A COMPARISON OF FORECASTING METHODS FOR ROTABLE SPARE PARTS IN A THAI LOW-COST AIRLINE

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การเปรียบเทียบวิธีการพยากรณ์สำหรับอะไหล่หมุนเวียนของสายการบินต้นทุนต่ำในประเทศไทย

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งานวิจัยนี้มีวัตถุประสงค์เพื่อเปรียบเทียบและประเมินวิธีการพยากรณ์ความต้องการของชิ้นส่วนอะไหล่เครื่องบินแบบที่เกิดขึ้นอย่างไม่สม่ำเสมอจำนวน 3 วิธี โดยเน้นที่กลุ่มชิ้นส่วนอะไหล่ที่หมุนเวียนกลับมาใช้ได้ (Rotable spare part) ของบริษัท A ซึ่งเป็นสายการบินต้นทุนต่ำชั้นนำของประเทศไทยและดำเนินกิจการโดยใช้เครื่องบินแอร์บัส (Airbus) รุ่น A320 จากการจำแนกประเภทของอุปสงค์ พบว่าความต้องการของอะไหล่ส่วนใหญ่มีรูปแบบความต้องการที่ไม่สม่ำเสมอ (Intermittent demand pattern) วิธีพยากรณ์ของครอสตัน (Croston's Method), วิธีปรับเรียบเอ็กซ์โพเนนเชียลแบบโฮลท์ (Holt's Linear Method) และวิธีโครงสร้างประสาทเทียมหลายชั้นแบบแพร่ย้อนกลับ (Multi-Layer Perceptron train with Backpropagation of Neural Network Model) จะถูกนำไปทดสอบกับชุดข้อมูลย้อนหลังของชิ้นส่วนอะไหล่ที่หมุนเวียนกลับมาใช้ได้จำนวนทั้งสิ้น 36 ชิ้น โดยแบ่งข้อมูลเป็น 2 ชุด คือ ชุดเริ่มต้น (initialization set) ระยะเวลา 60 เดือน (มกราคม 2557 – ธันวาคม 2561) และ ชุดทดสอบ (test set) ระยะเวลา 12 เดือน (มกราคม 2562 – ธันวาคม 2562) การตรวจสอบความแม่นยำของวิธีพยากรณ์จะถูกวัดค่าโดยใช้ ค่าเฉลี่ยความคลาดเคลื่อน (ME), ค่าเฉลี่ยความคลาดเคลื่อนสมบูรณ์ (MAE) และค่าเฉลี่ยเปอร์เซ็นต์ความคลาดเคลื่อนสมบูรณ์ (MAPE) เพื่อประเมินประสิทธิภาพของวิธีพยากรณ์ในชุดข้อมูลทดสอบ ผลการวิจัยพบว่าจากการทดสอบความแม่ยำของวิธีพยากรณ์ทั้ง 3 วิธี วิธีการพยากรณ์แบบโครงสร้างประสาทเทียมหลายชั้นแบบแพร่ย้อนกลับ (Multi-Layer Perceptron train with Backpropagation of Neural Network Model) มีประสิทธิภาพในการพยากรณ์ที่ให้ผลดีกว่าอีก 2 วิธี และมีแม่นยำถึง 81% เมื่อเปรียบเทียบกับข้อมูลอุปสงค์ที่เกิดขึ้นจริงในชุดข้อมูลทดสอบปี 2562 เป็นระยะเวลา 12 เดือน ดังนั้น จากการวิจัยนี้จึงสรุปได้ว่า วิธีพยากรณ์แบบโครงสร้างประสาทเทียมหลายชั้นแบบแพร่ย้อนกลับ (Multi-Layer Perceptron train with Backpropagation of Neural Network Model) เป็นวิธีพยากรณ์ทางเลือกที่ดีกว่าวิธีการพยากรณ์อนุกรมเวลาแบบดั้งเดิม และเป็นวิธีการพยากรณ์ที่แนะนำสำหรับบริษัท A เพื่อนำไปใช้ในการคาดการณ์ความต้องการชิ้นส่วนอะไหล่แบบหมุนเวียนได้ (Rotable spare part) ในประเภทอุปสงค์ที่มีความต้องการที่ไม่สม่ำเสมอ (Intermittent demand pattern)

สาขาวิชา	การจัดการทางวิศวกรรม	ลายมือชื่อนิสิต	....
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This research intents to compare and evaluate 3 different methods for forecasting irregular demand of aircraft spare parts by focusing on Rotable part group of Company A which is the leading low-cost airline in Thailand and operate by Airbus A320 model. Based on the demand classification, it is observed that most of the spare part demands presented an intermittent demand pattern. The forecasting methods Croston's, Holt's Linear and Multi-Layer Perceptron trained with Backpropagation of Neural Network Model are applied on the historical data of 36 Rotable spare parts by dividing into 2 sets which are initialization set period 60 months (January 2014 – December 2018) and test set for period 12 months (January 2019 – December 2019). The forecasting accuracy will be made by using ME, MAE and A-MAPE to evaluate the performance of the method over the test set. The results show that Multi-Layer Perceptron trained with Backpropagation of Neural Network Model outperform than other 2 methods in all forecasting accuracy measurement and the performance 81% accurate forecast when comparing with the actual observation over the test set data in 2019 for 12 months period. Therefore, from this research it concludes that Multi-Layer Perceptron trained with Backpropagation of Neural Network Model is superior alternative model over the traditional time series models and recommend to be a forecasting tool for Company A use to forecast Rotable spare part in intermittent demand pattern.

Field of Study:	Engineering Management	Student's Signature ....
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Introduction

1.1 Introduction

The airline industry is highly competitive market which there are a lot of airline companies to provide passenger air transportation services including scheduled and chartered with various strategies in order to maximize customers' satisfactions and gain high revenue. According to Thailand's statistic of number of passengers including domestic and international routes during the past 10 years (2010-2019), the passenger number has been increasing steadily every year in both domestic and international routes. As shown in Figure 1.1, the number of passengers in domestic route was around 27 million and international routes was around 35 million passengers in 2010. However, in 2019 it is shown the number of passengers was 76 and 89 million in domestic and international routes respectively. That means, the air transportation was highly popular for travelling which there was a growth rate of total number of passengers in 2019 almost triple when comparing to 2010.

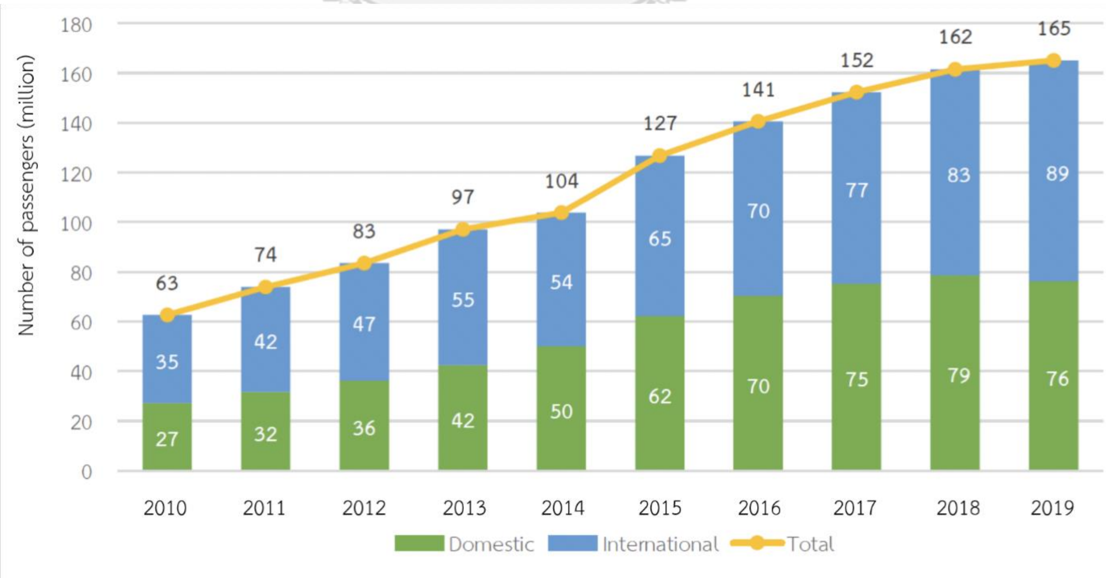

Figure 1.1: Thailand's statistics of number of passengers from 2010 until 2019

Source: Available from: https://www.caat.or.th/wp-content/uploads/2020/06/STATE-OF-THAI-AVIATION-INDUSTRY-2019.pdf [Accessed 5 Nov 2020]

It can be seen that the number of passengers in Thailand steadily increases because the air transportation provides high speed travel, save time, mostly on-time schedule and etc. which these causes attract passengers and induce a lot of airlines to compete in this market. Additionally, the low-cost airline business is a one of the player group in this market. The key success factors of low-cost airline business are to maximize service quality to highly satisfy the needs of various customer groups and also minimize unnecessary costs and carefully manage with the fluctuating demand of passengers. Similar to the concept of Company A which is the leading low-cost airline in Thailand.

Moving on to the details of Company A, the company A started to operate a low-cost airline business in Thailand since 2009 with single class and single-family aircraft fleet configuration concept. They generate revenues from scheduled passenger services and ancillary services. Moreover, the company vision is to be the largest of low-cost airline in Asia region and to serve for people who currently lack connectivity at low fares of air ticket. The company has four missions which are working and treating employees as a family, creation of globally recognized ASEAN brand, providing lowest cost for everyone and maintaining the highest service quality with embracing the technology to reduce cost and maximize service level.

Currently, Company A has 62 aircrafts of single aircraft type in the fleet which is Airbus A320 model. The age of aircrafts in the fleet vary from 2 years to 13 years and the average aircraft utilization is about 12 Flight Hours (FH) and 8 Flight Cycles (FC) per day per aircraft. However, the company still has a challenged in aircraft flight schedule delay issue which have costly effected to the company. These delays can be resulted from many different causes such as from crews, refueling, aircraft late arrival, weather, aircraft technical maintenance and etc. Focusing on the aircraft technical maintenance, it can be seen that this section is about company operation in which the company can monitor and enhance planning management to be high efficiency and effectiveness. The lack of spare parts stock is considered to be the main factor which causes the airline's operation delays due to aircraft technical maintenance issues as resulting from the unavailable spare parts supplied for the failures found during inspection or unexpected defects that occur at the time of aircraft is nearly to be released for the flight.

Table 1.1: The delay cost per flight of Company A Airline in the time frame 30 – 240 minutes

Time frame (Minutes)	Total Delay Cost per flight (THB)
30	47,680.40
45	123,175.28
60	228,180.08
75	347,335.92
90	514,620.08
105	709,258.16
120	951,865.20
135	1,216,354.56
150	1,524,148.96
165	1,864,799.76
180	2,236,791.68
195	2,608,942.80
210	2,997,440.00
225	3,445,907.68
240	3,909,005.44

To sum up, it can be expressed that the delay is the critical issue challenging to the company to manage in well-planning in order to avoid paying for unnecessary cost. Also, the one of company's missions is about cost efficiency which the company provides the low-fare airline services. Therefore, the well-scheduled service maintenance can enhance the company to save cost and maximize the satisfaction of customers.

1.2 Problem Statement

In the airline sectors, organizations have involved abundant of aircraft service spare parts for Stock Keeping Unit (SKU). There is a wide range of serviceable spare parts in holding stock with the important implications for its availability and the holding cost of inventory. That means, the unavailability of spare parts causes the aircraft operation delays and leads the huge extra aircraft downtime cost because of even the spare parts which is low in demand but it might be critical for the aircraft operation. On the other hand, excessive quantities of spare parts in inventory influences in high financial risk and increase the inventory holding cost as well.

