Analysis of Pandemic Impact Models on the Ridership of Light Rail Transit Line 2 in Metro Manila, Philippines using ARIMA and ARIMAX Models

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Abstract: Analyzing the impacts of untoward events affecting ridership in public transportation is essential for better planning and management. This study explores the effects of selected factors to the Light Rail Transit Line 2 (LRT 2) ridership in the Philippines. Using ARIMA and ARIMAX models and the LRT 2 ridership data from 2014 to 2024, time series models were evaluated with factors including the increasing number of remote workers, private vehicle owners and ride-hailing service users. The effect of these factors in estimating the future ridership was also checked and the month when the ridership goes back to its original trend was predicted. Results show that before pandemic, ride-hailing had a correlation with ridership decline due to remote working that became a trend after the pandemic. Models are expected to either increase or decrease the ridership in the next 10 years. Normal ridership trends became stable in October 2024.

Keywords: Ridership, Remote work, Ride-hailing, ARIMA, ARIMAX

1. INTRODUCTION

The planning for effective transportation begins with one of its most important steps, forecasting. According to Profillidis (2022), its purpose includes infrastructure development, service planning, resource allocation, staffing, revenue projections, commercial strategy, and management decision making. Forecasting of transportation demand is influenced by economic, demographic, institutional and regulatory, environmental, technological advancements, competition and temporal variations. One of the methods in forecasting is time series analysis.

LRT line 2 has experienced a significant decline in its number of passengers. In a report by Padilla (2019), a decrease of around 8 million passengers was observed from 2014 to 2018. Even after the pandemic, the forecast ridership recovery is still lower than the ridership compared to the data in the pre-pandemic period (Jose, 2024). In the year 2020 to 2022, COVID-19 pandemic happened which changed the working modes of most of the passengers of the transit system. In a study by Jiang et al. (2022), it highly suggests that the lockdown caused by the pandemic has made workers shift from face-to-face to remote work. Due to this restriction, the decline of public transportation was observed. Filipinos purchased private vehicles during the COVID-19 pandemic due to them seeking for freedom, protection, extra income, and transport in case of emergencies (Estabillo 2021). As the number of private vehicles increased, public ridership decreased. For people who cannot afford to purchase a private vehicle, ride-hailing services became their transportation mode during the pandemic period (Shi et al. 2021).

Although the COVID-19 pandemic had a strong effect on the ridership on public transportation, one of the main reasons for its decline is the problem with transit management. In 2014-2015, there were 11 trainsets provided during peak hour periods. This was reduced to 7 trainsets in 2019. Some of the noted causes in the decline in the number of trainsets were due to the collision of two trains in May 2019, power shortages and the closing of three stations including Anonas, Katipunan and Santolan, due to the fire that broke in October 2019 (Jose, 2024). Hence, before the pandemic, it has already been reported that one of the factors of the decline in ridership is the decreased number of trainsets. This also increased the waiting time of passengers. As these became problems, the riders changed to other transportation modes. It can also be observed that maintenance and trainset availability are also problems in LRT 2. It reflects that there is a need for improvement of the transportation planning and management in the transit system.

There are multiple methods to analyze time-series and one of them is Autoregressive Integrated Moving Average (ARIMA). ARIMA is often used for forecasting time-series data. It is a method for time series data that is not stationary. It involves integration to make sure that the data is stationary when forecasted. For more complex models, Autoregressive Integrated Moving Average with Exogenous Predictors or ARIMAX is utilized. To analyze cases in which there are factors that affect the time series, it is better to use this variation of ARIMA. Even though there were studies that utilized ARIMA and ARIMAX in transportation, there is a lack of studies that involve models of trends that emerged during the pandemic period. ARIMA and ARIMAX are also utilized in forecasting transportation data. In a study by Sultanbek, et al., (2024), ARIMA was used in predicting future values of rail freight demand patterns in Kazakhstan. It was compared with qualitative methods. In the end, it was proven to be more accurate after assessing both results on actual 2017 data. In another study, Dai et al., (2025) utilized ARIMAX in assessing the impact of COVID-19 on the station-area on Japanese railway stations which captures the non-transport factors such as leisure and shopping. It was concluded that involving external factors improved the model. Despite the studies that involve utilization of ARIMA and ARIMAX in forecasting and transportation, literature specifically applying ARIMA or ARIMAX to study emerging trends such as increased remote work, private vehicle ownership, or ride-hailing usage in the Philippines remains limited.

To contribute to the improvement of rail transit planning and management of the local rail transit systems, this study aims to analyze and forecast LRT line 2 ridership under emerging trends related to COVID-19 pandemic. It specifically aims to analyze the factors that influenced the decline of LRT 2 ridership; determine the model where LRT 2 ridership is expected to increase or decrease in the next 10 years; and identify the month following the onset of the COVID-19 pandemic during which LRT-2 ridership is projected to return to its pre-pandemic trend. This study contributes a new way to forecast rail demand for future planning and development. It specifically benefits the Department of Transportation (DOTr), Light Rail Transit Authority (LRTA), city developers and future researchers for planning for development and infrastructure improvements of LRT 2 and other train systems in the Philippines.

2. METHODOLOGY

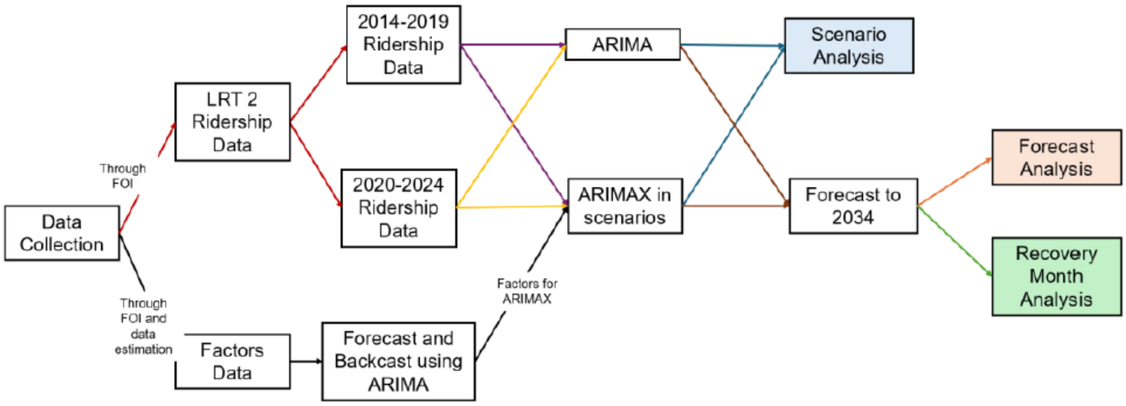


Figure 1. Research Framework

Figure 1 presents the methodology used in this research. First, data of LRT ridership was collected. Two sets of data were needed, the ridership data and the factors data. The LRT 2 ridership data was obtained from LRTA through Freedom of Information (FOI). Factors were requested from Philippine Statistics Authority (PSA) and Land Transportation Office (LTO) through FOI. The data provided was not complete, so the other parts were estimated from the reports of the Presidential Communications Office (PCO) and PSA.

2.1 Study Area

LRT is one of the highly utilized railway systems in the Philippines. Two lines are currently in operation. LRT line 1 extends from Quezon City to Cavite. It currently has 25 stations. LRT line 2 is a 13-station rail transit line. It operates from Manila to Rizal. Up until 2021, LRT 2 had only 11 stations. In this study, the ridership from 2014 to 2024 was assessed so only the 11 stations were observed. Figure 2 shows the map of LRT line 2. The highlighted purple line is the focus of the study.

This study focused on the analysis of ridership of the 11 stations of LRT 2 that were present in 2014. These stations are in Metro Manila Philippines along the corridor from Manila to Marikina. These stations include Recto, Legarda, Pureza, V.Mapa, J.Ruiz, Gilmore, Betty-Go Belmonte, Araneta-Cubao, Anonas, Katipunan, and Santolan. The stations are highlighted in purple on figure 2 below.

