Kiosk Strategic Demand Forecasting with Scenario Planning: A case study at SITA

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Summary

SITA is the world's leading specialist in air transport communications and information technology which works with around 400 air transport members and has 2800 customers in 190 countries. TS6 kiosk is the newest generation of its kiosk family and is facing a complicated situation now. Usually, the production of a kiosk is using make-to-order methods. However, if this method is adopted, the customers of SITA can not receive their productions within the expected periods of time. Besides this, SITA also can not get the procurement discount from the suppliers if they only purchase a low volume and do not make changes. In order to solve this problem, demand forecasting is conducted using the historical sales data of the TS6 kiosk. Through the literature review, suitable qualitative forecasting methods and quantitative forecasting methods which were mainly used in the FMCG industry are got together and combined to increase the forecast accuracy in this research to come out with the final forecast result of the TS6 kiosk. This research also explores the possibility of demand forecasting for the slow-moving consuming industry. By successfully conducting the final forecast, the result can help SITA to shorten procurement lead time so as to meet customers' expectations as well as save total costs.

Key Words: Demand Forecasting, Quantitative Forecasting Methods, Qualitative Forecasting Methods, ARIMA, SARIMA, Residual Analysis.

Contents

1 Introduction

1.1 Background

SITA is a world-leading company mainly providing service and IT support for airline operators and more than 400 airports. The main customers include airports, airlines, ground handlers and airport groups. As shown below in figure 1.1, SITA's self-service hardware products mainly include kiosks, bag-drop, and gates. The kiosk is a highly modular, cleverly designed, and highly customizable device that can be used in check-in, bag tagging, and border control within airports[36]. After optimizing the fourth and fifth generations of the product, the sixth generation is now available and has become more customized. The kiosk is designed to be used for 20 years, but due to the fast changes in technology, customers usually choose to replace it with the next generation in 5-7 years.

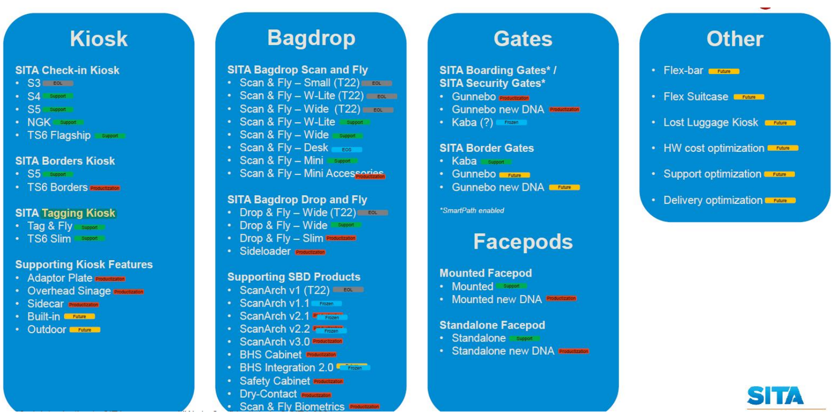

Figure 1.1: SITA self service hardware products[36]

The Tailored Series 6 (TS6) kiosk which SITA produces is now made in the Burlington factory in Canada and all kiosks are made to order(MTO). However, SITA now wants to introduce the made-to-stock(MTs) methodology to its production. The first reason for this change in strategy is that improved manufacturing efficiency will increase customer satisfaction, thus potentially increasing market share. Because normally the customers want to receive the kiosk in 3 months after placing the order, the lead time actually is 10-16 weeks in procurement and assembly normally takes 6-8 weeks. A figure which shows the timeline from procurement to delivery can be found below in figure 1.2. Since it is very difficult to shorten the production, customs and shipping times, the best way to satisfy customers is to find ways to shorten the procurement time. Forecasting kiosk sales in advance and placing orders with suppliers in advance can significantly reduce the lead time for procurement.

Figure 1.2: The timeline of one kiosk before reach the customers

The second reason is that if a large number of raw materials can be bought at once, SITA will receive a price discount from the suppliers. Volume discount quantities are in the range of 10-50-100-250-500-1000 and SITA is now buying 100 raw materials at a time, but the monthly sales are more than one hundred units. The relationship between price discount and quantity can be found below in figure 1.3. So shifting to annual forecasts and trying to make orders at 1000 quantity level will indeed have a chance to save cost. Sales forecasting can help determine the number of orders to be placed and thus avoid excessive over-ordered or under-ordered. Due to these two reasons, SITA wants to change its policy to MTS by performing yearly forecasting in advance for the next 4 years. More information about SITA, the TS6 Kiosks, and the available data can be found in the appendix.

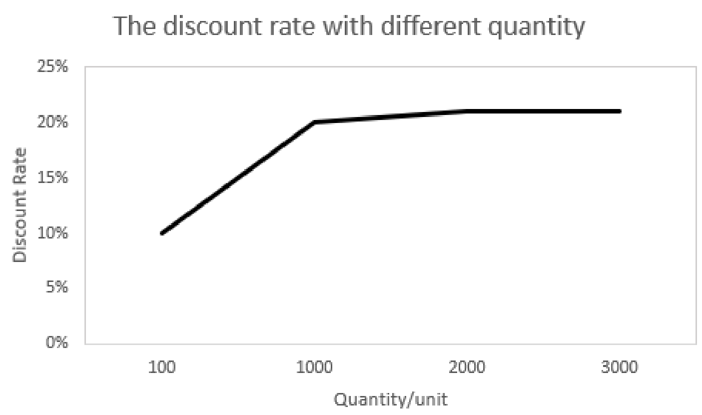

Figure 1.3: The discount rate with quantity

In addition to the advantages from the company's point of view, making TS6 sales forecasts in advance can prevent rising costs due to temporary investment in production, training, and recruiting due to unstable demand and insufficient production. Besides this, by taking into account obsolescence and inventory costs, forecasting in advance can help make production plans in advance, and smooth the customer's demand by producing in advance when there are fewer orders and using current inventory when are too many orders.

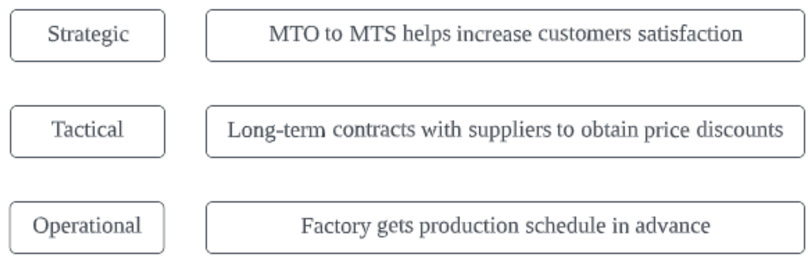

Figure 1.4: The company benefit

1.2 Data analysis for the current state

1.2.1 Market condition

In 2011, SITA divided its world customer market into 7 markets: EUR, APAC, AMER, MEIA, NAM, LAC and AFR. NAM was merged into AMER in 2014, AFR was merged into MEIA in 2015, and LAC was merged into AMER in 2021. In 2022, SITA divide the market into EUR, APAC, AMER and MEIA, and the sales for these markets in the last years can be found below in figure 1.5. Sales higher than 300 are marked in red to specify the good market condition for that specific market. AMER has the highest sales 3354 pcs, followed by APAC which is 3275 pcs. This figure also shows the 2015 has that best market condition.

300-1000/unit
150-300/unit
0-150/unit

	EUR	APAC	AMER	MEIA
2011	168	78	112	3
2012	275	75	230	74
2013	123	427	226	1
2014	260	227	270	4
2015	785	529	326	0
2016	160	361	323	0
2017	85	412	169	0
2018	14	341	272	102
2019	138	285	387	0
2020	46	216	266	0
2021	282	200	518	165
2022	61	125	255	16
Total	2397	3276	3354	365

Figure 1.5: The market condition

1.2.2 Kiosk sales in the last years

The historical sales data for kiosks S2, S3, S4, S5, TS6, NGK, Changi and T&F can be found below in figure 1.6 and 1.7. Among them, the S2, S3, S4, S5 and TS6 are the same kind of kiosks with different generations. The NGK and Changi are specifically customised for airport NGK and Changi. T&F already stops selling due to the very limited sales in the past years. Custom kiosk is the sum of NGK and Changi, and CUSS is the sum of all other kiosks. The highest sales in the life cycle which is the period between phase-out time and the phase-in time in the market of one generation is marked red in the figure. The figure shows that the total kiosk has the highest sales in 2015. The life cycle for S3, S4, and S5 is 10 years, 7 years, and 6 years(at least).

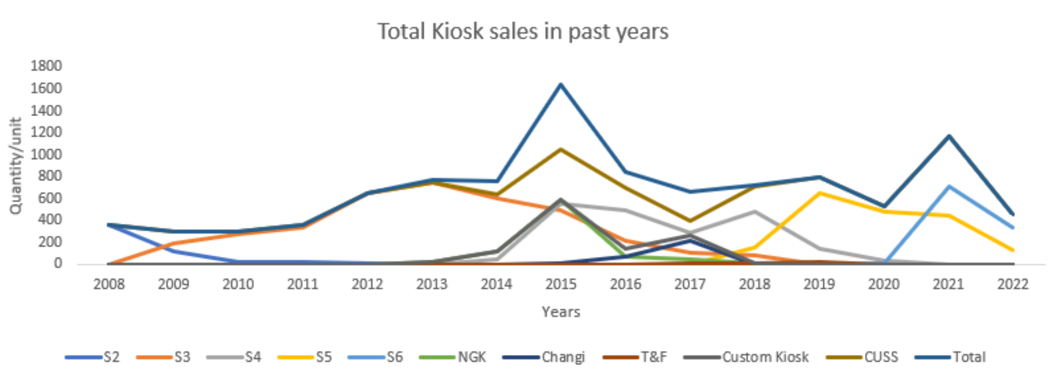

Figure 1.6: Total kiosk sales in the past years

	S2	S3	S4	S5	S6	NGK	Changi	T&F	Custom Kiosk	CUSS	Total
2008	365	0	0	0	0	0	0	0	0	365	365
2009	118	186	0	0	0	0	0	0	0	304	304
2010	18	281	0	0	0	0	0	0	0	299	299
2011	23	338	0	0	0	0	0	0	0	361	361
2012	4	650	0	0	0	0	0	0	0	654	654
2013	0	752	0	0	0	25	0	0	25	752	777
2014	0	598	43	0	0	120	0	0	120	641	761
2015	0	495	554	0	0	587	4	0	591	1049	1640
2016	0	210	491	0	0	76	67	0	143	701	844
2017	0	112	282	0	0	51	216	5	267	394	661
2018	0	85	477	151	0	12	0	4	12	713	725
2019	0	0	138	654	0	1	0	17	1	792	793
2020	0	0	36	480	10	0	0	2	0	526	526
2021	0	0	1	448	716	0	0	0	0	1165	1165
2022	0	0	0	126	331	0	0	0	0	457	457
Total	528	3707	2022	1859	1057	872	287	28	1159	9173	10332

Figure 1.7: Total sales data

Sales for one generation can also be found in the figures below. All of these sales curves except for S4 have one common feature, which is that there is only one peak. The reason why there is 2 peak for the sales line of S4 is not very clear in the interviews, but may be due to 3 reasons: (1) Fierce competition. (2) Customer buy advance in 2015. (3) Bad market condition. With these figures, one assumption can be made which is there are certain similarities in the sales patterns for these kiosks, so it is possible to use the historical sales data to make the prediction for future sales.

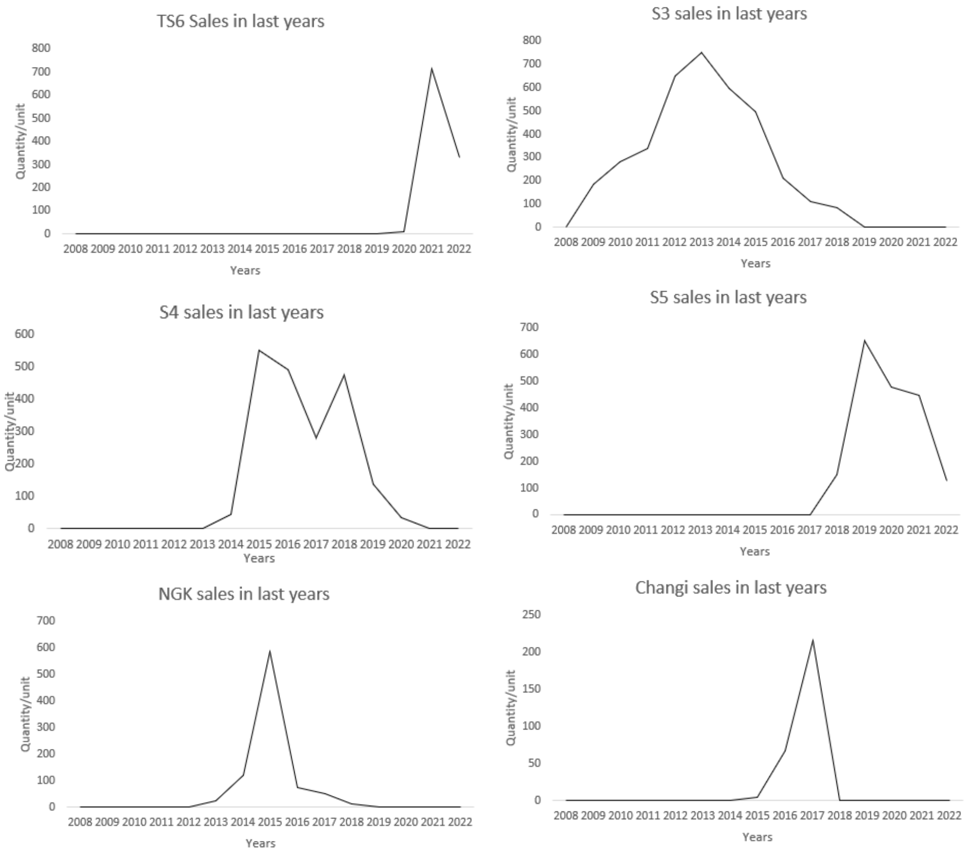

Figure 1.8: Historical sales data for one generation

1.2.3 Customer analysis

The customer analysis can also be found below in figure 1.9. In this analysis, the new customer is defined as the customer who only buys one generation of kiosks and the repeat customer is defined as the customer who buys serval different generations of kiosks. The total number of customers except NGK and Changi is 213. Among them, the number of new customers is 149 and the number of repeat customer is 64. The S2 to S3 is calculated by the average of the first date one customer buys S3 minus the first date that the customer buys S2, which is the same formula for S3 to S4, S4 to S5, etc. This analysis also shows that the repeat customer counts for most sales of the kiosks, especially for Ts6 which is more than 90%.

	Number	Rate
Total customer	213	1
New customer	149	0.70
repeat customer	64	0.30

repeat customer	S2->S3	S3->S4	S4->S5	S5->TS6	S3-S5	S3->TS6	S4-TS6
Time(month)	42.0	48.6	37.5	24.3	90.5	114.0	75.0

QTY	S2	S3	S4	S5	TS-6	Total
Repeat customer	22	2130	1516	1074	930	5672
RC_Rate	0.814815	0.605802	0.759519	0.611966	0.902913	0.681403
New customer	5	1386	480	681	100	2652
NC_Rate	0.185185	0.394198	0.240481	0.388034	0.097087	0.318597
Total	27	3516	1996	1755	1030	8324

Figure 1.9: The customer analysis

1.3 Research scope

Generally, the kiosk is designed with different versions for different application scenarios. Figure 1.10 shows different versions. However, only the normal kiosk which is especially used for check-in has the highest sales, and the kiosk for different versions share more than 90% raw materials. In the S3 kiosk family, the check-in S3 kiosk counts for 96.3% of total sales. The S4 family only have the check-in kiosk. Check-in S5 kiosk counts for 95.4% of the total sales for the S5 family. Check-in TS6 kiosk counts for 98.4% of the total sales for the TS6 family. Besides this, NGK and Changi are specially designed for airport NGK and Changi because they are big customers. The sales process of these two kiosks is different from other products. For this reason, this research only considers using the historical sales data of the check-in kiosk (S2 to S5) to forecast the total sales of the TS6 check-in kiosk which is also called the TS6 flagship. Hereinafter referred to as TS6

Figure 1.10: SITA's kiosk family[36]

Figure 1.10 and 1.11 shows the historical sales data for the check-in kiosks for different generations. Since these generations are substitutes for each other, the increase in sales of one generation is often followed by a decrease in sales of the next generation. Therefore, the sales of TS6 in the next four years must be related to the introduction of S7 into the market.

	S3	S4	S5	TS-6 Flags	ToTal
2008	0	0	0	0	0
2009	186	0	0	0	186
2010	281	0	0	0	281
2011	338	0	0	0	338
2012	650	0	0	0	650
2013	752	0	0	0	752
2014	598	43	0	0	641
2015	467	554	0	0	1021
2016	186	491	0	0	677
2017	72	282	0	0	354
2018	40	477	128	0	645
2019	0	138	606	0	744
2020	0	36	466	4	506
2021	0	1	448	707	1156
2022	0	0	126	329	455
Total	3570	2022	1774	1040	8406

Figure 1.11: Check-in kiosk sales data

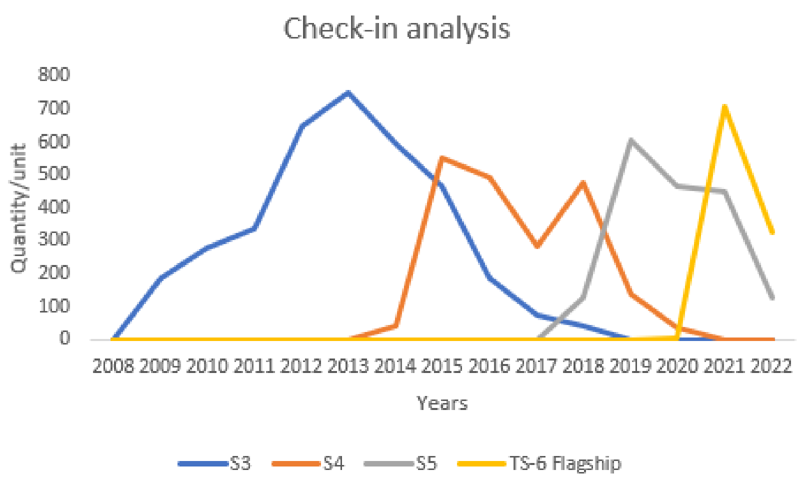

Figure 1.12: Total sales for the check in kiosk

1.4 Research questions

As mentioned before, the aim of this research is to provide SITA with accurate sales volume of TS6 Kiosk over the next 4 years. For this reason, the main research question is as follows:

How can SITA forecast TS6 Kiosk demand based on historical sales data?

To answer these questions, the main research question is divided into the following sub-questions and their relationships with research steps are also shown below.

Step 1	How to build the forecast scenarios by considering the existing external factors? eg: The introduction of S7 and the phase-out of S5.
Step 2	Which qualitative and quantitative forecast method is suitable to do the forecast with the available data?
Step 3	How to combine qualitative and quantitative forecast methods for data processing and sales forecasting?
Step 4	How to consider and validate the forecast model and forecast numbers?
Step 5	How to use the forecast outcome in the future and what's the benefit?

Figure 1.13: The steps with sub-questions

1.5 Research structure

The whole research is divided into 5 chapters. There will be an introduction to the research background and data analysis of the current state in the first chapter which aims to give a clear start for the readers. Followed by the literature review of qualitative and quantitative forecasting methods as well as the clear forecasting steps for the methods used in this research. The research methodology will be illustrated in chapter 3 which shows the way to combine different forecasting methods and the detailed process to do the experiments. The experiment outcome, any further adjustments as well as future applications will be shown in chapter 4. Then, research conclusion as well as research limitations will be illustrated in chapter 5.

1.6 Research contribution

This research will have two kinds of contributions. The first one is the contribution to theoretical research and practical application. This research tries to combine different forecasting methods for forecasting and verify them in practical situations. Thus it can provide reference value in the combination of different forecasting methods and practical applications. The second contribution is to be able to help SITA companies to make a strategic shift from MTO to MTS, through which they can help them to improve customer satisfaction by reducing delivery time, as well as to obtain price discounts from suppliers.

2 | Literature Review

2.1 Forecast methods

There are many forecasting methods. The following section first highlights some of the qualitative forecasting methods and quantitative forecasting methods, as well as explained how and why some of the methods are chose to be used this research. The second part of the literature review is going to do an introduction of the related techniques about the chose methods.

2.1.1 Qualitative forecasting

Qualitative forecasting is commonly used in practice. Normally, if the below 3 situations exist, the practitioners should consider using qualitative forecasting[24]. (1) No available historical data, so the only way to do the forecast is to use qualitative forecasting methods. (2) Historical data is available, statistical predictions are first made and then adjusted using the qualitative method; (3) Historical data is available, then combine both qualitative and quantitative methods to do the forecasting. Normally, the statistical predictions should be taken into consideration first if historical data exist. Also, the research shows that qualitative forecasting will have a better result if the predictor has important expertise and up-to-date information. Qualitative forecasting can be affected by excessive intervention, over-optimism[9], and a policy environment.

The Delphi method

The Delphi method is a structured, interactive forecasting method that relies on a panel of experts.[5], and this methods show certain advantages compared with other structured forecasting methods so has been widely used for the business forecast[15]. The Delphi method is based on the key assumption that predictions from groups are generally more accurate than those from individuals[34]. The Delphi method usually consists of the following stages[33]: (1)Formation of expert panels. (2) Assigned predictive tasks or challenges to the experts. (3)Experts submit preliminary projections and rationale. (4) Feedback will be given to the experts and they will review their forecast and make changes based on the feedback. This process will be repeated until the experts reach an agreement. (5)The final forecast is constructed by aggregating the experts' forecasts by certain calculation method. However, this research does not consider using this method due to the whole process time of the Delphi methods can be very long and it is quite difficult to find a panel of experts with corresponding experience.

The analogy forecast

The analogy forecast assumes one forecast model can also explain the behaviour of another phenomenon due to they share certain similarities[29] and this methods is widely used in the pricing of a house by comparing the land size, dwelling size, number of rooms between similar properties[19]. Analogical predictions can often produce biases, and these biases are often difficult to identify. Predictions should be based on multiple dimensions of analogy to reduce bias. And using a systematic approach to perform the comparison and prediction process can also reduce bias. One of the systematic prediction methods is proposed by Green& Armstrong[14], which is a method similar to the Delphi method but more focus on analogies. This methods involves the following steps: 1. Form a team of experienced experts. 2. Problem set and assigned to the experts. 3. Experts identify the analogues and make predictions. 4. By comparing the target situation and analogy, experts list similarities and differences, and then rate the similarity on a scale. 5. Come out the final forecast by weighted average, ranking scores or other rules.

