.83955	141.50016	-291.65930	286.30446	-.019	30	.493	.985
5PM	VAR00027 - VAR00028	-3.64516	886.86675	159.28597	-328.95051	321.66019	-.023	30	.491	.982
6PM	VAR00029 - VAR00030	-3.22581	694.13662	124.67062	-257.83717	251.38556	-.026	30	.490	.980
7PM	VAR00031 - VAR00032	3.51613	649.40310	116.63624	-234.68685	241.71911	.030	30	.488	.976
8PM	VAR00033 - VAR00034	-.48387	485.54614	87.20666	-178.58363	177.61589	-.006	30	.498	.996
9PM	VAR00035 - VAR00036	16.32258	349.16638	62.71213	-111.75268	144.39784	.260	30	.398	.796
10PM	VAR00037 - VAR00038	2.45161	114.57016	20.57741	-39.57306	44.47629	.119	30	.453	.906

Figure 21: Legarda Paired T-Test

Paired Samples Test

		Paired Differences							Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
4AM	VAR00001 - VAR00002	.74194	8.04557	1.44503	-2.20920	3.69307	.513	30	.306	.611
5AM	VAR00003 - VAR00004	-1.61290	62.06162	11.14660	-24.37729	21.15148	-.145	30	.443	.886
6AM	VAR00005 - VAR00006	.09677	200.59035	36.02709	-73.48036	73.67391	.003	30	.499	.998
7AM	VAR00007 - VAR00008	.25806	429.12166	77.07253	-157.14503	157.66116	.003	30	.499	.997
8AM	VAR00009 - VAR00010	3.83871	353.73974	63.53353	-125.91408	133.59150	.060	30	.476	.952
9AM	VAR00011 - VAR00012	-1.93548	206.42060	37.07423	-77.65117	73.78020	-.052	30	.479	.959
10AM	VAR00013 - VAR00014	-7.38710	204.88219	36.79793	-82.53849	67.76430	-.201	30	.421	.842
11AM	VAR00015 - VAR00016	.03226	245.09637	44.02061	-89.86982	89.93433	.001	30	.500	.999
12PM	VAR00017 - VAR00018	5.61290	264.03859	47.42273	-91.23723	102.46304	.118	30	.453	.907
1PM	VAR00019 - VAR00020	7.35484	369.99095	66.45234	-128.35894	143.06861	.111	30	.456	.913
2PM	VAR00021 - VAR00022	1.38710	369.86463	66.42965	-134.28035	137.05454	.021	30	.492	.983
3PM	VAR00023 - VAR00024	2.64516	334.68807	60.11175	-120.11941	125.40974	.044	30	.483	.965
4PM	VAR00025 - VAR00026	4.74194	397.02787	71.30831	-140.88906	150.37293	.066	30	.474	.947
5PM	VAR00027 - VAR00028	3.22581	452.31838	81.23878	-162.68591	169.13753	.040	30	.484	.969
6PM	VAR00029 - VAR00030	3.38710	501.31226	90.03834	-180.49572	187.26992	.038	30	.485	.970
7PM	VAR00031 - VAR00032	-7.67742	384.39046	69.03856	-148.67298	133.31814	-.111	30	.456	.912
8PM	VAR00033 - VAR00034	-6.19355	324.58809	58.29774	-125.25342	112.86632	-.106	30	.458	.916
9PM	VAR00035 - VAR00036	8.80645	185.22372	33.26716	-59.13416	76.74706	.265	30	.397	.793
10PM	VAR00037 - VAR00038	1.12903	37.95238	6.81645	-12.79201	15.05008	.166	30	.435	.870