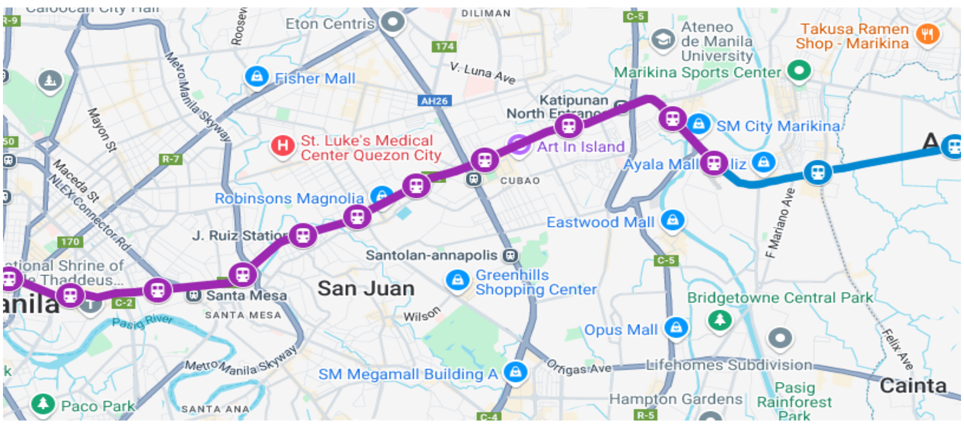


Figure 2. Light Rail Transit (LRT) line 2 route.
Source: Google maps (2024)

2.2 Data

The data considered in the time series models are the number of remote workers, number of private vehicle users and number of ride-hailing users in Metro Manila. The number of remote workers is estimated from the available data on the work-from-home (WFH) workers and call center agents. Only the data for the year 2022 WFH workers in Metro Manila is available from the Philippine Statistics Office (PSA). The other data is estimated using the percent change report on remote workers on 2019-2023 according to the PCO. Other values are from the number of call center agents in 2014 to 2019. The value in months is estimated by dividing the change in annual data to 12 and adding it to the values as presented below. After filling in the values, the factors are calculated using equation 1. For the months without data, the values are back casted and forecasted.

$$RW_t = 1 - \frac{(X_{(RW)_t} - X_{(RW)_{t-1}})}{X_{(RW)_{t-1}}} \tag{1}$$

Where,

RW_t : remote worker factor at time t,
$X_{(RW)_t}$: remote worker value at time t.

This equation evaluates the remote work factor later used as an exogenous factor for the change in ridership data. For this study, monthly ridership data of LRT 2 was used; hence, the t in the equation depicts monthly data from years 2014 to 2024 (i.e. t=1 as January 2014, t=132 as December 2024). The number of private vehicle users from 2014 to 2024 was requested from The Land Transportation Office (LTO). The data finally collected only include details from 2017 to 2024. The value in months is estimated by dividing the change in annual data to 12 and adding it to the values as presented below. The factors are obtained by subtracting the percentage increase of the values from 1 using equation 2. For the months without data, the values are backcasted and forecasted.

$$PV_t = 1 - \frac{(X_{(PV)_t} - X_{(PV)_{t-1}})}{X_{(PV)_{t-1}}} \tag{2}$$

where,

PV_t : private vehicle factor at time t,
$X_{(PV)_t}$: private vehicle value at time t.

This equation evaluates the private vehicle factor later used as an exogenous factor for the change in ridership data. Similar to the remote work factor, the t also depicts monthly data from years 2014 to 2024. The number of ride-hailing users in the years 2014 to 2024 was obtained from the annual report by GRAB. The data available was only from the years 2021 to 2024. The value in months is estimated by dividing the change in annual data to 12 and adding it to the values as presented below. The factors are obtained by subtracting the percentage increase of the values from 1. For the months without data, the values are backcasted and forecasted.

$$RH_t = 1 - \frac{(X_{(RH)_t} - X_{(RH)_{t-1}})}{X_{(RH)_{t-1}}} \quad (3)$$

where,
RH_t is the ride-hailing factor at time t
$X_{(RH)_t}$ is the ride-hailing value at time t

This equation evaluates the ride-hailing factor later used as an exogenous factor for the change in ridership data. Similar to the first two factors, the t also depicts monthly data from years 2014 to 2024. The main data that is analyzed in this study is the monthly passenger traffic of LRT line 2 which was requested through FOI. This is a program where the Order states, "Every Filipino shall have access to information, official records, public records, and to documents and papers pertaining to official acts, transactions or decisions, as well as to government research data used as basis for policy development." A government site for FOI requests was established in 2016, where people can request information from different agencies and departments. One of these is LRTA where people can request data from LRT line 2. The request for monthly ridership data of LRT 2 of all stations' entry and exit passenger traffic from the year 2014 to 2024 was made addressed to LRTA though FOI site portal. After it was approved, the ridership data was received through email. It was in Portable Document Format (PDF) so it was converted to a spreadsheet format so that it can be processed in MATLAB. The ridership data is a type of time series, a series of values of a quantity obtained at successive times, often with equal intervals between them. The passenger traffic data has monthly values in 11 years.

Table 1. Data used for Analysis using Remote Workers Factors

Year	Call center	Remote workers from PSA reports	After PCO reports	After Impact Estimate	After Filling based on call center agents numbers	Yearly Remote Workers factors
2014	445,539	-	-	-	89,108	1.000
2015	532,305	-	-	-	106,461	0.805
2016	622,797	-	-	-	124,560	0.830
2017	644,051	-	-	-	128,811	0.966
2018	631,415	-	95,999	95,999	95,999	1.255
2019	651,733	-	-	99,089	99,089	0.968
2020	670,494	-	-	1,098,197	1,098,197	-9.083
2021	751,984	-	1,231,668	1,231,668	1,231,668	0.878
2022	752,146	170,877	170,877	170,877	170,877	1.861
2023	814,426	-	156,109	156,109	156,109	1.086
2024	622,797	-	-		124,560	1.202

Table 1 presents the data transformed as the remote workers factor for analysis. It includes the values of call center agents and the report by PSA on the number of remote workers in Metro Manila in 2022. In the article released by the Presidential Communications Office (PCO) in

2023, it was stated that there has been 78% growth from 2018 to 2022, 60% growth in 2023 based on 10 months data, and 1183% increase for the year 2021. Logarithmic impacts were assumed in 2020 and 2023 as these years are the start and the end of pandemic. The other years were estimated by the change of the number of call center agents.

Table 2. Data used for analysis using Private Vehicle factors

Year	Registered Private Vehicles	Yearly Private Vehicles factors
2017	2,410,165	1.000
2018	2,588,043	0.926
2019	2,856,335	0.896
2020	2,763,841	1.032
2021	3,037,303	0.901
2022	3,359,837	0.894
2023	3,573,511	0.936
2024	3,456,280	1.033

The factors for the private vehicles are estimated at Table 2. The values of the registered Private vehicles were requested from Land Transport Office (LTO) through Freedom of Information (FOI) site. The values present were only from 2017 to 2024.

Table 3 Data used for analysis using Ride-Hailing Factors

Year	Percentage Change (GRAB)	Estimated values	Yearly Ride-Hailing factors
2020	-	1,000,000	1.000
2021	-8%	920,000	1.080
2022	30%	1,196,000	0.700
2023	7%	1,279,720	0.930
2024	16%	1,484,475	0.840

The only available data for the estimation of the number of ride-hailing application users were the annual report of GRAB. Only the percentages were reported from 2021 to 2024 as shown in table x. To estimate, 2020 is assumed to have 1 million users. The following values are based on the reported percentages which were used for the ride-hailing factors.