Regarding the requisition of spare parts, there will be a need of spare parts when aircraft components are failed or need replacement at their periodic time. Normally, if the spare parts are available in stock, the demands are able to be immediately satisfied, then the aircraft maintenance task can complete on schedule and generate good service level. However, if there is shortage of spare parts, it will lead to flight delay or flight cancellation which incur the extra costs and customer un-satisfaction with the company service. The current problem of Company A is the company only focuses to estimate the future demand by mainly considering on the scheduled maintenance in which the parts need to be replaced at the specified periodic time and less attention in the unscheduled maintenance such as from unforeseen defects which are mostly irregular demand pattern and it is difficulty in part demand forecasting. Since the demand in the future has a very important role for inventory management and production planning, therefore the accurate forecasting method is necessary for the company in order to develop inventory management system for approaching the company goals.

These below tables are shown the historical statistic of spare part service level for the one of critical case of Company A during 2017 to 2019 in Table 1.2 – 1.4.

Table 1.2: Spare part service level of Company A during 2017

	TOTAL CASE	IN LIMIT	OVER LIMIT ≤ 3	OVER LIMIT ≤ 5	OVER LIMIT ≤ 7	OVER LIMIT ≤ 10	OVER LIMIT ≤ 15	OVER LIMIT >15
Jan-17	14	10	2	1	-	1	-	-
Feb-17	13	9	1	-	1	1	1	-
Mar-17	24	19	1	-	2	1	-	1
Apr-17	18	15	2	1	-	-	-	-
May-17	12	8	1	1	1	1	-	-
Jun-17	29	25	-	1	2	-	1	-
Jul-17	22	18	1	2	1	-	-	-
Aug-17	10	7	2	1	-	-	-	-
Sep-17	15	10	1	2	1	-	-	1
Oct-17	29	23	4	-	1	1	-	-
Nov-17	6	4	-	1	1	-	-	-
Dec-17	5	4	1	-	-	-	-	-
SERVICE RATE	77%							

Table 1.3: Spare part service level of Company A during 2018

	TOTAL CASE	IN LIMIT	OVER LIMIT ≤ 3	OVER LIMIT ≤ 5	OVER LIMIT ≤ 7	OVER LIMIT ≤ 10	OVER LIMIT ≤ 15	OVER LIMIT >15
Jan-18	23	20	1	1	-	1	-	-
Feb-18	12	9	-	2	1	-	-	-
Mar-18	9	6	-	1	1	1	-	-
Apr-18	15	11	1	-	1	-	1	1
May-18	11	8	1	1	1	-	-	-
Jun-18	20	13	4	1	-	2	-	-
Jul-18	25	21	2	-	1	1	-	-
Aug-18	24	18	2	1	1	1	1	-
Sep-18	17	12	1	2	1	-	1	-
Oct-18	29	23	1	2	2	1	-	-
Nov-18	16	12	1	1	1	1	-	-
Dec-18	11	6	2	1	1	-	-	1
SERVICE RATE	75%							

Table 1.4: Spare part service level of Company A during 2019

	TOTAL CASE	IN LIMIT	OVER LIMIT ≤ 3	OVER LIMIT ≤ 5	OVER LIMIT ≤ 7	OVER LIMIT ≤ 10	OVER LIMIT ≤ 15	OVER LIMIT >15
Jan-19	10	5	1	1	1	-	2	-
Feb-19	6	4	-	1	-	1	-	-
Mar-19	16	12	1	1	-	2	-	-
Apr-19	20	18	-	1	1	-	-	-
May-19	16	12	1	1	-	1	1	-
Jun-19	22	18	2	1	1	-	-	-
Jul-19	15	11	-	1	1	-	1	1
Aug-19	15	9	2	1	1	1	1	-
Sep-19	24	18	3	1	1	1	-	-
Oct-19	19	16	1	-	1	1	-	-
Nov-19	28	24	1	1	2	-	-	-
Dec-19	12	8	1	1	1	1	-	-
SERVICE RATE	76%							

Although, service rates of these three years showed high values which were about 75-77% but in the missing percentage still made customer unsatisfied in the company service and increased company expenses. Moreover, the company goal is to be the largest low-cost airline in Asia. Therefore, the development of service rate is one of significant challenge for the company in order to upgrade valuable service.

1.3 Research Objective

The main objective of this research aims to compare the different forecasting methods and find the most suitable method to be the tool for aircraft maintenance planners to reduce the inaccuracy of forecasting for unscheduled spare part demands which have irregular demand pattern.

1.4 Hypothesis Development

From the research objective, it can be hypothetically developed base on the existing information that the accurate forecasting method can reduce the spare part unavailability occurrences which could consequently effect in aircraft schedule delay and incur the extra costs to the company.

1.5 Scope of the research

The intent of this research is to study, compare and evaluate 3 different forecasting methods for the irregular demand pattern by focusing on the aircraft component that falls into the most critical categorization if these parts are failed, no any allowable for flight permit and the aircraft will be immediately require to replace the parts otherwise the aircraft will not allow in the operation. More details of the selection scheme mention in Chapter 3. The three different forecasting methods, Croston's Method, Holt's Linear Method and Neural Network Method will be applied.

Since the company data accessibility of the historical record of spare part demands can be accessed furthermost backward up to year 2014 and the author intent to test and analyze the actual demand which were occurred at the Company A during its normal operation prior to Covid-19 pandemic situation that resulted the flight reduction and cancellation of the airline business which effected to the aircraft utilization and spare part consumption rate of the company. Therefore, the historical data during 2014 until 2019 have been used for this research.

1.6 Expected Outcomes

According to the research approach, the expected outcomes are to help the airline company to reduce the unaccurate of spare part demand forecasting and also reduce the consequent of unavailability of aircraft due to spare part shortage.

Chapter 2
Literature Review

This section of research involves 2 relevant topics which will be separately presented. The first part is about the literature that associating to the aircraft maintenance concepts and the second part will concern how to classify the irregular spare part demand pattern and the forecasting methods which could help the airlines to cope with these irregular demands including with the accuracy measurement.

2.1 Relevant Aircraft Maintenance Concepts

2.1.1 Primary Maintenance Process

The Civil Aviation Authority of Thailand (CAAT), 2016 recognized that the aircraft maintenances are comprised of 3 primary maintenance processes which are hard time, on condition and condition monitoring. The allocation and establishment of the primary maintenance process on each item is prescribed by the manufacturer's warranty. Basically, hard time and on condition maintenance are the actions that prevent failures to occur. But the condition monitoring is not, condition monitoring is the action which generate from the process and is required for further subsequent preventive actions.

2.1.1.1 Hard Time

The 'Hard Time' is a preventive aircraft maintenance process for the items such as component, system, part of structure which already known deterioration at an acceptable level at the periods of time in their services as aircraft flight hour, aircraft flight cycle or calendar time. These action process normally are about servicing, overhaul in accordance with the instructions stated in the relevant manuals. The items will be replaced or restored to such condition and can release to service for further specified period time until next maintenance. The failure of hard time item will directly effect on the airworthiness that the evidence has indicated it concerns to the wear or deterioration.

2.1.1.2 On Condition

The 'On Condition' maintenance process is also preventive maintenance process. But it differs from 'Hard Time' maintenance concept in which this process, the item will be tested or inspected at the specified periods in accordance with an appropriate standard to define whether it is able to continuing in service. The main purpose of On-Condition maintenance process is removing the items from their services before failure occur.

2.1.1.3 Condition Monitoring

The 'Condition Monitoring' is the aircraft maintenance process which is as a concept of implementing the corrective procedures and not a preventive action as 'Hard time' and 'On-Condition'. For this kind of maintenance process, the information of an item will be collected from its operational experiences then analysed and interpreted its continuing service

2.1.2 Inventory Classification

The International Air Transport Association, IATA (2015) presented that the inventory for aircraft has been classified into 3 types as Rotable inventory, Repairable inventory and Expendable inventory. The different of these 3 types in each determinant are as follows,

- Scrap rate. Rotable inventory have slightly low or even negligible scrap rate whereas Repairable inventory will have scrap rate to be considered in spares calculation, planning activity and contract and Expendable inventory will have 100% scrap rate by it will be discarded upon removal.

- Financial. Most of airline operators consider Rotable and Repairable inventory as an asset in aspect of an accounting department and also depreciate on the schedule. But expendable inventory will be considered as an asset only if they are kept at the warehouse. Once issued and used, it will be expensed to the department which consumed or installed these expendable inventories.

- Life-cycle. Relevant to the scarp rate, a life cycle relates to the persistence and durability of the component. Rotable inventory is considered as repairable indefinitely by getting through the repair or overhaul process many times and mostly persist in the inventory until fleet retirement. While the durability of repairable inventory is limited by its scrap rate, the certain percentage of repairable will be computed and continually replaced during the repair process by its scrap rate. Moreover, the distinction between Rotable and Repairable inventory are Rotable inventory is more often tracked for the accumulated hours and cycles of the component while Repairable inventory is not often tracked during its service time in regard to hours and cycles. Expendable inventory will persist in the inventory only until it is issued and installed on the aircraft.

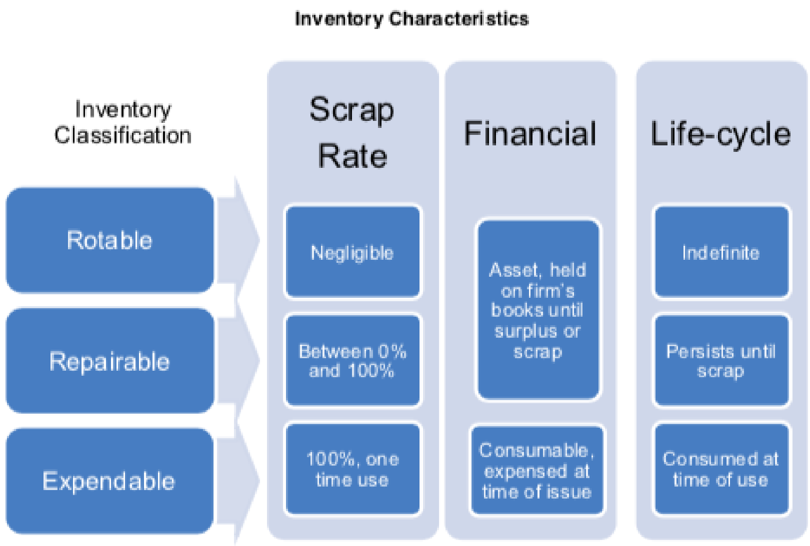

Figure 2.1: Aircraft inventory classifications and characteristics
Source: Guidance Material and Best Practices for Inventory Management (P.4) by IATA (2015)

2.1.2.1 Rotable Inventory

Rotable inventory is the restorable inventory that can be fully serviceable condition repeatedly over the life time period of the related aircraft component. By the scrap rate of Rotable inventory is assumed to be very low. In fact, Rotable inventory also has a scrap rate but the scrap rate can be so slight as to be inconsequential. The scrap rate of Rotable inventory may result of the related incidents such as Foreign Object Damage (FOD), bird strike, ground damage to aircraft or damage occur during the maintenance at installation or removal process or in shop maintenance etc. Since Rotable part is generally high cost therefore upon failure, it is more economical to repair rather than replace by new purchase.

2.1.2.2 Repairable Inventory

Repairable inventory is generally close to Rotable inventory but the one significant distinction is Repairable inventory has higher scrap rate rather than Rotable inventory. Airline will define their own differentiation between Rotable and Repairable inventory is depending on their own economic analysis. For some airlines might have only Rotable and Expendable categories not even classify their inventory as Repairable. However, Repairable classification is still important to vendors and airlines because of the terms and conditions about Rotable will not apply to Repairable in some situations such as exchange agreement, leasing, loaning parts to other airlines or pooling arrangement.