Figure 22: Pureza Paired T-Test

Paired Samples Test

		Paired Differences							Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
4AM	VAR00001 - VAR00002	.61290	9.28683	1.66796	-2.79353	4.01934	.367	30	.358	.716
5AM	VAR00003 - VAR00004	1.09677	57.81600	10.38406	-20.11031	22.30386	.106	30	.458	.917
6AM	VAR00005 - VAR00006	-6.74194	232.69278	41.79286	-92.09434	78.61047	-.161	30	.436	.873
7AM	VAR00007 - VAR00008	7.70968	441.71478	79.33432	-154.31261	169.73197	.097	30	.462	.923
8AM	VAR00009 - VAR00010	-6.09677	307.46180	55.22177	-118.87467	106.68112	-.110	30	.456	.913
9AM	VAR00011 - VAR00012	-1.19355	172.71294	31.02016	-64.54517	62.15807	-.038	30	.485	.970
10AM	VAR00013 - VAR00014	.06452	140.36760	25.21076	-51.42273	51.55177	.003	30	.499	.998
11AM	VAR00015 - VAR00016	5.41935	134.27950	24.11731	-43.83476	54.67347	.225	30	.412	.824
12PM	VAR00017 - VAR00018	-4.48387	173.49714	31.16101	-68.12314	59.15539	-.144	30	.443	.887
1PM	VAR00019 - VAR00020	4.03226	175.19769	31.46643	-60.23078	68.29529	.128	30	.449	.899
2PM	VAR00021 - VAR00022	1.41935	184.66614	33.16702	-66.31673	69.15544	.043	30	.483	.966
3PM	VAR00023 - VAR00024	6.83871	211.33387	37.95668	-70.67918	84.35660	.180	30	.429	.858
4PM	VAR00025 - VAR00026	-3.16129	271.94032	48.84192	-102.90981	96.58723	-.065	30	.474	.949
5PM	VAR00027 - VAR00028	-5.64516	315.10237	56.59406	-121.22564	109.93532	-.100	30	.461	.921
6PM	VAR00029 - VAR00030	8.48387	328.11602	58.93138	-111.87006	128.83780	.144	30	.443	.886
7PM	VAR00031 - VAR00032	15.16129	250.31182	44.95733	-76.65383	106.97641	.337	30	.369	.738
8PM	VAR00033 - VAR00034	.54839	185.64048	33.34202	-67.54509	68.64187	.016	30	.493	.987
9PM	VAR00035 - VAR00036	4.48387	140.95102	25.31555	-47.21738	56.18512	.177	30	.430	.861
10PM	VAR00037 - VAR00038	7.58065	37.77369	6.78435	-6.27486	21.43615	1.117	30	.136	.273

Figure 23: V. Mapa Paired T-Test

Paired Samples Test

		Paired Differences					t	df	Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			One-Sided p	Two-Sided p
4AM	VAR00001 - VAR00002	.06452	3.28568	.59013	-1.14068	1.26971	.109	30	.457	.914
5AM	VAR00003 - VAR00004	.77419	19.24008	3.45562	-6.28312	7.83151	.224	30	.412	.824
6AM	VAR00005 - VAR00006	-1.32258	99.79625	17.92394	-37.92814	35.28298	-.074	30	.471	.942
7AM	VAR00007 - VAR00008	-5.22581	136.01071	24.42825	-55.11494	44.66333	-.214	30	.416	.832
8AM	VAR00009 - VAR00010	.70968	98.76747	17.73916	-35.51852	36.93788	.040	30	.484	.968
9AM	VAR00011 - VAR00012	4.09677	63.23836	11.35794	-19.09924	27.29279	.361	30	.360	.721
10AM	VAR00013 - VAR00014	-.80645	55.74909	10.01283	-21.25538	19.64248	-.081	30	.468	.936
11AM	VAR00015 - VAR00016	-1.64516	40.15931	7.21282	-16.37571	13.08539	-.228	30	.411	.821
12PM	VAR00017 - VAR00018	1.54839	52.84432	9.49112	-17.83507	20.93184	.163	30	.436	.872
1PM	VAR00019 - VAR00020	1.51613	43.92787	7.88968	-14.59675	17.62900	.192	30	.424	.849
2PM	VAR00021 - VAR00022	.90323	49.89212	8.96089	-17.39735	19.20380	.101	30	.460	.920
3PM	VAR00023 - VAR00024	5.93548	51.01172	9.16198	-12.77577	24.64673	.648	30	.261	.522
4PM	VAR00025 - VAR00026	3.06452	77.37611	13.89716	-25.31727	31.44630	.221	30	.413	.827
5PM	VAR00027 - VAR00028	-.25806	135.82243	24.39443	-50.07813	49.56200	-.011	30	.496	.992
6PM	VAR00029 - VAR00030	-2.03226	118.76798	21.33136	-45.59670	41.53219	-.095	30	.462	.925
7PM	VAR00031 - VAR00032	-.80645	79.79992	14.33249	-30.07730	28.46440	-.056	30	.478	.956
8PM	VAR00033 - VAR00034	.48387	35.25892	6.33269	-12.44921	13.41695	.076	30	.470	.940
9PM	VAR00035 - VAR00036	-.93548	26.57309	4.77267	-10.68257	8.81160	-.196	30	.423	.846
10PM	VAR00037 - VAR00038	2.12903	8.33763	1.49748	-.92924	5.18730	1.422	30	.083	.165