2.3 Analysis and Model Development

This study utilized the Econometric Modeler application in MATLAB to input time-series and use forecasting models such as ARIMA and ARIMAX. It also has tools to test the stationarity of the model and check the goodness of fit. ARIMA is a time-series model utilized in forecasting. It is divided into three parts: the autoregressive (AR) which is depicted by letter p; the integrated (I) which is depicted by letter d; and the moving average (MA) which is depicted by letter q. This method is used for the backcasting and forecasting of factors data and forecasting ridership of LRT 2 for assessment. The ARIMA model is described below.

$$Ay_t = C + (1 + \theta_1 L + \theta_2 L^2 \dots \theta_q L^q)\varepsilon_t \tag{4}$$

where:

A	is $(1 - \phi_1 L - \phi_2 L^2 \dots \phi_p L^p)(1 - L)^d$
ϕ	is the autoregressive parameter
θ	is the moving average parameter
L	is the lag operator
y_t	is the time series value at t
C	is the constant term
ε_t	is the residual errors at time t
p	is the order of the autoregressive parameters
d	is the degree of integration
q	is the order of the moving average parameters

Verification of Stationary Data

In using the ARIMA model, the data must be stationary. To do this, the Augmented Dickey-Fuller Test (ADT) was used in testing if it has a unit root. Having a unit root implies that the data is stationary. If it doesn't pass ADT, it means that it needs to be differentiated, and the value of d is 1. If the differentiated series still doesn't pass ADT, it means it still needs another differentiation. If the data is differentiated twice, the value of d is 2. The equation that follows is the equation for ADT.

$$\Delta y_t = c + \delta\, t + \phi y_{t-1} + \beta_1\, \Delta\, y_{t-1} - 1 + \dots + \beta_p\ \Delta\ _{y_{t-p}} + \varepsilon_t \tag{5}$$

$$H_0\colon \phi = 1$$

$$H_a\colon \phi < 1$$

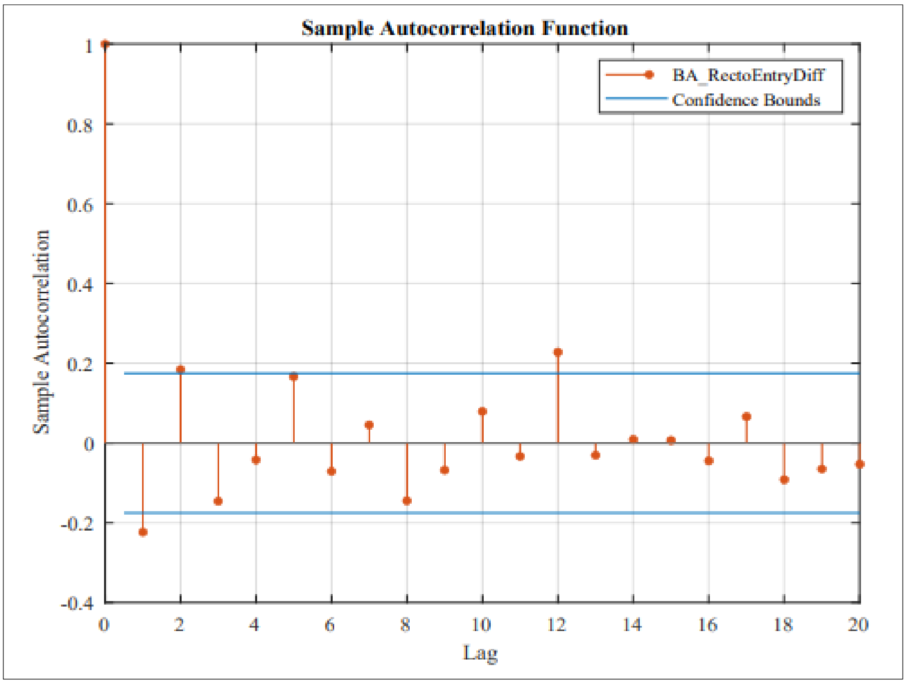
where:

Δy_t	is the first difference of the time series at time t
c	is the constant or the intercept
δ	is the trend coefficient
t	is the time
β	is the coefficient of the lagged differences
p	is the number of lags in the model
ε_t	is the residual errors at time t
H	is the hypothesis
ϕ	is the coefficient of the lagged level term

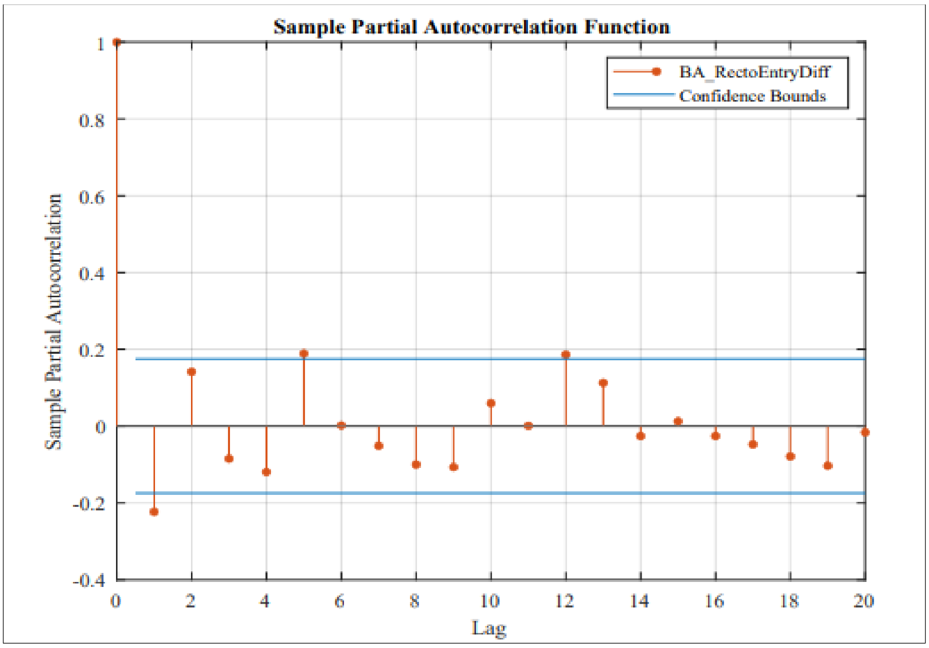
Observation of ACF and PACF Plots

Once the data is differentiated based on the value of d, the Autocorrelation Function (ACF) plot and the Partial Autocorrelation Function (PACF) plot were checked. ACF and PACF project the highest possible lags for modelling ARIMA on the lags of Moving Average (MA) and Autoregression (AR) respectively. By observing these plots, the lags and orders of ARIMA models to be tested and compared can be determined. In analyzing these plots, the spikes are observed and the first cut. Here, the values of lags of the time-series are obtained where the maximum orders of AR and MA are found. The lag from ACF was the maximum MA (q) value, and the lag from PACF was the maximum AR (p). The choices for the best fitting model were the maximum lag to 0 of these two parts of the ARIMA model. For reference,

Figure 3a and 3b show an example of ACF and PACF plots.



(a) Example of ACF plot



(b) Example of PACF plot

Figure 3. Sample ACF and PACF plot.

These figures are the PACF and ACF graphs for Recto station data. Both graphs show strong spikes at lag 1 which makes the maximum values for AR and MA for analysis. After the designating the highest possible lags, the models for testing were finalized as (1,1,1), (1,1,0), (0,1,1) and (0,1,0). This was applied to the other data as well.

Selection of Best Model Based on Goodness of Fit

After the ridership was modeled in different modes of ARIMA, the choice for the best model is based on the goodness of fit. All the models from the highest lag and order to the lowest were checked using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. AIC is a measure used to assess the model's ability to fit in with the data given. It provides estimates from the likelihood of the model and the number of the estimated parameters as shown in equations 6. The values of AIC of all the ARIMA models were compared. The model with the lowest value of AIC is the best model for the time series.

$$AIC = -2ln(L) + 2k \tag{6}$$

where:

L is the maximum value of the likelihood function for the model
k is the number of estimated parameters in the model

Similar to AIC, Bayesian Information Criterion or BIC is also a measure used to assess how fitting the model is to the time series data. The difference is that the BIC value is higher when there are more parameters. This makes the simpler model more fitting than the more complex ones. BIC is defined in equation 7. Like AIC, the lower the BIC value, the more fitting the model is.

$$BIC = -2ln(L) + kln(n) \tag{7}$$

where:

L is the maximum value of the likelihood function for the model
k is the number of estimated parameters in the model
n is the number of data points in the time series

Modelling Scenario Using ARIMAX

ARIMAX model is an extension of ARIMA model which also includes exogenous (external) variables. These variables are the factors that were mentioned earlier. Equation 8 shows the equation of ARIMAX with three factors. These variables are interchanged to assess the ridership data in different model scenario.