2.1.2.3 Expendable Inventory

Expendable Inventory is the inventory which is 100% scrap rate and need 100% new unit replacement after use and removal.

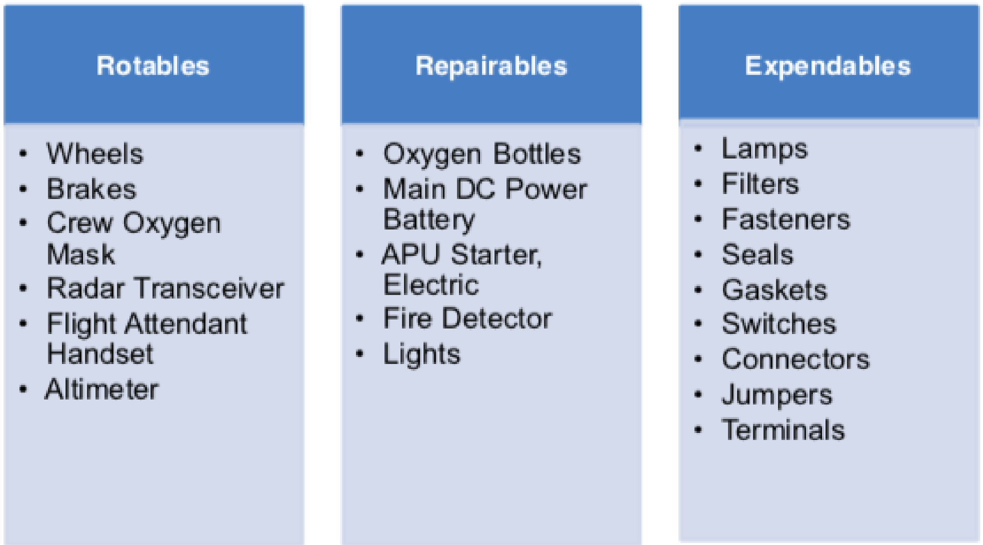

Figure 2.2: Examples of spare parts allocated by material type

Source: Guidance Material and Best Practices for Inventory Management (P.5) by IATA (2015)

2.1.3 Aircraft Minimum Equipment List (MEL)

The minimum equipment list (MEL) is a document manual for the aircraft operators to alleviate the regulations. In which, all of installed components on the aircraft must be operative at the time of flight. Some of components may be allowed to be inoperative but require some procedures for an aircraft to operate under the specific conditions in order to maintain the aircraft's airworthiness for a period of time until the repair or replacement are accomplished at the earliest opportunity. The MEL is originated from the aircraft manufacturer's Master Minimum Equipment list (MMEL) which had been approved during the certification of the aircraft. The aircraft operators then use MMEL and add on their operational conditions and more particular equipment in order to develop their own MEL to permits the aircraft operation with the inoperative equipment. The MEL may include the items not stated in the MMEL but it cannot be less restrictive than MMEL. (NATA, n.d.)

The repair interval of MEL has been categorized as follows,

1) Category A – There is no specified standard interval.
2) Category B – The inoperative item must be repaired within 3 consecutive calendar days or 72 hours excluding the day of discovery.
3) Category C - The inoperative item must be repaired within 10 consecutive calendar days or 240 hours excluding the day of discovery.
4) Category D - The inoperative item must be repaired within 120 consecutive calendar days or 2880 hours excluding the day of discovery.

In this research, the author will focus on the Rotable part which has categorized in MEL category A no standard time interval is specified if the components are inoperative to be studied in next section.

2.2 Relevant Methods

2.2.1 Demand Classification Method

Many authors tried to classify the demand pattern in order for identifying the best fit forecasting method for each demand category. Firstly, Croston (1972) evaluated demand based on the size of demand and the inter-demand interval in order to provide the method of forecasting for intermittent demand. Then, Williams (1984) studied variance of the order number and their size with given the lead time to classify the items into 5 categories according to high and low demand sporadic and size. But Eaves and Kingsman (2004) found that the classification which proposed by Williams did not provide the solutions to differentiate the steady demand solely based on the transaction variability.

However, a concept of Average Demand Interval (ADI) which was introduced by Johnston and Boylan (1996) is defined as per Equation 2.1 and then was supplemented by Syntetos et al. (2005) to introduce the coefficient of variation (CV) as per Equation 2.2.

Average inter-demand interval (ADI) is the average of time periods interval between two successive demands and express as Equation 1.

$$ADI = \frac{\sum_{i=1}^{N} T_i}{N} \tag{2.1}$$

Where, T_i = the time period between the two consecutive demands

N = the number of non-zero demand periods

Coefficient of Variation (CV) is the standard deviation of demand and divided by the average demand d_i and express as Equation 2.

$$CV = \frac{\sqrt{\frac{\sum_{i=1}^{N}(d_i^n - d_i)^2}{N}}}{d_i} \tag{2.2}$$

Where, $d_i = \frac{\sum_{i=1}^{N} d_i^n}{N}$

N = the number of non-zero demand periods

d_i^n = the demand at time t

d_i = the average of non-zero demand

There are 4 categorizations for the demand types as smooth, intermittent, erratic and lumpy based on modified the criteria of William (1984) which have the definitions of each category as follows,

- Smooth demand ($ADI \leq x, CV^2 \leq y$). It is regular demand occurrence over time period with less quantity of variations and not very intermittent and erratic. This demand pattern does not raise any difficulties of inventory control and any significant in forecasting.
- Intermittent demand ($ADI > x, CV^2 \leq y$). It is extremely sporadic demand and no highly variable in demand sizes.
- Erratic demand ($ADI \leq x, CV^2 > y$). It is regular demand occurrence over the time period but high variation in the quantity.

- Lumpy demand ($ADI > x, CV^2 > y$). It is also extremely sporadic demand with many zero-demand periods and high variation in the quantity.

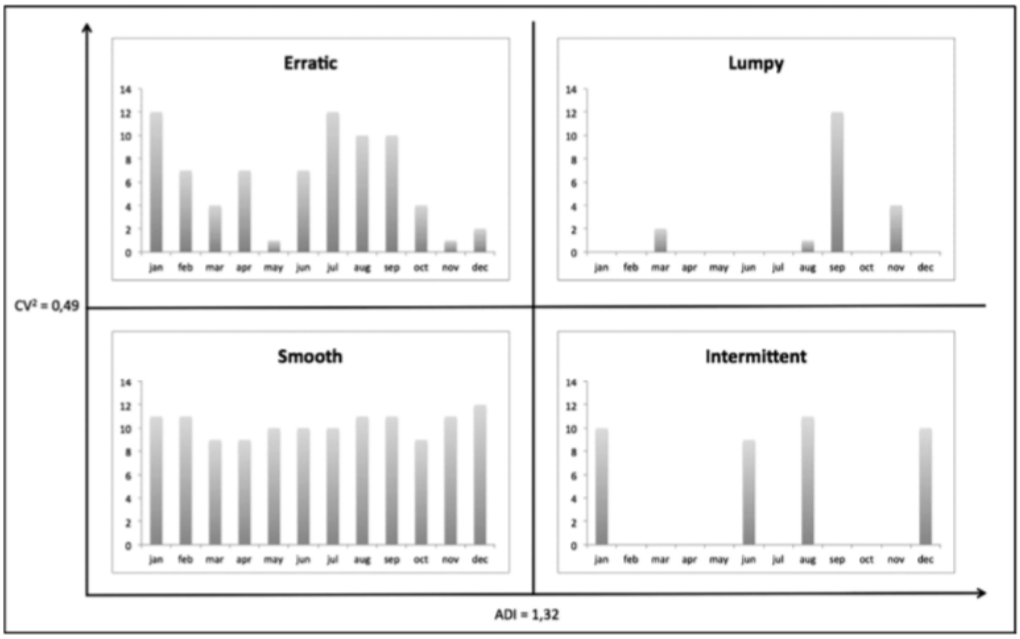

Figure 2.3: Demand patterns as Erratic, Lumpy, Intermittent and Smooth
Source: Spare parts management for irregular demand items (P.59) by Costantino, Di Gravio, Patriarca and Petrella (2018)

Smooth and erratic demand present the regular demand by smooth demand has little variability in demand sizes than erratic demand. Whereas, intermittent and lumpy demand present the irregular demand intervals over the periods by intermittent demand having little variability in demand sizes than lumpy demand. In this paper, the author uses the cut-off values of ADI = 1.32 denoted by x and the CV^2 = 0.49 denoted by y that reflect a measurement of the different forecasting methods (Williams, 1984).

2.2.2 Demand forecasting

Demand forecasting has an important role for the inventory management system. As Gamberini et al. (2005) stated that “good forecasts of spare part demand consumption are important and influence both airline fleet performance and economic returns on capital”. Even using the advanced inventory management model but base on the poor demand forecasting, it will not generate the satisfying results. So that, the way to build a useful inventory management system is to combine the solid inventory management systems with the efficient demand forecasting methods.

Ghobbar and Friend (2003) mentioned the difficulty in forecasting spare parts demand for aircraft maintenance is the problem that affected the aircraft industry worldwide. The great difficulty of sporadic demand forecasting is high variability of demand which are the size of demand and the interval time between demands. The traditional forecasting methods should not be applied to predict the irregular demand pattern for spare parts management (Willemain, Smart and Schwarz, 2004). The reason is that demand is stochastic resulting in the inaccurate results (Morris, 2013; Shenyang, Zhijie, Qian and Chen, 2017). Many authors had emphasized the importance of their studies and the methods to predict these sporadic demands to reduce the uncertainty of forecasting these spare parts demand pattern.

2.2.2.1 Forecasting Overview

According to Makridakis (1998), there are 2 major categories of the forecasting techniques as,

1. Quantitative: For sufficient quantitative information is available.
2. Qualitative: For no or only little quantitative information is available but there is adequate qualitative information. For example, predicting the communication speed and forecasting how large increase of the oil prices which affect to its consumption.

However, if no or only little information is available both in qualitative and quantitative categories. It can be considered as “unpredictable” scheme. For example, predicting the discovery of a new energy form or the effect from the interplanetary travel.

In this research, the quantitative forecasting technique will be studied which the approaches can be divided into 2 major groups as follows,

1. Time series: An approach to predict the continuation of historical patterns. The methodological approaches are as,

- Decomposition methods – The approaches that try to decompose time series by identifying a trend-cycle or seasonal component such as Additive Decomposition, Multiplicative Decomposition.
- Smoothing methods – The approaches that use the mean of historical data as forecasting tool such as Simple Average, Moving Average, Single Exponential Smoothing, Holt's Linear Method (trend-adjusted), Holt-Winters' Multiplicative and Additive Methods (seasonal and trend adjusted).

2. Explanatory: Understand how explanatory variables. For example, the prices and advertising affect to sales such as Simple and Multiple Regression Method.

In order to apply a quantitative forecasting, 3 conditions must exist which are,

1. The availability of historical information
2. The information can be quantified as the numerical data
3. Assumption that the pattern in the past will carry on into the future

2.2.2.2 Traditional Time-Series Forecasting Methods

Boylan and Syntetos (2009) stated that intermittent demand pattern is common among spare parts. It is characterized by the sequences of zero demand and intersperse by the occasional non-zero demand observations. As indicated by Nikolopoulos et al. (2012), the academic literature of the demand forecasting on intermittent focused on the adaptation of traditional time-series forecasting methods such as Simple Exponential Smoothing and Moving Average which are still widely used in practice. (Bacchetti and Saccani, 2012)

The intermittent demand forecasting emerged as another branch of forecasting demand after the Croston's method introduced in 1972. The study of Croston (1972) on the intermittent demand is the exploring study that addressed the sporadic demand forecasting. Croston method is a parametric method which developed from the time series exponential smoothing method. Silva, Santos, Dias and Tadeu (2019) stated that the Croston's method is the most widely used approach for forecasting irregular demand. Most of the conducted research after that were based on the Croston's method (Nikolopoulos et al, 2012). He claimed that his method was theoretically superior and unbiased. However, there were the acclaimed theoretical superiority and also empirical evidence suggested that the gained performance of Croston's Method was moderate or even loss the performance when comparing to the simple forecasting techniques (Syntetos and Boylan, 2001).