Figure 24: J. Ruiz Paired T-Test

Paired Samples Test

		Paired Differences					t	df	Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			One-Sided p	Two-Sided p
4AM	VAR00001 - VAR00002	-.38710	4.19267	.75303	-1.92498	1.15079	-.514	30	.305	.611
5AM	VAR00003 - VAR00004	-.51613	17.24504	3.09730	-6.84166	5.80940	-.167	30	.434	.869
6AM	VAR00005 - VAR00006	-3.03226	112.75415	20.25124	-44.39082	38.32630	-.150	30	.441	.882
7AM	VAR00007 - VAR00008	.64516	128.05456	22.99928	-46.32563	47.61595	.028	30	.489	.978
8AM	VAR00009 - VAR00010	-2.09677	100.51214	18.05251	-38.96492	34.77138	-.116	30	.454	.908
9AM	VAR00011 - VAR00012	-4.51613	71.72116	12.88150	-30.82366	21.79140	-.351	30	.364	.728
10AM	VAR00013 - VAR00014	-2.06452	77.01123	13.83162	-30.31246	26.18343	-.149	30	.441	.882
11AM	VAR00015 - VAR00016	4.16129	76.50451	13.74062	-23.90079	32.22337	.303	30	.382	.764
12PM	VAR00017 - VAR00018	-1.90323	93.45457	16.78494	-36.18264	32.37619	-.113	30	.455	.910
1PM	VAR00019 - VAR00020	.67742	85.52403	15.36057	-30.69305	32.04789	.044	30	.483	.965
2PM	VAR00021 - VAR00022	-3.74194	113.48920	20.38326	-45.37011	37.88624	-.184	30	.428	.856
3PM	VAR00023 - VAR00024	.64516	152.39981	27.37181	-55.25554	56.54586	.024	30	.491	.981
4PM	VAR00025 - VAR00026	1.80645	183.42636	32.94435	-65.47488	69.08778	.055	30	.478	.957
5PM	VAR00027 - VAR00028	-2.12903	287.36315	51.61195	-107.53469	103.27662	-.041	30	.484	.967
6PM	VAR00029 - VAR00030	-1.93548	260.92501	46.86352	-97.64355	93.77258	-.041	30	.484	.967
7PM	VAR00031 - VAR00032	.29032	190.49308	34.21357	-69.58310	70.16375	.008	30	.497	.993
8PM	VAR00033 - VAR00034	-3.87097	94.49506	16.97181	-38.53204	30.79010	-.228	30	.411	.821
9PM	VAR00035 - VAR00036	6.74194	64.06193	11.50586	-16.75617	30.24004	.586	30	.281	.562
10PM	VAR00037 - VAR00038	1.45161	14.95959	2.68682	-4.03561	6.93883	.540	30	.296	.593