From interviews, for the development of kiosk, there is a big innovation and changes from S2 to S3, but small innovation and changes from S3 to S4 and S4 to S5. For S5 to TS6, there is another big innovation and changes, and the sale line of TS6 already shows some similarity compared with S3. For TS6 to S7, there will be only small changes and innovation. By using the analogy forecast, the assumption is the sales line of S7, S4 and S5 will have some similarities. With this assumption, the forecast of S7 will be coming out by using the sales data of S4and S5.

Scenario forecasting

The scenarios forecast is to come out forecast based on plausible scenarios, and each scenarios may have some possibility to be occurrence. According to the scenario forecasting approach which is commonly used by Shell, the process is as follows [26]: Find the drivers and build the assumptions based on the drivers, first produce 7-9 mini-scenarios and try to reduce or combine them to only 2-3 by bringing the drivers together.
During the historical data analysis, it is obviously that the sales life cycle of TS6 will be influenced by the phase in date of S7. So in this research, different scenarios for phase in date of S7 will be take into consideration, which helps to come out a more comprehensive forecast.

Judgmental adjustments

If there are available historical sales data and statistical forecast generated by it, then apply the judgmental adjustments will be very common for practitioners. The judgmental adjustments can provide information for the factors that may not be accounted for in the statistical models, such as promotion, holidays, Large orders.etc.[19]. The judgmental adjustments should not used to correct a missing patterns in the statistical model, which has be proven to be effective. This methods can also cause bias, because the users usually adjust much more than they should. It is be proven that judgmental adjustments will be more accurate when there is a significant missing information and the change is large in size, so the small adjustments should be avoid. Besides this, a negative adjustment tends to help more in increasing the forecast accuracy than positive adjustments. [10]
After coming out the final forecast by statistical model, the result will be send to the expert of SITA to do some judgmental adjustments. However, in order to avoid bias, only the significant changes are allowed to make and the record document will be kept for further check.

2.1.2 Quantitative methods

Quantitative methods should only be applied when there is available historical data and there is reason to believe that certain patterns will persist into the future[19]. After observing the sales figure for different series of kiosk, there are certain similarity between the sales line of different series of kiosks. Therefore, it can be assumed that the past patterns will continue into the future. Thus, kiosk's prediction using a quantitative methods satisfies the previous two preconditions.
Generally, the forecast model can be divided into explanatory model, time series models, and other advanced forecasting methods like neural network models and bootstrapping and bagging etc. which include computer Modeling and Simulation. However, after considering the disadvantages of machine learning methods which are as follows: (1) The long-term accuracy improvements are not significant compared with the traditional methods particularly when forecast time-series data at a weekly and even daily frequency[30]. (2) The machine learning methods require the strong programming skills of the user and are more difficult to implement. (3) Need a lot of data. The machine learning method is not used in the project.

Explanatory model

The explanatory model attempts to explain the relationship between the predictor variables and various factors using formulas for situations where marketing plans, competitor activity, economic conditions, etc. have a very strong influence on the forecast results. The explanatory model usually including the time series regression models and dynamic regression models.
According to the information got from SITA's expert, SITA normally does not have marketing plans and the market for the kiosk is quite stable. Besides this, it is very difficult to collect data for different factors. So in this research, the assumption is that the external factors do not have a fluctuating effect on the predicted results and any big effect of these effects caused by the external factors can be adjusted through the judgemental adjustment after the statistical forecast.

Time series regression models
The core idea of the regression model is to assume some relationship between the predicted variable y and the predictor variable x. Among them, the simplest linear regression model assumes the relationship between the predicted variable y and the individual predictor as shown below, where theβ_0, β_1, ε_t represent the intercept, slope and residuals.

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{2.1}$$

When there are k predictor variables, the model is called a multiple linear regression model, and the general form is as follows:

$$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \cdots + \beta_k x_{k,t} + \varepsilon_t \tag{2.2}$$

The basic assumptions of the linear regression model are as follows[23]: (1) The sample is representative. (2) Sample data measured without error. (3) The expectation of residuals is zero. (4) Residuals are not correlated with each other. (4)Residuals are not correlated with predictor variables. Besides this, in order to get the forecast interval, a general assumption is to assume the residuals follow a normal distribution with a constant variance σ^2 [19], and in order to do the experiment, the forecast variable is also assumed to be not a random variable.
Usually, the model coefficients $\beta_0, \beta_1, \ldots, \beta_k$ can be estimated using Least squares estimation[28]. The purpose of the Least squares estimation is to minimize the sum of the squared errors, and its mathematical expression is as follows:

$$\sum_{t=1}^{T} \varepsilon_t^2 = \sum_{t=1}^{T} \left(y_t - \beta_0 - \beta_1 x_{1,t} - \beta_2 x_{2,t} - \cdots - \beta_k x_{k,t}\right)^2 . \tag{2.3}$$

When performing regression analysis, we usually assume that the error term is zero to calculate the fitted value of the predicted term with the following expression:

$$\hat{y}_t = \hat{\beta}_0 + \hat{\beta}_1 x_{1,t} + \hat{\beta}_2 x_{2,t} + \cdots + \hat{\beta}_k x_{k,t}. \tag{2.4}$$

When testing the goodness of fit of a model, it can usually be judged using the coefficient of determination(R^2), which is derived by calculating the correlation between the observed y and predicted values $\hat{y}$ with the following expressions[7]:

$$R^2 = \frac{\sum \left(\hat{y}_t - \bar{y}\right)^2}{\sum \left(y_t - \bar{y}\right)^2} \tag{2.5}$$

When the predicted value is close to the observed value, the R^2 will be close to 1. Otherwise, R^2 will be close to 0. However, R^2 will also increase with the number of explained variables. This problem can be solved by using the adjusted R^2 which can be expressed below[32], where T is the number of observations and k is the number of predictor.

$$\bar{R}^2 = 1 - \left(1 - R^2\right) \frac{T-1}{T-k} \tag{2.6}$$

Adjusted R also shows some problems when there are too many predictors[19]. Another way is to use AIC, BIC, etc. to determine the goodness of fit of a model which can be found in the later paragraph.
Dynamic regression models
The dynamic regression model is actually the combination of the regression model and the time series model. This model also tries to explain the relationship between a predicted variable and the predictors, but it also takes into consideration the relationship between the predicted variable itself. This model can be expressed below, where y_t represents the predicted variables, x_t represents the predictors, and η_t represents the error term, However, in the dynamic regression model, the error term is allowed to be auto-correlation[19]. The disadvantages of this model are as follows: (1) The model can be very difficult to understand. (2) It is very difficult to get the predictors value in the further. (3) Compared with the normal time series model and regression model, the accuracy of the predictions did not improve significantly. Due to these problems, this method is not considered in the research.

$$y_t = y_{t-1} + \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \cdots + \beta_k x_{k,t} + \eta_t \tag{2.7}$$

Time series model

The simplest time series forecasting methods use only information about the predictor variables and do not look for factors that affect the predictor variables. Therefore, these methods can infer the trend component and the seasonal component. The exponential smoothing and ARIMA models are the most widely used time series forecasting method. Due to ARIMA model is more widely used compared with the exponential smoothing methods, this research decided to used ARIMA model to do the statistical forecasting.

Exponential smoothing methods

Exponential smoothing method is an important method for making time series forecasts and was first proposed by [11], the main idea behind this method relies on that the weighted average of the past observations will be larger if the past observations closer to the forecast point. One advantage of this method is that it is able to generate predictions very quickly and is suitable for a wide range of time series data. The simple exponential smoothing(SES) represents the simplest form of this method with no clear trend or seasonal patterns[3] and can be expressed using the formula below, where$\hat{y}_{T+1|t}$ represents the time series data and α represent the smoothing factor, and $0 \leq \alpha \leq 1$. When α is close to 1, then assign more weight to the most recent observation. When α is close to 0, then assign more weight to the observations in the past.

$$\hat{y}_{T+1|T} = \alpha y_T + \alpha(1-\alpha) y_{T-1} + \alpha(1-\alpha)^2 y_{T-2} + \alpha(1-\alpha)^3 y_{T-3} + \cdots \tag{2.8}$$

The same as the regression model, the method of minimising the sum of the squared errors(SSE) can also be used to determine the value of α [16], if e_t is used to represent the residuals, then the SSE can be expressed in the formula below:

$$\mathrm{SSE} = \sum_{t=1}^{T} \left(y_t - \hat{y}_{t|t-1}\right)^2 = \sum_{t=1}^{T} e_t^2 \tag{2.9}$$

This method was further studied by Holt[17] to include trends and can be expressed below, where ℓ_t denotes the estimation of the level of time series data at time t,b_t denotes an estimate of the trend of the time series data at time t, and β^* denotes the smoothing parameter for the trend($0 \leq \beta^* \leq 1$).

$$\begin{aligned} \hat{y}_{t+h|t} &= \ell_t + h b_t \\ \ell_t &= \alpha y_t + (1-\alpha)\left(\ell_{t-1} + b_{t-1}\right) \\ b_t &= \beta^*\left(\ell_t - \ell_{t-1}\right) + (1-\beta^*) b_{t-1} \end{aligned} \tag{2.10}$$

However, empirical evidence indicates the trend tends to be over-forecast. To solve this problem, the damped trend parameter ϕ which was between o and 1 was introduced by Gardner & McKenzie in 1985 and shows great success[12].

$$\begin{aligned} \hat{y}_{t+h|t} &= \ell_t + \left(\phi + \phi^2 + \cdots + \phi^h\right) b_t \\ \ell_t &= \alpha y_t + (1-\alpha)\left(\ell_{t-1} + \phi b_{t-1}\right) \\ b_t &= \beta^*\left(\ell_t - \ell_{t-1}\right) + (1-\beta^*) \phi b_{t-1} \end{aligned} \tag{2.11}$$

This methods was further developed by Holt and Winters[39] to include seasonal patterns $\mathcal{S}_t$. This approach has two different seasonal components. The additive model is usually chosen when the seasonal variation remains approximately constant in that time series, while the multiplicative model is usually chosen when the seasonal variation varies proportionally with the level of the time series. The mathematical expression of the two model can be shown below, where m is the frequency of the seasonality, α, β^* and γ is the smoothing parameters.
The mathematical expression of the additive model is as below:

$$\begin{aligned} \hat{y}_{t+h|t} &= \ell_t + h b_t + s_{t-m+h_m^+} \\ \ell_t &= \alpha\left(y_t - s_{t-m}\right) + (1-\alpha)\left(\ell_{t-1} + b_{t-1}\right) \\ b_t &= \beta^*\left(\ell_t - \ell_{t-1}\right) + (1-\beta^*) b_{t-1} \\ s_t &= \gamma\left(y_t - \ell_{t-1} - b_{t-1}\right) + (1-\gamma) s_{t-m} \end{aligned} \tag{2.12}$$

The mathematical expression of the multiplicative model is as below:

$$
\begin{aligned}
\hat{y}_{t+h|t} &= (\ell_t + hb_t)\, s_{t-m+h_m^+} \\
\ell_t &= \alpha \frac{y_t}{s_{t-m}} + (1-\alpha)(\ell_{t-1} + b_{t-1}) \\
b_t &= \beta^* (\ell_t - \ell_{t-1}) + (1-\beta^*)\, b_{t-1} \\
s_t &= \gamma \frac{y_t}{(\ell_{t-1} + b_{t-1})} + (1-\gamma) s_{t-m}
\end{aligned}
\tag{2.13}
$$

The classification of the exponential smoothing methods was first proposed by Pegels in 1069 and was further studied and developed by several other scholars[31], Now, by considering different combinations of the trend and seasonal components, nine exponential smoothing methods can be obtained, which can be found in the figure 2.1 below. The same as the time series regression model, the information criteria like AIC and BIC can be used for model selection too. The information criteria will be introduced in the later paragraphs.

Trend Component	Seasonal Component		
	N	A	M
	(None)	(Additive)	(Multiplicative)
N (None)	(N,N)	(N,A)	(N,M)
A (Additive)	(A,N)	(A,A)	(A,M)
A_d (Additive damped)	(A_d,N)	(A_d,A)	(A_d,M)

Figure 2.1: A two-way classification of exponential smoothing methods[19]

ARIMA

ARIMA model (Autoregressive Integrated Moving Average model) is a widely used classical time series forecasting method with high forecasting accuracy. After transforming a non-stationary time series into a stationary time series by using the difference method, ARIMA model regresses the dependent variable on its lagged values only and on the present and lagged values of the random error term to create a predictive model, and thus is sufficent to describe a regular wide-sense stationary time series data[38]. When the seasonality exists in the time series data, the SARMA model can be used or a seasonal-differencing should be applied before putting the data into the ARIMA model[18]. ARIMA model which is usually used in short term forecast only find the patterns from existing historical data and do not require strong structural data[19].Therefore, it is suitable for a wide range of applications.

The non-seasonal ARIMA models is the combination of differencing(I), autoregression(AR) and moving average(MA), and is usually written as ARIMA(p,d,q).

The mathematical expression of the non-seasonal ARIMA model is as follows:

$$
Y_t = \lambda_1 Y_{t-1} + \lambda_2 Y_{t-2} + \cdots \lambda_p Y_{t-p} + \varepsilon_t + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \cdots + \varphi_q \varepsilon_{t-q} \tag{2.14}
$$

The AR(p) model is used when the forecast variable only related to past value of the forecast variable, and the mathematical expression is as below:

$$
Y_t = \lambda_1 Y_{t-1} + \lambda_2 Y_{t-2} + \cdots + \lambda_p Y_{t-p} + \varepsilon_t \tag{2.15}
$$

The MR(q) model only used past residuals in the model, the mathematical expression is as follows:

$$
Y_t = \varepsilon_t + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \cdots \varphi_q \varepsilon_{t-q} \tag{2.16}
$$

The I(d) indicates the number of times doing the difference. From equation 2.1 to 2.3, y_t is the predictor, p is the order of AR model.λ is the coefficient of lagged values of predictor. φ is the coefficient of the lagged values of residuals.ε_j is the white noise. q is the order of MR model. d is the degree of differencing involved.

By including another seasonal terms in the ARIMA model, the ARIMA model is capable of modelling the seasonal data, which can be written as follows ARIMA $(p, d, q)(P, D, Q)_m$ and m is the number of observations per year, and uppercase P, D, Q refer to the autoregressive, difference, and moving average for the seasonal patterns in the SARIMA model.[27].

2.2 Theory related to ARIMA model construction

This section will introduce the theory and methods related to the construction of ARIMA models.

Data stationary

Determining the whether the time series data is stationary is the first step in building ARIMA models. A stationary time series data is one whose properties do not depend on the time of the observation[19]. Before building the ARIMA model, it is usually required that the time series data should be stationary. Below highlight 3 popular methods to help determine whether the time series data is stationary or not.
Observation Method: If the observed values in the plotted time series fluctuate randomly above and below a certain value, the time series data is considered to be stationary; on the contrary, the non-stationary series data generally do not change around a certain level, but have different mean values at different time periods, such as single increase, single decrease, showing the same trend of change at intervals, etc.
ACF test: The autocorrelation function(ACF) reflects the degree of correlation between the current observation of the time series and its historical observations up to k lags [35] The mathematical expression is as following:

$$ACF(k)=\frac{\operatorname{cov}\left(y_t, y_{t-k}\right)}{\sqrt{\operatorname{var}\left(y_t\right)} \sqrt{\operatorname{var}\left(y_{t-k}\right)}} \tag{2.17}$$

k refers to the number of lags, cov refers to the covariance, and var refers to the variance. As the value of k gradually increases, the value of its corresponding autocorrelation function may appear in two cases. One case is that the ACF value decreases rapidly and the autocorrelation plot decays exponentially which indicates that the series is stationary. The other case is that the ACF value decreases slowly and the autocorrelation plot decays linearly, which indicates that the series is not stable and needs to be further differenced[40].
ACF test might cause a problem for determine the correlation between Y_t and Y_t-2 if Y_t and Y_t-1 are correlated, because Y_t and Y_t-2 are all related to Y_t-1. However, this problem can be overcome by using the partial autocorrelations (PACF), because this meethod removed the effect of lags[19].
Autocorrelation (ACF) and partial autocorrelations (PACF) can help determine the order of p,d,q for ARIMA model[21]. It also shows applicable when determine the p,q values for AR models and MA models, but do not shows a good result in determine the p,q in ARMA model[19]. When selection the p,q order for ARMA model, it is better to use the Information Criteria (eg. AIC,BIC)

	MA(q)	AR(q)	ARMA(p,q)
ACF	Tail off	Cut off, q lag	Tail off
PACF	Cut off, p lag	Tail off	Tail off

Figure 2.2: Model selection between ARMA, AR, and MA by using ACF and PACF figures[21]

Unit root test: The unit root test is one of the most common statistical tests to determine whether a time series is stationary or not. Two unit root tests will be described below.
Dickey-Fuller(DF)test: The Dickey-Fuller test was introduced by David Dickey and Wayne Fuller in 1979, the null hypothesis and the alternative hypothesis can be expressed below[8]. The DF unit root test can only be used to test the stationarity of the first-order autoregressive process, which can be expressed as AR(1). The null hypothesis assumes that the unit root is without the unit cycle which means the time series is not stationary.

$$\begin{aligned} & y_t=\rho y_{t-1}+\varepsilon_t \\ & H_0:|\rho| \geq 1 \text{ vs } H_1:|\rho|<1 \end{aligned} \tag{2.18}$$

Augmented Dickey-Fuller(ADF): The ADF test allows the higher-order autoregressive processes and was created by modifying the DF test to include lags of the order p to make it suitable to be used by more widely time series data, eg. AR(p). The test procedure for the ADF test is the same as the DF test, and the null hypothesis is that a unit root is present in a time series sample. The ADF test can be expressed as below.[4]

$$\begin{aligned}&\mathrm{DF}_\tau = \frac{\hat{\gamma}}{\mathrm{SE}(\hat{\gamma})}\\&H_0 : \gamma = 0 vs H_1 : \gamma < 0\end{aligned} \tag{2.19}$$

If the series is found to be non-stationary after data stationary identification, and the series has a significant tendency to fluctuate up and down then the data needs to be processed before putting into the ARIMA model. The logarithmic transformation, smoothing, and difference operation are the three commonly used method of stabilization[40].

Differencing: Differencing is a method of eliminating the correlation between pre and post data by subtracting the series term by term according to the order of the time series[25]. If y_t represent the time series data, the first-order difference can be expressed as follow, where the ε_t represent the white noise and c is the average of the changes in consecutive observations. If c is positive, then the average change of the time series data is increasing, otherwise, the time series data is decreasing. If the c equals 0, then the time series data can be referred to as a "random walk" model.

$$y_t - y_{t-1} = c + \varepsilon_t \quad \text{or} \quad y_t = c + y_{t-1} + \varepsilon_t \tag{2.20}$$

Sometimes the differenced data is still not stationary, so it may be necessary to differ the data again to get a stationary series. The expression of the second order difference is as follows. In practice, it is almost never need to go beyond second-order differences[19].

$$\begin{aligned}y''_t &= y'_t - y'_{t-1}\\&= (y_t - y_{t-1}) - (y_{t-1} - y_{t-2})\\&= y_t - 2y_{t-1} + y_{t-2}\end{aligned} \tag{2.21}$$

Seasonal differencing is the differencing between one observation and the corresponding observation of the previous season and can be expressed below, where m denotes the number of seasons in a year. Seasonal differencing can be used to handle data with very severe seasonal or cyclical trends[22].

$$y'_t = y_t - y_{t-m} \tag{2.22}$$

Log transformation: Logarithmic transformation can usually be used in combination with differencing, where logarithmic transformation is used to change the exponential trend into a linear trend and then differencing is used to eliminate the linear trend. Logarithmic transformation can only be used with positive numbers.

Smoothing method: The smoothing method mainly includes the moving average method and the weighted moving average method, where the estimates of the moving average method represents the average value over a certain time period, while the estimated value of the weighted moving average method is calculated according to the different weights. This method is often used in combination with differencing to eliminate periodic effects.

Information Criteria

The Akaike information criterion (AIC) and the Bayesian information criterion (BIC) are normally used to estimate the error and quality of the statistical models[37]. The information criteria can be used to choose the order of p and q for the ARIMA model. However, this method does not show a good result in helping chose the order of d, because differencing changes the data for calculating the likelihood and the information criterion between different models so that the value of the information criterion cannot be compared. [19]

(1)Akaike's Information Criterion (AIC):

AIC is found by the Japanese statistician Hirotugu Akaike[1] and is very wildly used in the field for estimating the quality of statistical models. Generally, some information will be lost due to the statistical model trying to represent the generation of the data and the AIC is used to estimate the amount of lost information, and the less the AIC is, the better the statistical models.

The AIC values can be represented as the following, where k is the number of estimated parameters in the model and $\hat{L}$ is the maximized value of the likelihood function.

$$\mathrm{AIC} = 2k - 2\ln(\hat{L}) \tag{2.23}$$

The mathematical expression of AIC for ARIMA model is showen below[19]:

$$\text{AIC} = -2\log(L) + 2(p+q+k+1) \tag{2.24}$$

One of the biggest drawbacks of AIC is that the number of unknown parameters of the model cannot exceed 2. However, in a long time series forecast, which often contains multiple unknown parameters, thus, using the AIC criterion will not be suitable for fitting long time series[40].
(2)Bayesian Information Criterion(BIC):
BIC was developed by Gideon E. Schwarz in 1978[13] and is closely related to the AIC. Both AIC and BIC are tended to resolve a problem which is overfitting due to the model tens increasing the likelihood by adding more parameters by developing a penalty term for the number of parameters in the model. In BIC the penalty term is larger than in AIC, especially for a sample size larger than 7[37].
Using the same definition of parameters, the BIC is defined as follows:

$$\text{BIC} = k\ln(n) - 2\ln(\widehat{L}) \tag{2.25}$$

For ARIMA model, the BIC can be written as follows[19]:

$$\text{BIC} = \text{AIC} + [\log(T) - 2](p+q+k+1) \tag{2.26}$$

Time series decomposition

To better understand the time series data, it is useful to split a time series into several components[19]. Usually 3 types of time series patterns will be exist in the forecast: trend, seasonality and cycle.The trend does not require a straight line, but rather a long-term direction of change that may show a long-term up or down, or a trend that rises and then falls.Seasonality is a fixed frequency which can occur daily, monthly or yearly. A cycle occurs when the the time series data does not fluctuate with a fixed frequency, which is always causes by the economic conditions. The time series decomposition is to decompose the time series data into a trend-cycle component, a seasonal component, and residuals that including everything else.
Generally, the time series decomposition can be divided into additive decomposition (Equation 2.27) and multiplicative decomposition (Equation 2.28). Additive decomposition is suitable when the magnitude of the seasonal fluctuations does not vary with the level of the time series. Otherwise, multiplicative decomposition will be more appropriate. In this research the multiplicative decomposition is used to decompose the data.

$$y_t = S_t + T_t + R_t \tag{2.27}$$

$$y_t = S_t \times T_t \times R_t \tag{2.28}$$

In classical decomposition, the seasonal patterns are assumed to be constant for all the following years. Below are the steps to use multiplicative decomposition[19]:
(1)The first step is to come out with the trend and cycle components. The moving average is used to calculate the trend-cycle patterns. $2 \times m - MA$ is used when the m is an odd number, otherwise, m-MA will be used. The m is equal to 2k+1 and k is the number of time series data used in the averages.

$$\hat{T}_t = \frac{1}{m}\sum_{j=-k}^{k} y_{t+j} \tag{2.29}$$

(2) The detrended series is come out by $y_t - \hat{T}_t$. which will be used to calculate the seasonal component.
(3) The seasonal component is calculated by simply averaging the detrended value of the corresponding season.
(4) The residual is come out by dividing out the estimated seasonal and trend-cycle component: $\hat{R}_t = y_t / \left(\hat{T}_t \hat{S}_t\right)$

Ljung-Box(LB) test

The LB test which was developed by Greta M. Ljung and George E. P. Box is widely used in time series analysis. The main idea of this method is to check the autocorrelation of a set of data. If the test result is 0, then it indicates that the set of data is not correlated at all[2].
The LB test is defined as:
H_0: The data are independently distributed.