$$Ay_t = C + X_1\beta_1 + X_2\beta_2 + X_3\beta_3 + B\varepsilon_t \tag{8}$$

where:

A is $(1 - \phi_1 L - \phi_2 L^2 \ldots \phi_p L^p)(1 - L)^d$
B is $(1 + \theta_1 L + \theta_2 L^2 \ldots \theta_q L^q)$
X_n is one of the exogenous factors
β_n is the coefficient of the exogenous factor
ϕ is the autoregressive parameter
θ is the moving average parameter
L is the lag operator
C is the constant term
y_t is the time series value at t
ε_t is the residual errors at time t
p is the order of the autoregressive parameters

d is the order of the integration
q is the order of the moving average parameters

Scenario Analysis of Best ARIMAX Model

Models were established to evaluate ARIMAX models. From the best model of ARIMA, the factors (remote workers, private vehicle users and ride-hailing users) were incorporated into the equation depending on the model scenario as follows:

Model Scenario 1: All of factors included
Model Scenario 2: Remote Workers, Private Vehicle Users
Model Scenario 3: Remote Workers
Model Scenario 4: Ride-Hailing Users
Model Scenario 5: Private Vehicle Users, Ride-Hailing Users
Model Scenario 6: Private Vehicle Users
Model Scenario 7: Remote Workers, Ride-Hailing Users

Include here reasons of selecting the scenario….

After modeling all the scenarios, AIC and BIC were checked again by comparing the criterion on all the ARIMAX models or models with factors to the best ARIMA model for the time series. Like the analysis in choosing the best ARIMA model per time series, the best model was chosen again by checking the lowest criterion values. This addresses the first objective of the study. Depending on the model with the lowest criterion value means that the factors that affect that model scenario are the factors that affect the LRT line 2 ridership.

Forecast Analysis of Scenario Models

The best ARIMA model and seven ARIMAX models were exported to the main interface of MATLAB and the forecasting was done. In forecasting ridership, code was run in MATLAB. For the 2014-2019 data, the ridership was forecasted for 180 steps as the goal is to forecast until 2034. Due to the closure of stations Anonas, Katipunan and Santolan from the last two months of 2019, the ridership was forecasted from October 2019 to December 2034 with an additional two months. To include additional months for these stations, the forecast runs for 182 steps. For the 2020-2024 data, the ridership was forecasted for 120 steps until 2034.

Per station, there were a total of four forecasts for 2034. To address the second objective, the last values of the scenarios were checked. The scenario with the highest ridership means that the factors associated with it would most likely increase the ridership data in the next 10 years. The scenario with the lowest ridership was also noted.

Recovery Trend Analysis

After forecasting, two sets of ridership until 2034 per station were further forecasted. One data set is done by forecasting pre-pandemic data (2014-2019) and another data set is done by forecasting during and post-pandemic data (2020-2024). These two data sets were compared from July 2023 to December 2034, which is assumed to be a post-pandemic period. Here, the recovery month or the closest ridership values per scenario were noted. This addressed the third objective.

3. RESULTS AND DISCUSSION

3.1 Factors

After the values of the factors were filled in as much as possible, the annual values were converted into monthly data by distributing the change in values linearly across the months. The data was input into the Econometric Modeler to be analyzed using ARIMA to model what to be used for backcasting and forecasting. The model for remote work factors is (1,1,1); for private vehicle factors is (0,2,1); and for ride-hailing factors is (0,2,1). Backcast and forecast were done in the main interface and the backcasted and forecasted data were exported. The backcast was done until January 2014 and the forecast was done until December 2034.

Figure 4 shows the graphs of the forecasted and backcasted factors. The figures at the left presents the graph of the factors before the forecasting and backcasting while the figures at the right show the plots after backcasts and forecasts. The orange lines on the right graphs are the original plot, blue lines are the backcast plots and the green lines are the forecast plot of the factors.

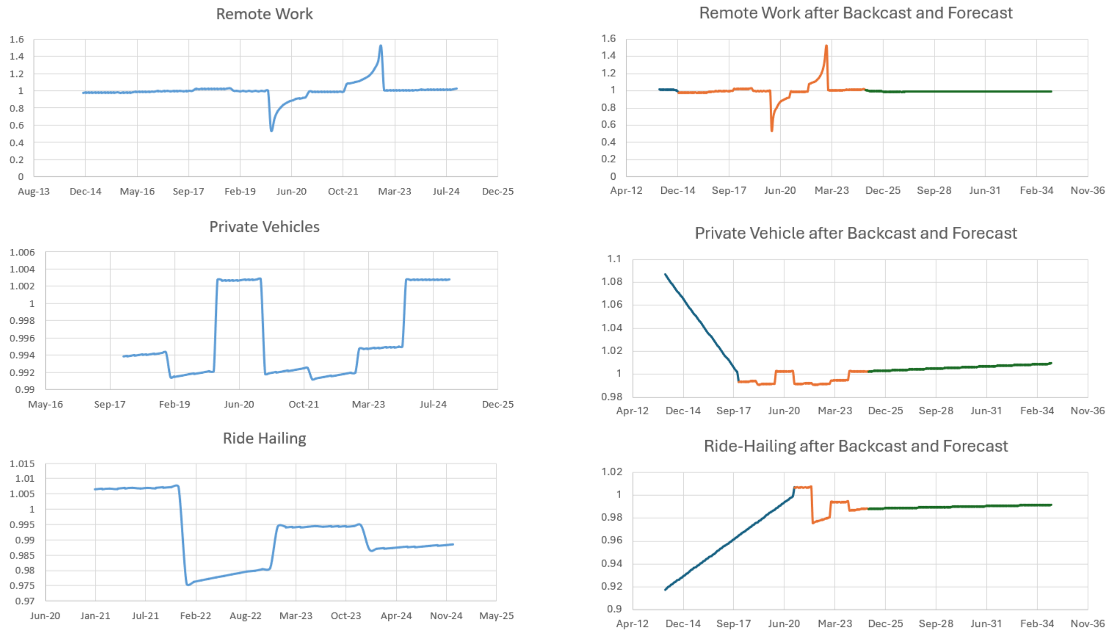


Figure 4. Result of Forecast and Backcast of Factors

It can be observed that remote worker factors are expected to stabilize around 2024. Meaning, it might not have affected the ridership as much in the forecasting using ARIMAX. As observed in the ARIMA forecast for private vehicle factors, there is an increasing trend after 2024. This means that private vehicle ownership might decline, which could result in an increase of transit ridership in the next few years. Lastly, for ride-hailing factors, the forecast shows an increase after 2024. It stabilized under value 1 which means that this factor might still cause a decline in the ridership in the forecasted years. Due to the factors above forecast being stabilized, it can be expected that the ridership under ARIMAX model is not as different to the forecast with ARIMA.

3.2 Scenario Assessment

After the factors were forecasted and back casted, the ridership of stations was modeled using ARIMA. The ridership data was divided into two periods, 2014-2019 and 2020-2024. Table 4 presents the best ARIMA model for each of the stations per period. Most of the stations lagged at first and at the third period. In the year 2014 to 2019, it was observed that most of the stations' ridership was high in January and March. For years 2020-2024, during the pandemic period of pandemic, it was observed that the lag was usually at 2. This means that the high number of ridership was observed the month before the announcement of the lockdown due to the pandemic.