In 2005, Gamberini et al. conducted study of analyzing the forecasting techniques behaviour when forecasting the lumpy demand. Lumpy demand is one of four demand classification categories based on Syntetos and Boylan's modified William's criteria (Syntetos, Boylan and Croston, 2005). This study evaluated and compared the performance of many forecasting methods as Single Exponential Smoothing, Trend-adjusted Exponential Smoothing, both Additive and Multiplicative Holt's Winters' Method, Moving Weighted Averages, Exponentially Weighted Averages, Croston's Method.

In 2012, Bacchetti et al. (2012) indicated that most of the comparison studies that support the superiority of Croston's method and the variants which used in the method over the traditional time series methods referred to as the method was the best performance. However, there was still no consensus which the forecasting method is the best for predicting spare parts demand.

2.2.2.3 Neural Network Methods

Neural Networks method is another class of forecasting method for sporadic demand which is useful for modeling nonlinear relationship between the variables. The Neural Network model consists of many inputs and an output. The main capability on processing of the neural network depending on the multiplied weights with each input values.

There are studies in lumpy demand forecasting by using neural network had been done before as Carmo. Also, Rodrigues (2004) applied the Neural Network model by using Radial Basis Function (RBF) on 10 irregularly spaced time-series which described to be sufficient models for the forecasting of irregularly spaced time series in short term and generate the better performance of forecasting than alternative approaches by taking the correlation of nonlinear into account. Then, Gutierrez et al. (2008) developed the Neural Network method as a multilayer perceptron (MLP) trained by the back-propagation (BP) algorithm. This research intention was to assess the Neural Network based approach that is the superior alternative than the traditional approaches in order to model and forecast the lumpy demand. Moreover, Amin-Naseri and Tabar (2008) also utilized the generalized regression neural network (GRNN) for forecasting the spare parts which had lumpy demand and showed that the neural network techniques lead to more accurate forecasting than the conventional methods. According to the characteristic of spare parts demand, a multi-layered perceptron (MLP) trained by a back-propagation (BP) which proposed by Gutierrez et al (2008) and commonly used method in the literature has been developed for forecasting the demand in this study.

2.2.2.4 In Summary

Choosing the best forecasting method for an intermittent demand is a very difficult task and the literature still does not conclude which method performs the best (Babai, Ali and Nikolopoulos, 2012). Many companies still use simple exponential smoothing and Mean Time Between Removals (MTBR) methods to forecast their spare part demand (Muller, 2019). However, the studies of Ghobbar and Friend (2003) had a question to the use of these methods since they consistently generated the poor forecasting results on the intermittent demand.

For the intermittent demand data, the time series exponential forecasting Croston's method is still considered the standard method in forecasting. Although the Croston's method and the variants seem adequate for forecasting intermittent data but there are some constraints of the level of lumpiness that may be dealt with the parametric distribution. More recently, other approaches were studied a non-linear forecasting method, neural network which is the mathematical model that try to imitate the way of human brain think to work (Makridakis, Wheelwright and Hyndman, 1998) and bootstrapping.

Moreover, the comparison between non-parametric and parametric forecasting methods had also been topic of discussion in literature. In 2004, Willemain et al. (2004) compared the performances of single exponential smoothing method, Croston's method and bootstrapping method and concluded that the bootstrapping approach had improved the forecasting accuracy when comparing to other 2 methods.

Regarding the neural network forecasting, there are the expectation that this forecasting technique can deal with the unusual features and irregularities in the time series of interest. However, this technique is no explicit model and providing black box approach to the forecasting and does not allow much understanding of the data because. (Makridakis, Wheelwright and Hyndman, 1998).

For this section, the study of Syntetos et al (2005) are used for the conclusion for selecting the forecasting methods to be studied. The decision is supported by the fact that most of literature supported the superiority of Croston's method. In addition, to allow forecasting data with trend-adjused, therefore Holt's Linear Method is also applied. Another method, Neural Network is also considered to evaluate and compare the performance.

2.2.3 Forecast Accuracy Measurement

To measure the appropriateness of the forecasting methods on the data set given and analyze how well the forecasting methods can predict the data and comparing with the data that are already known.

If the actual observation for the time period t is defined by Y_t and the forecast value for the same period is defined by F_t, then the error (e_t) is then defined as Equation 2.3 (Makridakis, Wheelwright and Hyndman, 1998)

$$e_t = Y_t - F_t \tag{2.3}$$

If there are the actual values and the forecast values for n time periods, therefore there will be n error terms. The standard statistical measurement can be defined as follows

Mean error

$$ME = \frac{1}{n}\sum_{t=1}^{n} e_t \tag{2.4}$$

Equation 2.3 can be applied to calculate the error in each time period and can be then averaged in a form the mean error as Equation 2.4. However, the ME is able to tell only if there is under-forecasting or over-forecasting called the forecasting bias. The positive and negative errors will cancel one another out therefore, the ME is likely to be small value and does not provide much indication of the typical errors. The positive ME values point out that the forecast values are too low, while the negative ME values point out the forecast are too high. However, the forecast method will be unbiased if ME value is close to zero.

Mean absolute error

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| \quad (2.5)$$

Mean squared error

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \quad (2.6)$$

For MAE, the error will be made to be positive error by taking the absolute value and then average its results. Similarly, to the MSE which will be made to positive by squaring its values and then average as well. The MAE is more understandable to inexpert person and the MSE usually use in the statistical optimization due to it is easier to deal with mathematically.

The relative or percentage error measurement is defined as,

$$PE_t = \left(\frac{Y_t - F_t}{Y_t}\right) x\ 100 \quad (2.7)$$

The relative measures which are often used,

$$MPE = \frac{1}{n}\sum_{t=1}^{n} PE_t \quad (2.8)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}|PE_t| \quad (2.9)$$

Equation 2.7 can be applied to calculate the percentage error at the time period and then average as Equation 2.8 to provide the mean percentage error. The positive and negative PEs can be offset one another therefore, the ME and MPE are likely to be small. The absolute values are then defined as the MAPE, Equation 2.9. The drawback of MAPE is the difficulty will arise when the data time series contain zero values, then the percentage error PE cannot be calculated and the computation involving PE will be meaningless.

Since lumpy and intermittent demand involves many zero demands period, the traditional definition of MAPE which involves the terms of $|e_t|/Y_t$ is failed. Hoover (2006) suggested many variations on the MAPE, the adjusted MAPE (A-MAPE) which is the ratio of MAE and MEAN is therefore applied in this research.

$$A - MAPE = \frac{\frac{\sum_{i=1}^{n}|Y_t - F_t|}{n}}{\frac{\sum_{i=1}^{n}Y_t}{n}} \tag{2.10}$$

Or

$$A - MAPE = \frac{\sum_{t=1}^{n}|E_t|}{\sum_{t=1}^{n}Y_t} \tag{2.11}$$

To select the best forecasting method on the irregular demand pattern is a very difficult task and the literatures did not conclude which method perform the best (Babai, Ali and Nikolopoulos, 2012).

In this research, MSE will be used to find the optimization value of smoothing constant (α and β) of the exponential smoothing forecasting, Croston and Holt's Linear Methods. And ME (forecasting bias), MAE and the adjusted MAPE will be applied to measure the performance of forecasting methods in the test set time series in order to find the best fit forecasting method of the given data set.

Chapter 3
Research Methodology

This chapter aims to present the overview of research methodology and approach the achievement of research objectives. There are 4 procedures including Data selection, Demand classification, Demand Forecasting and Forecasting Accuracy Measurement. All sections are outlined as shown in Figure 3.1.

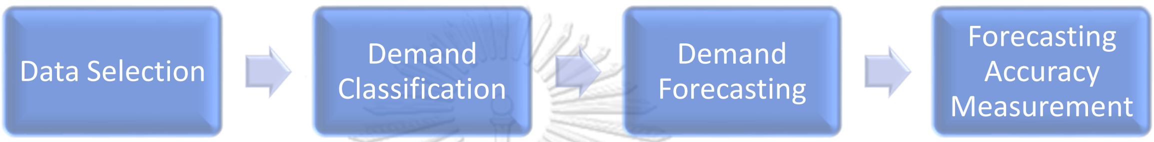

Figure 3.1: Research methodology procedures

3.1 Data Selection

Data selection is applying all available data in the ERP-AMOS from company's stock control system in both of relevant and non-relevant information. It will use a dataset with 6 years (72 months) of historical part transaction which is from January 2014 – December 2019. Moreover, the condition of relevant data selection is categorized from the importance of aircraft spare parts for the aircraft operation and also, there are divided into three stages including Primary maintenance process, Spare part classification and MEL release.

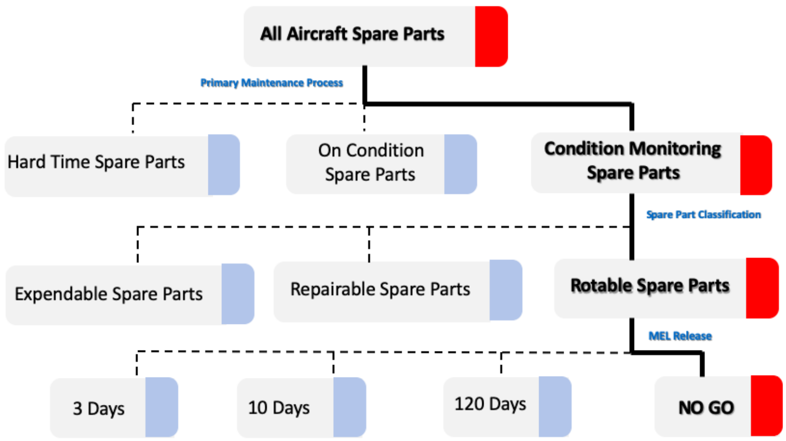

Figure 3.2: Aircraft spare part's focused group diagram

3.1.1 Primary Maintenance Process

The first stage is classified all data by using condition of Primary maintenance process so there are separately in three groups which are Hard time, On-condition and Condition monitoring spare parts. So, the research focuses on Condition monitoring spare parts since this part is not the preventive maintenance neither Hard time nor On-condition spare parts. As can be seen, there is no specified period in flight hour, flight cycle or calendar time to be set from manufacturers in order to inspect or remove the part from aircraft. As a result, this part will be used until failure so it affects to poor management of company and also, there is requirement to cope with the unforeseen occurrences which avoids to affect in the flight operation schedule.

3.1.2 Spare Part Classification

This stage is spare part classification from Condition monitoring spare parts. In this research, it will focus on Rotable spare parts group because this group is able to repeatedly restored to fully serviceable condition over their life period neither consumable nor expendable parts. In addition, Rotable spare parts can enhance economy of the company if there is well management.

3.1.3 MEL Release

The last step is considered in MEL release for aircraft operation and there will be selection in 'No go' or Category A item of MEL release because there is no standard interval specification to allow the aircraft operation if there are some parts are inoperable. Therefore, spare parts in 'No go' is significant group to manage in well operation in order to avoid unexpected situation and strengthen the company performance.

3.2 Demand Classification

To identify the classification the demand pattern of each item, the classification performs according to the method suggested by Syntetos et al (2005). The average inter-demand interval (ADI) and the squared coefficient of demand variation (CV^2) are both calculated for the demand record of each item which been selected during January 2014 – December 2018 period. Base on this, the demand pattern is classified as erratic, smooth, lumpy and intermittent demand pattern by use the cut-off values of ADI = 1.32 and CV^2 = 0.49 as mentioned in the literature review section.