H_1: The data are not independently distributed and the autocorrelation exists.
The test statistic is defined as the following, where n is the sample size, k is the lag, $\hat{\rho}_k$ is the autocorrelation, and h is the number of lags being tested.

$$LB = n(n+2)\sum_{k=1}^{h}\left(\frac{\rho_k^2}{n-k}\right) \sim \chi^2(h) \tag{2.30}$$

The LB test is now commonly used in the ARIMA model to test whether autocorrelation exists in the residuals, not the original series. And in the application of the ARIMA(p,0,q) model, the degree of freedom should be set to h-p-q.[6]

3 | Methodology

The methodology chapter elaborates on the methods found in the literature review and combines them together to build a forecast structure. The forecast scenarios are first developed according to the analogy forecast. Then, the prediction process of the ARIMA model is constructed according to the literature review, and the prediction structure for the TS6 kiosk is concluded. Finally, the detailed experiments process mainly using the SARIMA model according to the forecast structure is implemented to come out with the forecast result.

3.1 Forecast scenario

The goal of this research is to forecast the total sales of TS6 for the next 4 years. However, due to TS6 only being introduced to the market in one year, the sales data is very limited. During the background data analysis which can be found in section 1.2. It is obvious that the sales quantity of TS6 will be influenced by the sales quantity of S5 and S7 because they are substitutes for each other, and the total sales quantity of all the kiosks seems to be stationary and predictable. For this reason, this research tries to forecast the total sales quantity for all the kiosks as well as the sales quantity of S5 and S7 in the next 4 years. Then the sales quantity of TS6 is calculated by the formula below:

$$\text{TS6} \ = \ \text{Total kiosk} \ - S7 - S5 \tag{3.1}$$

S5 is planned to be forecasted by its own historical sales data. Because the S5 is already being introduced to the market for 5 years, the historical sales data is very sufficient and the S5 is expected to be phased out in 2024 during the discussion in the interview.
Due to S7 is a new product and do not have historical sales data, the qualitative forecast methods are the first to be used to build the forecast scenario for S7. During the interview, information related to design innovation was got. There is a big update from S2 to S3 which leads to the sales for S3 being quite good and the lifetime for S3 is also longer compared with other generations. However, both S3 to S4 and S4 to S5 are only small updates. Another big update comes from S5 to TS6, for this reason, the lifetime for TS6 is expected to be longer as well as the sales quantity is expected to be higher compared with other generations. TS6 to S7 will be only a small update. In conclusion, referring to the analogy forecast, the sales condition for S7 is expected to be very similar to S4 and S5. For this reason, this research tries to forecast the sales quantity of S7 based on the historical sales data for S4 and S5. The detailed method is shown below in figure 3.1.

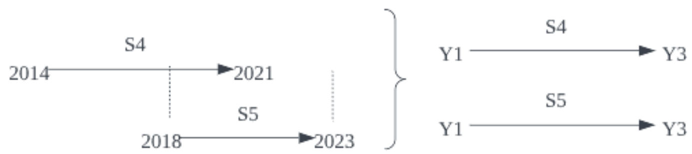

Figure 3.1: Prediction for sales quantity of S7

It is expected that the S7 will not be introduced into the market in 2023, so only 3 years of sales data for the S7 need to be forecasted. Firstly, the historical sales data for S4 and S5 will be taken out from the whole time series. Then, they will be matched from the first data to the last data and added up to each other to create the time series data for S7. Finally, referring to the scenario forecasting method, different forecast scenarios for the phase in time of S7 are created. All the scenarios are as follows: S7 phased Q1 2024, Q3 2024, Q1 2025, Q3 2025, Q1 2026, and Q3 2026.

3.2 Construction of ARIMA prediction model

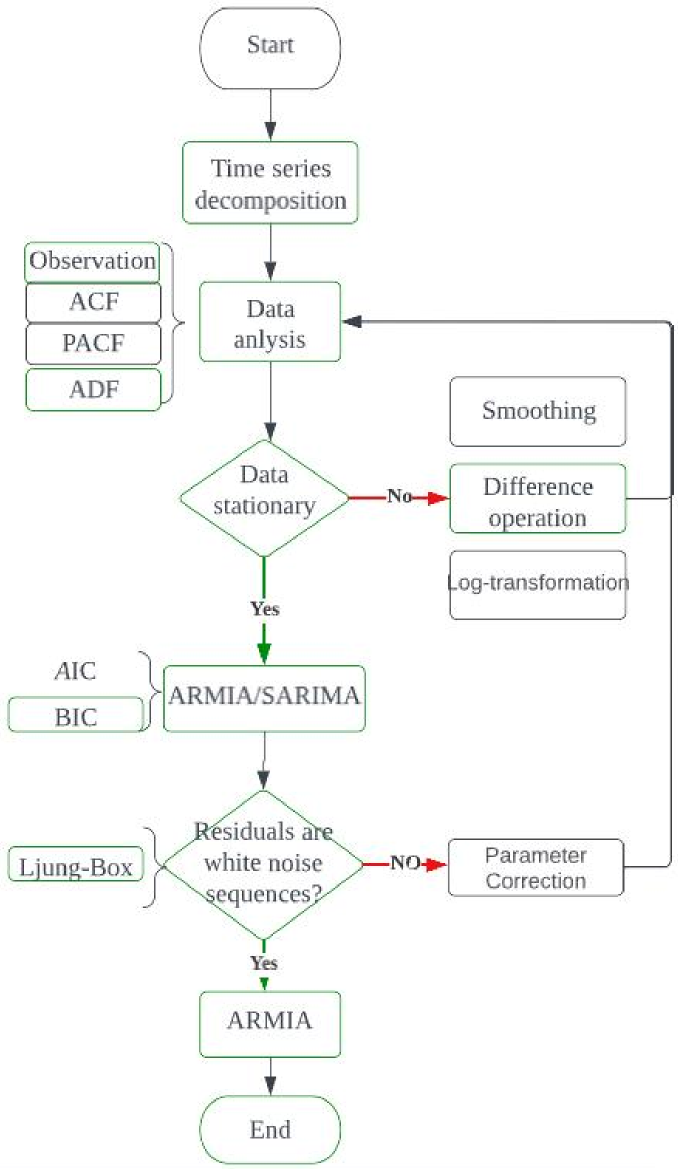

Figure 3.2: ARIMA model building

After getting all the time series data for S5, S7 and total kiosks, the first thing to do is to use the time series decomposition to check whether there is seasonality exists in the time series. If yes, the SARIMA model will be used instead of ARIMA in the statistical forecasting part. Secondly, the Observation, ACF test, PACF test as well as ADF test will be conducted to check whether the time series data is stationary. If the time series data is not stationary, the differencing will be chosen to do a data transfer. Then, repeat the stationary check until the time series data be stationary. If the time series data is stationary, then put them into the ARIMA model or SARIMA model and use BIC information criteria to help find the order of the parameters. The next step is to run the model and use the Ljung-Box test to test whether this model is statistically significant, if not, the next step is to find out a way to do the parameter correction. Sometimes, the outcome will still be accepted although the model fails in the Ljung-Box test. Finally, the result of the model will be exported and kept in excel. The detailed steps for using the ARIMA/SARIMA model can be found in figure 3.2

3.3 Research structure

In a conclusion, this research tries to combine the quantitative forecast methods which are the ARIMA/SARIMA model with qualitative methods which are the analogy forecast, scenario forecasting and judgmental adjustments. The research structure of this project can be found in figure 3.3. In order to get the time series data of S7, the analogy forecast method and scenario will be used. After getting all the 3 time series data for S5, total kiosk and S7, they will be put into the ARIMA or SARIMA model for making a statistical forecast. All the outcomes of the model will be discussed with the expert of SITA to do the judgemental adjustment. In order to avoid bias, only big changes are allowed to be made and the adjustment will be kept for further check. The sales quantity of TS6 will be calculated by the total sales quantity minus the sales quantity of S5 and S7. After getting the sales quantity of TS6 in the 6 different scenarios, the outcome will be discussed and only 2 scenarios will be chosen for making plans for future applications.

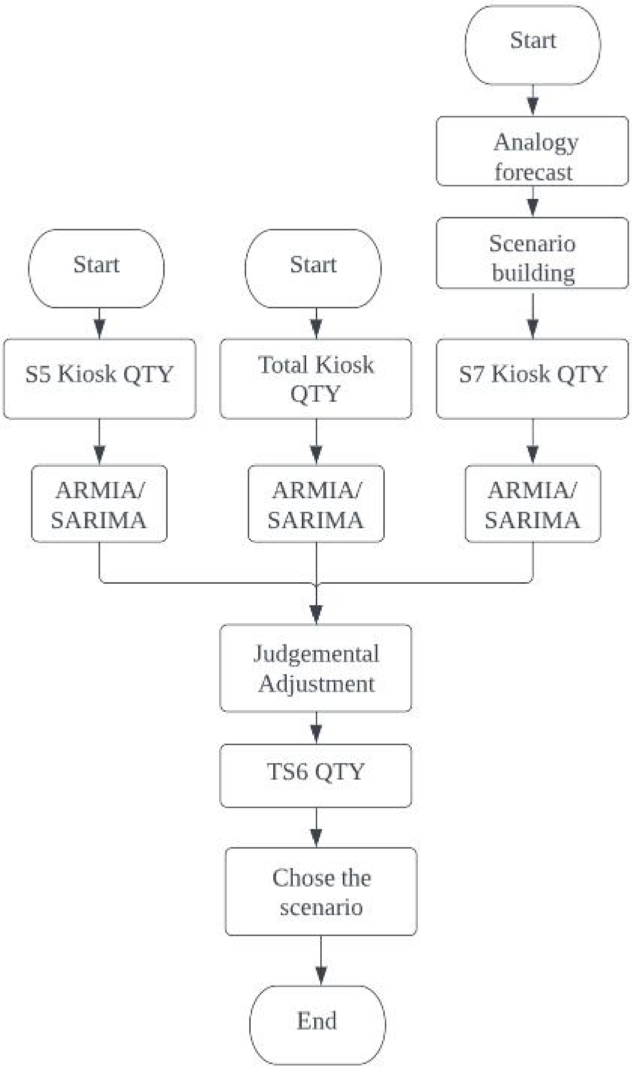

Figure 3.3: Research structure

3.4 Experiment

This section going to elaborate on the detailed steps to do the statistical forecast for the sales number of S5, S7, and total kiosks using the methods discussed before. Firstly, the time series decomposition with the multiplicative model is used to determine where the ARIMA or SARIMA model should be used for further experiments. Secondly, the stationary of the time series is determined before putting it into the forecast model by using the observation, differencing, and ADF tests. Thirdly, the SARIMA/ARIMA model is constructed and the Ljung-Box test is used to test the validity of the model. Finally, the in-sample and out-sample test results came out.

3.4.1 Prediction for the total sales quantity

Time series decomposition

According to the theory discussed in section 2.2, the time series decomposition is used first to find out whether there is seasonality, trend or cycle exists in the time series. After using the multiplicative model, the outcome can be found below in figure 3.4 which is a combination of 4 plots. The first plot shows the total quantity varies with time. The second plot shows the trend or cycle in the time series, in which the number of sales has a slight increasing trend in the last 10 years. The third plot shows seasonality, which means there are certain patterns repeated occurrence in the past and the SARIMA model instead of the ARIMA model should be chosen in the forecast. If there is no seasonality exist in the time series, this plot will show only the strength line. The last figure shows the distribution of the residual.

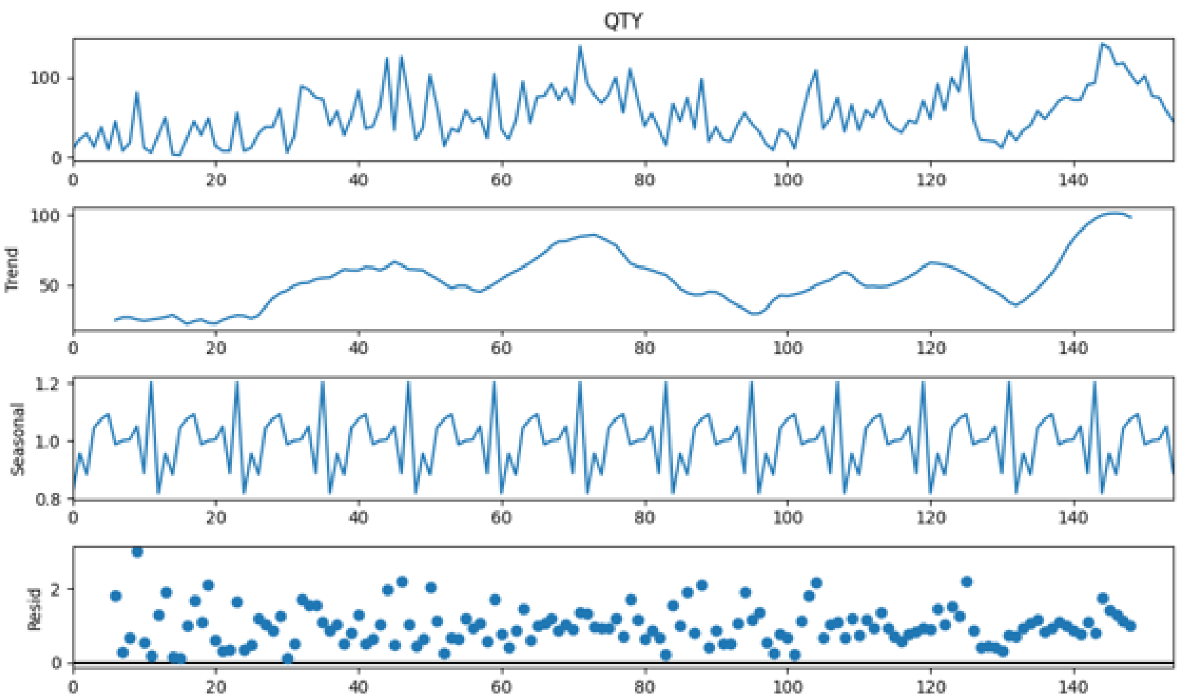

Figure 3.4: Time series decomposition with multiplicative model-Total Kiosk

Stationarity

As introduced in section 2.2, the observation method and ADF test are used in the research to determine whether the time series is stationary. If the time series is not stationary, the differencing will be applied to the time series. Two principles are used here for the differencing: (1) Higher-order differencing will not be used when the time series can be made stationary by using lower-order differencing. (2) In order to protect the integrity of the data, more than second-order differencing will not be applied to the time series.

Observation and differencing

According to figure 3.5, which is a combination of 3 plots. The first plot shows the number of sales for total kiosks varied with time in the past years. The second and third plot shows the time series data after applying the first-order differencing and second-order differencing. All three plots do not show a clear upward or downward trend, but fluctuate roughly up and down around a fixed value, for this reason, all three-time series can be assumed to be stationary through observation.

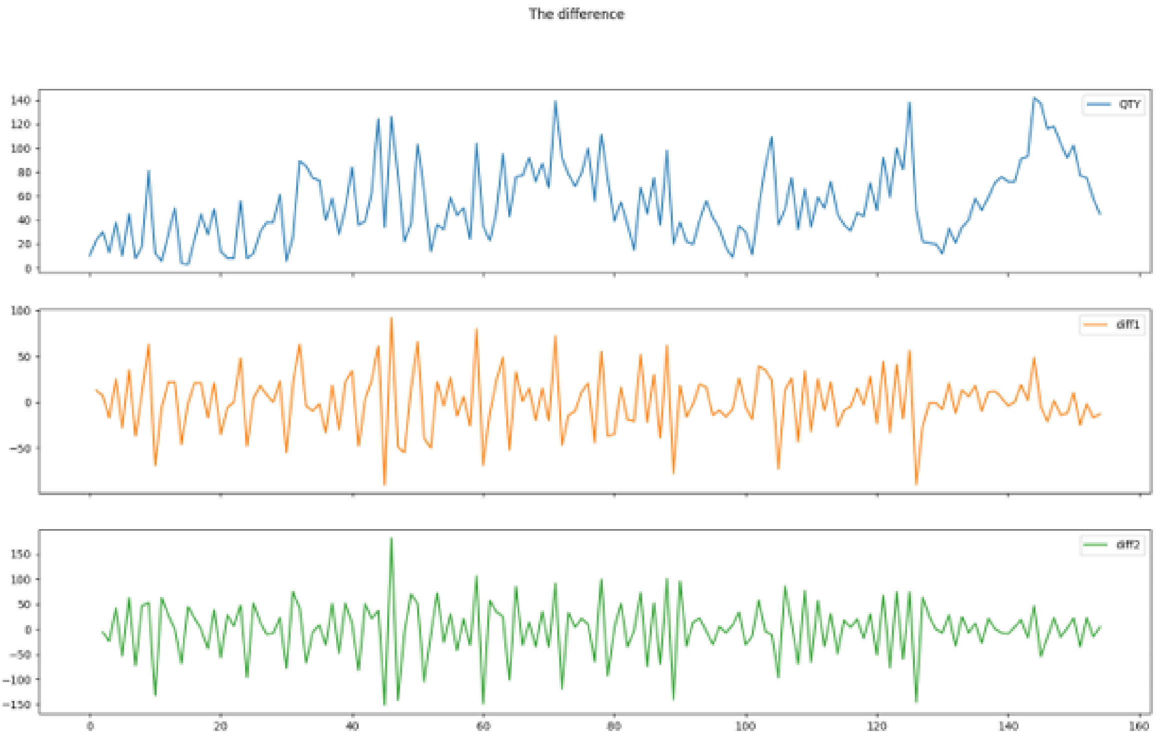

Figure 3.5: Stationary test-Total kiosk

ADF test

After using the observation method, the second method is to use the ADF test which is more accurate. The test result of the original sales of the total kiosk and the original sales after applying the first order differencing can be found below in figure 3.5 and 3.6. The first four numbers are the Test statistic which is the hypothesis test value, p-value which is the result of the hypothesis test, used lag which is the lag in the time series data, used numbers which is the number of observations used in the ADF regression and in the calculation of the critical values.

In the result of the ADF test for the original sales number for the total kiosk, the t-value which equals -3.54 is smaller than -3.47, -2.88 and -2.58,and the P value of 0.006 is less than the significance level of 0.05. This means that unit root test results reject the original hypothesis that the series is non-stationary, and the time series data for the original total kiosk is 99% accept to be stationary.

```
ADF test:

(-3.549661384113361, 0.006799612092609476, 4, 153, {'1%': -3.473829775724492, '5%': -2.880622899711496, '10%': -2.5769448985432954}, 1357.3637942721398)
```

Figure 3.6: ADF test result-Total orginal kiosk

In the result of the ADF test for the original sales number for the total kiosk after applying the first order differencing, the t-value which equals -7.55 is smaller than -3.47, -2.88 and -2.58, nd the P value of 0.000... is less than the significance level of 0.05. This means that unit root test results reject the original hypothesis that the series is non-stationary, and the time series data for the original total kiosk after first order dfferencing is also 99% accept to be stationary.

```
ADF test:

(-7.554023928955587, 3.133961408019786e-11, 4, 152, {'1%': -3.474120870218417, '5%': -2.880749791423677, '10%': -2.5770126333102494}, 1357.0424834959972)
```

Figure 3.7: ADF test result-Total kiosk for one level differencing

Combining the observation method with the unit root test we are able to conclude that both the original data and the first order difference data are stationary and can be used in the SARIMA model

SARIMA construction

Because the original sales data for the total kiosk is already stationary, it is used first in the SARIMA model. If the outcome of the SARIMA model using the original data is not good enough, then the first-order differencing time series data will be chosen.