Figure 25: Gilmore Paired T-Test

Paired Samples Test

		Paired Differences					t	df	Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			One-Sided p	Two-Sided p
4AM	VAR00001 - VAR00002	-.06452	2.15925	.38781	-.85654	.72750	-.166	30	.434	.869
5AM	VAR00003 - VAR00004	-.22581	15.43310	2.77187	-5.88671	5.43510	-.081	30	.468	.936
6AM	VAR00005 - VAR00006	.00000	91.57001	16.44646	-33.58815	33.58815	.000	30	.500	1.000
7AM	VAR00007 - VAR00008	-2.48387	124.79313	22.41351	-48.25836	43.29062	-.111	30	.456	.912
8AM	VAR00009 - VAR00010	-5.64516	104.13630	18.70343	-43.84267	32.55234	-.302	30	.382	.765
9AM	VAR00011 - VAR00012	-1.54839	68.52875	12.30813	-26.68493	23.58816	-.126	30	.450	.901
10AM	VAR00013 - VAR00014	-1.35484	58.01008	10.41892	-22.63311	19.92343	-.130	30	.449	.897
11AM	VAR00015 - VAR00016	-2.22581	54.11575	9.71947	-22.07562	17.62401	-.229	30	.410	.820
12PM	VAR00017 - VAR00018	4.32258	60.70826	10.90352	-17.94539	26.59055	.396	30	.347	.695
1PM	VAR00019 - VAR00020	.25806	48.83780	8.77153	-17.65579	18.17192	.029	30	.488	.977
2PM	VAR00021 - VAR00022	1.70968	53.85734	9.67306	-18.04535	21.46471	.177	30	.430	.861
3PM	VAR00023 - VAR00024	.54839	48.49525	8.71000	-17.23981	18.33659	.063	30	.475	.950
4PM	VAR00025 - VAR00026	-1.22581	64.47000	11.57915	-24.87359	22.42198	-.106	30	.458	.916
5PM	VAR00027 - VAR00028	4.09677	111.67165	20.05682	-36.86472	45.05827	.204	30	.420	.840
6PM	VAR00029 - VAR00030	-3.12903	83.50000	14.99704	-33.75708	27.49901	-.209	30	.418	.836
7PM	VAR00031 - VAR00032	.83871	57.13265	10.26133	-20.11772	21.79514	.082	30	.468	.935
8PM	VAR00033 - VAR00034	.61290	33.78331	6.06766	-11.77891	13.00472	.101	30	.460	.920
9PM	VAR00035 - VAR00036	.38710	18.85325	3.38614	-6.52833	7.30253	.114	30	.455	.910
10PM	VAR00037 - VAR00038	1.16129	5.60415	1.00653	-.89433	3.21691	1.154	30	.129	.258

Figure 26: Betty Go Paired T-Test

Paired Samples Test

		Paired Differences					t	df	Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			One-Sided p	Two-Sided p
4AM	VAR00001 - VAR00002	-.06452	17.34154	3.11463	-6.42544	6.29641	-.021	30	.492	.984
5AM	VAR00003 - VAR00004	-.70968	101.54184	18.23745	-37.95553	36.53617	-.039	30	.485	.969
6AM	VAR00005 - VAR00006	-10.45161	377.84854	67.86360	-149.04758	128.14435	-.154	30	.439	.879
7AM	VAR00007 - VAR00008	-4.58065	508.86513	91.39487	-191.23388	182.07259	-.050	30	.480	.960
8AM	VAR00009 - VAR00010	-5.00000	381.72538	68.55990	-145.01800	135.01800	-.073	30	.471	.942
9AM	VAR00011 - VAR00012	5.87097	318.44610	57.19461	-110.93600	122.67794	.103	30	.459	.919
10AM	VAR00013 - VAR00014	3.03226	278.89598	50.09120	-99.26761	105.33213	.061	30	.476	.952
11AM	VAR00015 - VAR00016	-3.77419	287.51623	51.63944	-109.23600	101.68761	-.073	30	.471	.942
12PM	VAR00017 - VAR00018	-16.19355	333.65895	59.92692	-138.58064	106.19354	-.270	30	.394	.789
1PM	VAR00019 - VAR00020	-2.54839	333.76727	59.94637	-124.97521	119.87844	-.043	30	.483	.966
2PM	VAR00021 - VAR00022	4.74194	339.36519	60.95179	-119.73822	129.22209	.078	30	.469	.939
3PM	VAR00023 - VAR00024	.41935	379.87952	68.22838	-138.92158	139.76029	.006	30	.498	.995
4PM	VAR00025 - VAR00026	-1.54839	440.68211	79.14884	-163.19189	160.09512	-.020	30	.492	.985
5PM	VAR00027 - VAR00028	-1.32258	524.38544	94.18241	-193.66871	191.02355	-.014	30	.494	.989
6PM	VAR00029 - VAR00030	11.16129	617.22357	110.85663	-215.23814	237.56072	.101	30	.460	.920
7PM	VAR00031 - VAR00032	6.70968	673.04097	120.88173	-240.16374	253.58310	.056	30	.478	.956
8PM	VAR00033 - VAR00034	19.35484	518.15522	93.06343	-170.70603	209.41571	.208	30	.418	.837
9PM	VAR00035 - VAR00036	47.77419	392.50458	70.49590	-96.19765	191.74604	.678	30	.252	.503
10PM	VAR00037 - VAR00038	9.06452	101.55423	18.23968	-28.18588	46.31491	.497	30	.311	.623