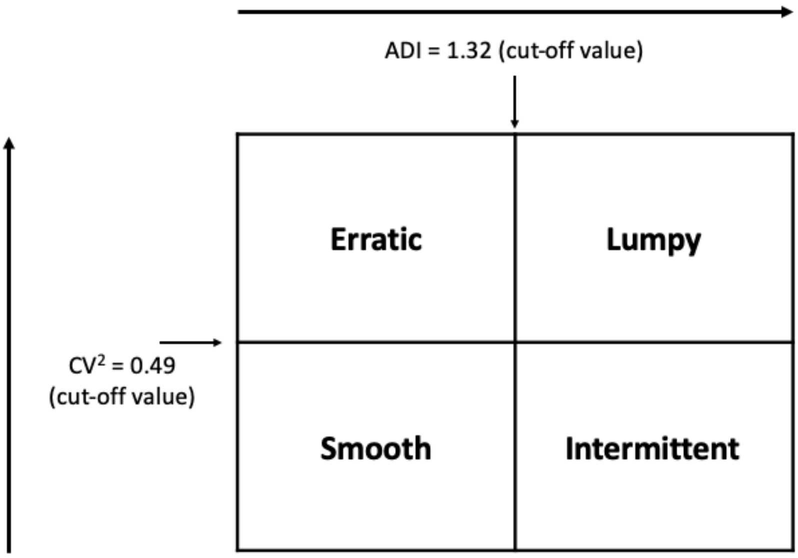

Figure 3.3: Demand pattern categorizations

3.3 Demand Forecasting Methods and Accuracy Measurement

3.3.1 Demand Forecasting Overview

To set the stage for forecasting, Figure 3.4 represents the forecasting scenario. From a certain point of reference on the time scale and if look backward to the past observation and forward into the future. When selected the forecasting methods and fit the method to the known data, the fitted values can be obtained and can calculate the fitted errors then examine the forecasting errors.

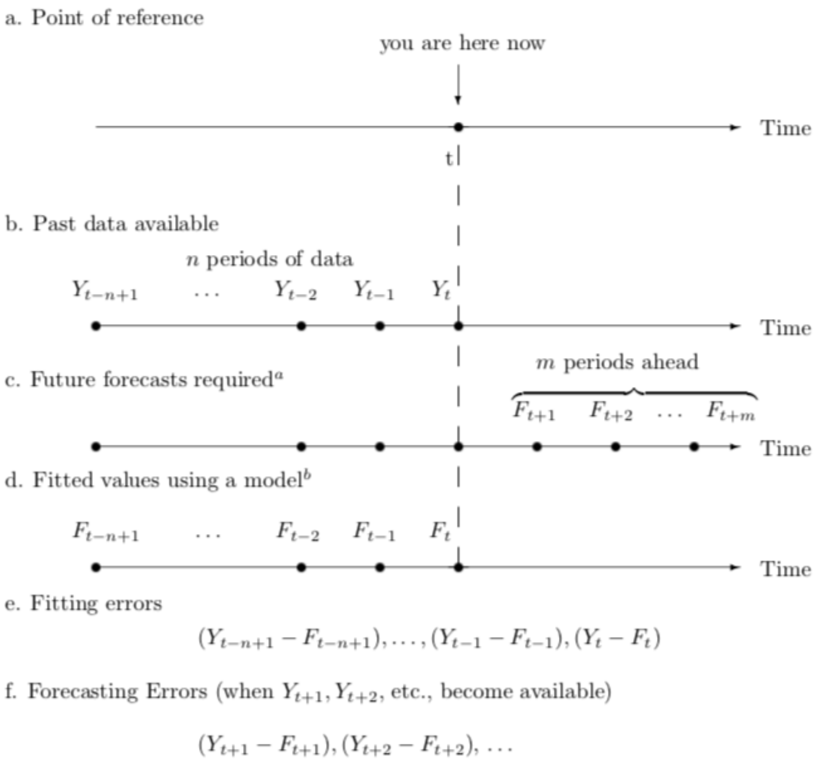

Figure 3.4: The forecasting scenario

Source: Forecasting: Methods and Applications. 3rd edition (P.139) by Makridakis, Wheelwright and Hyndman (1998)

The procedures for evaluating the forecasting methodology are as follows,

Step 1 – To divide the time series of data set into 2 set (initialization and test set) and conduct the evaluation for forecasting method.

Step 2 – To select a forecasting method.

Step 3 – The initialization set is used in order to get started the forecasting method. The estimations of any parameter values, trend and seasonal components are made at this step.

Step 4 – To apply a forecasting method over the test set and see how well it does on the data set which were not used in estimation stage of the model. After forecasting performed, the forecasting error is determined to measure the accuracy over the test set. This is an iterative phase to find the optimal values of initial parameters. The initialization process's modification or finding the optimum values of parameters are required at this step. Test measure can be made by using MSE, MAPE, etc. to find the optimal values of parameters.

Step 5 – The forecasting method is finally appraised for the suitability for the given data set.

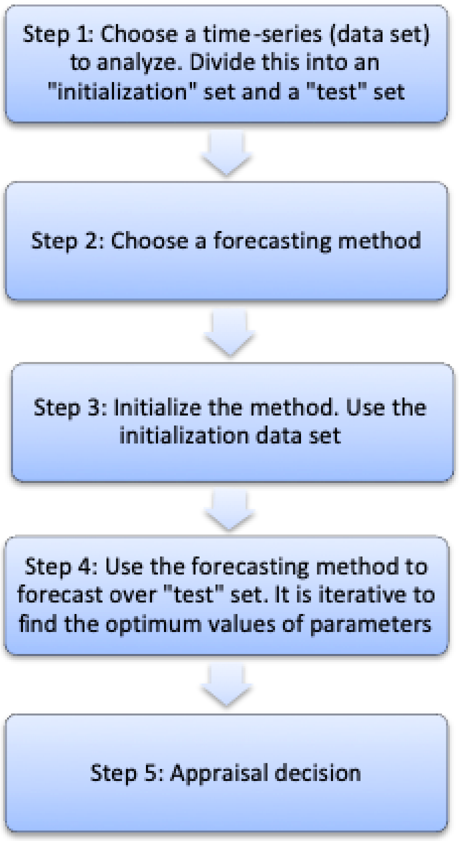

Figure 3.5: A procedure for appraising the forecasting methods

Refer to literature review section (Chapter 2), the forecasting methods which will be used in this research are 2 of time series exponentially smoothing forecasting methods which are Croston's and Holt's Linear methods and 1 of Neural Network, Multi-layer Perceptron (MLP) trained by Backpropagation (BP) algorithm. The time series data set are divided into 2 sets as an initialization set (January 2014 – December 2018) and a test set (January 2019 – December 2019). The initialization set is used to estimate parameters in the forecasting model and initialize the method. Forecasts are then made over the test set. The errors will be computed on the test set to measure the forecast accuracy and then evaluate the performance of forecasting methods. A Microsoft excel spreadsheet is used for computation of the time series exponential smoothing forecasting method, Croston's and Holt's Linear Methods. And MATLAB programming with Deep Learning Toolbox is used to model and calculate for the Neural Network method.

3.3.2 Demand Forecasting with Croston Method

In the algorithm of Croston method, the historical demands were separated into 2 series which are the non-zero demand and the inter-arrival time. Croston's method uses the exponential smoothing to forecast the non-zero demand size and inter-arrival time between the successive demands individually. Then, the forecast is calculated by using the ratio of the forecast value for the size of demand and the interval of demand. The notation are as follows,

$$Y_t = \alpha X_{t-1} + (1-\alpha)Y_{t-1} \tag{3.1}$$

$$P_t = \alpha Q_{t-1} + (1-\alpha)P_{t-1} \tag{3.2}$$

$$F_t = \frac{Y_t}{P_t} \tag{3.3}$$

Where, Y_t = The estimate mean size of non-zero demand at time t

P_t = The estimate mean interval between non-zero demands at time t

X_t = The actual demand at time t

Q = The time interval since last non-zero demand

α = Smoothing constant

A smoothing constant α is a parameter that has value between 0 to 1. When α is close to 0, the new forecast is very little adjustment but if is close to 1, the new forecast is the substantial adjustment the error in the previous forecast.

To initialize the method, the initial variables have been set as Table 3.1. The demand values and interval between non-zero demand of the initialization set have been used as the training data to find the optimal value of α between 0 to 1 by increment 0.1 and find α value which gives the minimum MSE. There are 11 values for the smoothing constant α will be computed. The value of α which generates the smallest MSE will be used for forecasting over the test set as shown in Figure 3.6. Then, the comparison between the forecasted values and the real observations during year 2019 have been made to measure the performance of the method by using ME, MAE and A-MAPE.

Table 3.1: The initial variables for Croston method

If $X_{t=1} > 0$	If $X_{t=1} = 0$
$Y_{t=1} = X_{t=1}$	$Y_{t=1} = 1$
$P_{t=1} = 1$	$P_{t=1} = 2$
$Q_{t=1} = 1$	$Q_{t=1} = 2$

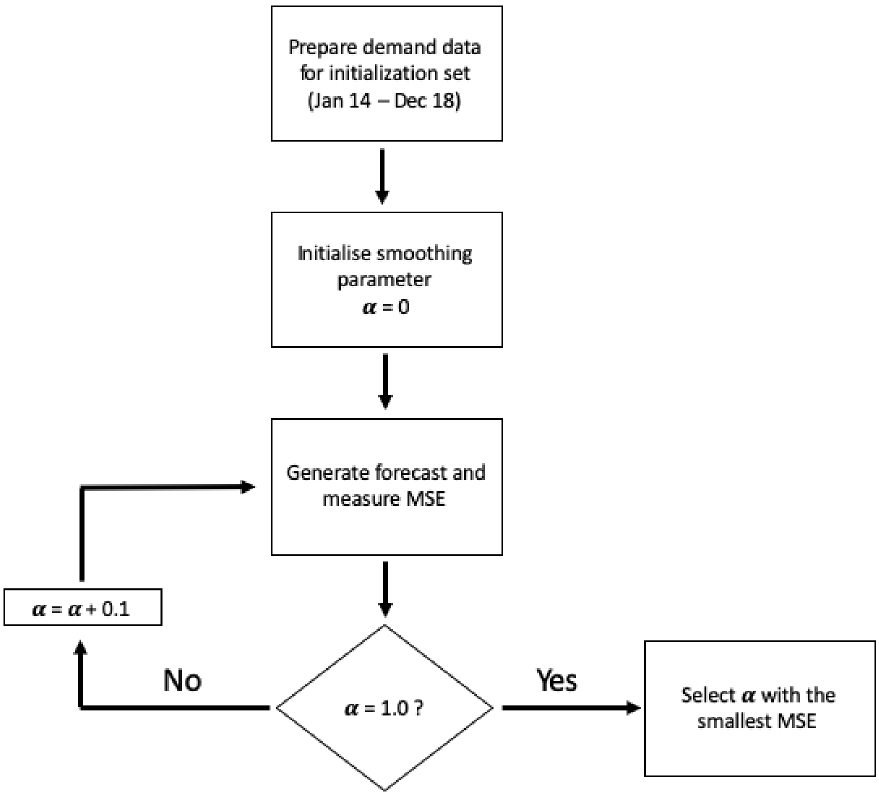

Figure 3.6: The algorithm of the Croston method for initialization set

3.3.3 Demand Forecasting with Holt's Linear Method

Holt (1957) expaned the single exponential smoothing to the linear exponential smoothing which allow forecasting the data with trend-adjusted. Holt's linear exponential smoothing forecasting method uses two smoothing parameters, α and β with the values between 0 and 1. There are 3 equations as follows.