Table 4. Summary of results of Scenario Assessment

STATION	FLOW DIRECTION	2014-2019		2020-2024	
		BEST MODEL	BEST SCENARIO	BEST MODEL	BEST SCENARIO
Recto	Entry	(1,1,0)	Scenario 4	(2,1,2)	Scenario 2
	Exit	(1,1,0)	Scenario 3	(2,1,2)	Scenario 2
Legarda	Entry	(3,1,2)	Scenario 4	(1,1,1)	Scenario 4
	Exit	(3,1,2)	Scenario 4	(2,1,1)	Scenario 2
Pureza	Entry	(3,1,3)	Scenario 6	(2,1,2)	Scenario 7
	Exit	(3,1,1)	Scenario 4	(2,1,2)	Scenario 7
V. Mapa	Entry	(1,1,0)	Scenario 4	(2,1,2)	Scenario 4
	Exit	(1,1,0)	Scenario 4	(2,1,2)	Scenario 2
J.Ruiz	Entry	(1,1,1)	Scenario 4	(2,1,2)	Scenario 3
	Exit	(1,1,1)	Scenario 4	(2,1,2)	Scenario 3
Gilmore	Entry	(1,1,1)	Scenario 4	(2,1,2)	Scenario 6
	Exit	(1,1,0)	Scenario 4	(2,1,2)	Scenario 6
Betty-Go Belmonte	Entry	(3,1,1)	Scenario 4	(2,1,2)	Scenario 7
	Exit	(1,1,3)	Scenario 6	(2,1,2)	Scenario 7
Araneta-Cubao	Entry	(1,1,0)	Scenario 7	(2,1,2)	Scenario 7
	Exit	(1,1,0)	Scenario 4	(2,1,2)	Scenario 2
Anonas	Entry	(1,1,1)	Scenario 4	(1,1,0)	Scenario 7
	Exit	(3,1,0)	Scenario 7	(3,1,3)	Scenario 7
Katipunan	Entry	(3,1,2)	Scenario 7	(1,1,0)	Scenario 7
	Exit	(3,1,3)	Scenario 1	(1,1,1)	Scenario 7
Santolan	Entry	(1,1,1)	Scenario 4	(0,1,1)	Scenario 3
	Exit	(1,1,0)	Scenario 4	(0,1,1)	Scenario 3
TOTAL	Entry	(1,1,1)	Scenario 4	(2,1,2)	Scenario 5
	Exit	(1,1,0)	Scenario 4	(2,1,2)	Scenario 3

Table 5. AIC and BIC values of the ARIMA and ARIMAX models of 2014-2019 LRT 2 Monthly Ridership

Station		Model	Criterion	ARIMA	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Best Scenario	Final Scenario
Recto	Entry	(1,1,0)	AIC	1872.1782	1827.9351	1825.6458	1823.6827	1823.6644	1825.9206	1823.6716	1826.2107	Scenario 4	Scenario 4
			BIC	1876.6752	1839.1776	1834.6398	1830.4282	1830.4099	1834.9145	1830.4171	1835.2047	Scenario 4	
	Exit	(1,1,0)	AIC	1888.2829	1843.5913	1841.5388	1839.551	1839.553	1841.6323	1839.5614	1841.6653	Scenario 3	Scenario 3
			BIC	1892.7799	1854.8338	1850.5328	1846.2965	1846.2985	1850.6263	1846.3069	1850.6593	Scenario 3	
Legarda	Entry	(3,1,2)	AIC	1798.8526	1705.8703	1704.6496	1702.4691	1702.4531	1704.72	1702.4738	1704.0275	Scenario 4	Scenario 4
			BIC	1812.1697	1725.8459	1722.4057	1718.0056	1717.9897	1722.476	1718.0104	1721.7836	Scenario 4	
	Exit	(3,1,2)	AIC	1839.8687	1745.4981	1746.0765	1743.6958	1743.6903	1745.6849	1743.7045	1744.5631	Scenario 4	Scenario 4
			BIC	1853.1858	1765.4736	1763.8326	1759.2324	1759.2269	1763.441	1759.2411	1762.3191	Scenario 4	
Pureza	Entry	(3,1,3)	AIC	1763.7404	1679.0223	1678.091	1677.3031	1677.3103	1678.1679	1677.2982	1677.8292	Scenario 6	Scenario 6
			BIC	1779.2769	1701.2174	1698.0666	1695.0592	1695.0664	1698.1435	1695.0542	1697.8048	Scenario 6	
	Exit	(3,1,1)	AIC	1764.2878	1703.2185	1702.3368	1700.1438	1700.1342	1702.1441	1700.1458	1701.3612	Scenario 4	Scenario 4
			BIC	1801.8951	1720.9745	1717.8734	1713.4609	1713.4512	1717.6807	1713.4629	1716.8977	Scenario 4	
V.Mapa	Entry	(1,1,0)	AIC	1722.2342	1681.2344	1678.9091	1676.8468	1676.831	1679.1128	1676.8479	1679.341	Scenario 4	Scenario 4
			BIC	1726.7312	1692.4769	1687.9031	1683.5923	1683.5765	1688.1068	1683.5934	1688.335	Scenario 4	
	Exit	(1,1,0)	AIC	1675.1681	1635.3819	1633.063	1631.1209	1631.1009	1633.3999	1631.1095	1633.7371	Scenario 4	Scenario 4
			BIC	1679.6651	1646.6244	1642.057	1637.8664	1637.8464	1642.3939	1637.855	1642.7311	Scenario 4	

J.Ruiz	Entry	(1,1,1)	AIC	1537.8066	1502.5855	1500.7935	1498.7944	1498.7936	1500.7989	1498.7937	1500.6903	Scenario 4	Scenario 4
			BIC	1544.552	1516.0765	1512.036	1507.7883	1507.7876	1512.0413	1507.7877	1511.9328	Scenario 4	
	Exit	(1,1,1)	AIC	1538.9004	1503.6284	1501.9192	1500.0009	1499.9932	1501.7049	1500.0047	1501.6049	Scenario 4	Scenario 4
			BIC	1545.6458	1517.1193	1513.1616	1508.9948	1508.9871	1512.9473	1508.9987	1512.8474	Scenario 4	
Gilmore	Entry	(1,1,1)	AIC	1619.5546	1582.8969	1580.3975	1578.4888	1578.4695	1580.4233	1578.4994	1580.875	Scenario 4	Scenario 4
			BIC	1626.3001	1596.3879	1591.64	1587.4828	1587.4635	1591.6658	1587.4934	1592.1174	Scenario 4	
	Exit	(1,1,0)	AIC	1628.2044	1591.2455	1588.4287	1586.3348	1586.2963	1588.6948	1586.3587	1589.2493	Scenario 4	Scenario 4
			BIC	1632.7014	1602.4879	1597.4227	1593.0803	1593.0418	1597.6888	1593.1042	1598.2432	Scenario 4	
Betty-Go Belmonte	Entry	(3,1,1)	AIC	1499.0504	1428.2973	1426.7145	1424.7181	1424.7144	1426.7094	1424.7178	1426.712	Scenario 4	Scenario 4
			BIC	1510.148	1446.0534	1442.251	1438.0352	1438.0315	1442.246	1438.0348	1442.2485	Scenario 4	
	Exit	(1,1,3)	AIC	1504.8198	1468.5232	1467.1662	1465.2065	1465.2244	1467.0445	1465.1789	1466.8271	Scenario 6	Scenario 6
			BIC	1516.0623	1486.5112	1482.9057	1478.6975	1478.7154	1482.7839	1478.6699	1482.5665	Scenario 6	
Araneta-Cubao	Entry	(1,1,0)	AIC	1806.138	1776.4909	1776.5426	1775.1981	1775.1453	1775.4126	1775.2362	1774.5129	Scenario 7	Scenario 7
			BIC	1826.6486	1787.7333	1785.5366	1781.9435	1781.8908	1784.4066	1781.9817	1783.5069	Scenario 4	
	Exit	(1,1,0)	AIC	1851.3932	1807.8277	1806.1356	1804.0687	1804.0538	1806.3878	1804.0737	1806.138	Scenario 4	Scenario 4
			BIC	1855.8902	1819.0702	1815.1296	1810.8142	1810.7993	1815.3818	1810.8192	1815.1319	Scenario 4	
Anonas	Entr	(1,1,	AIC	1749.9721	1707.8872	1706.2631	1705.4562	1705.4283	1705.5877	1705.4867	1705.957	Scenario 4	Scenario 4