Python has the model auto-order function auto.arima, and this research uses the auto command that comes with Python to calculate AR (autoregressive term in the model) with 0-5 order lags and MA (moving average term in the model) with 0-5 order lags. As discussed in section 2.2, the BIC is chosen to be used to find the best parameter of the model. With the auto. arima, all the combined BIC information of the SARIMA model and the optimal parameters of the model are given, and the auto.arima will stop the calculation if it finds the best parameter, as shown in figure 3.8. From the figure, it can be seen that the model with the minimum BIC information is ARIMA (1,0,1)(0,0,0)[12].

```
ARIMA(2,0,1)(0,0,1)[12] intercept   : BIC=1524.150, Time=0.33 sec
ARIMA(0,0,0)(0,0,0)[12] intercept   : BIC=1562.301, Time=0.01 sec
ARIMA(1,0,0)(1,0,0)[12] intercept   : BIC=1529.001, Time=0.20 sec
ARIMA(0,0,1)(0,0,1)[12] intercept   : BIC=1545.002, Time=0.10 sec
ARIMA(0,0,0)(0,0,0)[12]             : BIC=1757.881, Time=0.01 sec
ARIMA(2,0,1)(0,0,0)[12] intercept   : BIC=1519.955, Time=0.13 sec
ARIMA(2,0,1)(1,0,0)[12] intercept   : BIC=1524.271, Time=0.42 sec
ARIMA(2,0,1)(1,0,1)[12] intercept   : BIC=1534.974, Time=0.36 sec
ARIMA(1,0,1)(0,0,0)[12] intercept   : BIC=1514.984, Time=0.10 sec
ARIMA(1,0,1)(1,0,0)[12] intercept   : BIC=1519.333, Time=0.30 sec
ARIMA(1,0,1)(0,0,1)[12] intercept   : BIC=1519.215, Time=0.23 sec
ARIMA(1,0,1)(1,0,1)[12] intercept   : BIC=inf, Time=0.46 sec
ARIMA(0,0,1)(0,0,0)[12] intercept   : BIC=1541.664, Time=0.05 sec
ARIMA(1,0,0)(0,0,0)[12] intercept   : BIC=1525.587, Time=0.04 sec
ARIMA(1,0,2)(0,0,0)[12] intercept   : BIC=1519.937, Time=0.13 sec
ARIMA(0,0,2)(0,0,0)[12] intercept   : BIC=1534.602, Time=0.11 sec
ARIMA(2,0,0)(0,0,0)[12] intercept   : BIC=1519.903, Time=0.10 sec
ARIMA(2,0,2)(0,0,0)[12] intercept   : BIC=1522.704, Time=0.16 sec
ARIMA(1,0,1)(0,0,0)[12]             : BIC=1517.702, Time=0.04 sec

Best model:  ARIMA(1,0,1)(0,0,0)[12] intercept
```

Figure 3.8: BIC for total kiosk

The outcome of the model can be found in figure 3.9, After determining the parameter composition of the SARIMA model, in order to evaluate the actual fitting effect of the proposed model, the effectiveness of the model needs to be tested. As discussed in section 2.2, the Ljung-Box test is chosen to test whether the residuals of the model are white noise sequences. As shown in the figure 3.9, the Ljung-Box test for the SARIMA(1,0,1)(0,0,0)[12] model resulted in a p-value of 0.83 much greater than the significance level of 0.05, and the results of the test accepted the original hypothesis, proving that the residual series is white noise and the established SARIMA(1,0,1)(0,0,0)[12] model is significantly valid.

```
Best model:  ARIMA(1,0,1)(0,0,0)[12] intercept
Total fit time: 4.007 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  158
Model:               SARIMAX(1, 0, 1)   Log Likelihood                -747.367
Date:                Mon, 17 Oct 2022   AIC                           1502.734
Time:                        17:13:28   BIC                           1514.984
Sample:                             0   HQIC                          1507.709
                                - 158
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept      6.2142      3.570      1.741      0.082      -0.783      13.212
ar.L1          0.8798      0.066     13.339      0.000       0.750       1.009
ma.L1         -0.5632      0.106     -5.337      0.000      -0.770      -0.356
sigma2       749.4207     92.291      8.120      0.000     568.534     930.308
===================================================================================
Ljung-Box (L1) (Q):                   0.05   Jarque-Bera (JB):                 6.75
Prob(Q):                              0.83   Prob(JB):                         0.03
Heteroskedasticity (H):               0.85   Skew:                             0.50
Prob(H) (two-sided):                  0.57   Kurtosis:                         2.91
===================================================================================
```

Figure 3.9: Outcome of SARIMA(1,0,1)(0,0,0)[12]

Figure 3.10shows the comparison between the predicted data and the original data using the SARIMA(1,0,1)(0,0,0)[12]. However, although this model is statistically significant, this figure shows that the model is not good at predicting the peak of the number of sales. For this reason, the model building based on the first-level differencing is also considered in this research, and the outcome from these two models will be compared to find the best model for predicting the sales of the total kiosk.

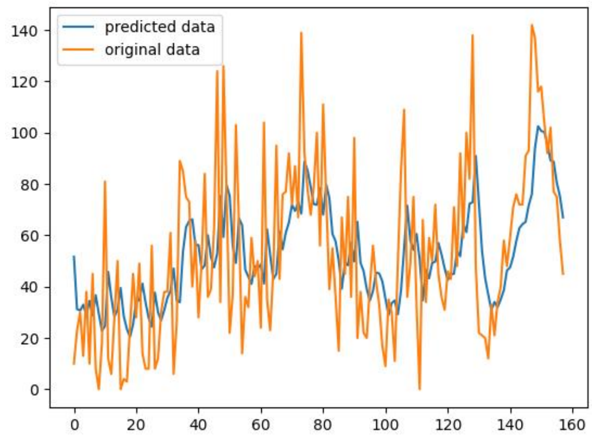

Figure 3.10: Prediction comparison for original total sales quantity

By using the auto.arima with the same steps to build the SARIMA model for the first-level differencing of the original time series data, the best model with the minimum BIC is SARIMA(0,1,1)(0,1,1)[12]. The forecast outcome can be found in figure 3.11. The Ljung-Box test for the SARIMA(0,1,1)(0,1,1)[12] model resulted in a p-value of 0.82 which is much greater than the significance level of 0.05, so the results of the test accepted the original hypothesis, proving that the residual series is white noise and the developed SARIMA(0,1,1)(0,1,1)[12] model is significantly valid.

```
Best model:  ARIMA(0,1,1)(0,1,1)[12]
Total fit time: 12.347 seconds
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                                  y   No. Observations:                  158
Model:             SARIMAX(0, 1, 1)x(0, 1, 1, 12)   Log Likelihood                -704.156
Date:                            Tue, 18 Oct 2022   AIC                           1414.313
Time:                                    02:47:53   BIC                           1423.243
Sample:                                         0   HQIC                          1417.941
                                            - 158
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.6494      0.063    -10.327      0.000      -0.773      -0.526
ma.S.L12      -0.8727      0.102     -8.561      0.000      -1.073      -0.673
sigma2       858.1087    109.475      7.838      0.000     643.542    1072.676
===================================================================================
Ljung-Box (L1) (Q):                   0.05   Jarque-Bera (JB):                 0.34
Prob(Q):                              0.82   Prob(JB):                         0.85
Heteroskedasticity (H):               0.91   Skew:                            -0.08
Prob(H) (two-sided):                  0.74   Kurtosis:                         2.83
===================================================================================
```

Figure 3.11: Outcome of SARIMA(0,1,1)(0,1,1)[12]

Figure 3.12shows the comparison between the predicted data and the original data using the SARIMA(0,1,1)(0,1,1)[12]. Compared with figure 3.10, the prediction made by SARIMA(0,1,1)(0,1,1)[12] model shows a better result, for this reason, the SARIMA(0,1,1)(0,1,1)[12] model is chosen to do a further prediction. The prediction for the further can be found in the figure 3.13

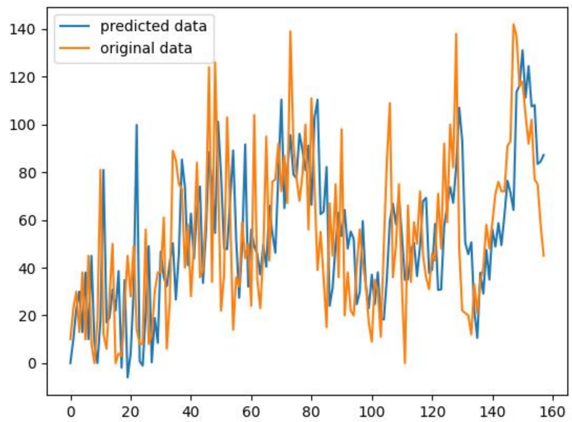

Figure 3.12: Prediction comparison for total sales quantity applying first-order differencing

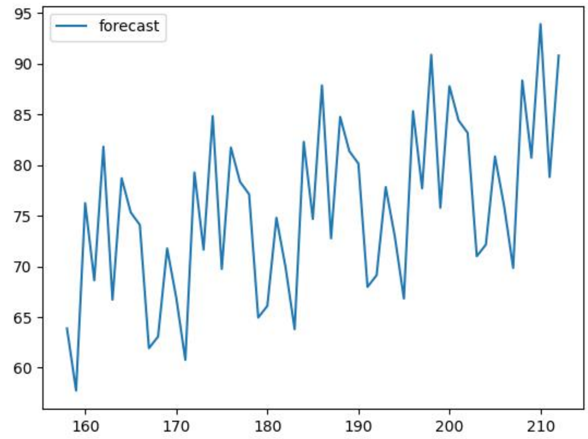

Figure 3.13: Prediction for future sales of total kiosk

3.4.2 Prediction for the sales quantity of S5

The same as the first step for the prediction of the number of sales for the total kiosk, the time series decomposition with multiplicative model is also used for time series data of S5 to find out whether there is seasonality or trend that exists in the time series. According to the second and third plots of figure 3.14, the number of sales of S5 has an increasing trend until Oct 2019, and a subsequent number of sales trended downward. Seasonality also exists in the time series data of S5, so the SARIMA model should also be used for prediction.

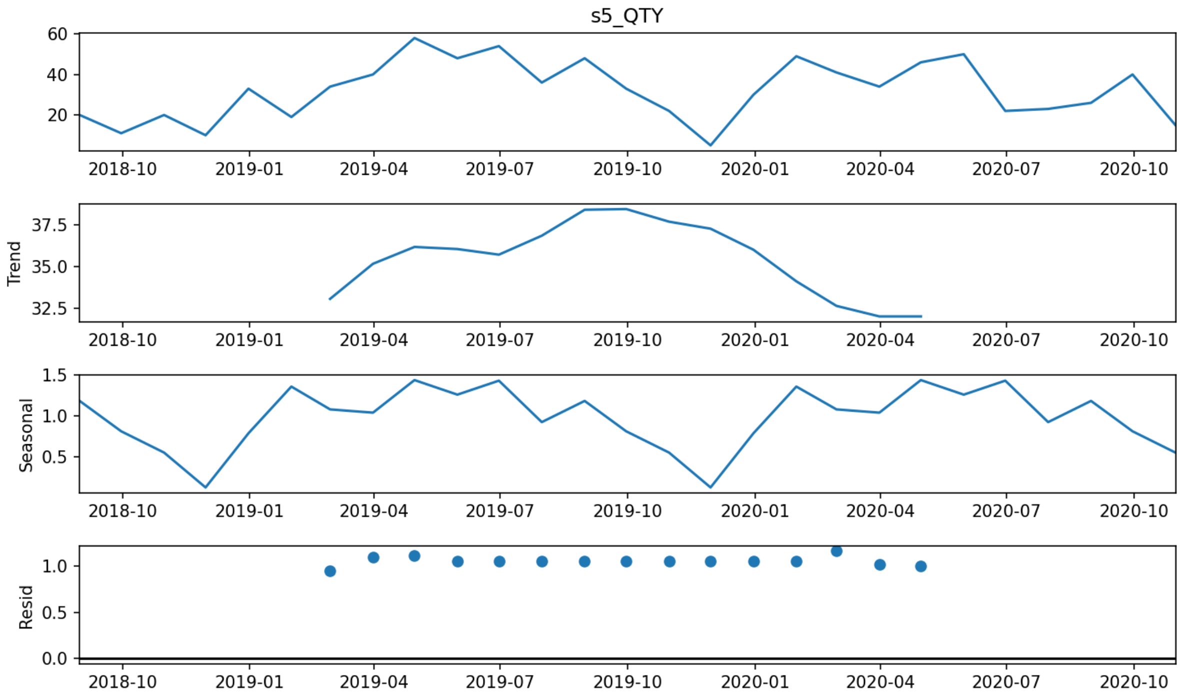

Figure 3.14: Time series decomposition with multiplicative model-S5

In order to determine whether the time series data of S5 is stationary or not, the first method used is observation. By observing the plot which can be found in figure 3.15 for the original sales quantity of S5 and the original sales quantity after the first and second differencing varies with time, it is obvious that all the 3 figures, especially the last two figures fluctuate up and down around '0" which means all the 3-time series data seems to be stationary through observation.

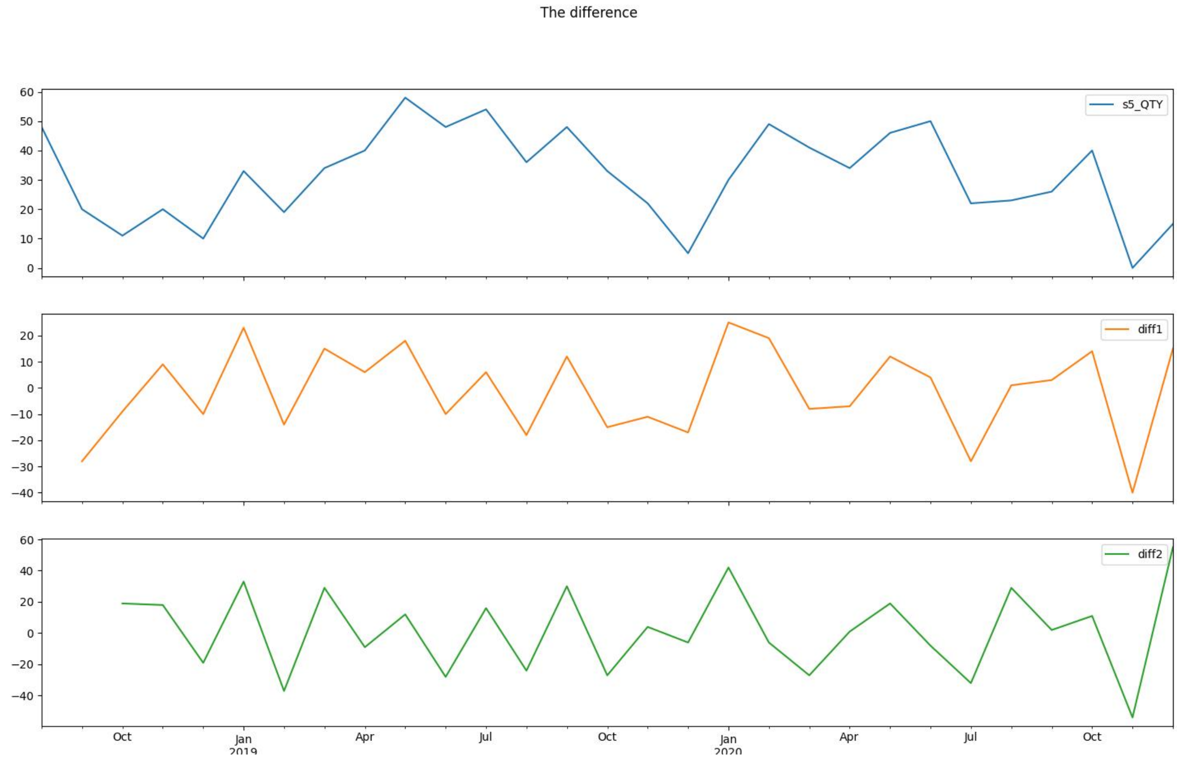

Figure 3.15: Stationary test-S5

The ADF test is also used for the time series of S5 and the result can be found in figure 3.15. In the result of the ADF test for the original sales number for the S5, the t-value which equals -3.58 is smaller than -2.99, -2.63 but larger than -3.737 and the P-value of 0.006 is less than the significance level of 0.05. This means that ADF test results reject the original hypothesis that the series is non-stationary, and the time series data for S5 is 95% accepted to be stationary.

```
ADF test:

(-3.583731176786426, 0.006079778935777238, 4, 24, {'1%': -3.7377092158564813, '5%': -2.9922162731481485, '10%': -2.635746736111111}, 150.2788296511418)
```

Figure 3.16: ADF test result-S5

The same as the forecast for the number of sales for the total kiosk, the SARIMA model for d equals 0 and 1 are both built for comparison. The information criteria AIC is used here as the data of the time series for S5 is much less than the data for the time series of the total kiosk, and AIC is more suitable to be applied in this situation because the model will not be too complicated. Because S5 is discussed to phase out the market in 2024, it is expected will have a decreasing trend in the number of sales, for this reason, only the data after Oct-2019 are considered to be used as they show a decreasing trend. After comparing using the first data from Oct-2019 to Feb-2022, the outcome of using Feb-2022 as the first data is more reasonable, so the SARIMA model is considered to use Feb-2022 as the start. After the comparison the outcome of SARIMA model (p,0,q) and (p,d,q), the SARIMA model(0,1,1)(0,1,0)[12] have a better result and is chosen for further prediction. The outcome can be found in figure 3.17. The Ljung-Box test for the SARIMA(0,1,1)(0,1,0)[12] model resulted in a p-value of 0.90 which is much greater than the significance level of 0.05, and the results of the test accepted that the residual series is white noise and the established SARIMA(1,0,1)(0,0,0)[12] model is statistically significant.

```
Best model:  ARIMA(0,1,1)(0,1,0)[12]
Total fit time: 3.112 seconds
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                                  y   No. Observations:                   29
Model:             SARIMAX(0, 1, 1)x(0, 1, [], 12)   Log Likelihood                 -69.354
Date:                             Tue, 18 Oct 2022   AIC                            142.707
Time:                                     04:08:13   BIC                            144.252
Sample:                                 08-31-2018   HQIC                           142.786
                                      - 12-31-2020
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.7722      0.211     -3.662      0.000      -1.185      -0.359
sigma2       322.0922    159.140      2.024      0.043      10.183     634.001
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):                 0.88
Prob(Q):                              0.90   Prob(JB):                         0.64
Heteroskedasticity (H):               0.78   Skew:                             0.41
Prob(H) (two-sided):                  0.79   Kurtosis:                         2.19
===================================================================================
```

Figure 3.17: Outcome of SARIMA(0,1,1)(0,1,0)[12]

The in-sample prediction comparison and out-sample prediction can be found in figure 3.18. The out-sample prediction shows the future sales of S5 will show a fluctuating downward trend and drop to 0 points for the first time at the end of 2021 and for the second time at the beginning of 2023.

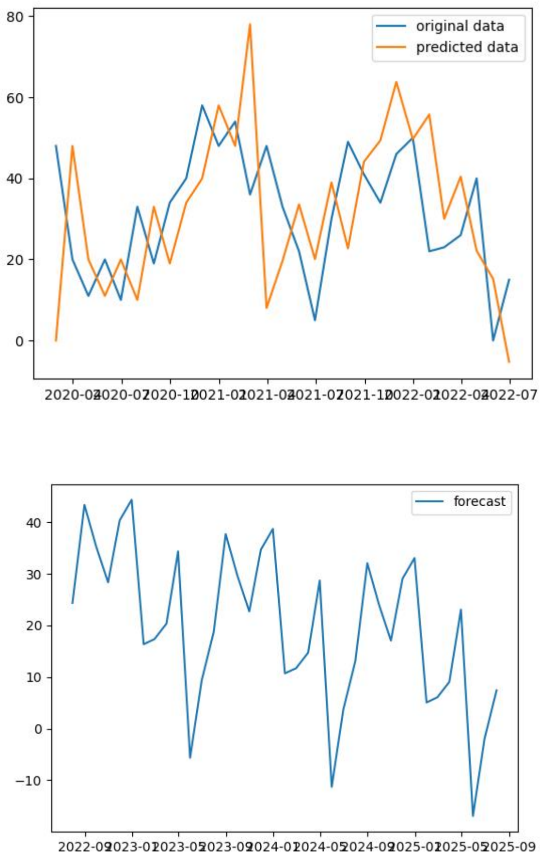

Figure 3.18: Prediction for S5 quantity applying first-order differencing

3.4.3 Prediction for the sales quantity of S7

The first step to forecast the sales quantity of S7 is to build the historical data as S7 is a new product and has not been introduced to the market. By using the method discussed in section 3.1, the historical sales data of S7 is developed based on the historical sales data of S4 and S5 and can be found in figure 3.19.

```
[ 1.  7. 24. 30. 22.  3. 20. 39. 25. 60. 40. 56. 40. 74. 50. 85. 64. 69.
 58. 37. 13. 32. 21. 22. 21. 36. 58. 43. 62. 37. 33. 34. 26. 23. 20. 26.
 41. 29. 20. 40. 40. 16. 34. 56. 66. 18. 32.]
```

Figure 3.19: Building the historical data for S7

The same as the steps before, the time series decomposition with the multiplicative model is also used for the time series data of S7. The result is shown in figure 3.20, which means there are both trend and seasonality exist in the time series, so the SARIMA model should be used instead of ARIMA for making predictions.

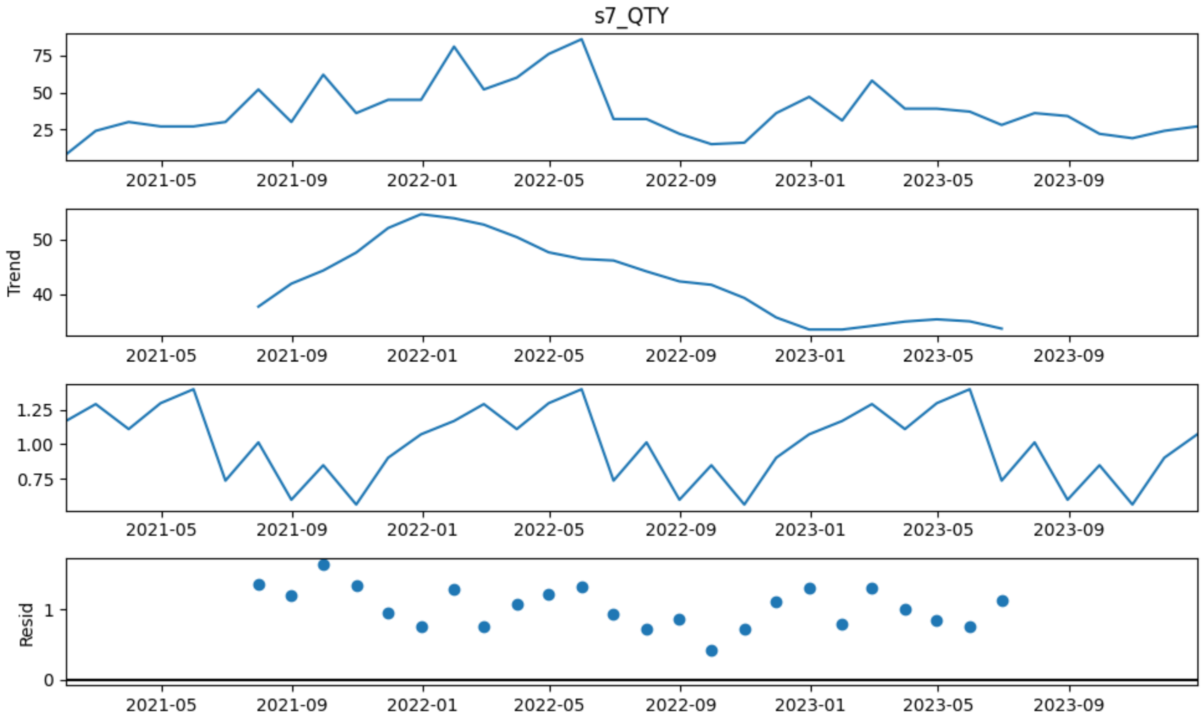

Figure 3.20: Time series decomposition with multiplicative model-S7

After that, both the observation method and the ADF test are used to find out whether the time series is stationary or not. The figure shows the original sales quantity of S7 and the original sales quantity after the first and second differencing varies with time can be found in figure 3.21. From this figure, it is clear that the original sales quantity after differencing almost fluctuated up and down around “0”, which means the time series data after differencing looks stationary.