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{3.4}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{3.5}$$

$$F_{t+m} = L_t + b_t m \tag{3.6}$$

Where, L_t = an estimate of level of the series at the time t

b_t = an estimate of slope of the series at the time t

m = the number of periods ahead to be forecast.

The algorithm of Holt's linear method to find the optimal values of smoothing constant parameters is similar to Croston method. But Holt's Linear method has 2 smoothing constant parameters α and β with the value between 0 to 1 for each constant. If increment by 0.1, there are 11 values for each constant parameter resulting in a total of 121 values in combination will be computed. The iterative are performed over the initialization set to find the optimal combination values of α and β. The combination with the smallest MSE will be selected and use to forecast for the test set. Then, the forecasting accuracy will be made by using ME, MAE and A-MAPE to evaluate the performance of the method over the test set.

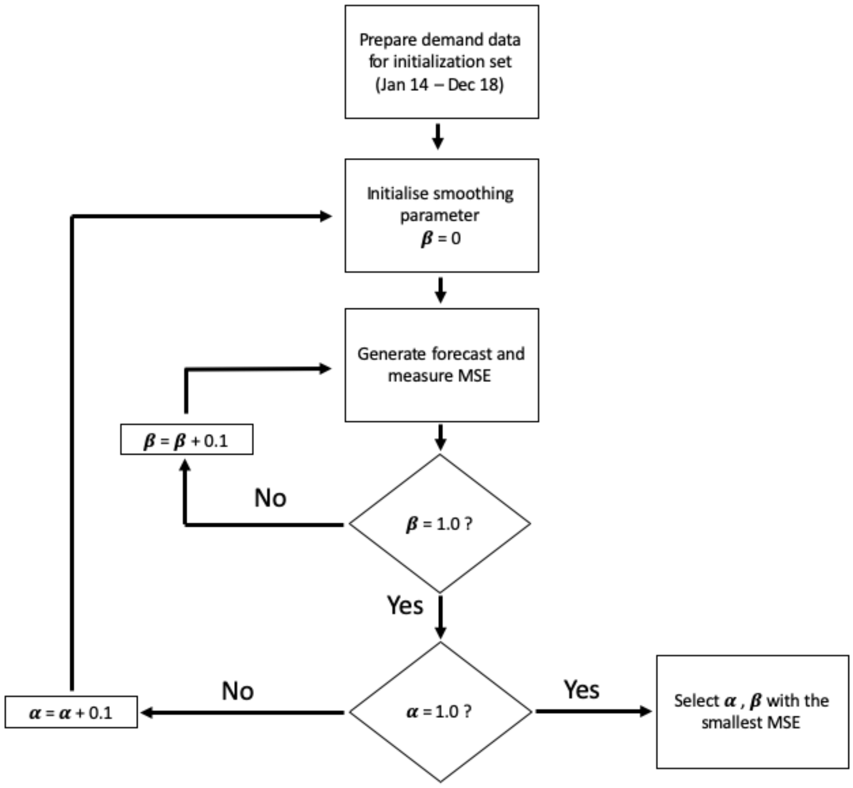

Figure 3.7: The algorithm of the Holt's linear method for initialization set

The initialization process of Holt's Linear exponential smoothing method is required two estimations in order to get the first smoothed value for L_1 and the other to get the trend for b_1. The initialization parameters are as follows,

$$L_1 = Y_1 \tag{3.7}$$

$$b_1 = Y_2 - Y_1 \tag{3.8}$$

or $$b_1 = \frac{(Y_4 - Y_1)}{3} \tag{3.9}$$

3.3.4 Demand Forecasting with Neural Network Method

Multi-layer Perceptron (MLP) trained by Backpropagation (BP) algorithm as proposed by Gutierrez et al (2008) has been selected for this study. According to Gutierrez et al

(2008), the structure of MLP network has 3 layers which are 1. Input layer which represents 2 variables 2. Hidden layer that has 3 nodes and 3. Output as shown in Figure 3.8. The 2 input variables are univariate data, the first one is demand values in monthly and another input is also derived from the demand data itself as well which are as follows,

1) The demand at the end of the immediately preceding period
2) The number of periods separating the last 2 non-zero demand transactions as of the end of the immediately preceding period

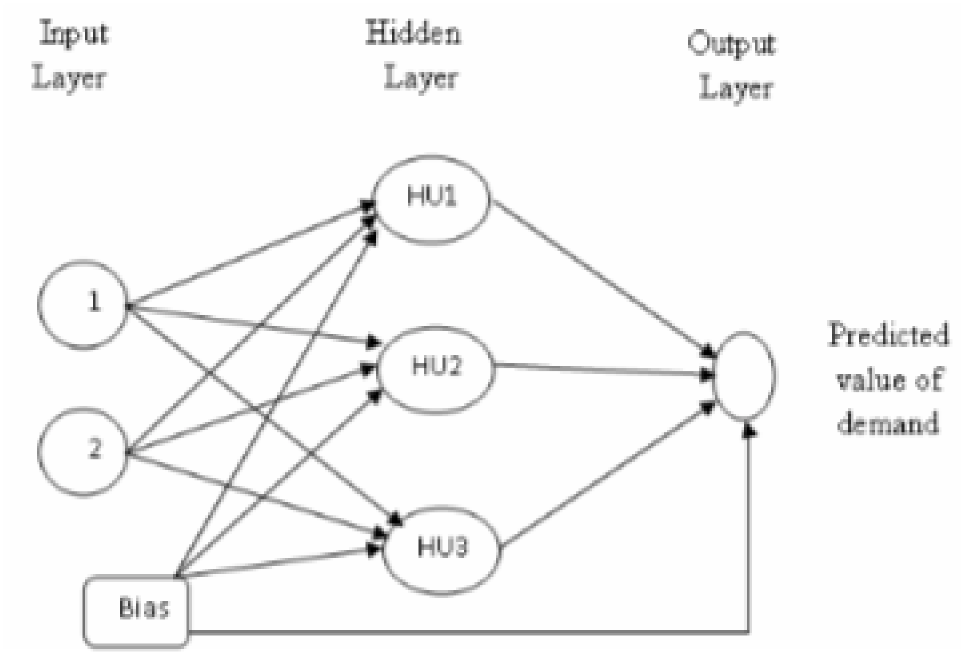

Figure 3.8: The MLP schematic diagram applied by Gutierrez et al (2008)
Source: A Hybrid Neural Network and Traditional Approach for Forecasting Lumpy Demand (P.1030) by Nasiri Pour, Rostami Tabar and Rahimzadeh (2008)

The output node will represent the forecasted value of demand transaction. There are 3 phases in modeling the neural network: (Gutierrez, Solis and Mukhopadhyay, 2008).
1. Training phase – In this phase, the network will learn the relationship between the values of input and output. And the defined error will be reduced in every iteration.
2. Validation phase – In this phase, the best solutions of weights and biases are saved.

3. Testing phase – The model's performance is measured with the new data values in this phase.

For the computation, MATLAB toolbox is used for this Neural Network Method. Primarily, the data set is divided into 3 sets which are training sets (first 48 months, Jan 14 – Dec 16), validation set (next 12 months, Jan 17 – Dec 18) and testing set (last 12 months, Jan 19 – Dec 19). After applying method to the data set of 40 demand series, then calculate the forecasting accuracy will be measured by using ME, MAE and A-MAPE on the test set.

3.3.5 Summary

All 3 forecasting methods have set the same generic algorithm of the initialization set and test set to predict the monthly demand values. The comparison between the forecasted values and the real observations during year 2019 have been made to measure the performance of each method by using the statistic measurement ME, MAE and A-MAPE. The best fit model can be used to forecast the future spare part demand of Company A.

Chapter 4
Results and Analysis

Upon the implement of forecasting method to the historical data series, the next step is to evaluate its performance. Each process will be evaluated separately in this chapter as Data Selection, Demand Classification, Demand Forecasting Methods and Forecasting Accuracy Measurement.

4.1 Data Selection

According to the data selection criteria as mentioned in Chapter 3, the spare parts which will be chosen to study in this research are focusing on the group of Rotable spare parts that their characteristics are important to the company both in term of financial and flight operation which are expensive items and usually low in demand. Finally, there are total 40 Rotable spare parts have been selected. Since it is expensive so keeping it as spares would be a considerable investment for airlines. Meanwhile, these parts are also critical to operations and there is also considerable cost associated if the aircraft down time (Ghobbar and Friend, 2003) as well. Therefore, this kind of spare parts are so crucial for the company need to be managed in well-planning.

4.2 Demand Classification

The datasets have been used in this research are the monthly demand of 40-part items which chosen from spare part inventory database of Company A. In order to classify the demand pattern, each item is used the historical demand record during 2014 – 2018 (initialization set) to calculate an average demand interval (ADI) and the squared coefficient of variation of demand (CV^2) for the demand classification process. The breakpoints for the boundary values of the demand classification matrix were 0.49 for CV^2 and 1.32 for ADI (Williams, 1984). The calculated values of ADI and CV^2 of 40 demand data are shown as Table 4.1. And in Table 4.2, it can be seen that throughout 60 months period, a large portion of the historical data series 36 items out of total 40 items correspond to intermittent demand pattern which is accounted for 90% of overall and only 2 items or 5% for each correspond to smooth and lumpy demand pattern and no erratic category. From this result, it can confirm that good example of irregular demand datasets has been selected in this sampling group.

Table 4.1: Calculated values of ADI and CV^2 for each component

Item	Component Part Number	Component Description	Average Demad Interval (ADI)	Squared Coefficient of Variation of Demand $(CV)^2$	Demand Classification
1	20790-03AC	VALVE OUTFLOW	20.00	0.13	Intermittent
2	2100-1025-02	COCKPIT VOICE RECORDER	1.88	0.24	Intermittent
3	AMU4031SA140204	AUDIO MANAGEMENT UNIT	20.00	0.13	Intermittent
4	1700667D	GROUND AND AUXILIARY POWER CTRL UNIT	7.50	0.12	Intermittent
5	640CC04A2Y00	200A SINGLE POLE CONTACTOR	6.00	0.25	Intermittent
6	1-002-0102-1830	STATIC INVERTER	15.00	0.12	Intermittent
7	TAAI3-03CE20-01	FIRST OFFICER SEAT	7.50	0.09	Intermittent
8	TAAI3-03PE20-01	POWERED PILOT SEAT	6.00	0.07	Intermittent
9	321000M03	SIDE STICK TRANSDUCER UNIT	3.53	0.11	Intermittent
10	6137-5	RUDDER TRIM ACTUATOR	5.45	0.24	Intermittent
11	9028A0004-01	POS.PICK OFF UNIT	15.00	0.12	Intermittent
12	DV8456701-5	TRAVEL LIMITATION UNIT	6.67	0.08	Intermittent
13	1407KID02-03	FUEL QUANTITY INDICATOR	4.00	0.09	Intermittent
14	C12CB0013	PUMP,APU FUEL	5.45	0.07	Intermittent
15	HTE190001-2	TWIN MOTOR ACTUATOR	7.50	0.12	Intermittent
16	HTE200002-1	FUEL TRANSFER VALVE ACTUATOR	4.29	0.12	Intermittent
17	L95F50-603	FUEL TK OVERPRESSURE PROTECTOR	4.00	0.18	Intermittent
18	SIC5059-14-20	FUEL QUANTITY INDICATION COMPUTER	8.57	0.12	Intermittent
19	4101002-11	POWER TRANSFER UNIT	5.45	0.11	Intermittent
20	450-2-3100-00	SWITCH PRESSURE HYD.	3.33	0.28	Intermittent
21	51154-04	ELECTRICAL MOTOR PUMP	12.00	0.33	Intermittent
22	974540	EATON ACMP	20.00	0.13	Intermittent
23	C82LL0010	DRAIN VALVE	4.29	0.09	Intermittent
24	38E93-6	WING ANTI ICING CONTROL VALVE	15.00	0.12	Intermittent
25	2100-4043-02	FLIGHT DATA RECORDER	6.00	0.12	Intermittent
26	2234320-01-01	FLT DATA INTERFACE MANAGEMENT UNI	5.45	0.22	Intermittent
27	088256-04644	ACCUMULATOR BRAKE	10.00	0.10	Intermittent
28	114122014	DOOR ACTUATOR, MLG	12.00	0.25	Intermittent
29	1905A0000-01	SAFETY VALVE L.G.S.	12.00	0.11	Intermittent
30	3022016-000	RELIEF VALVE	15.00	0.12	Intermittent
31	C24993000	ALTN BRAKE SELECTOR VALVE	12.00	0.11	Intermittent
32	D23119751	NLG ELECTRICAL BOX	6.00	0.07	Intermittent
33	D24001000	PARK BRAKE CTL VALVE	12.00	0.11	Intermittent
34	E21327006	BRAKING/STEERING CONTROL UNIT	2.22	0.28	Intermittent
35	528-70	WING TIP NAVIGATION LIGHT	5.00	0.10	Intermittent
36	528-80	WING TIP NAVIGATION LIGHT	3.16	0.08	Intermittent
37	35-0L0-1003-06	ECAM CONTROL PANEL	1.71	0.52	Lumpy
38	E21336000	NWS FEEDBACK SENSOR	15.00	0.55	Lumpy
39	568-1-27202-006	FUEL PUMP	1.20	0.45	Smooth
40	D53132110000	NOSE RADOME	1.13	0.30	Smooth