	y	1)	BIC	1756.7175	1721.3782	1717.5056	1714.4502	1714.4223	1716.8301	1714.4807	1717.1995	Scenario 4	
	Exit	(3,1, 0)	AIC	1747.6218	1654.2309	1654.8986	1653.5079	1653.3962	1653.6707	1653.4814	1652.2373	Scenario 7	Scenario 7
			BIC	1756.4998	1669.7675	1668.2157	1664.6054	1664.4937	1666.9877	1664.5789	1665.5544	Scenario 4	
Katipunan	Entr y	(3,1, 2)	AIC	1843.1124	1751.0403	1752.8791	1751.8315	1751.7507	1751.0019	1751.8965	1749.0384	Scenario 7	Scenario 7
			BIC	1856.4294	1771.0158	1770.6352	1767.3681	1767.2873	1768.7579	1767.4331	1766.7945	Scenario 7	
	Exit	(3,1, 3)	AIC	1778.5327	1683.6775	1688.5352	1686.6195	1686.5311	1687.6086	1686.6585	1684.5169	Scenario 1	Scenario 1
			BIC	1794.0692	1705.8726	1708.5108	1704.3755	1704.2872	1707.5842	1704.4146	1704.4925	Scenario 4	
Santolan	Entr y	(1,1, 1)	AIC	1939.4389	1894.0883	1890.4011	1889.1058	1889.074	1891.6971	1889.1516	1892.1323	Scenario 4	Scenario 4
			BIC	1946.1844	1907.5793	1901.6436	1898.0998	1898.068	1902.9396	1898.1456	1903.3748	Scenario 4	
	Exit	(1,1, 0)	AIC	1913.6782	1865.6656	1864.3528	1863.5285	1863.4717	1863.7322	1863.6049	1864.0534	Scenario 4	Scenario 4
			BIC	1918.1751	1876.9081	1873.3468	1870.274	1870.2172	1872.7262	1870.3504	1873.0474	Scenario 4	
TOTAL	Entr y	(1,1, 1)	AIC	2119.5894	2067.8425	2065.928	2064.0446	2064.0232	2065.7966	2064.0598	2065.9654	Scenario 4	Scenario 4
			BIC	2126.3349	2081.3334	2077.1705	2073.0385	2073.0171	2077.0391	2073.0538	2077.2079	Scenario 4	
	Exit	(1,1, 0)	AIC	2115.13	2064.4933	2061.9777	2060.0569	2060.0305	2062.1372	2060.0873	2062.5389	Scenario 4	Scenario 4
			BIC	2119.627	2075.7357	2070.9717	2066.8024	2066.776	2071.1312	2066.8328	2071.5329	Scenario 4	

Table 6. AIC and BIC values of the ARIMA and ARIMAX models of 2020-2024 LRT 2 Monthly Ridership

Station	Mod el	Criteri on	ARIMA	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Best Scenario	Final Scenario

Recto	Entry	(2,1,2)	AIC	1546.2149	1439.2905	1436.9332	1439.4336	1440.1763	1441.5576	1440.138	1437.1384	Scenario 2	Scenario 2
			BIC	1556.4302	1455.6349	1451.2346	1451.6919	1452.4346	1455.8589	1452.3963	1451.4397	Scenario 2	
	Exit	(2,1,2)	AIC	1554.2756	1450.2745	1446.6048	1446.9707	1448.0201	1450.4928	1448.306	1448.1743	Scenario 2	Scenario 2
			BIC	1564.4908	1466.6189	1460.9062	1459.229	1460.2784	1464.7942	1460.5643	1462.4757	Scenario 3	
Legarda	Entry	(1,1,1)	AIC	1468.809	1429.1986	1426.9296	1425.2975	1425.2788	1427.4732	1425.2803	1426.9678	Scenario 4	Scenario 4
			BIC	1474.9903	1441.5613	1437.2318	1433.5393	1433.5206	1437.7754	1433.5221	1437.27	Scenario 4	
	Exit	(2,1,1)	AIC	1479.001	1372.0885	1368.604	1379.4695	1380.2234	1381.559	1380.19	1369.5148	Scenario 2	Scenario 2
			BIC	1487.1732	1386.3899	1380.8623	1389.6848	1390.4387	1393.8174	1390.4053	1381.7731	Scenario 2	
Pureza	Entry	(2,1,2)	AIC	1419.4716	1319.8284	1316.7344	1316.7599	1317.4165	1320.2113	1317.3593	1316.5018	Scenario 7	Scenario 7
			BIC	1429.6869	1429.6869	1331.0358	1329.0182	1334.3223	1334.5126	1329.6176	1330.8032	Scenario 3	
	Exit	(2,1,2)	AIC	1415.7686	1324.6577	1321.4234	1321.4098	1322.064	1325.1711	1322.0164	1321.216	Scenario 7	Scenario 7
			BIC	1425.9839	1341.0021	1335.7248	1333.6681	1322.064	1339.4725	1334.2747	1335.5173	Scenario 4	
V.Mapa	Entry	(2,1,2)	AIC	1399.5233	1292.6376	1289.7299	1288.4492	1288.0962	1292.3678	1288.1023	1289.7179	Scenario 4	Scenario 4
			BIC	1409.7385	1308.982	1304.0313	1300.7076	1300.3545	1306.6691	1300.3607	1304.0193	Scenario 4	
	Exit	(2,1,2)	AIC	1384.4531	1293.4354	1285.7724	1286.0217	1286.5126	1291.5096	1286.5292	1291.2658	Scenario 2	Scenario 2
			BIC	1394.6684	1309.7798	1300.0737	1298.28	1298.7709	1305.8109	1298.7875	1305.5671	Scenario 3	
J.Ruiz	Entr	(2,1,	AIC	1259.4706	1168.9375	1166.9699	1166.0283	1166.4589	1168.8603	1166.435	1166.9432	Scenario 3	Scenario 3

	y	2)	BIC	1269.6858	1185.2819	1181.2713	1178.2866	1178.7172	1183.1616	1178.6934	1181.2445	Scenario 3	
	Exit	(2,1, 2)	AIC	1246.6466	1164.4985	1162.4983	1162.4268	1162.9755	1165.34	1162.9558	1162.499	Scenario 3	Scenario 3
			BIC	1256.8618	1180.8429	1176.7996	1174.6851	1175.2339	1179.6413	1175.2141	1176.8004	Scenario 3	
Gilmore	Entr y	(2,1, 2)	AIC	1341.7129	1253.5572	1252.0086	1250.0724	1250.0435	1251.856	1250.0227	1252.0396	Scenario 6	Scenario 6
			BIC	1351.9282	1269.9017	1266.3099	1262.3307	1262.3018	1266.1574	1262.281	1266.341	Scenario 6	
	Exit	(2,1, 2)	AIC	1337.9622	1256.5926	1253.8607	1251.9737	1251.9157	1254.1664	1251.9067	1253.9035	Scenario 6	Scenario 6
			BIC	1348.1775	1272.937	1268.1621	1264.232	1264.174	1268.4678	1264.165	1268.2049	Scenario 6	
Betty-Go Belmonte	Entr y	(2,1, 2)	AIC	1233.1337	1136.8312	1134.8846	1135.8039	1136.3742	1137.8769	1136.3462	1134.8214	Scenario 7	Scenario 7
			BIC	1243.349	1153.1756	1149.1859	1148.0622	1148.6325	1152.1782	1148.6045	1149.1228	Scenario 3	
	Exit	(2,1, 2)	AIC	1232.8715	1132.1237	1130.2151	1131.4858	1132.1593	1133.8246	1132.13	1130.1109	Scenario 7	Scenario 7
			BIC	1243.0868	1148.4681	1144.5164	1143.7441	1144.4176	1148.126	1144.3883	1144.4123	Scenario 3	
Araneta-Cubao	Entr y	(2,1, 2)	AIC	1548.9006	1429.4929	1428.1697	1428.4625	1429.0535	1429.6457	1428.9579	1427.434	Scenario 7	Scenario 7
			BIC	1559.1158	1445.8373	1442.471	1440.7208	1441.3118	1443.947	1441.2162	1441.7353	Scenario 3	
	Exit	(2,1, 2)	AIC	1571.6806	1447.4283	1443.367	1448.4599	1449.1603	1444.2594	1449.067	1445.794	Scenario 2	Scenario 2
			BIC	1581.8958	1463.7727	1457.6683	1460.7182	1461.4186	1458.5607	1461.3253	1460.0954	Scenario 2	
Anonas	Entr y	(1,1, 0)	AIC	1362.6589	1318.4295	1317.3241	1317.1326	1317.8254	1318.5083	1317.7748	1317.0594	Scenario 7	Scenario 7
			BIC	1366.7798	1328.7317	1325.5659	1323.3139	1324.0067	1326.75	1323.9561	1325.3012	Scenario 3	