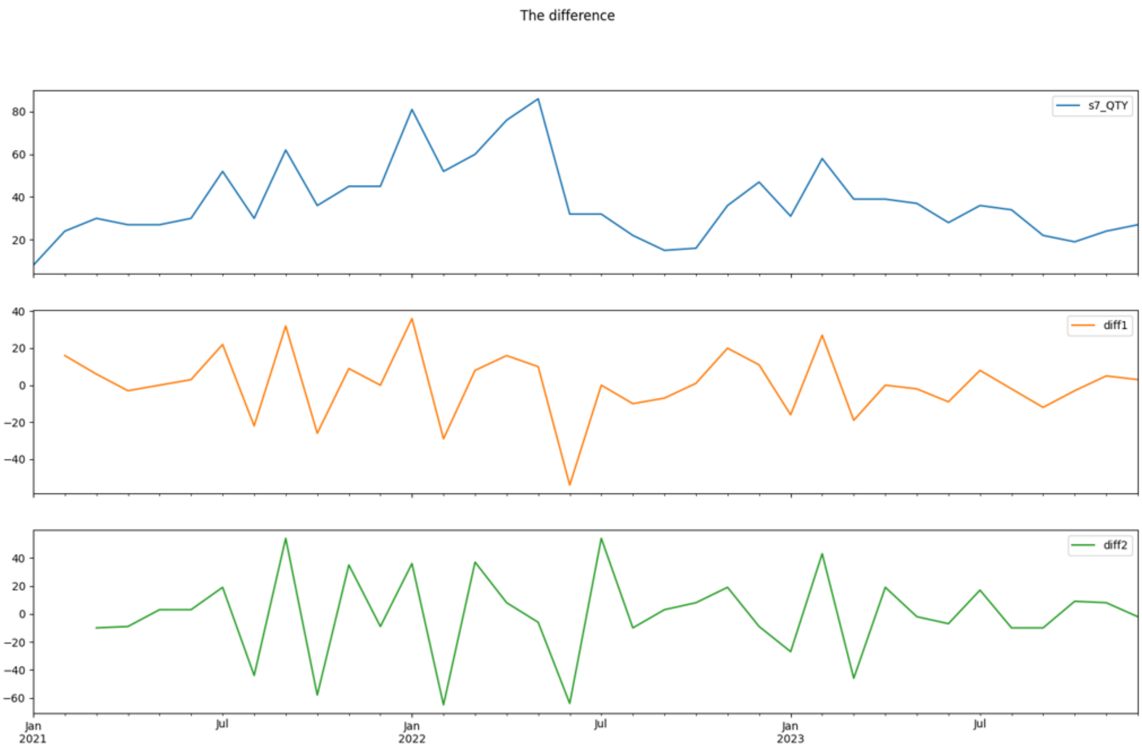

Figure 3.21: Stationary test-S7

The result of the ADF test can also be found in the figure 3.22. In the results of the ADF test for the original sales number of theS7, the t-value which equals -2.66 is larger than -3.59, -2.93 but a litter bit smaller than -2.60 and the P-value of 0.08 is larger than the significance level of 0.05. This means that ADF test results accept the original hypothesis that the series is non-stationary. The results of the ADF test for the original sales number of the S7 after the first-level differencing show that, the t-value which equals -10.24 is smaller than -3.59, -2.93 and -2.60 and the P-value of 0.000… is smaller than the significance level of 0.05. This means that ADF test results reject the original hypothesis that the series is non-stationary, and the time series data for S5 is 99% accepted to be stationary.

```
ADF test-original:

(-2.6661402397085285, 0.08008297698782219, 4, 42, {'1%': -3.596635636000432, '5%': -2.933297331821618, '10%': -2.6049909750566895}, 303.8345630935485)
ADF test-first-level differencing:

(-10.249320595743747, 4.52931411269368le-18, 0, 45, {'1%': -3.584828853223594, '5%': -2.9282991495198907, '10%': -2.602343827160493 7}, 301.38827430013845)
```

Figure 3.22: ADF test result-S7

The SARIMA(p,1,q)(P,1,Q)[12] model is built based on the minimum of BIC, and the result can be found in the figure 3.23. The Ljung-Box test for the SARIMA(1,1,0)(0,1,1)[12] model resulted in a p-value of 0.92 which is much greater than the significance level of 0.05, and the results of the test accepted that the residual series is white noise and the established SARIMA(1,1,0)(0,1,1)[12] model is statistically significant.

```
Best model:  ARIMA(1,1,0)(0,1,1)[12]
Total fit time: 7.020 seconds
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                                 y   No. Observations:                   47
Model:             SARIMAX(1, 1, 0)x(0, 1, [1], 12)   Log Likelihood                -152.672
Date:                           Tue, 18 Oct 2022   AIC                            311.344
Time:                                   09:33:55   BIC                            315.923
Sample:                               01-31-2021   HQIC                           312.906
                                    - 11-30-2024
Covariance Type:                             opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.4643      0.193     -2.410      0.016      -0.842      -0.087
ma.S.L12      -0.5228      0.358     -1.460      0.144      -1.225       0.179
sigma2       414.0900    108.025      3.833      0.000     202.366     625.814
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):                 0.70
Prob(Q):                              0.92   Prob(JB):                         0.71
Heteroskedasticity (H):               1.39   Skew:                            -0.30
Prob(H) (two-sided):                  0.60   Kurtosis:                         2.62
===================================================================================
```

Figure 3.23: Outcome of SARIMA(1,1,0)(0,1,1)[12]

Both the in-sample prediction comparison and out-sample prediction can be found in figure 3.24. The out sample prediction shows that the sales of S7 in the future will have a fluctuating upward trend.

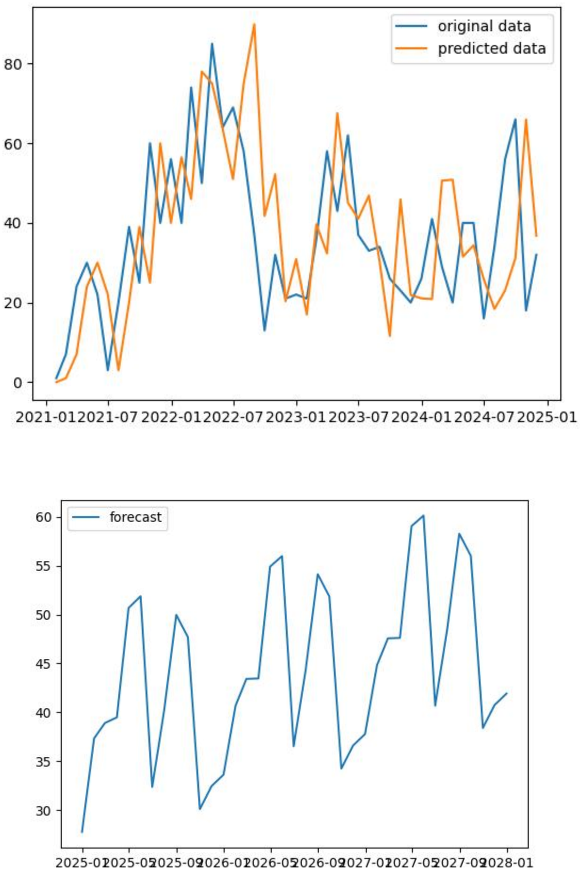

Figure 3.24: Prediction for S7 quantity applying first-order differencing

4 Research Result

After the forecast result from the experiment is available, in order to make the forecast result become more accuracy, some adjustments need to be made before putting the result into the application. The process of making adjustments together with the final outcome after the adjustment is elaborated on in this chapter. And then the outcome after adjustment is put into applications. By doing the demand forecasting, it is possible to shorten the procurement lead time by 4 weeks and save about 1%-5% total cost.

4.1 Residual analysis

4.1.1 Residual correction

Although all the SARIMA models have passed the Ljung-Box test, as shown in figure 3.12, 3.18 and 3.24, all the prediction data shows a little bit of lag compared with the original data. In order to make the forecast outcome more accurate, the lags in the result of all the time series outcomes of sales quantity for total kiosk, S5 and S7 should be correct before getting the final result. In this project, the MAE(Mean Absolute Error), which was commonly used to evaluate model errors in time series prediction[20], is chosen to test the residuals.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|(y'_t - y_t)| \tag{4.1}$$

Equation 5.1 aims to calculate the sum of the average difference between the prediction series and the forecast series and compare the outcome by changing the lags of the prediction series to -1, -2, and -3. And the result of this test for all time series data of total kiosk, S5, and S7 can be found in figure 4.1. The result shows that for all the time series data(Total kiosk, S5 and S7), the prediction result with lag -1 has the lowest residual, so it is best to adjust the prediction series with lag -1. For total kiosks, S5 and S7, the monthly difference is around 17 pc, 8pc, and 9 pc respectively. Besides this, the residuals for time series data of S5 is slightly lower than that of S7 and total kiosk and the sample size for making predictions for S5, S7 and total kiosk are 29, 47 and 158, which may indicate simpler models tend to produce more accurate predictions.

	Original	lag -1	lag -2	lag -3
Total Kiosk	25.32	17.07	20.32	21.09
S5	17.18	8.43	16.83	15.91
S7	16.60	9.02	13.85	16.50

Figure 4.1: Residual adjustment/unit

4.1.2 Residual comparison for monthly, quarterly and yearly data before prediction

Because the sample size for the total kiosk is 158, in order to get the quarterly and yearly data, the earliest two data in the sample set were removed by considering the data which is closer to the present will be more important. According to the principle of adding up every three data and every 12 data in sequence, the resulting monthly data consisted of 52 sample data and the annual data consisted of 13 sample data. Figure 4.2 shows the test outcome using equation 5.1 for the original monthly, quarterly and yearly data. Due to yearly data having too less samples, the model prediction for year residual lag-1 seems to be wired and has less too much information. However, the residual outcome for monthly data plus 3 is larger than the quarterly residual and the quarterly residual plus 4 is larger than the yearly residual indicates for one prediction model, the prediction accuracy tends to increase when forecast granularity decrease.

Original Total Kiosk	Original	lag -1	lag -2	lag -3
Monthly	25.32	17.07	20.32	21.09
Quarterly	57.20	23.63	58.74	69.66
Yearly	173.15	0.00	134.36	201.40

Figure 4.2: Residual for monthly, quarterly, and yearly time series data of total kiosk/unit

The same as making quarterly and yearly time series data for the total kiosk, by removing the first 2 data in S5 and keeping all the sample data for S7, the quarterly and yearly data for S5 and S7 are obtained, and the sample size is 9 and 2.25 for quarterly and yearly data of S5 and 19 and 4.75 for quarterly and yearly data of S7. The test result is shown in figure 4.3. Because the yearly sample size is too small, and already less than the parameters in the SARIMA model, so SARIMA model automatically stops to do the prediction and can't get the forecast residuals. The same as the test result of time series data for the total kiosk, the residuals for the monthly data plus 3 are larger than that for quarterly data. However, in the test outcome of S7, the monthly residual lag-1 plus 3 is smaller than that of the quarterly residual but larger than that of the yearly residuals. By doing this analysis, the conclusion can already be got that using yearly data to do the prediction tends to be more accurate compared with monthly and quarterly data if the sample size is large enough.

Original S5	Original	lag -1	lag -2	lag -3
Monthly	17.183	8.429	16.827	15.915
Quarterly	47.836	26.440	58.503	74.921
Yearly	nan	nan	nan	nan

Original S7	Original	lag -1	lag -2	lag -3
Monthly	16.60	9.02	13.85	16.50
Quarterly	47.80	32.93	52.54	62.67
Yearly	158.77	94.35	92.00	nan

Figure 4.3: Residual for monthly, quarterly, and yearly time series data of S5 and S7/unit

4.1.3 Residual comparison for monthly, quarterly and yearly data after prediction

By using the monthly predicted time series data of total kiosk, S5 and S7 as the base to create the quarterly and yearly time series, the residual test result using equation 5.1 after prediction is obtained and shown in figure 4.4. The same has the conclusion got in section 4.1.2, in most case, the forecast accuracy tends to increase when the forecast granularity decrease. However, the yearly residual comparison is also not accurate enough due to the small sample data. All the residual test outcome shows the same conclusion as section 4.1.1 too, the prediction data with lag-1 has the best forecast result. By comparing the figure 4.4 with 4.3 and 4.2, the residual test result for total kiosk, S5 and S7 at monthly, quarterly and yearly granularity after prediction is better in most cases, which means using the monthly prediction to make the quarterly and yearly data will be more accurate.

Total Kiosk Prediction	Original	lag -1	lag -2	lag -3
Monthly	25.32	17.07	20.32	21.09
Quarterly	45.52	28.77	53.17	64.10
Yearly	66.94	175.88	233.50	287.00

S5 Prediction	Original	lag -1	lag -2	lag -3
Monthly	17.183	8.429	16.827	15.915
Quarterly	21.157	34.376	64.411	54.148
Yearly	59.53	57.09	nan	nan

S7 Prediction	Original	lag -1	lag -2	lag -3
Monthly	16.60	9.02	13.85	16.50
Quarterly	30.10	24.74	48.74	56.21
Yearly	57.48	248.89	93.32	nan

Figure 4.4: Residual for monthly, quarterly, and yearly time series data after prediction/unit

4.2 Forecast outcome

As mentioned in section 4.1.1, the forecast time series data need to be moved back one month in order to make the forecast result to be more accurate. By using the predicted total sales quantity for all the kiosks minus the predicted sales quantity of S5 and the predicted sales quantity of S7, the forecast result for the sales quantity of TS6 is obtained and below are the monthly, quarterly and yearly forecast outcomes before doing judgemental adjustments for the year 2022 to the year 2026 for all 6 assumptions. Each assumption is calculated separately, and as discussed in section 4.1.3, the yearly forecast outcome has the highest accuracy which is shown in figure 4.7

	2022												2023												2024					
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
Total Kiosk	92	102	77	75	58	45	58	77	69	82	67	79	76	75	62	64	72	67	61	80	72	85	70	82	79	78	65	67	75	70
S5	22	23	26	40	0	15	44	36	29	41	45	17	18	21	35	0	10	19	38	30	23	35	39	11	12	15	29	0		
S6&S7	70	79	51	35	58	30	14	41	40	41	22	62	58	54	27	64	62	48	23	50	49	50	31	71	67	63	36	67	75	70
Assumption 1:																														
S7 H1 2024																									38	39	40	51	52	33
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	58	54	27	64	62	48	23	50	49	50	31	71	29	24	0	16	23	37
Assumption 2:																														
S7 H2 2024																														
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	58	54	27	64	62	48	23	50	49	50	31	71	67	63	36	67	75	70
Assumption 3:																														
S7 H1 2025																														
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	58	54	27	64	62	48	23	50	49	50	31	71	67	63	36	67	75	70
Assumption 4:																														
S7 H2 2025																														
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	58	54	27	64	62	48	23	50	49	50	31	71	67	63	36	67	75	70
Assumption 5:																														
S7 H1 2026																														
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	58	54	27	64	62	48	23	50	49	50	31	71	67	63	36	67	75	70
Assumption 6:																														
S7 H2 2026																														
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	58	54	27	64	62	48	23	50	49	50	31	71	67	63	36	67	75	70

	2024						2025												2026											
	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Total Kiosk	64	83	75	88	73	85	82	81	68	70	78	73	67	86	78	91	76	88	85	84	72	73	81	76	70	89	81	94	79	91
S5																														
S6&S7	64	83	75	88	73	85	82	81	68	70	78	73	67	86	78	91	76	88	85	84	72	73	81	76	70	89	81	94	79	91
Assumption 1:																														
S7 H1 2024	41	50	48	31	33	34	41	44	44	55	56	37	45	55	52	35	37	38	45	48	48	60	61	41	49	59	56	39	41	42
S6 outcome	23	33	27	57	40	51	41	37	24	15	22	36	22	31	26	56	39	50	40	36	24	13	20	35	21	30	25	55	38	49
Assumption 2:																														
S7 H2 2024	38	39	40	51	52	33	41	50	48	31	33	34	41	44	44	55	56	37	45	55	52	35	37	38	45	48	48	60	61	41
S6 outcome	26	44	35	37	21	52	41	31	20	39	45	39	26	42	34	36	20	51	40	29	20	38	44	38	25	41	33	34	18	50
Assumption 3:																														
S7 H1 2025							38	39	40	51	52	33	41	50	48	31	33	34	41	44	44	55	56	37	45	55	52	35	37	38
S6 outcome	64	83	75	88	73	85	44	42	28	19	26	40	26	36	30	60	43	54	44	40	28	18	25	39	25	34	29	59	42	53
Assumption 4:																														
S7 H2 2025													38	39	40	51	52	33	41	50	48	31	33	34	41	44	44	55	56	37
S6 outcome	64	83	75	88	73	85	82	81	68	70	78	73	29	47	38	40	24	55	44	34	24	42	48	42	29	45	37	39	23	54
Assumption 5:																														
S7 H1 2026																			38	39	40	51	52	33	41	50	48	31	33	34
S6 outcome	64	83	75	88	73	85	82	81	68	70	78	73	67	86	78	91	76	88	47	45	32	22	29	43	29	39	33	63	46	57
Assumption 6:																														
S7 H2 2026																									38	39	40	51	52	33
S6 outcome	64	83	75	88	73	85	82	81	68	70	78	73	67	86	78	91	76	88	85	84	72	73	81	76	32	50	41	43	27	58

Figure 4.5: The original monthly forecast result/unit

	2022				2023				2024				2025				2026			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Total Kiosk	271	178	204	228	213	203	213	237	222	212	222	246	231	221	231	255	241	230	240	264
S5	71	55	109	103	74	29	91	85	56	0	0	0	0	0	0	0	0	0	0	0
S6&S7	200	123	95	125	139	174	122	152	166	212	222	246	231	221	231	255	241	230	240	264
Assumption 1:																				
S7 H1 2024	0	0	0	0	0	0	0	0	117	136	139	98	129	148	152	110	141	162	164	122
S6 outcome	200	123	95	125	139	174	122	152	53	76	83	148	102	73	79	145	100	68	76	142
Assumption 2:																				
S7 H2 2024	0	0	0	0	0	0	0	0	0	0	117	136	139	98	129	148	152	110	141	162
S6 outcome	200	123	95	125	139	174	122	152	166	212	105	110	92	123	102	107	89	120	99	102
Assumption 3:																				
S7 H1 2025	0	0	0	0	0	0	0	0	0	0	0	0	117	136	139	98	129	148	152	110
S6 outcome	200	123	95	125	139	174	122	152	166	212	222	246	114	85	92	157	112	82	88	154
Assumption 4:																				
S7 H2 2025	0	0	0	0	0	0	0	0	0	0	0	0	0	0	117	136	139	98	129	148
S6 outcome	200	123	95	125	139	174	122	152	166	212	222	246	231	221	114	119	102	132	111	116
Assumption 5:																				
S7 H1 2026	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	117	136	139	98
S6 outcome	200	123	95	125	139	174	122	152	166	212	222	246	231	221	231	255	124	94	101	166
Assumption 6:																				
S7 H2 2026	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	117	136
S6 outcome	200	123	95	125	139	174	122	152	166	212	222	246	231	221	231	255	241	230	123	128

Figure 4.6: The original quarterly forecast before adjustment/unit

	2022	2023	2024	2025	2026
Total Kiosk	881	866	902	938	975
S5	338	279	56	0	0
S6&S7	543	587	846	938	975
Assumption 1:					
S7 H1 2024	0	0	490	539	589
S6 outcome	543	587	360	399	386
Assumption 2:					
S7 H2 2024	0	0	253	514	565
S6 outcome	543	587	593	424	410
Assumption 3:					
S7 H1 2025	0	0	0	490	539
S6 outcome	543	587	846	448	436
Assumption 4:					
S7 H2 2025	0	0	0	253	514
S6 outcome	543	587	846	685	461
Assumption 5:					
S7 H1 2026	0	0	0	0	490
S6 outcome	543	587	846	938	485
Assumption 6:					
S7 H2 2026	0	0	0	0	253
S6 outcome	543	587	846	938	722

Figure 4.7: The original yearly forecast before adjustment/unit

4.3 Judgemental adjustment

As discussed in the section 2.1.1, the original forecast result will be sent to the expert in SITA to do the judgemental adjustment. 3 proposals to do the adjustment have been proposed in the interview. 2 of them are accepted as important missing information in the model, and 1 is rejected due to not being consistent with past historical data.

Market condition is expected to be better

Due to the fact that some orders for 2023 have already been received at the end of the year 2022, the market condition is expected to be very good in the year 2023 and the following years and has a growth rate of 15% compared with 2022. This growth rate is expected to decline smoothly in the coming years, with a growth rate of 10% in 2024 and 5% in 2025. Due to the fact that the demand information about the surge in market demand is not included in the forecasting model, the model predicts a lower growth rate than the experts' forecasts, as well as taking into account the fact that statistical models are better able to grasp the patterns in the data. The growth rates for 2023, 2024 and 2025 are therefore adjusted to the expert's estimated growth rates but retain the monthly fluctuations predicted by the SARIMA model. The specific model growth rate calculation results and formulas are shown below.

$$\text{Model Adjusted Growth Rate } = \frac{\text{Model Prediction }_{y1} * \text{ Growth Rate }_{y1}}{\text{Model Prediction }_{y2}} \tag{4.2}$$

- **2022-2023** increase 15%–> Growth rate in the model be 1.169

- **2023-2024** increase 10%–>Growth rate in the model be 1.06

- **2024**-2025 increase 15%–>Growth rate in the model be 1.01

Missing market growth for S7 from 2018 to the year when phase in the market

The forecast result for S7 seems to be too small due to the total market demand for the kiosk is continuously increasing. However, the time series data of S4 which was used to make predictions for the sales quantity of S7 ended in 2018, but the prediction for S7 starts after 2024, which shows a lack of market growth from 2018 to 2024. Expert's opinion is to expect the sales of the S7 will reach 1000 pcs in the first year after phasing into the market, however, refer to figure 1.7, no generation of the kiosk has the experience to sales 1000 pcs in the first year. For this reason, this adjustment is not accepted in this research. However, the forecast result for S7 is indeed too low due to this reason, so the growth rate for the total kiosk from 2018 to the year when S7 is phased in is used to correct the missing market growth. The formula to calculate the growth rate is shown below, and the growth rate of S7 for 2024, 2025 and 2026 is 1.34,1.32 and 1.36 respectively. The application for the growth rate of S7 is not the same as that of the total kiosk. The Growth rate of the total kiosks for 2023,2024 and 2025 is applied to each year respectively, but the growth rate of S7 for 2024 is only applied to assumptions 1 and 2, the growth rate of S7 for 2025 is only applied to assumptions 3 and 4, and the growth rate of S7 for 2026 is only applied to assumptions 5 and 6.

$$\text{Growth Rate of S7 in } y_n = \frac{\text{Sum of Total Kiosk in } y_n}{\text{Sum of Total Kiosk in 2018}} \tag{4.3}$$

4.4 Final forecast outcome

In the conclusion, 3 adjustments are applied to the original forecast series in order to get the final outcome for all the assumptions.

- In order to solve the fact that the prediction time series sequence is always behind the original time series sequence, all the 3 time series sequences agreed to move back to lag -1 to increase the forecast accuracy.

- In order to solve the fact that the market condition for years 2023 to 2025, especially 2023 will be much better than the forecast condition, the annual growth rate for 2023, 2024 and 2025 are taken into the calculation to make adjustments for the final forecast outcome.