Table 4.2: Quantity and percentage of demand in each category

Nature of demand	Demand characteristic		Quantity of parts	Percentage (%)
	Demand occurrence	Demand size		
Smooth	Regular demand	Little variability	2	5
Erratic	Regular demand	High variability	0	0
Lumpy	Irregular demand	High variability	2	5
Intermittent	Irregular demand	Little variability	36	90
Total			**40**	**100**

The sampling demand data are plotted in Figure 4.1 – 4.3 to illustrate the behavior of monthly demand pattern in each category.

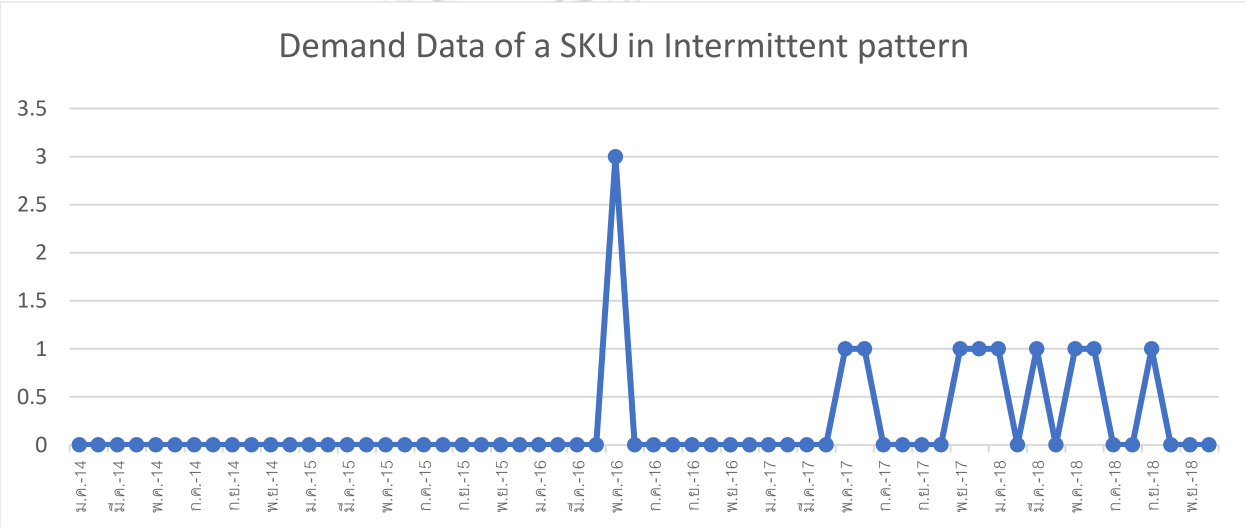

Figure 4.1: Example of monthly demand of one Stock Keeping Unit of Company A in Intermittent pattern

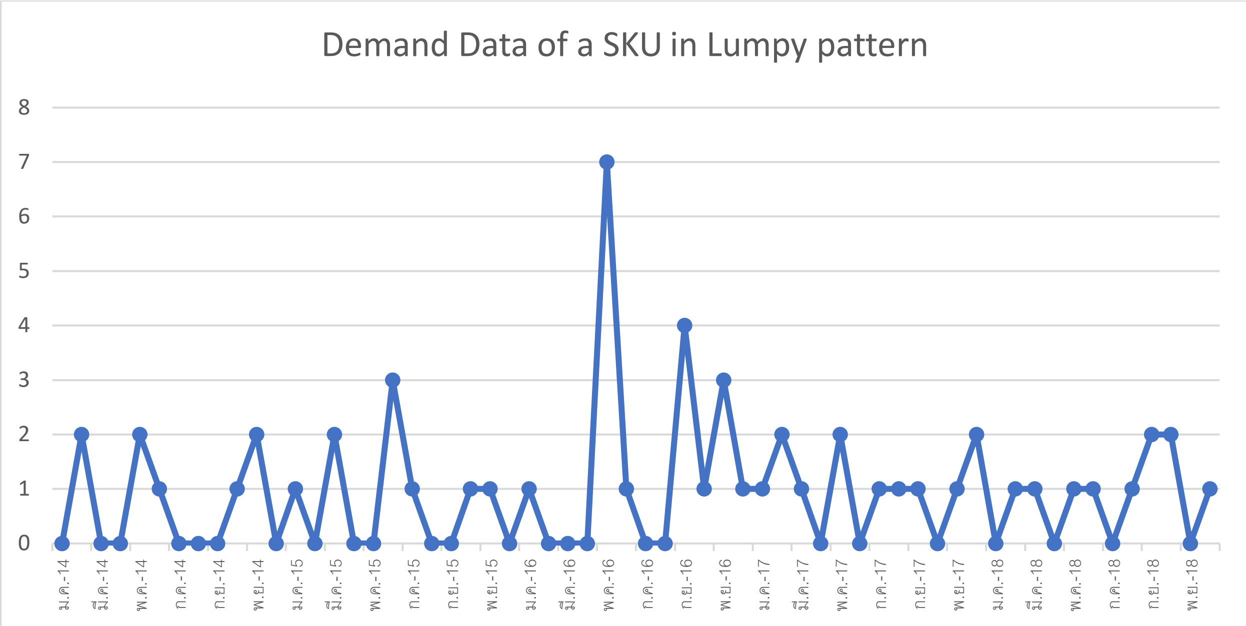

Figure 4.2: Example of monthly demand of one Stock Keeping Unit of Company A in Lumpy pattern

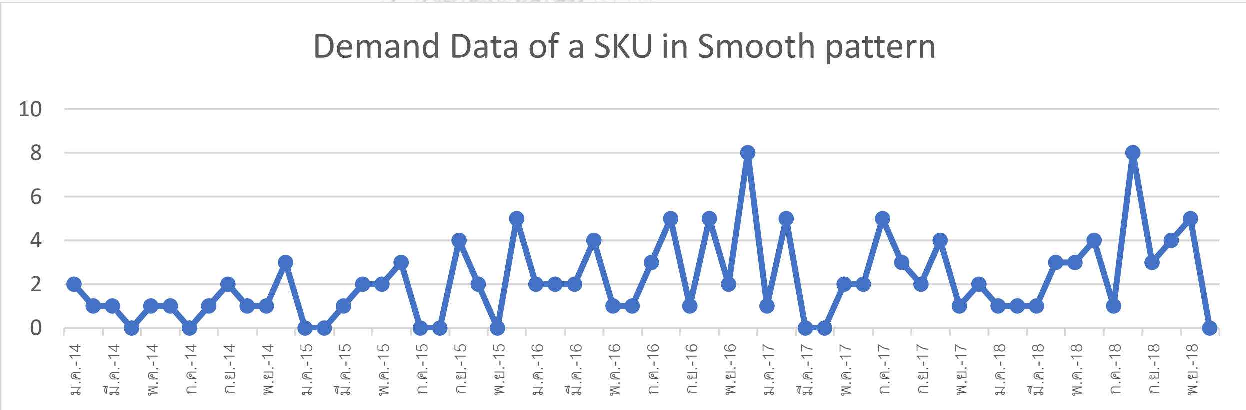

Figure 4.3: Example of monthly demand of one Stock Keeping Unit of Company A in Smooth pattern

However, since the majority demand pattern in this sampling group are falling into ‘Intermittent’ category and there are only a few items in lumpy and smooth which are too little data to analyze and conclude the forecast performance for these 2 demand patterns. Therefore, only intermittent demand pattern items (Item no. 1-36 in Table 4.1) will be further analyzed in this research.

4.3 Demand Forecasting

For this section, there are 2 analysis being performed. The first analysis is to estimate the parameter values in the initialization set data (January 2014 – December 2018) which is an iterative phase to find the optimal values of the initial parameters and initialize the methods. The second analysis is to measure the actual forecasting error on the test set data (January 2019 – December 2019). The forecasting methods will be used to forecast demand data and compare with the real demand observation. In this research, Croston's Method, Holt's Linear Method and Multi-Layer Perceptron trained with Back-Propagation approach of Neural Network Method have been employed to forecast monthly demand for the 36 Rotable spare parts in intermittent category of Company A.

For the first analysis, in term of the time series exponential smoothing forecasting method, the statistical measurement uses in this stage is MSE to compare the demand observations with the forecasts during 2014 – 2018. The MSE is used to find the optimal value of smoothing constants which give the smallest MSE for each data series for Croston's and Holt's Linear methods. There is 1 smoothing constant value for Croston's Method which is α and there are 2 smoothing constant values for Holt's Linear Method which are α and β. In each data series, the iterative actions are performed 11 times for Croston's Mehtod (α value from 0 to 1, increment by 0.1) and 121 times for Holt's Linear Method (α and β values from 0 to 1, increment by 0.1 for each). The specific obtained smoothing constant values which generate the smallest MSE for each item will be used to forecast and measure the forecast accuracy on the test set. The obtained values of α and β for each method are shown in Table 4.3.