	Exit	(3,1, 3)	AIC	1382.3548	1291.0685	1289.0061	1295.4615	1296.3543	1296.4386	1296.2858	1288.6984	Scenario 7	Scenario 7
			BIC	1396.5322	1311.322	1307.2343	1311.6643	1312.5571	1314.6667	1312.4886	1306.9266	Scenario 7	
Katipunan	Entr y	(1,1, 0)	AIC	1389.6965	1344.4074	1343.2749	1343.5144	1344.2435	1344.9113	1344.1951	1342.9818	Scenario 7	Scenario 7
			BIC	1393.8174	1354.7096	1351.5167	1349.6957	1350.4248	1353.1531	1350.3764	1351.2236	Scenario 3	
	Exit	(1,1, 1)	AIC	1418.9513	1371.6237	1370.1338	1371.2887	1372.0812	1373.2389	1372.0383	1369.8702	Scenario 7	Scenario 7
			BIC	1425.1326	1383.9864	1380.436	1379.5305	1380.3229	1383.5411	1380.2801	1380.1724	Scenario 3	
Santolan	Entr y	(0,1, 1)	AIC	1368.5855	1350.3905	1348.6891	1347.4038	1347.709	1349.3817	1347.6929	1348.3992	Scenario 3	Scenario 3
			BIC	1372.7406	1360.7781	1356.9993	1353.6364	1353.9416	1357.6919	1353.9256	1356.7094	Scenario 3	
	Exit	(0,1, 1)	AIC	1361.9631	1343.9281	1342.25	1340.9169	1341.2138	1342.8711	1341.1974	1342.1769	Scenario 3	Scenario 3
			BIC	1366.3668	1354.3158	1350.5603	1347.1495	1347.4464	1351.1812	1347.43	1350.487	Scenario 3	
TOTAL	Entr y	(2,1, 2)	AIC	1702.1854	1578.0034	1571.6428	1570.6524	1570.0472	1569.1098	1571.2664	1571.37	Scenario 5	Scenario 5
			BIC	1712.4007	1594.3478	1585.9441	1582.9107	1582.3055	1583.4111	1583.5247	1585.6714	Scenario 4	
	Exit	(2,1, 2)	AIC	1707.489	1579.609	1575.9954	1573.1423	1577.3475	1576.2516	1577.358	1577.1861	Scenario 3	Scenario 3
			BIC	1717.7042	1595.9534	1590.2968	1585.4006	1589.6058	1590.553	1589.6163	1591.4874	Scenario 3	

To address the first objective, the best scenario was determined based on the AIC and BIC. Lowest AIC and BIC mean that the model fits the time series the best among the scenarios. Here, it was concluded which of the factors or combination of factors affects the ridership more accurately compared to others. It can be observed in Table 1 that there is no station that has ARIMA scenario or no factors scenario as their best model. In fact, when using the 2014-2019 data, all ARIMA scenario AIC and BIC values are the highest. As mentioned before, BIC value is high if the model is more complicated and that this criterion prefers simpler ones. Having a lower BIC despite this criterion strongly means that including the factor did improve the model. This highly suggests that factors are needed to make a more accurate prediction for this time series and that there are factors that do affect the LRT 2 ridership.

Scenario 4 or having only ride-hailing users as the factor is the most fitting scenario to the time series of most of the LRT 2 stations ridership. This highly suggests that the decline of the LRT 2 ridership is caused by the increasing number of ride-hailing users pre-pandemic. Three stations have scenario 7 or have only remote work and ride hailing users as the factor as their best fitting scenario. This suggests that the decline in this three ridership is caused by both remote work and ride-hailing. These two scenario have ride-hailing as their factor which means ride-hailing is the most probable cause of LRT 2 ridership decline. In the years before the pandemic, the trend of using ride-hailing services was partly driven by workers seeking reliability, safety, affordability and reduction of congestion (Napalang & Regidor, 2017). According to Fitzsimmons (2017), subway ridership dropped by 0.3% in 2016 and the weekend subway ridership declined by 3%. These studies show that ride-hailing has become a substitute for rail transit. Although this is in the perspective of Americans with US transportation, factors that might have led to ride-hailing becoming a substitution in the Philippines is also evident. Ride-hailing did become a substitute in the Philippines based on a few factors. As stated by Jose (2024), in 2014-2015, there were 11 trainsets during peak hour, and it has decreased to 7 trainsets in 2019. Due to this, the waiting time in LRT line 2 increased which can make commuters change modes (Dimla 2024) . With these problems in the transit, people change modes and use ride-hailing services instead. This is how ride-hailing substitute transit in the Philippines.

Connecting with the result per station, it can be observed the ridership is affected by the students. The stations Recto, Legarda, Pureza, Gilmore, Anonas, and Katipunan are stations that have students as one of their main users. Since there are schedules for their classes, it is important to reach their classrooms on time. With the issues on the transit services during this period, the decline of ridership and the rise of ride-hailing services during this period can be highly affected by the students' change of transportation mode. For years during and after the pandemic, Table 1 shows that Scenario 7 or only remote workers and ride-hailing users' factors are most likely the cause of the decrease of ridership. Scenario 3 or only using remote workers factor, and scenario 2 or only using remote workers and private vehicle factors comes second. This highly suggests that during and after the pandemic is highly caused by the factor of increasing number of remote workers. This result aligns with that of Jiang et al. (2022), where it was found that lockdown that caused people to work from home is the main cause of the decline of ridership. Another study by Zheng (2024), shows that the decline in on-site workers caused a decrease in transit ridership.

These studies can also be applied in the Philippines setting. According to Mejia (2020), 74% of chief financial officers (CFO) found that remote work is cost efficient and planned to continue it even after the pandemic period. In addition, a study by Parilla et al. (2022) found that remote work arrangements enhanced job satisfaction and performance among Filipino employees. These reasons further extend remote working even after the pandemic period. It also aligns with the study by Erhardt (2022), where the factors are compared using regression analysis and the result shows that ride-hailing is the factor that caused the decline in transit ridership in the US. In a study by Co et al. (2022) for Metro Manila, the percentage of public transportation has shifted to ride-hailing after the pandemic period. They showed how the public transportation usage fell after COVID by more than half and has only recovered around 4% back after restrictions were lifted. Compared to before and after lockdown for ride-hailing, it increased to 4.4 percent from the public transport commuters. This shows the increasing demand for ride-hailing services after the pandemic.

All the stations except Gilmore show that remote working was the main reason for the ridership decline during and after the pandemic. Gilmore shows that private vehicles were the main reason for the decline. This may be due to the location of the station which is close to St. Luke's Medical Center. During COVID-19, the frontliners were the people in the medical fields and that the private vehicles were highly used at that time, especially in that area. The other stations mostly consisted of students and workers which had to adapt remote set-up that ultimately declined ridership during the pandemic period. After the pandemic, ridership declined more as people used more ride-hailing services.

3.3 Forecast Assessment

To address objective 2, forecasting future values of LRT line 2 ridership was done under the factors of remote workers, private vehicles and ride-hailing. Scenario 0 or Scenario without factors, which is forecasting using ARIMA, was also done like the scenario assessment above Here, the divided data was also divided into two sets, ridership before pandemic period and ridership during and after pandemic.