Figure 27: Araneta Paired T-Test

Paired Samples Test

		Paired Differences					t	df	Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			One-Sided p	Two-Sided p
4AM	VAR00001 - VAR00002	2.35484	12.25982	2.20193	-2.14210	6.85178	1.069	30	.147	.293
5AM	VAR00003 - VAR00004	4.38710	85.78021	15.40658	-27.07734	35.85153	.285	30	.389	.778
6AM	VAR00005 - VAR00006	-1.64516	351.20711	63.07866	-130.46897	127.17865	-.026	30	.490	.979
7AM	VAR00007 - VAR00008	4.09677	419.70429	75.38112	-149.85200	158.04555	.054	30	.479	.957
8AM	VAR00009 - VAR00010	-3.54839	311.89323	56.01768	-117.95175	110.85497	-.063	30	.475	.950
9AM	VAR00011 - VAR00012	5.22581	228.43551	41.02823	-78.56501	89.01663	.127	30	.450	.899
10AM	VAR00013 - VAR00014	.77419	168.42065	30.24924	-61.00300	62.55139	.026	30	.490	.980
11AM	VAR00015 - VAR00016	-4.93548	145.28017	26.09309	-58.22468	48.35371	-.189	30	.426	.851
12PM	VAR00017 - VAR00018	-.09677	172.91026	31.05560	-63.52077	63.32722	-.003	30	.499	.998
1PM	VAR00019 - VAR00020	2.61290	139.14158	24.99056	-48.42464	53.65045	.105	30	.459	.917
2PM	VAR00021 - VAR00022	3.19355	127.08197	22.82460	-43.42050	49.80759	.140	30	.445	.890
3PM	VAR00023 - VAR00024	-7.45161	123.89211	22.25168	-52.89561	37.99238	-.335	30	.370	.740
4PM	VAR00025 - VAR00026	-1.48387	143.86750	25.83937	-54.25490	51.28715	-.057	30	.477	.955
5PM	VAR00027 - VAR00028	-.48387	238.46102	42.82886	-87.95208	86.98434	-.011	30	.496	.991
6PM	VAR00029 - VAR00030	9.58065	247.74110	44.49561	-81.29152	100.45281	.215	30	.415	.831
7PM	VAR00031 - VAR00032	-5.54839	179.71474	32.27772	-71.46829	60.37151	-.172	30	.432	.865
8PM	VAR00033 - VAR00034	6.25806	105.56229	18.95955	-32.46250	44.97863	.330	30	.372	.744
9PM	VAR00035 - VAR00036	6.41935	67.59476	12.14038	-18.37460	31.21331	.529	30	.300	.601
10AM	VAR00037 - VAR00038	.87097	6.16302	1.10691	-1.38965	3.13158	.787	30	.219	.438