- In order to solve the fact that the market growth from 2018 to the year when S7 is introduced to the market is missing, the special market growth rate for each assumption is calculated and applied in the final adjustment.

The final forecast outcome in the monthly, quarterly and yearly levels for the total kiosk, S5 and S7 is shown in the figures below. By referring to the historical sales data of S3, which is in similar condition as TS6, both of them have a big change in the technique compared with the generation before. The S3 is introduced to the market in the year 2009 and reached the highest sales point in the year 2013 which is the fifth year after phasing in, and the S4 is introduced in the market in 2015 which is the seventh year after S3 appears in the market. As the technology iteration is getting faster and faster, the time interval for releasing new products afterwards is expected to be shorter and shorter. TS6 is introduced into the market in 2020 and assumes to reach the highest sales point in 2024 to 2025, the introduction of S7 is expected to be between 2025 to 2026, for this reason, assumptions 4 and 5 for the phase in data of S7 are more realistic compared with others.

	2022												2023												2024					
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
Total Kiosk	92	102	77	75	58	45	58	77	69	82	67	79	89	88	73	75	85	79	72	94	85	100	82	96	84	83	69	71	80	74
S5	22	23	26	40	0	15	44	36	29	41	45	17	18	21	35	0	10	19	38	30	23	35	39	11	12	15	29	0		
S6&S7	70	79	51	35	58	30	14	41	40	41	22	62	71	67	38	75	75	60	34	64	62	65	43	85	72	68	40	71	80	74
Assumption 1:																														
S7 H1 2024																									52	53	54	69	70	45
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	71	67	38	75	75	60	34	64	62	65	43	85	20	15	0	2	10	29
Assumption 2:																														
S7 H2 2024																														
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	71	67	38	75	75	60	34	64	62	65	43	85	72	68	40	71	80	74
Assumption 3:																														
S7 H1 2025																														
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	71	67	38	75	75	60	34	64	62	65	43	85	72	68	40	71	80	74
Assumption 4:																														
S7 H2 2025																														
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	71	67	38	75	75	60	34	64	62	65	43	85	72	68	40	71	80	74
Assumption 5:																														
S7 H1 2026																														
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	71	67	38	75	75	60	34	64	62	65	43	85	72	68	40	71	80	74
Assumption 6:																														
S7 H2 2026																														
S6 outcome	70	79	51	35	58	30	14	41	40	41	22	62	71	67	38	75	75	60	34	64	62	65	43	85	72	68	40	71	80	74

	2024						2025												2026											
	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Total Kiosk	68	88	80	93	78	90	83	82	69	71	79	74	68	87	79	92	77	89	85	84	72	73	81	76	70	89	81	94	79	91
S5																														
S6&S7	68	88	80	93	78	90	83	82	69	71	79	74	68	87	79	92	77	89	85	84	72	73	81	76	70	89	81	94	79	91
Assumption 1:																														
S7 H1 2024	56	68	65	42	45	46	56	60	60	74	76	50	61	74	70	48	50	52	61	65	65	81	82	56	66	80	76	53	56	57
S6 outcome	12	20	15	51	33	44	27	22	9	0	3	24	7	13	9	44	27	37	24	19	7	0	0	20	4	9	5	41	23	34
Assumption 2:																														
S7 H2 2024	52	53	54	69	70	45	56	68	65	42	45	46	56	60	60	74	76	50	61	74	70	48	50	52	61	65	65	81	82	56
S6 outcome	16	35	26	24	8	45	27	14	4	29	34	28	12	27	19	18	1	39	24	10	2	25	31	24	9	24	16	13	0	35
Assumption 3:																														
S7 H1 2025							51	52	54	68	69	44	55	67	64	42	44	46	55	59	59	73	75	50	60	73	69	47	50	51
S6 outcome	68	88	80	93	78	90	32	30	15	3	10	30	13	20	15	50	33	43	30	25	13	0	6	26	10	16	12	47	29	40
Assumption 4:																														
S7 H2 2025													51	52	54	68	69	44	55	67	64	42	44	46	55	59	59	73	75	50
S6 outcome	68	88	80	93	78	90	83	82	69	71	79	74	17	35	25	24	8	45	30	17	8	31	37	30	15	30	22	21	4	41
Assumption 5:																														
S7 H1 2026																			52	54	55	70	71	45	56	69	66	43	45	47
S6 outcome	68	88	80	93	78	90	83	82	69	71	79	74	68	87	79	92	77	89	33	30	17	3	10	31	14	20	15	51	34	44
Assumption 6:																														
S7 H2 2026																									52	54	55	70	71	45
S6 outcome	68	88	80	93	78	90	83	82	69	71	79	74	68	87	79	92	77	89	85	84	72	73	81	76	18	35	26	24	8	46

Figure 4.8: The monthly final forecast result /unit

	2022				2023				2024				2025				2026			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Total Kiosk	271	178	204	228	250	239	251	278	236	225	236	261	234	224	234	258	241	230	240	264
S5	71	55	109	103	74	29	91	85	56	0	0	0	0	0	0	0	0	0	0	0
S6&S7	200	123	95	125	176	210	160	193	180	225	236	261	234	224	234	258	241	230	240	264
Assumption 1:																				
S7 H1 2024	0	0	0	0	0	0	0	0	159	184	189	133	176	200	205	150	191	219	222	166
S6 outcome	200	123	95	125	176	210	160	193	35	41	47	128	58	27	29	108	50	20	18	98
Assumption 2:																				
S7 H2 2024	0	0	0	0	0	0	0	0	0	0	159	184	189	133	176	200	205	150	191	219
S6 outcome	200	123	95	125	176	210	160	193	180	225	77	77	45	91	58	58	36	80	49	48
Assumption 3:																				
S7 H1 2025	0	0	0	0	0	0	0	0	0	0	0	0	157	181	186	132	173	198	202	148
S6 outcome	200	123	95	125	176	210	160	193	180	225	236	261	77	43	48	126	68	32	38	116
Assumption 4:																				
S7 H2 2025	0	0	0	0	0	0	0	0	0	0	0	0	0	0	157	181	186	132	173	198
S6 outcome	200	123	95	125	176	210	160	193	180	225	236	261	234	224	77	77	55	98	67	66
Assumption 5:																				
S7 H1 2026	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	161	186	191	135
S6 outcome	200	123	95	125	176	210	160	193	180	225	236	261	234	224	234	258	80	44	49	129
Assumption 6:																				
S7 H2 2026	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	161	186
S6 outcome	200	123	95	125	176	210	160	193	180	225	236	261	234	224	234	258	241	230	79	78

Figure 4.9: The final quarterly forecast result/unit

Assumption 4:					
S7 H2 2025	0	0	0	338	689
S6 outcome	543	739	902	612	286

Assumption 5:					
S7 H1 2026	0	0	0	0	673
S6 outcome	543	739	902	950	302

Figure 4.10: The final yearly forecast result/unit

4.5 Future Application

As mentioned in section 1.1, the main aim of this project is to forecast the sales quantity for TS6 in the next 4 years so as to find a way to shorten the product lead time to meet the customer's satisfaction as well as try to get the price discount from the suppliers. The following going aims to elaborate on these two applications with the forecast result obtained in the section 4.4.

4.5.1 Shorten the product lead time

The visualization of product production plan

As discussed in the section1.1, normally the customers want to receive the products within 12 weeks after placing the order. However, as shown in figure 1.2, the overall time from procurement to final delivery needs about 10 to 16 weeks, and the procurement time takes up the most time which is about 6-8 weeks. In order to shorten the overall lead time to meet the customer's expectations, with the forecasting result, the procurement process can be started 6- 8 weeks in advance, so that the overall lead time can be shortened to 4-8 weeks. However, considering the inventory holding cost, the inventory holding time should also be kept as short as possible. For this reason, the best plan is to start the procurement process 4 weeks in advance. If considering the production and assembling process, the customs and shipment process, and the final delivery process will take 8 weeks in total, the monthly, quarterly, and yearly product production plan for TS6 and S7 is visualized and can be found in the figures below.

	2022	2023	2024	2025	2026
Assumption 1:					
S7 H1 2024	0	105	676	741	672
S6 outcome	532	636	265	216	143
Assumption 2:					
S7 H2 2024	0	0	467	709	630
S6 outcome	532	741	460	245	179
Assumption 3:					
S7 H1 2025	0	0	103	667	607
S6 outcome	532	741	824	287	199
Assumption 4:					
S7 H2 2025	0	0	0	460	567
S6 outcome	532	741	927	494	239
Assumption 5:					
S7 H1 2026	0	0	0	106	567
S6 outcome	532	741	927	848	239
Assumption 6:					
S7 H2 2026	0	0	0	0	347
S6 outcome	532	741	927	954	459

Figure 4.11: The product production plan yearly/unit

	2022				2023				2024				2025				2026			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Assumption 1:																				
S7 H1 2024	0	0	0	0	0	0	0	105	193	169	152	162	210	185	168	178	228	202	185	57
S6 outcome	144	85	103	200	188	158	170	120	12	61	99	93	12	44	80	80	7	33	69	34
Assumption 2:																				
S7 H2 2024	0	0	0	0	0	0	0	0	0	105	193	169	152	162	210	185	168	178	228	56
S6 outcome	144	85	103	200	188	158	170	225	191	125	58	86	67	67	38	73	58	57	29	35
Assumption 3:																				
S7 H1 2025	0	0	0	0	0	0	0	0	0	0	0	103	191	166	150	160	207	183	166	51
S6 outcome	144	85	103	200	188	158	170	225	191	230	251	152	28	63	98	98	19	52	88	40
Assumption 4:																				
S7 H2 2025	0	0	0	0	0	0	0	0	0	0	0	0	0	103	191	166	150	160	207	50
S6 outcome	144	85	103	200	188	158	170	225	191	230	251	255	219	126	57	92	76	75	47	41
Assumption 5:																				
S7 H1 2026	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	106	196	170	154	47
S6 outcome	144	85	103	200	188	158	170	225	191	230	251	255	219	229	248	152	30	65	100	44
Assumption 6:																				
S7 H2 2026	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	106	196	45
S6 outcome	144	85	103	200	188	158	170	225	191	230	251	255	219	229	248	258	226	129	58	46

Figure 4.12: The product production plan quarterly/unit

2022	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Assumption 1: S7 H1 2024												
S6 outcome	51	35	58	30	14	41	40	41	22	62	71	67
Assumption 2: S7 H2 2024												
S6 outcome	51	35	58	30	14	41	40	41	22	62	71	67
Assumption 3: S7 H1 2025												
S6 outcome	51	35	58	30	14	41	40	41	22	62	71	67
Assumption 4: S7 H2 2025												
S6 outcome	51	35	58	30	14	41	40	41	22	62	71	67
Assumption 5: S7 H1 2026												
S6 outcome	51	35	58	30	14	41	40	41	22	62	71	67
Assumption 6: S7 H2 2026												
S6 outcome	51	35	58	30	14	41	40	41	22	62	71	67

2023	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Assumption 1: S7 H1 2024											52	53
S6 outcome	38	75	75	60	34	64	62	65	43	85	20	15
Assumption 2: S7 H2 2024												
S6 outcome	38	75	75	60	34	64	62	65	43	85	72	68
Assumption 3: S7 H1 2025												
S6 outcome	38	75	75	60	34	64	62	65	43	85	72	68
Assumption 4: S7 H2 2025												
S6 outcome	38	75	75	60	34	64	62	65	43	85	72	68
Assumption 5: S7 H1 2026												
S6 outcome	38	75	75	60	34	64	62	65	43	85	72	68
Assumption 6: S7 H2 2026												
S6 outcome	38	75	75	60	34	64	62	65	43	85	72	68

2024	Jan	Feb	Mar	Apr	May	Jun
Assumption 1: S7 H1 2024	54	69	70	45	56	68
S6 outcome	0	2	10	29	12	20
Assumption 2: S7 H2 2024					52	53
S6 outcome	40	71	80	74	16	35
Assumption 3: S7 H1 2025						
S6 outcome	40	71	80	74	68	88
Assumption 4: S7 H2 2025						
S6 outcome	40	71	80	74	68	88
Assumption 5: S7 H1 2026						
S6 outcome	40	71	80	74	68	88
Assumption 6: S7 H2 2026						
S6 outcome	40	71	80	74	68	88

2024	Jul	Aug	Sep	Oct	Nov	Dec
Assumption 1: S7 H1 2024	65	42	45	46	56	60
S6 outcome	15	51	33	44	27	22
Assumption 2: S7 H2 2024	54	69	70	45	56	68
S6 outcome	26	24	8	45	27	14
Assumption 3: S7 H1 2025					51	52
S6 outcome	80	93	78	90	32	30
Assumption 4: S7 H2 2025						
S6 outcome	80	93	78	90	83	82
Assumption 5: S7 H1 2026						
S6 outcome	80	93	78	90	83	82
Assumption 6: S7 H2 2026						
S6 outcome	80	93	78	90	83	82

2025	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Assumption 1: S7 H1 2024	60	74	76	50	61	74	70	48	50	52	61	65
S6 outcome	9	0	3	24	7	13	9	44	27	37	24	19
Assumption 2: S7 H2 2024	65	42	45	46	56	60	60	74	76	50	61	74
S6 outcome	4	29	34	28	12	27	19	18	1	39	24	10
Assumption 3: S7 H1 2025	54	68	69	44	55	67	64	42	44	46	55	59
S6 outcome	15	3	10	30	13	20	15	50	33	43	30	25
Assumption 4: S7 H2 2025					51	52	54	68	69	44	55	67
S6 outcome	69	71	79	74	17	35	25	24	8	45	30	17
Assumption 5: S7 H1 2026											52	54
S6 outcome	69	71	79	74	68	87	79	92	77	89	33	30
Assumption 6: S7 H2 2026												
S6 outcome	69	71	79	74	68	87	79	92	77	89	85	84

2026	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Assumption 1: S7 H1 2024	65	81	82	56	66	80	76	53	56	57		
S6 outcome	7	0	0	20	4	9	5	41	23	34		
Assumption 2: S7 H2 2024	70	48	50	52	61	65	65	81	82	56		
S6 outcome	2	25	31	24	9	24	16	13	0	35		
Assumption 3: S7 H1 2025	59	73	75	50	60	73	69	47	50	51		
S6 outcome	13	0	6	26	10	16	12	47	29	40		
Assumption 4: S7 H2 2025	64	42	44	46	55	59	59	73	75	50		
S6 outcome	8	31	37	30	15	30	22	21	4	41		
Assumption 5: S7 H1 2026	55	70	71	45	56	69	66	43	45	47		
S6 outcome	17	3	10	31	14	20	15	51	34	44		
Assumption 6: S7 H2 2026					52	54	55	70	71	45		
S6 outcome	72	73	81	76	18	35	26	24	8	46		

Figure 4.13: The product production plan monthly/unit

Procurement plan

According to the figure1.2, if it is assumed that the time of each process is calculated according to the maximum time, the new timeline is shown in the figure 4.14.

Figure 4.14: The overall timeline

Raw material purchases need to be made 8 weeks prior to production. Together with the plan to increase the purchased quantity to 1000 pcs which is discussed in section 4.5.2. The purchase plan start from 2023 for TS6 and S7 for assumption 4 and 5 can be found below.

	2023												2024											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Assumption 4:																								
S7 H2 2025																								
S6 outcome	1000															1000								
Assumption 5:																								
S7 H1 2026																								
S6 outcome	1000															1000								

	2025												2026											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Assumption 4:																								
S7 H2 2025					1000																	1000		
S6 outcome						1000(599)																		
Assumption 5:																								
S7 H1 2026											1000													
S6 outcome						1000(245)																		

Figure 4.15: The overall procurement plan/unit

It is worth noting that the procurement values in the figure with yellow criteria are larger than the forecasted values, as the demand in 2027 is outside the forecasted interval. In assumption 4, 599 more pcs of raw materials are ordered, and 245 more pcs of raw materials in assumption 5. However, it is expected these over-ordered raw materials will be completely consumed in the future.

4.5.2 Obtained the purchasing discounts to save total cost

As discussed in section 1.1, SITA can get 10% more discount if they change their procurement plan from 100 pcs to 1000 pcs. Since the relationship between price discount and purchase volume is not linear, as shown in figure 1.3, the increase in the price discount obtained decreases significantly when the purchase volume exceeds 1000 pcs. According to the interview, the material stands for 50% to 60% of the total cost of the TS6 kiosk, and the annual inventory cost stands for 2% to 5% of the total cost. In addition to this, the raw materials have a very long shelf life, much longer than four weeks. According to the figure 4.15, the maximum time of raw materials in storage is 18 months, and the average time is 9 months. The following formula calculates the cost savings of increasing the purchase plan from 100 pcs to 1000 pcs. If SITA successfully gets the 20% discount on buying the raw materials, it will save 1.25.6% to 4.5% on the original price.

$$\text{Lower Bond: Price } * 50\% * 10\% - \text{ Price } * 5\% * \frac{9}{12} \approx 1.25\% \text{ Price} \tag{4.4}$$

$$\text{Upper Bond: Price } * 60\% * 10\% - \text{ Price } * 2\% * \frac{9}{12} \approx 4.5\% \text{ Price} \tag{4.5}$$

5 | Conclusion

Since 2010, kiosk's market has maintained a steady slow growth. With the increasing number of competitors in the market, it is necessary to continuously improve customer satisfaction and reduce costs in order to maintain or even increase SITA's market share and enable the company to continue to grow and develop. According to the research, the customers wanted to receive the products earlier, but the traditional make-to-order method of SITA did not meet the customers' expectations, so SITA wanted to use the make to stock method of production through demand forecasting. In addition, the supplier offered an additional 10% price discount if SITA could increase the number of units ordered from 100 to 1000. By forecasting demand in advance, SITA was able to determine whether it will be benefit to receive the additional price discount from the supplier.

Demand forecasting is necessary to improve customer satisfaction and to obtain price discounts. In this paper, a comprehensive forecasting method combining qualitative and quantitative forecasts is developed based on the iterative of different generation of product from a time series perspective. The main results achieved as well as the answers for the research questions are as the following. Through the answers to the five subquestions, the main research question which is how can SITA forecast Kiosk demand based on historical sales data can be answered.

(1)How to build the forecast scenarios by considering the existing external factors?By analyzing the historical sales data, the important factors affecting the sales of the target product TS6 kiosk were identified, i.e. the phase in time of the new product and the phase out time of the old product, and six forecast scenarios were created using the scenario forecasting method, considering all possibilities.

(2)Which qualitative and quantitative forecast method is suitable to do the forecast with the available data? Through the analysis of historical data, interviews of product characteristics, and literature reviews, both suitable qualitative and quantitative forecasting methods were found to be used for demand forecasting. The qualitative forecasting methods are: The analogy forecast, Scenario forecasting, and Judgemental adjustment. The quantitative forecasting method chosen to be used is the ARIMA model. All the methods are combined in the project to get the final forecast results.

(3)How to combine qualitative and quantitative forecast methods for data processing and sales forecasting? Based on the literature review and historical sales analysis, this project uses scenario forecast to create different forecasting scenarios. By using analogy forecast, the historical sales data of S4 and S5 are used to forecast the sales of S7. Based on the historical sales analysis, the total kiosk sales were chosen to be forecast and the forecast of the sales of TS6 is done by subtracting the sales of S5 and S7 from the sales of total kiosk. The ARIMA model was chosen to use to forecast the time series data, firstly, to understand the trend and seasonality of the historical sales data in more detail, the time series decomposition was used to decompose the time series. Based on the seasonality of the time series, the SARIMA model was selected for the subsequent forecasting. The differencing and ADF tests are used to determine whether the time series is stationary or not. The BIC information criteria is used to perform the order selection of the SARIMA model. The forecasting results of the SARIMA model were discussed with experts and the data were modified by referring to the judgmental adjustment method. Finally, the prediction results were obtained.

(4)How to consider and validate the forecast model and forecast numbers? To verify the accuracy of the prediction. First, for the SARIMA model, the Ljung-Box test is applied to test whether the residuals are white noise series. The final test result is that all model residuals are white noise series and SARIMA model is valid. Second, by observing the graphs and performing residual analysis using MAE, it was found that the prediction results lagged one period compared with the original data, and the annual prediction results were more accurate than the monthly and quarterly prediction results, which were in line with the experience. Among them, the quarterly and annual data obtained after using monthly data for forecasting are more accurate than the forecast results obtained from forecasting with original monthly and annual data.

(5) How to use the forecast outcome in the future and what's the benefit? The forecast results of this research can be used to improve customer satisfaction by reducing lead times and total cost savings by obtaining price discounts. The study provides a visualization of monthly, quarterly and annual production plan and a chart of the procurement plan in 1000 units. It was calculated that obtaining an additional 10% price discount from suppliers could reduce the price of TS6 products about 1.25% to 4.5%.

Due to the limited information available, this project has some limitations to be developed and added in the future.

(1)Abnormal values in the original data. In this research, only the very obvious abnormal values were processed when performing data cleaning before prediction. However, there are some data with abnormal values that cannot be traced due to the long time, so they just be kept in the forecast sample data. Suitable hypotheses for these abnormal values can be explored later to handle the abnormal values more rationally.

(2)Treatment of residuals. In order to reduce the prediction error, the ARIMA model can be combined with machine learning, neural network prediction and other methods to increase the accuracy of prediction, and develop the combined ARIMA-neural network algorithm.

(3)In this project, due to consider the influence of environmental factors on the prediction results will be small and the difficulty of to measure of explanatory variables, the time series statistical model was chosen for the study, but using a time series model may ignore the influence of political, economic, social and environmental factors on the prediction results. Therefore, subsequent studies can add explanatory variables to the ARIMA model and change the time data series into panel data to develop a dynamic forecast model, making the prediction become more comprehensive.

(4)To make the forecasting process easier, the forecasting model can be integrated with the company's order management system, making it possible for the forecasting model to automatically update forecasts based on monthly orders, as well as do the data validation and corrections.

This study has both scientific and practical contributions.

Scientific contribution: Demand forecasting is widely used in the FMCG industry, and for companies like SITA, due to the low demand for their products and high production costs. Usually, the production method is based on order-based production. This research explores the possibility of demand forecasting for the slow-moving consuming industry based on real historical sales data of SITA kiosks by using the forecasting method widely used in the FMCG industry.

Practical contribution: In this research, the forecasting scenario which is suitable for TS6 is developed by analyzing the historical sales data of the TS6 Kiosk, and selecting suitable qualitative forecasting methods which are the analogy forecast, Scenario forecasting, and Judgemental adjustment and quantitative forecasting methods: SARIMA/ ARIMA model through the method of literature review. The TS6 kiosk's sales volume up to 2026 was successfully calculated using a combination of qualitative and quantitative forecasting methods by first filtering, reviewing, and differencing the historical sales data before putting it into the statistical models.