Table 7. Summary of results of Forecast Assessment

STATION		2014-2019		2020-2024	
		Min Scenario	Max Scenario	Min Scenario	Max Scenario
Recto	Entry	Scenario 5	Scenario 1	Scenario 1	Scenario 2
	Exit	Arima	Scenario 2	Scenario 1	Scenario 5
Legarda	Entry	Scenario 5	Arima	Arima	Scenario 1
	Exit	Scenario 2	Scenario 1	Scenario 1	Scenario 4
Pureza	Entry	Arima	Scenario 1	Arima	Scenario 3
	Exit	Scenario 2	Arima	Arima	Scenario 1
V. Mapa	Entry	Scenario 5	Arima	Scenario 1	Scenario 3
	Exit	Scenario 5	Arima	Scenario 7	Scenario 1
J. Ruiz	Entry	Scenario 1	Arima	Scenario 1	Scenario 4
	Exit	Scenario 1	Arima	Scenario 1	Scenario 4
Gilmore	Entry	Scenario 1	Arima	Arima	Scenario 4
	Exit	Arima	Scenario 1	Arima	Scenario 6
Betty-Go Belmonte	Entry	Scenario 4	Arima	Scenario 1	Arima
	Exit	Arima	Scenario 4	Arima	Scenario 6
Araneta- Cubao	Entry	Arima	Scenario 7	Arima	Scenario 1
	Exit	Scenario 1	Scenario 6	Scenario 1	Arima
Anonas	Entry	Scenario 2	Scenario 6	Arima	Scenario 5
	Exit	Scenario 1	Arima	Arima	Scenario 1

Katipunan	Entry	Arima	Scenario 1	Arima	Scenario 5
	Exit	Scenario 1	Scenario 6	Scenario 4	Scenario 2
Santolan	Entry	Scenario 1	Scenario 6	Scenario 1	Scenario 5
	Exit	Scenario 1	Arima	Scenario 1	Scenario 5
TOTAL	Entry	Arima	Scenario 6	Scenario 3	Scenario 1
	Exit	Arima	Scenario 7	Scenario 2	Arima

As observed in Table 7, the highest occurrence scenario that would most likely decrease ridership in the future is scenario 1 (with all factors). For the highest forecasts, the most common scenario is ARIMA (no factors). With this, the factor that would most likely decrease the ridership is private vehicle numbers in some areas. In other areas, the factor that would most likely increase is also private vehicle numbers. As expected, most of the stations didn't show significant differences in the forecasted highest and lowest ridership. Anonas and Katipunan stations gap on the lowest and highest forecast was influenced by the sudden low ridership in October 2019 which is due to the station's temporary closing from the fire that happened on October 3rd.

Most of the stations on the ARIMA scenario projected the minimum and maximum forecast. In the minimum forecast, scenario 5 or only private vehicles and ride-hailing factors are used comes second to ARIMA scenario. This reflects the factors that are projected to decline the ridership in years after without a pandemic period in the trend. For the maximum, the tally of factors that are most likely to affect the increase of ridership is fair. This means that if all the factors still affect the ridership, it is expected to have an upward trend. This could be due to the trends canceling each other. The forecasted trend for private vehicles is expected to increase the ridership while the other two are expected to decline but the remote work factor is projected to stabilize and is close to 1. This made the forecast, either ARIMA or Scenario 1 being the most likely scenario to increase the ridership.

For the second set of ridership, the highest occurrence scenario that would be most likely to decrease ridership in the future is scenario 1 (all factors). For the highest forecasts, the most common scenario is Scenario 1 (all factors) as well. With this, the factor that would most likely decrease the ridership is remote work numbers. The factor that would most likely increase is ride-hailing. Except for V. Mapa and TOTAL, all the stations didn't show big gaps between the highest and lowest forecasts. This could be due to the big change in the middle of the time series as this period includes pandemic. Most of the stations have ARIMA as the scenario for the lowest ridership and scenario 1 and 3 for the highest ridership. Scenario 1 includes all factors and as mentioned earlier, the increase in ridership could be due to the cancellation of forecasted factors. Scenario 3 includes only remote work ridership. This trend is stabilizing throughout the forecast, which is why the effect on the ridership must have been like ARIMA. The ridership also increased due to the downward trend of the factors after the pandemic.

3.4 Projected Return to Original Trend

In addressing the third objective, the ridership is projected using two datasets, before pandemic, which is from 2014-2019, and during and after pandemic, which is from 2020-2024. The two-time series are compared and checked which month they are the closest to the trend.

Table 8. Summary of results of Projected Return to Original Trend

STATION	FLOW DIRECTION	MOST COMMON MONTH	CLOSEST SCENARIO
Recto	Entry	Nov-24	ARIMA
	Exit	Jul-25	Scenario 3
Legarda	Entry	May-24	Scenario 5
	Exit	Oct-23	Scenario 1
Pureza	Entry	Nov-24	Scenario 1
	Exit	Oct-23	Scenario 3
V.Mapa	Entry	Oct-24	Scenario 1
	Exit	Nov-24	Scenario 7
J.Ruiz	Entry	Jan-25	Scenario 6
	Exit	Mar-24	ARIMA
Gilmore	Entry	Jun-24	ARIMA
	Exit	Jul-23	Scenario 7
Betty-Go Belmonte	Entry	Oct-24	Scenario 1
	Exit	Oct-24	Scenario 1
Araneta- Cubao	Entry	Oct-24	ARIMA
	Exit	Mar-25	Scenario 5
Anonas	Entry	Jul-23	Scenario 1
	Exit	Jul-23	ARIMA
Katipunan	Entry	Oct-23	Scenario 3
	Exit	Jul-23	ARIMA
Santolan	Entry	Oct-23	Scenario 1
	Exit	Oct-23	Scenario 1
TOTAL	Entry	Aug-23	ARIMA
	Exit	May-25	Scenario 6

As observed in Table 8, it can be concluded that it is most likely to have come back to its original trend before the end of 2024. Most of the stations are most likely to have returned to the original trend by October 2024. Although it was the most common month to come back to its original trend, other stations might have come back to their trends at a different month as presented.

4. SUMMARY AND CONCLUSIONS

This study aimed to analyze and forecast LRT line 2 ridership under emerging trends related to COVID-19 pandemic impact scenarios. These scenarios were based on the increasing number of remote workers, increasing number of private vehicle users and increasing number of ride-hailing users. These factors that had affected the ridership pre-pandemic and during to post-pandemic were checked using ARIMA and ARIMAX models. The ridership was forecasted for more analysis.

For pre-pandemic data, results show that including only the factor of ride-hailing users is the best-fitting model to the time-series. This means that the increasing number of ride-hailing users most likely is the cause of the decline of ridership in LRT 2. For the “during to post-pandemic data”, results show that including both remote working and ride-hailing is the best fitting model to the time series. This means that the increasing number of remote workers and ride-hailing users is the cause of the decline of ridership users in the 2020 to 2024.

After forecasting the future values in different scenarios and comparing them, scenario 1 and ARIMA scenario either caused an increase or decrease in ridership of the stations. In pre-pandemic period data, most of the station's ridership increased in ARIMA (no factors). However, most of the stations declined in ARIMA (no factors) which are the ones that didn't increase using ARIMA model. Some of the station's ridership declined in scenario 1 (all factors) as well. In post-pandemic period data, the ridership of most of the stations increased in scenario 1 (all factors). However, most of the stations declined in scenario 1 (all factors). Some of the station's ridership declined in the ARIMA scenario (no factors) as well.

Lastly, stations showed a return to their original trend at the end of 2024. Most of the stations showed that their ridership most likely came back to their original trend in pre-pandemic last October 2024.

5. RECOMMENDATIONS

Knowing the factors that would most likely affect the ridership in LRT 2 before the COVID-19 pandemic is needed for forecasting future ridership. Planners can also get an idea on how ridership declined after the impact of pandemic. Additionally, the factors that likely caused the change in ridership can be used to forecast future ridership in case another untoward event just like the pandemic happens. The forecast ridership can also be used for planning for needed interventions to meet the demand like improving facilities and increasing train capacities. They can check these forecasts in case the scenarios observed are the ones that would most likely yield a high ridership. The recovery month is recommended to be used for planning as this is the expected month in which the ridership will come back to its original trend. Meaning, high ridership is expected to start the month of recovery.

For researchers, it is recommended to include a qualitative evaluation in this study. It is also recommended to try other time-series models such as GARCH or machine learning models. Using a bigger data set is also recommended as time-series models work better with bigger data sets. The ARIMA distribution used is Gaussian and it is recommended to try t distribution for future research. It is also advised to address the seasonality as it was observed multiple times in the ridership data 3. It is also recommended to try other factors such as increase of ticket price or heat index in the Philippines to have a deeper understanding on why there is a decline in the ridership data. Lastly, it is recommended to try this method in other rail transits.

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