Figure 28: Anonas Paired T-Test

Paired Samples Test

		Paired Differences					t	df	Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			One-Sided p	Two-Sided p
4AM	VAR00001 - VAR00002	-3.03226	35.69826	6.41160	-16.12648	10.06197	-.473	30	.320	.640
5AM	VAR00003 - VAR00004	.54839	270.22593	48.53401	-98.57129	99.66806	.011	30	.496	.991
6AM	VAR00005 - VAR00006	1.09677	825.12481	148.19679	-301.56145	303.75500	.007	30	.497	.994
7AM	VAR00007 - VAR00008	-2.35484	949.65280	170.56268	-350.69030	345.98062	-.014	30	.495	.989
8AM	VAR00009 - VAR00010	-3.77419	790.95473	142.05966	-293.89873	286.35034	-.027	30	.489	.979
9AM	VAR00011 - VAR00012	-1.16129	494.99166	88.90313	-182.72570	180.40312	-.013	30	.495	.990
10AM	VAR00013 - VAR00014	-3.45161	374.44437	67.25219	-140.79892	133.89569	-.051	30	.480	.959
11AM	VAR00015 - VAR00016	.64516	314.89263	56.55639	-114.85839	116.14871	.011	30	.495	.991
12PM	VAR00017 - VAR00018	1.80645	315.30772	56.63094	-113.84936	117.46226	.032	30	.487	.975
1PM	VAR00019 - VAR00020	4.45161	289.95170	52.07686	-101.90353	110.80676	.085	30	.466	.932
2PM	VAR00021 - VAR00022	-6.35484	214.60142	38.54355	-85.07128	72.36160	-.165	30	.435	.870
3PM	VAR00023 - VAR00024	1.19355	210.99691	37.89616	-76.20074	78.58784	.031	30	.488	.975
4PM	VAR00025 - VAR00026	.29032	215.57322	38.71809	-78.78257	79.36322	.007	30	.497	.994
5PM	VAR00027 - VAR00028	-.64516	292.67975	52.56684	-108.00096	106.71064	-.012	30	.495	.990
6PM	VAR00029 - VAR00030	-2.64516	249.50759	44.81289	-94.16528	88.87496	-.059	30	.477	.953
7PM	VAR00031 - VAR00032	5.09677	181.43968	32.58753	-61.45584	71.64939	.156	30	.438	.877
8PM	VAR00033 - VAR00034	-4.22581	126.99835	22.80958	-50.80918	42.35756	-.185	30	.427	.854
9PM	VAR00035 - VAR00036	8.03226	89.80367	16.12922	-24.90799	40.97251	.498	30	.311	.622
10PM	VAR00037 - VAR00038	.22581	5.73126	1.02936	-1.87644	2.32805	.219	30	.414	.828

Figure 29: Katipunan Paired T-Test

Paired Samples Test

		Paired Differences					t	df	Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			One-Sided p	Two-Sided p
4AM	VAR00001 - VAR00002	5.93548	110.65259	19.87379	-34.65221	46.52318	.299	30	.384	.767
5AM	VAR00003 - VAR00004	2.54839	692.58144	124.39130	-251.49254	256.58931	.020	30	.492	.984
6AM	VAR00005 - VAR00006	-.58065	2207.38839	396.45866	-810.25724	809.09595	-.001	30	.499	.999
7AM	VAR00007 - VAR00008	11.19355	2465.18086	442.75955	-893.04209	915.42919	.025	30	.490	.980
8AM	VAR00009 - VAR00010	-10.09677	1769.52171	317.81548	-659.16258	638.96903	-.032	30	.487	.975
9AM	VAR00011 - VAR00012	1.83871	1080.51004	194.06533	-394.49557	398.17299	.009	30	.496	.993
10AM	VAR00013 - VAR00014	-7.41935	687.15587	123.41684	-259.47016	244.63145	-.060	30	.476	.952
11AM	VAR00015 - VAR00016	-16.77419	589.67634	105.90900	-233.06922	199.52083	-.158	30	.438	.875
12PM	VAR00017 - VAR00018	5.00000	490.95906	88.17885	-175.08524	185.08524	.057	30	.478	.955
1PM	VAR00019 - VAR00020	10.41935	366.06892	65.74792	-123.85581	144.69452	.158	30	.438	.875
2PM	VAR00021 - VAR00022	-3.35484	404.44040	72.63964	-151.70477	144.99510	-.046	30	.482	.963
3PM	VAR00023 - VAR00024	8.67742	326.77907	58.69125	-111.18611	128.54095	.148	30	.442	.883
4PM	VAR00025 - VAR00026	-.32258	360.86816	64.81383	-132.69009	132.04493	-.005	30	.498	.996
5PM	VAR00027 - VAR00028	7.25806	277.99196	49.92883	-94.71021	109.22634	.145	30	.443	.885
6PM	VAR00029 - VAR00030	5.38710	269.12075	48.33551	-93.32719	104.10139	.111	30	.456	.912
7PM	VAR00031 - VAR00032	6.51613	264.04215	47.42337	-90.33531	103.36757	.137	30	.446	.892
8PM	VAR00033 - VAR00034	-.51613	170.03076	30.53843	-62.88391	61.85166	-.017	30	.493	.987
9PM	VAR00035 - VAR00036	22.06452	96.22887	17.28322	-13.23252	57.36155	1.277	30	.106	.212
10PM	VAR00037 - VAR00038	.06452	.72735	.13064	-.20228	.33131	.494	30	.312	.625