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Kiosk Strategic Demand Forecasting with Scenario Planning: A case study at SITA

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***Abstract*—SITA is the world's leading specialist in air transport communications and information technology which works with around 400 air transport members and has 2800 customers in 190 countries. TS6 kiosk is the newest generation of its kiosk family and is facing a complicated situation now. Usually, the production of a kiosk is using make-to-order methods. However, if this method is adopted, the customers of SITA can not receive their productions within the expected periods of time. Besides this, SITA also can not get the procurement discount from the suppliers if they only purchase a low volume and do not make changes. In order to solve this problem, demand forecasting is conducted using the historical sales data of the TS6 kiosk. Through the literature review, suitable qualitative forecasting methods and quantitative forecasting methods which were mainly used in the FMCG industry are got together and combined to increase the forecast accuracy in this research to come out with the final forecast result of the TS6 kiosk. This research also explores the possibility of demand forecasting for the slow-moving consuming industry. By successfully conducting the final forecast, the result can help SITA to shorten procurement lead time so as to meet customers' expectations as well as save total costs.**

***Index Terms*—Demand Forecasting, Quantitative Forecasting Methods, Qualitative Forecasting Methods, ARIMA, SARIMA, Residual Analysis.**

I. Introduction

SITA is a world-leading company mainly providing service and IT support for airline operators and more than 400 airports. The main customers include airports, airlines, ground handlers, and airport groups. The Tailored Series 6 (TS6) kiosk which SITA produces is now made in the Burlington factory in Canada and all kiosks are made to order(MTO). However, SITA now wants to introduce the made-to-stock(MTs) methodology to its production. The first reason for this change in strategy is that improved manufacturing efficiency will have a chance to increase customer satisfaction, thus potentially increasing market share. Because normally the customers want to receive the kiosk in 3 months after placing the order, the lead time actually is 10-16 weeks in procurement and assembly normally takes 6-8 weeks. Since it is very difficult to shorten the production, customs, and shipping times, the best way to satisfy customers is to find ways to shorten the procurement time. The second reason is that if a large number of raw materials (1000 unit) can be bought at once, SITA will receive a 10% more price discount from the suppliers. Sales forecasting can help determine the number of orders to be placed and thus avoid excessive over-ordered or under-ordered at the suppliers and also help to reduce the lead time for the

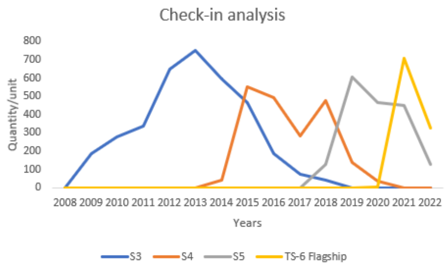


Fig. 1: Total sales for the check-in kiosk

procurement so as to meet the customer's expectations. Due to these two reasons, SITA wants to change its policy to MTS by performing yearly forecasting in advance for the next 4 years.

Generally, the kiosk is designed with different versions for different application scenarios. However, only the normal kiosk which is especially used for check-in has the highest sales, and the kiosk for different versions share more than 90% raw materials. In the S3 kiosk family, the check-in S3 kiosk counts for 96.3% of total sales. The S4 family only has the check-in kiosk. Check-in S5 kiosk counts for 95.4% of the total sales for the S5 family. Check-in TS6 kiosk counts for 98.4% of the total sales for the TS6 family. Besides this, the historical data analysis shows that the total sales quantity of the S6 check-in kiosks will be influenced by the total sales quantity of S5 and S7 which will be introduced to the market in the future. The sales volume changes of kiosk generations can be found in the figure below.For this reason, this research only considers using the historical sales data of the check-in kiosk (S2 to S5) to forecast the total sales of the TS6 check-in kiosk which is also called the TS6 flagship. Hereinafter referred to as TS6.

This paper tries to propose a method to combine both quantitative and qualitative forecasting methods which are commonly used in the FMCG industry to do the demand forecasting for the TS6 kiosks which is a slow-moving good with low demand and high sales prices. The used qualitative methods are analogy forecast, scenario forecasting, and judgmental adjustments. The used quantitative method is the ARIMA(Autoregressive Integrated Moving Average model) /SARIMA(Seasonal Autoregressive Integrated Moving Average model). The outcome of this research hopes to help SITA to meet the customer's expectations as well as to get the price discount from the suppliers. .

The rest of the paper is organized as follows. Section II describe the qualitative and quantitative forecasting methods as well as the methodology related to the clear forecasting steps for the methods used in this research. Section III presents the way to combine different forecasting methods and the detailed process to do the experiments. Section IV discusses the experiment outcome, and any further adjustments as well as future applications. Finally, conclusions are drawn in Section V

II. Literature Review

A. *Forecast methods*

There are many forecasting methods. The following section first highlights some of the qualitative forecasting methods and quantitative forecasting methods, as well as explained how and why some of the methods are chose to be used this research. The second part of the literature review is going to do an introduction of the related techniques about the chose methods.

Qualitative forecasting

Qualitative forecasting is commonly used in practice. Besides this, the research shows that qualitative forecasting will have a better result if the predictor has important expertise and up-to-date information. Qualitative forecasting can be affected by excessive intervention, over-optimism [1], and changes in the policy environment.

The Delphi method is a structured, interactive forecasting method that relies on a panel of experts. [2], and these methods show certain advantages compared with other structured forecasting methods so has been widely used for the business forecast [3]. The Delphi method is based on the key assumption that predictions from groups are generally more accurate than those from individuals [4]. However, this research does not consider using this method due to the whole process time of the Delphi methods can be very long and it is quite difficult to find a panel of experts with corresponding experience.

The analogy forecast assumes one forecast model can also explain the behavior of another phenomenon due to they share certain similarities [5] and this method is widely used in the pricing of a house by comparing the land size, dwelling size, number of rooms between similar properties [6]. Analogical predictions can often produce biases, and these biases are often difficult to identify. Predictions should be based on multiple dimensions of analogy to reduce bias. And using a systematic approach to perform the comparison and prediction process can also reduce bias [7]. This method is chosen to produce forecast scenarios in this research.

The scenarios forecast is to come out forecast based on plausible scenarios, and each scenario may have some possibility to be an occurrence. [8]: During the historical data analysis, it is obvious that the sales life cycle of TS6 will be influenced by the phase-in date of S7. So in this research, different scenarios for the phase-in date of S7 will be taken into consideration, which helps to come out with a more comprehensive forecast.

The judgmental adjustments can provide information for the factors that may not be accounted for in the statistical models, such as promotion, holidays, Large orders.etc. [6]. This method can also cause bias because the users usually adjust much more than they should. It is proven that judgmental adjustments will be more accurate when there is significant missing information and the change is large in size, so small adjustments should be avoided. Besides this, a negative adjustment tends to help more in increasing the forecast accuracy than positive adjustments. [9]. After coming out with the final forecast by a statistical model, the result will be sent to the expert of SITA to do some judgmental adjustments.

Quantitative methods

Quantitative methods should only be applied when it is available historical data and there is reason to believe that certain patterns will persist into the future [6]. After observing the sales figure for different series of kiosks, there is a certain similarity between the sales line of different series of kiosks. Therefore, it can be assumed that the past patterns will continue into the future.

Generally, the forecast model can be divided into the explanatory model, time series models, and other advanced forecasting methods like neural network models and bootstrapping and bagging, etc. which include computer Modeling and Simulation. However, after considering the disadvantages of machine learning methods which are as follows: (1) The long-term accuracy improvements are not significant compared with the traditional methods particularly when forecast time-series data at a weekly and even daily frequency [10]. (2) The machine learning methods require the strong programming skills of the user and are more difficult to implement. (3) Need a lot of data. The machine learning method is not used in the project.

The explanatory model attempts to explain the relationship between the predictor variables and various factors using formulas for situations where marketing plans, competitor activity, economic conditions, etc. have a very strong influence on the forecast results. The explanatory model usually includes time series regression models and dynamic regression models [6]. The assumption for this research is that the external factors do not have a fluctuating effect on the predicted results and any big effect of these effects caused by external factors can be adjusted through the judgemental adjustment after the statistical forecast.

The simplest time series forecasting methods use only information about the predictor variables and do not look for factors that affect the predictor variables. Therefore, these methods can infer the trend component and the seasonal component. The exponential smoothing [11] [12] which was further developed to include seasonal patterns [13] and ARIMA models [14] or SARIMA models when the seasonality exists in the time series data [15] are the most widely used time series forecasting method. Due to the ARIMA model being more widely used compared with the exponential smoothing methods, this research decided to use the ARIMA model to do the statistical forecasting.

B. Theory related to ARIMA model construction

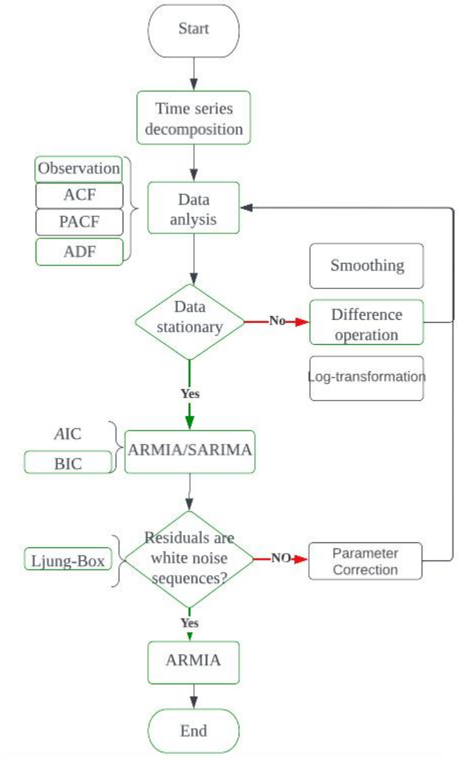


Fig. 2: ARIMA model building

The detailed steps for using the ARIMA/SARIMA model can be found in figure 2. The first thing to do before building the ARIMA model is to use the time series decomposition to check whether there is seasonality exists in the time series. The time series decomposiation will decompose the time series into trend, seasonality and cycle [6]. In this research the multiplicative decomposition is used to decompose the data as it is more suitable compared with additive decomposition for the economical situation.If yes, the SARIMA model will be used instead of ARIMA in the statistical forecasting part. Secondly, the Observation [16], as well as ADF test [17] [18]will be conducted to check whether the time series data is stationary. The ACF and PACF [19] can also help to determine whether the time series is stationary or not. If the time series data is not stationary, the differencing will be chosen to do a data transfer [20]. Then, repeat the stationary check until the time series data be stationary. If the time series data is stationary, then put them into the ARIMA model or SARIMA model and use BIC (Bayesian Information Criterion) information criteria instead of AIC (Akaike's Information Criterion) because BIC is more suitable in a long term forecasting [16] to help find the order of the parameters [21]. The next step is to run the model and use the Ljung-Box test [22] to test whether this model is statistically significant, if not, the next step is to find out a way to do the parameter correction. Sometimes, the outcome will still be accepted although the model fails in the Ljung-Box test. Finally, the result of the model will be exported and kept in excel.

III. METHODOLOGY

A. Research structure

It is obvious that the sales quantity of TS6 will be influenced by the sales quantity of S5 and S7 as introduced in the section I because they are substitutes for each other, and the total sales quantity of all the kiosks seems to be stationary and predictable. For this reason, this research tries to forecast the total sales quantity for all the kiosks as well as the sales quantity of S5 and S7 in the next 4 years. S5 is planned to be forecasted by its own historical sales data. Due to S7 being a new product and do not have historical sales data, the qualitative forecast methods are the first to be used to build the forecast scenario for S7. During the interview, information related to design innovation was got. There is a big update from S2 to S3 which leads to the sales for S3 being quite good and the lifetime for S3 is also longer compared with other generations. However, both S3 to S4 and S4 to S5 are only small updates. Another big update comes from S5 to TS6, for this reason, the lifetime for TS6 is expected to be longer as well as the sales quantity is expected to be higher compared with other generations. TS6 to S7 will be only a small update. In conclusion, referring to the analogy forecast, the sales condition for S7 is expected to be very similar to S4 and S5. For this reason, this research tries to forecast the sales quantity of S7 based on the historical sales data for S4 and S5. Finally, referring to the scenario forecasting method, different forecast scenarios for the phase in time of S7 are created. All the scenarios are as follows: S7 phased Q1 2024, Q3 2024, Q1 2025, Q3 2025, Q1 2026, and Q3 2026. The sales volume for TS6 will be calculated by the sales volume of the total kiosk minus that of S5 and S7. The forecast for all the time series will be conducted by ARIMA or SARIMA model. All the outcomes of the model will be discussed with the expert of SITA to do the judgemental adjustment. In order to avoid bias, only big changes are allowed to be made and the adjustment will be kept for further check. In a conclusion, this research tries to combine the quantitative forecast methods which are the ARIMA/SARIMA model with qualitative methods which are the analogy forecast, scenario forecasting, and judgmental adjustments. The research structure of this project can be found in figure 3.

B. Research experiments

Prediction for the total sales quantity According to the theory discussed in section II, the time series decomposition is used first to find out whether there is seasonality, trend or cycle exists in the time series. After using the multiplicative model, the outcome can be found below in figure 4 which is a combination of 4 plots. The first plot shows the total quantity varies with time. The second plot shows the trend or cycle in the time series, in which the number of sales has a slight increasing trend in the last 10 years. The third plot shows

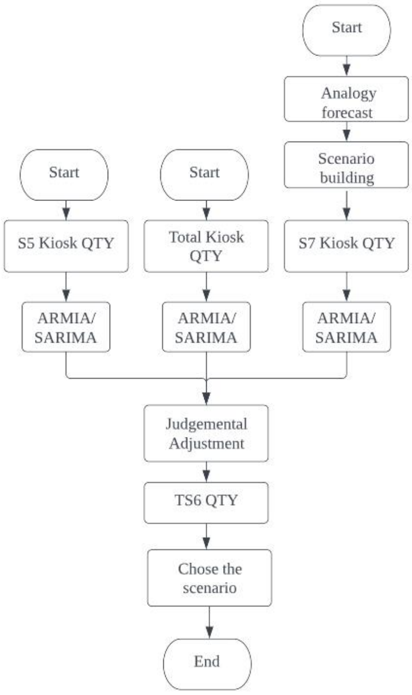


Fig. 3: Research structure

seasonality, which means there are certain patterns repeated occurrence in the past and the SARIMA model instead of the ARIMA model should be chosen in the forecast. If there is no seasonality exist in the time series, this plot will show only the strength line. The last figure shows the distribution of the residual.

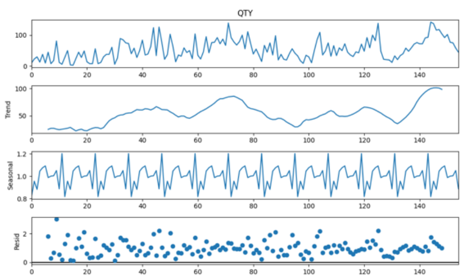


Fig. 4: Time series decomposition with multiplicative model-Total Kiosk

The next step is to determine whether the time series is stationary or not. According to figure 5, which is a combination of 3 plots. The first plot shows the number of sales for total kiosks varied with time in the past years. The second and third plot shows the time series data after applying the first-order differencing and second-order differencing. All three plots do not show a clear upward or downward trend, but fluctuate roughly up and down around a fixed value, for this reason, all three-time series can be assumed to be stationary through observation.

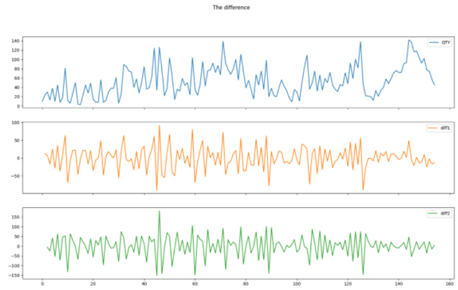


Fig. 5: Stationary test-Total kiosk

In the result of the ADF test for the original sales number for the total kiosk, the t-value which equals -3.54 is smaller than -3.47, -2.88 and -2.58,and the P value of 0.006 is less than the significance level of 0.05. This means that unit root test results reject the original hypothesis that the series is non-stationary, and the time series data for the original total kiosk is 99% accept to be stationary. In the result of the ADF test for the original sales number for the total kiosk after applying the first order differencing, the t-value which equals -7.55 is smaller than -3.47, -2.88 and -2.58, nd the P value of 0.000... is less than the significance level of 0.05. This means the time series data for the original total kiosk after first order dfferencing is also 99% accept to be stationary.

Combining the observation method with the unit root test we are able to conclude that both the original data and the first order difference data are stationary and can be used in the SARIMA model

Because the original sales data for the total kiosk is already stationary, it is used first in the SARIMA model. If the outcome of the SARIMA model using the original data is not good enough, then the first-order differencing time series data will be chosen.

Python has the model auto-order function auto.arima, and this research uses the auto command that comes with Python to calculate AR (autoregressive term in the model) with 0-5 order lags and MA (moving average term in the model) with 0-5 order lags. As discussed in section II, the BIC is chosen to be used to find the best parameter of the model. With the auto. arima, all the combined BIC information of the SARIMA model and the optimal parameters of the model are given, and the auto.arima will stop the calculation if it finds the best parameter. After running the model, the model with the minimum BIC information is ARIMA (1,0,1)(0,0,0)[12]. The Ljung-Box test is chosen to test whether the residuals of the model are white noise sequences next to test whether the model are statistical signficant. As shown in the figure 6, the Ljung-Box test for the SARIMA(1,0,1)(0,0,0)[12] model resulted in a p-value of 0.83 much greater than the significance level of 0.05, and the results of the test accepted the original hypothesis, proving that the residual series is white noise and the established SARIMA(1,0,1)(0,0,0)[12] model is significantly valid.

Figure 7shows the comparison between the predicted data

```
Best model:  ARIMA(1,0,1)(0,0,0)[12] intercept
Total fit time: 4.007 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  158
Model:               SARIMAX(1, 0, 1)   Log Likelihood                -747.367
Date:                Mon, 17 Oct 2022   AIC                           1502.734
Time:                        17:13:28   BIC                           1514.984
Sample:                             0   HQIC                          1507.709
                                - 158
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept      6.2142      3.570      1.741      0.082      -0.783      13.212
ar.L1          0.8798      0.066     13.339      0.000       0.750       1.009
ma.L1         -0.5632      0.106     -5.337      0.000      -0.770      -0.356
sigma2       749.4207     92.291      8.120      0.000     568.534     930.308
===================================================================================
Ljung-Box (L1) (Q):                   0.05   Jarque-Bera (JB):                 6.75
Prob(Q):                              0.83   Prob(JB):                         0.03
Heteroskedasticity (H):               0.85   Skew:                             0.50
Prob(H) (two-sided):                  0.57   Kurtosis:                         2.91
===================================================================================
```

Fig. 6: Outcome of SARIMA(1,0,1)(0,0,0)[12]

and the original data using the SARIMA(1,0,1)(0,0,0)[12]. However, although this model is statistically significant, this figure shows that the model is not good at predicting the peak of the number of sales. For this reason, the model building based on the first-level differencing is also considered in this research, and the outcome from these two models will be compared to find the best model for predicting the sales of the total kiosk.

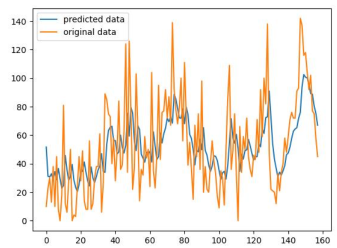


Fig. 7: Prediction comparison for original total sales quantity

By using the auto.arima with the same steps to build the SARIMA model for the first-level differencing of the original time series data, the best model with the minimum BIC is SARIMA(0,1,1)(0,1,1)[12]. The Ljung-Box test for the SARIMA(0,1,1)(0,1,1)[12] model resulted in a p-value of 0.82 which is much greater than the significance level of 0.05, so the results of the test accepted the original hypothesis, proving that the residual series is white noise and the developed SARIMA(0,1,1)(0,1,1)[12] model is significantly valid.

Figure 8shows the comparison between the predicted data and the original data using the SARIMA(0,1,1)(0,1,1)[12]. Compared with figure 7, the prediction made by SARIMA(0,1,1)(0,1,1)[12] model shows a better result, for this reason, the SARIMA(0,1,1)(0,1,1)[12] model is chosen to do a further prediction.

Prediction for the sales quantity of S5

The same as the first step for the prediction of the number of sales for the total kiosk, the time series decomposition with the multiplicative model is also used for time series data of S5 to find out whether there is seasonality or trend that exists in the

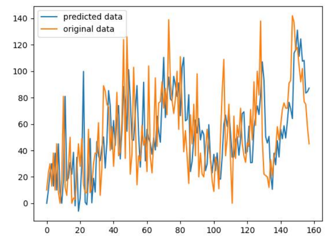


Fig. 8: Prediction comparison for total sales quantity applying first-order differencing

time series. According to the second and third plots of figure 9, the number of sales of S5 has an increasing trend until Oct 2019, and a subsequent number of sales trended downward. Seasonality also exists in the time series data of S5, so the SARIMA model should also be used for prediction.

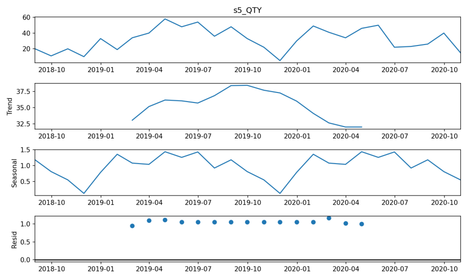


Fig. 9: Time series decomposition with multiplicative model-S5

In order to determine whether the time series data of S5 is stationary or not, the first method used is observation. By observing the plot which can be found in figure 10 for the original sales quantity of S5 and the original sales quantity after the first and second differencing varies with time, it is obvious that all the 3 figures, especially the last two figures fluctuate up and down around ‘0” which means all the 3-time series data seems to be stationary through observation.

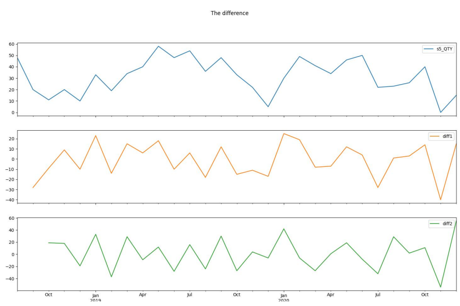


Fig. 10: Stationary test-S5

The ADF test is also used for the time series of S5. In the result of the ADF test for the original sales number for the S5, the t-value which equals -3.58 is smaller than -2.99, -2.63 but larger than -3.737 and the P-value of 0.006 is less than the significance level of 0.05. This means that ADF test results reject the original hypothesis that the series is non-stationary, and the time series data for S5 is 95% accepted to be stationary.