Figure 30: Santolan Paired T-Test

VI. Review of Related Studies

According to the project of F. Tallroth, J. Rappu (2016) is to use a technology called Discrete Event Simulation to evaluate manufacturing (DES). The thesis aims to examine AutoMod's Path Mover System's ability to simulate freight train traffic in a rail port by utilizing theory and methodologies often utilized in production systems. To do this, the Path Mover System's ability to construct and control the components required to mimic train activity in a rail port will be evaluated. To test the software, it will be deployed in a case study in the Port of Gothenburg. The goal of this case is to use a production approach to DES and develop a simulation model of the railroad system in and around the Port of Gothenburg in terms of freight train throughput and arrival time discrepancies. For the Port of Gothenburg, the simulation model serves two goals. The initial goal is to stress test the system in order to determine its maximum capacity [10].

As stated from the goal of the research of G. Decknatel & E. Schnieder (2000), it is to investigate the modeling possibilities for railway systems that have both continuous and discrete processes, thereby falling into the category of mixed continuous-discrete systems, also known as hybrid systems. More precisely, we wish to look into a type of integrated modeling that uses a vocabulary that can represent both continuous and discrete processes as well as their interactions. They choose to use a hybrid Petri nets variant described in. A tool for high-level Petri nets, which we expanded with certain functions for the new continuous transitions, is used to model, simulate, and analyze these hybrid nets. They used two different approaches for the simulation, one of which is based on a simple numerical integration [13].

Because of the complexity and expanding significance of rail transportation, a growing number of research on railway timetable analysis have been published. The most important contributions are described in the following sections. For the stability analysis of periodic Swiss network timetables, (Noordeen, 1996) developed the FASTA stochastic discrete event simulation (DES) system. Different constraints, such as minimum headway restrictions between trains and rail connections at stations, are modeled in FASTA. Carey and Carville (2003) use a simulation approach to improve the generated timetables by reducing the effects of delay propagation in major stations. (Rudolph and Demitz, 2003) explores ways to optimize the size and allocation of time supplements in railway systems. A discrete-event simulation model (SIMONE) is utilized for timetable robustness analysis in (Vromans, 2005). SIMONE accounts for numerous complicated elements in railway systems, such as train interactions, track headway times, platform occupations, and traveler connections [15].

VII. Conclusion

Simulating the LRT 2 Hourly ridership includes a lot of variables, but the current study just used few of them, such as: timestamp and entry ridership. The other variables are just created to determine the month income, passengers waiting in the loading area, and passengers's average waiting time. Estimating the ridership per hour uses poisson distribution which the current study used, only mean, min, and max are used as arguments. Verifying the model was the comparison of the created flowchart diagram and the execution model itself if it is doing the same process. For the validation, the proponents get the average ridership per hour in each station, and compare it to the actual data, and then get the percentage similarity of it. The percentage results are mostly 99% which is good output. But, there are ridership that have big differences which makes the simulation not good for estimation. The proponents also include the month income, it uses the price fare according to the uploaded table diagram of LRTA in the website. In terms of testing different “what ifs”, the proponents tested 4 changes in variables to get the results, and also to see if it has an impact with the output. First, when the train max capacity and train delay use the default values; second, when train max capacity is changed; third, when the train delay is changed; and lastly, when both variables are changed. The outputs were giving different results, and the passengers’ average time and passengers waiting in loading are increasing and decreasing. Based on the dataset included and the test done, the model is working according to the data that the proponents feed to it, and it is changing the output based on the calculated values.

VIII. Recommendations

For the future researchers, the current study can be improved by including more variables such as holiday, percentage that the train will stop in the middle of the journey, trains that collide, and adding the two stations that are not part of the dataset.

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