The same as the forecast for the number of sales for the total kiosk, the SARIMA model for d equals 0 and 1 are both built for comparison. The information criteria AIC is used here as the data of the time series for S5 is much less than the data for the time series of the total kiosk, and AIC is more suitable to be applied in this situation because the model will not be too complicated. Because S5 is discussed to phase out the market in 2024, it is expected will have a decreasing trend in the number of sales, for this reason, only the data after Oct-2019 are considered to be used as they show a decreasing trend. After comparing using the first data from Oct-2019 to Feb-2022, the outcome of using Feb-2022 as the first data is more reasonable, so the SARIMA model is considered to use Feb-2022 as the start. After the comparison the outcome of SARIMA model (p,0,q) and (p,d,q), the SARIMA model(0,1,1)(0,1,0)[12] have a better result and is chosen for further prediction. The outcome can be found in figure 11. The Ljung-Box test for the SARIMA(0,1,1)(0,1,0)[12] model resulted in a p-value of 0.90 which is much greater than the significance level of 0.05, and the results of the test accepted that the residual series is white noise and the established SARIMA(1,0,1)(0,0,0)[12] model is statistically significant.

```
Best model:  ARIMA(0,1,1)(0,1,0)[12]
Total fit time: 3.112 seconds
                                    SARIMAX Results
==========================================================================================
Dep. Variable:                                  y   No. Observations:                   29
Model:             SARIMAX(0, 1, 1)x(0, 1, [], 12)   Log Likelihood                 -69.354
Date:                            Tue, 18 Oct 2022   AIC                            142.707
Time:                                    04:08:13   BIC                            144.252
Sample:                                08-31-2018   HQIC                           142.786
                                     - 12-31-2020
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.7722      0.211     -3.662      0.000      -1.185      -0.359
sigma2       322.0922    159.140      2.024      0.043      10.183     634.001
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):                 0.88
Prob(Q):                              0.90   Prob(JB):                         0.64
Heteroskedasticity (H):               0.78   Skew:                             0.41
Prob(H) (two-sided):                  0.79   Kurtosis:                         2.19
===================================================================================
```

Fig. 11: Outcome of SARIMA(0,1,1)(0,1,0)[12]

The in-sample prediction comparison and out-sample prediction can be found in figure 12. The out-sample prediction shows the future sales of S5 will show a fluctuating downward trend and drop to 0 points for the first time at the end of 2021 and for the second time at the beginning of 2023.

Prediction for the sales quantity of S7

The first step to forecast the sales quantity of S7 is to build the historical data as S7 is a new product and has not been introduced to the market. It is expected that the S7 will not be introduced into the market in 2023, so only 3 years of sales data for the S7 need to be forecasted. Firstly, the historical sales data for S4 and S5 will be taken out from the whole time series. Then, they will be matched from the first data to the last data and added up to each other to create the time series data for S7. Finally, referring to the scenario forecasting

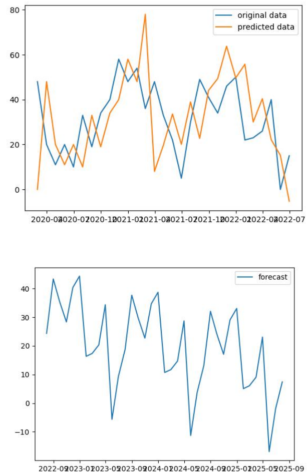


Fig. 12: Prediction for S5 quantity applying first-order differencing

method, different forecast scenarios for the phase in time of S7 are created. All the scenarios are as follows: S7 phased Q1 2024, Q3 2024, Q1 2025, Q3 2025, Q1 2026, and Q3 2026. The historical sales data of S7 is developed based on the historical sales data of S4 and S5 and can be found in figure 13.

```
[ 1.  7. 24. 30. 22.  3. 20. 39. 25. 60. 40. 56. 40. 74. 50. 85. 64. 69.
 58. 37. 13. 32. 21. 22. 21. 36. 58. 43. 62. 37. 33. 34. 26. 23. 20. 26.
 41. 29. 20. 40. 40. 16. 34. 56. 66. 18. 32.]
```

Fig. 13: Building the historical data for S7

The same as the steps before, the time series decomposition with the multiplicative model is also used for the time series data of S7. The result is shown in figure 14, which means there are both trend and seasonality exist in the time series, so the SARIMA model should be used instead of ARIMA for making predictions.

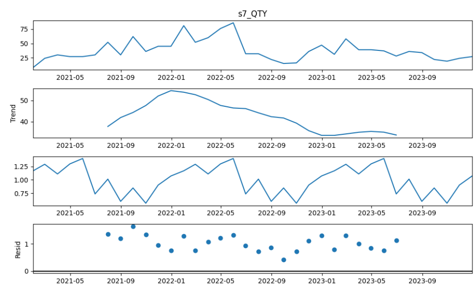


Fig. 14: Time series decomposition with multiplicative model-S7

After that, both the observation method and the ADF test are used to find out whether the time series is stationary or not. The figure shows the original sales quantity of S7 and the original sales quantity after the first and second differencing varies with time can be found in figure 15. From this figure, it is clear that the original sales quantity after differencing almost fluctuated up and down around "0", which means the time series data after differencing looks stationary.

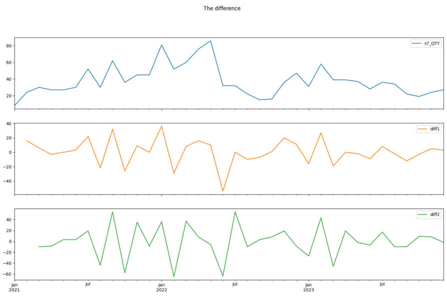
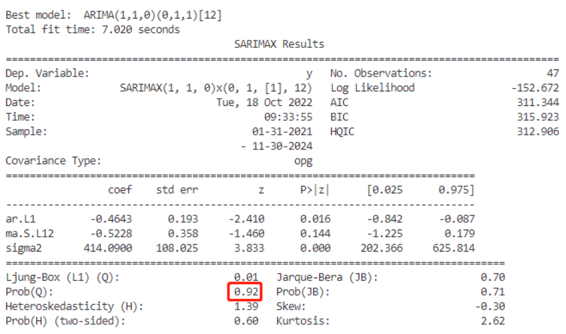


Fig. 15: Stationary test-S7

In the results of the ADF test for the original sales number of theS7, the t-value which equals -2.66 is larger than -3.59, -2.93 but a litter bit smaller than -2.60 and the P-value of 0.08 is larger than the significance level of 0.05. This means that ADF test results accept the original hypothesis that the series is non-stationary. The results of the ADF test for the original sales number of theS7 after the first-level differencing show that, the t-value which equals -10.24 is smaller than -3.59, -2.93 and -2.60 and the P-value of 0.000... is smaller than the significance level of 0.05. This means that ADF test results reject the original hypothesis that the series is non-stationary, and the time series data for S5 is 99% accepted to be stationary.

The SARIMA(p,1,q)(P,1,Q)[12] model is built based on the minimum of BIC, and the result can be found in the figure 16. The Ljung-Box test for the SARIMA(1,1,0)(0,1,1)[12] model resulted in a p-value of 0.92 which is much greater than the significance level of 0.05, and the results of the test accepted that the residual series is white noise and the established SARIMA(1,1,0)(0,1,1)[12] model is statistically significant.



```
Best model:  ARIMA(1,1,0)(0,1,1)[12]
Total fit time: 7.020 seconds
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                  y   No. Observations:                   47
Model:             SARIMAX(1, 1, 0)x(0, 1, [1], 12)   Log Likelihood                -152.672
Date:                            Tue, 18 Oct 2022   AIC                            311.344
Time:                                    09:33:55   BIC                            315.923
Sample:                                01-31-2021   HQIC                           312.906
                                     - 11-30-2024
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.4643      0.193     -2.410      0.016      -0.842      -0.087
ma.S.L12      -0.5228      0.358     -1.460      0.144      -1.225       0.179
sigma2       414.0900    108.025      3.833      0.000     202.366     625.814
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):                 0.70
Prob(Q):                              0.92   Prob(JB):                         0.71
Heteroskedasticity (H):               1.39   Skew:                            -0.30
Prob(H) (two-sided):                  0.60   Kurtosis:                         2.62
===================================================================================
```

Fig. 16: Outcome of SARIMA(1,1,0)(0,1,1)[12]

Both the in-sample prediction comparison and out-sample prediction can be found in figure 17. The out sample prediction shows that the sales of S7 in the future will have a fluctuating upward trend.

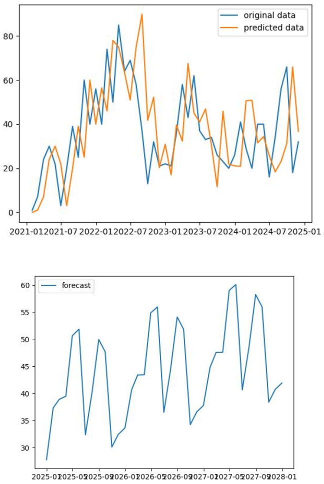


Fig. 17: Prediction for S7 quantity applying first-order differencing

IV. Research Results

A. Residual analysis

Although all the SARIMA models have passed the Ljung-Box test, as shown in figure 8, 12 and 17, all the prediction data shows a little bit of lag compared with the original data. In order to make the forecast outcome more accurate, the lags in the result of all the time series outcomes of sales quantity for total kiosks, S5, and S7 should be correct before getting the final result. In this project, the MAE(Mean Absolute Error), which was commonly used to evaluate model errors in time series prediction [23], is chosen to test the residuals by changing the lags of the prediction series to -1, -2, and -3. The result of this test can be found in figure 18. The result shows that for all the time series data(Total kiosk, S5, and S7), the prediction result with lag -1 has the lowest residual, so it is best to adjust the prediction series with lag -1. For total kiosks, S5 and S7, the monthly difference is around 17 pc, 8pc, and 9 pc respectively. Besides this, the residuals for time series data of S5 is slightly lower than that of S7 and total kiosks and the sample size for making predictions for S5, S7 and total kiosks are 29, 47, and 158, which may indicate simpler models tend to produce more accurate predictions.

	Original	lag -1	lag -2	lag -3
Total Kiosk	25.32	17.07	20.32	21.09
S5	17.18	8.43	16.83	15.91
S7	16.60	9.02	13.85	16.50

Fig. 18: Residual adjustment/unit

B. Judgemental adjustment

As discussed in the section II, the original forecast result will be sent to the expert in SITA to do the judgemental adjustment. 3 proposals to do the adjustment have been proposed in the interview. 2 of them are accepted as important missing information in the model, and 1 is rejected due to not being consistent with past historical data.

Market condition is expected to be better

Due to the fact that some orders for 2023 have already been received at the end of the year 2022, the market condition is expected to be very good in the year 2023 and the following years and has a growth rate of 15% compared with 2022. This growth rate is expected to decline smoothly in the coming years, with a growth rate of 10% in 2024 and 5% in 2025. Due to the fact that the demand information about the surge in market demand is not included in the forecasting model, the model predicts a lower growth rate than the experts' forecasts, as well as taking into account the fact that statistical models are better able to grasp the patterns in the data. The growth rates for 2023, 2024 and 2025 are therefore adjusted to the expert's estimated growth rates but retain the monthly fluctuations predicted by the SARIMA model. The specific model growth rate calculation results and formulas are shown below.

$$\text{Model Adjusted Growth Rate} = \frac{\text{Model Prediction}_{y1} * \text{Growth Rate}_{y1}}{\text{Model Prediction}_{y2}} \tag{1}$$

- **2022-2023** increase 15%. Growth rate in the model be 1.169
- **2023-2024** increase 10%.Growth rate in the model be 1.06
- **2024**-2025 increase 15%.Growth rate in the model be 1.01

Missing market growth for S7 from 2018 to the year when phase in the market

The forecast result for S7 seems to be too small due to the total market demand for the kiosk is continuously increasing. However, the time series data of S4 which was used to make predictions for the sales quantity of S7 ended in 2018, but the prediction for S7 starts after 2024, which shows a lack of market growth from 2018 to 2024. Expert's opinion is to expect the sales of the S7 will reach 1000 pcs in the first year after phasing into the market, however, referring to historical sales data, no generation of the kiosk has the experience to sales 1000 pcs in the first year. For this reason, this adjustment is not accepted in this research. However, the forecast result for S7 is too low for this reason, so the growth rate for the total kiosk from 2018 to the year when S7 is phased in is used to correct the missing market growth. The formula to calculate the growth rate is shown below, and the growth rate of S7 for 2024, 2025 and 2026 is 1.34,1.32 and 1.36 respectively. The application for the growth rate of S7 is not the same as that of the total kiosk. The Growth rate of the total kiosks for 2023,2024 and 2025 is applied to each year respectively, but the growth rate of S7 for 2024 is only applied to assumptions 1 and 2, the growth rate of S7 for 2025 is only applied to assumptions 3 and 4, and the growth rate of S7 for 2026 is only applied to assumptions 5 and 6.

$$\text{Growth Rate of S7 in } y_n = \frac{\text{Sum of Total Kiosk in } y_n}{\text{Sum of Total Kiosk in 2018}} \tag{2}$$

In the conclusion, 3 adjustments are applied to the original forecast series in order to get the final outcome for all the assumptions.

- In order to solve the fact that the prediction time series sequence is always behind the original time series sequence, all the 3 time series sequences agreed to move back to lag -1 to increase the forecast accuracy.
- In order to solve the fact that the market condition for years 2023 to 2025, especially 2023 will be much better than the forecast condition, the annual growth rate for 2023, 2024 and 2025 are taken into the calculation to make adjustments for the final forecast outcome.
- In order to solve the fact that the market growth from 2018 to the year when S7 is introduced to the market is missing, the special market growth rate for each assumption is calculated and applied in the final adjustment.

C. *Future Application*

As mentioned in section I, the main aim of this project is to forecast the sales quantity for TS6 in the next 4 years so as to find a way to shorten the product lead time to meet the customer's satisfaction as well as try to get the price discount from the suppliers.

1) Shorten the product lead time: **The visualization of product production plan**

As discussed in the sectionI, normally the customers want to receive the products within 12 weeks after placing the order. However, , the overall time from procurement to final delivery needs about 10 to 16 weeks, and the procurement time takes up the most time which is about 6-8 weeks. In order to shorten the overall lead time to meet the customer's expectations, with the forecasting result, the procurement process can be started 6- 8 weeks in advance, so that the overall lead time can be shortened to 4-8 weeks. However, considering the inventory holding cost, the inventory holding time should also be kept as short as possible. For this reason, the best plan is to start the procurement process 4 weeks in advance. If considering the production and assembling process, the customs and shipment process, and the final delivery process will take 8 weeks in total, the yearly product production plan for TS6 and S7 is visualized and can be found in the figures below.

Procurement plan

If it is assumed that the time of each process is calculated according to the maximum time, the new timeline is shown in the figure 20.

Raw material purchases need to be made 8 weeks prior to production. Together with the plan to increase the purchased quantity to 1000 pcs which is discussed in section I. The purchase plan start from 2023 for TS6 and S7 for assumption 4 and 5 can be found below.

It is worth noting that the procurement values in the figure with yellow criteria are larger than the forecasted values, as

	2022	2023	2024	2025	2026
Assumption 1:					
S7 H1 2024	0	105	676	741	672
S6 outcome	532	636	265	216	143
Assumption 2:					
S7 H2 2024	0	0	467	709	630
S6 outcome	532	741	460	245	179
Assumption 3:					
S7 H1 2025	0	0	103	667	607
S6 outcome	532	741	824	287	199
Assumption 4:					
S7 H2 2025	0	0	0	460	567
S6 outcome	532	741	927	494	239
Assumption 5:					
S7 H1 2026	0	0	0	106	567
S6 outcome	532	741	927	848	239
Assumption 6:					
S7 H2 2026	0	0	0	0	347
S6 outcome	532	741	927	954	459

Fig. 19: The product production plan yearly/unit

Fig. 20: The overall timeline

the demand in 2027 is outside the forecasted interval. In assumption 4, 599 more pcs of raw materials are ordered, and 245 more pcs of raw materials in assumption 5. However, it is expected these over-ordered raw materials will be completely consumed in the future.

Obtained the purchasing discounts to save total cost

According to the interview, the material stands for 50% to 60% of the total cost of the TS6 kiosk, and the annual inventory cost stands for 2% to 5% of the total cost. In addition to this, the raw materials have a very long shelf life, much longer than four weeks. According to the figure 21, the maximum time of raw materials in storage is 18 months, and the average time is 9 months. The following formula calculates the cost savings of increasing the purchase plan from 100 pcs to 1000 pcs. If SITA successfully gets the 20% discount on buying the raw materials, it will save 1.25.6% to 4.5% on the original price.

$$\begin{aligned} &\text{Lower Bond: Price } * 50\% * 10\% - \\ &\text{Price } * 5\% * \frac{9}{12} \approx 1.25\% \text{ Price} \end{aligned} \tag{3}$$

$$\begin{aligned} &\text{Upper Bond: Price } * 60\% * 10\% - \\ &\text{Price } * 2\% * \frac{9}{12} \approx 4.5\% \text{ Price} \end{aligned} \tag{4}$$

V. Conclusion

This study has both scientific and practical contributions. **Scientific contribution**: Demand forecasting is widely used in the FMCG industry, and for companies like SITA, due to the low demand for their products and high production costs. Usually, the production method is based on order-based production. This research explores the possibility of demand forecasting for the slow-moving consuming industry based on real historical sales data of SITA kiosks by using the forecasting method widely used in the FMCG industry. **Practical contribution**: In this research, the forecasting scenario which is suitable for TS6 is developed by analyzing the historical sales data of the TS6 Kiosk, and selecting suitable qualitative forecasting methods which are the analogy forecast, Scenario forecasting, and Judgemental adjustment and quantitative forecasting methods: SARIMA/ ARIMA model through the method of literature review. The TS6 kiosk's sales volume up to 2026 was successfully calculated using a combination of qualitative and quantitative forecasting methods by first filtering, reviewing, and differencing the historical sales data before putting it into the statistical models. Besides these contribution, this research can help SITA to meet the customers' expectations as well as to save 1.25.6% to 4.5% on the original price for the total cost.

	2023											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Assumption 4:												
S7 H2 2025												
S6 outcome	1000											
Assumption 5:												
S7 H1 2026												
S6 outcome	1000											

	2024											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Assumption 4:												
S7 H2 2025												
S6 outcome				1000								
Assumption 5:												
S7 H1 2026												
S6 outcome				1000								

	2025											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Assumption 4:												
S7 H2 2025					1000							
S6 outcome						1000(599)						
Assumption 5:												
S7 H1 2026											1000	
S6 outcome						1000(245)						

	2026											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Assumption 4:												
S7 H2 2025										1000		
S6 outcome												
Assumption 5:												
S7 H1 2026												
S6 outcome												

Fig. 21: The overall procurement plan/unit

Due to the limited information available, this project also has some limitations to be developed and added in the future.

(1)Abnormal values in the original data. In this research, only the very obvious abnormal values were processed when performing data cleaning before prediction. However, there are some data with abnormal values that cannot be traced due to the long time, so they just be kept in the forecast sample data. Suitable hypotheses for these abnormal values can be explored later to handle the abnormal values more rationally.

(2)Treatment of residuals. In order to reduce the prediction error, the ARIMA model can be combined with machine learning, neural network prediction and other methods to increase the accuracy of prediction, and develop the combined ARIMA-neural network algorithm.

(3)In this project, due to consider the influence of environmental factors on the prediction results will be small and the difficulty of to measure of explanatory variables, the time series statistical model was chosen for the study, but using a time series model may ignore the influence of political, economic, social and environmental factors on the prediction results. Therefore, subsequent studies can add explanatory variables to the ARIMA model and change the time data series into panel data to develop a dynamic forecast model, making the prediction become more comprehensive.

(4)To make the forecasting process easier, the forecasting model can be integrated with the company's order management system, making it possible for the forecasting model to automatically update forecasts based on monthly orders, as well as do the data validation and corrections.

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SITA

SITA is the world-leading specialist in air transport communications and information technology that mainly provides service and IT support for airline operators and works with around 400 air transport members and has 2800 customers in 190 countries. The main customers include airports, airlines, ground handlers and airport groups. Almost every airline and airport does business with SITA. They work not only to connect the global airline industry but also apply expertise to address virtually all core business, operational, baggage and passenger processes in the air transport. SITA's portfolio for the global air transport industry is shown below in figure 1. SITA divides their global customers into four segments and is named four Geographical regions(GEO's): North and South America (AMER), Europe (EURO), Asia, India, and the Pacific (APAC) and the Middle East and Africa(MEA).

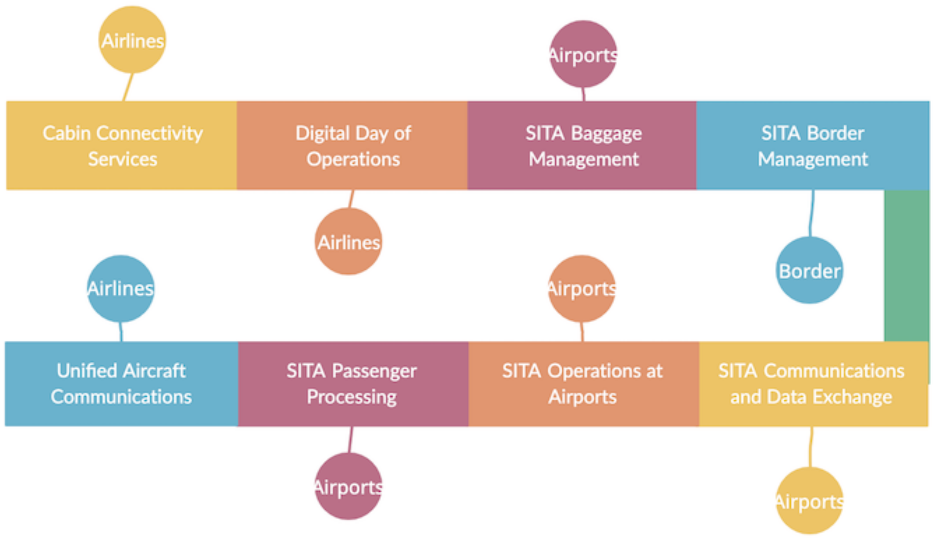

Figure 1: The main portfolio of the SITA

TS6 Kiosk

Kiosk is the SITA's product for processing passenger information. After optimizing the fourth and fifth generations of the product, the sixth generation is now available and has become more customized. TS6 is a highly modular, cleverly designed, and highly customizable device that can be used in check-in, bag tagging, and border control within airports. It aims to increase the efficiency of customer journeys and provide cost reductions to airports. The TS6 kiosk has the following main modules: Payment module, ADA keypad, Advanced Branding, Mobility (Battery & Wheels), Overhead display, spares and a biometric sensor. Due to its high modularity, the customers can choose their own modules to design their own Kiosk, which also means it is possible to divide a kiosk into standardization parts that can be made to stock and customized parts which can be made to order. In addition, the TS6 is also available in different series to meet customer needs which can be found in figure 2.

Figure 2: The TS6 series