Table 4.3: The obtained smoothing constant values and smallest MSE of Croston and Holt's Linear Methods

Item	Part number	Description	Classificaton	Croston Method		Holt's Linear Method		
				α	Smallest MSE	α	β	Smallest MSE
1	20790-03AC	VALVE OUTFLOW	Intermittent	1	0.103	0.1	0	0.104
2	2100-1025-02	COCKPIT VOICE RECORDER	Intermittent	0	0.86	0.1	0	0.824
3	AMU4031SA140204	AUDIO MANAGEMENT UNIT	Intermittent	1	0.102	0.1	0	0.105
4	1700667D	GROUND AND AUXILIARY POWER CTRL UNIT	Intermittent	0.3	0.285	0.1	0	0.269
5	640CC04A2Y00	200A SINGLE POLE CONTACTOR	Intermittent	0.4	0.277	0.1	0	0.264
6	1-002-0102-1830	STATIC INVERTER	Intermittent	0.4	0.113	0.6	0.4	0.297
7	TAAI3-03CE20-01	FIRST OFFICER SEAT	Intermittent	0.6	0.177	0.5	0.6	0.32
8	TAAI3-03PE20-01	POWERED PILOT SEAT	Intermittent	0.9	0.208	0.2	0	0.229
9	321000M03	SIDE STICK TRANSDUCER UNIT	Intermittent	0	0.352	0.1	0	0.323
10	6137-5	RUDDER TRIM ACTUATOR	Intermittent	0.1	0.311	0.1	0	0.29
11	9028A0004-01	POS.PICK OFF UNIT	Intermittent	1	0.12	0.1	0	0.12
12	DV8456701-5	TRAVEL LIMITATION UNIT	Intermittent	0.4	0.199	0.1	0	0.186
13	1407KID02-03	FUEL QUANTITY INDICATOR	Intermittent	0.5	0.3	0.1	0	0.29
14	568-1-27202-006	FUEL PUMP	Smooth	0	3.559	0.3	0.2	4.673
15	C12CB0013	PUMP,APU FUEL	Intermittent	0.4	0.21	0.1	0.1	0.186
16	HTE190001-2	TWIN MOTOR ACTUATOR	Intermittent	0.6	0.234	0.1	0	0.226
17	HTE200002-1	FUEL TRANSFER VALVE ACTUATOR	Intermittent	0.1	0.383	0.1	0	0.385
18	L95F50-603	FUEL TK OVERPRESSURE PROTECTOR	Intermittent	0.4	0.316	0.3	0	0.308
19	SIC5059-14-20	FUEL QUANTITY INDICATION COMPUTER	Intermittent	0.5	0.216	0.1	0	0.212
20	4101002-11	POWER TRANSFER UNIT	Intermittent	0.1	0.276	0.1	0	0.26
21	450-2-3100-00	SWITCH PRESSURE HYD.	Intermittent	0.1	0.707	0.6	0.2	1.011
22	51154-04	ELECTRICAL MOTOR PUMP	Intermittent	0.1	0.218	0.1	0	0.226
23	974540	EATON ACMP	Intermittent	0.3	0.096	0.7	0.4	0.266
24	C82LL0010	DRAIN VALVE	Intermittent	0.4	0.298	0.5	0.4	0.509
25	38E93-6	WING ANTI ICING CONTROL VALVE	Intermittent	0.2	0.09	0.4	1	0.207
26	2100-4043-02	FLIGHT DATA RECORDER	Intermittent	0.1	0.292	0.1	0	0.297
27	2234320-01-01	FLT DATA INTERFACE MANAGEMENT UNI	Intermittent	0.1	0.366	0.1	0	0.383
28	35-010-1003-06	ECAM CONTROL PANEL	Lumpy	0	1.674	0.4	0.4	3.011
29	088256-04644	ACCUMULATOR BRAKE	Intermittent	0.1	0.148	0.1	0	0.151
30	114122014	DOOR ACTUATOR, MLG	Intermittent	0.1	0.258	0.1	0	0.275
31	1905A0000-01	SAFETY VALVE L.G.S.	Intermittent	0.5	0.133	0.1	0	0.135
32	3022016-000	RELIEF VALVE	Intermittent	0.7	0.119	0.1	0	0.121
33	C24993000	ALTN BRAKE SELECTOR VALVE	Intermittent	0.4	0.128	0.7	0.4	0.272
34	D23119751	NLG ELECTRICAL BOX	Intermittent	0.6	0.208	0.1	0	0.196
35	D24001000	PARK BRAKE CTL VALVE	Intermittent	0.6	0.135	0.1	0	0.131
36	E21327006	BRAKING/STEERING CONTROL UNIT	Intermittent	0.1	0.862	0.1	0	0.788
37	E21336000	NWS FEEDBACK SENSOR	Lumpy	0.6	0.321	0.1	0	0.329
38	528-70	WING TIP NAVIGATION LIGHT	Intermittent	0.3	0.287	0.1	0	0.262
39	528-80	WING TIP NAVIGATION LIGHT	Intermittent	0	0.318	0.5	0.4	0.595
40	D53132110000	NOSE RADOME	Smooth	0.2	1.85	0.1	0.1	1.725

However, for Neural Network (Multi-Layer Perceptron trained with Back-Propagation approach) which is a typical stochastic model based on a black box approach, MATLAB programming with Deep Learning Toolbox is used to model the neural network in order to calculate and find the optimal values of weights and biases of inputs and hidden layers on the training phase (January 2014 – December 2017). For each item, the neural network with the best values of weights and biases are recorded on the validation phase (January 2018 – December 2018). Next, such model is used in the testing phase (January 2019 – December 2019) to measure the performance between actual and obtained values.

Finally, the integer forecast values on the test set data (year 2019) of each method are shown in Table 4.4 – 4.6.

Table 4.4: Actual data vs. Forecast values on year 2019 by Croston's Method

Item	Jan-19		Feb-19		Mar-19		Apr-19		May-19		Jun-19		Jul-19		Aug-19		Sep-19		Oct-19		Nov-19		Dec-19	
	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
2	2	1	1	1	0	1	1	1	4	1	0	1	3	1	1	1	2	1	2	1	1	1	1	1
3	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
7	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
8	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
9	1	1	1	1	1	1	1	1	0	1	0	1	0	1	1	1	1	1	1	1	1	1	0	1
10	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
13	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
14	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
16	1	0	2	0	1	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	1	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	2	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0
19	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0
22	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
25	0	0	2	0	3	0	0	0	0	0	0	0	2	0	1	0	1	0	1	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
28	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
30	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0
32	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	0	0
33	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
35	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	1	0
36	0	1	1	1	0	1	1	1	3	1	0	1	1	1	0	1	0	1	0	1	0	1	1	1

Table 4.5: Actual data vs. Forecast values on year 2019 by Holt's Linear Method

Item	Jan-19		Feb-19		Mar-19		Apr-19		May-19		Jun-19		Jul-19		Aug-19		Sep-19		Oct-19		Nov-19		Dec-19	
	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
2	2	1	1	1	0	1	1	1	4	1	0	1	3	1	1	1	2	1	2	1	1	1	1	1
3	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
7	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	1	0	0	0	0	1	0
8	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
9	1	0	1	0	1	1	1	1	0	1	0	1	0	0	1	0	1	0	1	1	1	1	0	1
10	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
13	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
14	0	1	0	1	1	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
16	1	0	2	0	1	1	0	1	2	1	1	1	0	1	0	1	0	1	0	1	0	0	0	0
17	0	1	0	1	0	0	0	0	0	0	2	0	0	1	0	0	1	0	0	1	2	0	0	1
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0
19	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0
22	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	1	0	2	0	1	0	0
24	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	1	0	0	1	0	0
25	0	0	2	0	3	0	0	1	0	1	0	0	2	0	1	1	1	1	1	1	0	1	0	1
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
28	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
30	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	1	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	1
32	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	0	0
33	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	1	0	0	0	0	2	0	0	1	0	1	0	0	0	0	2	0	0	1	0	0	0	0
35	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	1	0
36	0	0	1	0	0	1	1	0	3	1	0	2	1	1	0	1	0	0	0	0	0	0	1	0

Table 4.6: Actual data vs. Forecast values on year 2019 by MLP approach of Neural Network Method

Item	Jan-19		Feb-19		Mar-19		Apr-19		May-19		Jun-19		Jul-19		Aug-19		Sep-19		Oct-19		Nov-19		Dec-19	
	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
2	2	2	1	1	0	2	1	1	4	1	0	0	3	2	1	0	2	1	2	1	1	1	1	1
3	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
7	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
8	0	0	0	0	0	1	0	0	2	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
9	1	1	1	1	1	0	1	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	0	1
10	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
13	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
14	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	1	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
16	1	1	2	2	1	1	0	0	2	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0
17	0	1	0	1	0	1	0	0	0	0	2	0	0	0	0	1	1	1	0	0	2	1	0	1
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0
19	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	1
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0
22	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	2	1	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0
25	0	0	2	1	3	0	0	0	0	0	0	0	2	1	1	0	1	0	1	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
28	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
30	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	1	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1	0	0	0
32	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	0	1	0	0	0
33	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	2	1	0	0	0	0	0	1	0	0	2	1	0	0	0	1	0	1
35	2	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2	1	0	0	0	0	1	0
36	0	0	1	1	0	0	1	0	3	2	0	0	1	1	0	1	0	0	0	0	0	0	1	1

4.4 Forecasting Accuracy Measurement

The most important issue in the study of forecasting is to measure the accuracy of forecasting methods. Although, there are many forecasting performance measurements available in the literatures but all the forecasting error is based on the difference between the actual data and the forecasted values. The statistical measurement to be used in this research to measure the forecasting accuracy are ME, MAE and the adjusted MAPE (A-MAPE) over the test set data on year 2019.

4.4.1 Mean Error (ME)

As shown in Table 4.7 and Figure 4.4, ME values of 3 forecasting methods are under consideration. The interpretations of ME techniques are, if positive values, it indicates that the forecast is too low and if negative value shows the forecast is too high. Also, the forecast method is unbiased if the ME values is close to zero.

For Croston’s Method, most of MEs are positive except series 9 and 36. It means that Croston’s Method usually generates lower forecast values than the actual data. The maximum forecast bias value of this method is 0.833 in the positive sign of series 25 which is also the highest forecast bias values among all 3 methods.

For Holt’s Linear Method, most of MEs are also positive. There are only 4 data series (series 14, 16, 23 and 24) which its ME are negative sign. Hence, it can be concluded that Holt’s Linear Method usually generates lower forecast values than the actual data as well. The maximum forecast bias value of this method is 0.5 for series 2 and 35 in the positive sign.

For MLP approach of Neural Network Method, most of ME values are also positive and generally generate too low forecast values for the demand data same as Croston’s and Holt’s Linear Method. There are 2 series (series 17 and 34) which have the negative signs. However, the maximum forecast bias value of this method is 0.417 in positive sign of series no.2 which is the lowest forecast bias value comparison to another 2 methods.

In term of the measurement on the overall data series, the MLP approach also gives the lowest sum MEs and average of MEs which are 4.5 and 0.125 respectively among all 3 methods. While, the second rank is Holt’s Linear Method which its sum MEs is 4.667 and average MEs is 0.130 and the last method is Croston’s Method which its sum MEs is 7.167 and average MEs is 0.199 as shown in Table 4.7.

Table 4.7: ME values of different forecasting methods

Series	Croston	Holt's Linear	MLP
1	0.167	0.167	0.167
2	0.500	0.500	0.417
3	0.083	0.167	0.167
4	0.083	0.083	0.083
5	0.250	0.250	0.250
6	0.167	0.083	0.167
7	0.250	0.000	0.250
8	0.250	0.250	0.083
9	-0.333	0.083	0.083
10	0.250	0.250	0.167
11	0.083	0.083	0.083
12	0.167	0.167	0.167
13	0.250	0.250	0.250
14	0.167	-0.167	0.083
15	0.250	0.250	0.083
16	0.583	-0.083	0.000
17	0.333	0.000	-0.167
18	0.167	0.167	0.167
19	0.167	0.167	0.000
20	0.167	0.167	0.000
21	0.167	0.167	0.167
22	0.167	0.083	0.167
23	0.250	-0.083	0.000
24	0.167	-0.083	0.083
25	0.833	0.250	0.667
26	0.167	0.167	0.167
27	0.083	0.083	0.083
28	0.083	0.083	0.083
29	0.083	0.083	0.083
30	0.083	0.083	0.083
31	0.250	0.000	0.083
32	0.250	0.250	0.083
33	0.167	0.167	0.000
34	0.333	0.000	-0.083
35	0.500	0.500	0.250
36	-0.417	0.083	0.083
SUM	**7.167**	**4.667**	**4.500**
MEAN	**0.199**	**0.130**	**0.125**

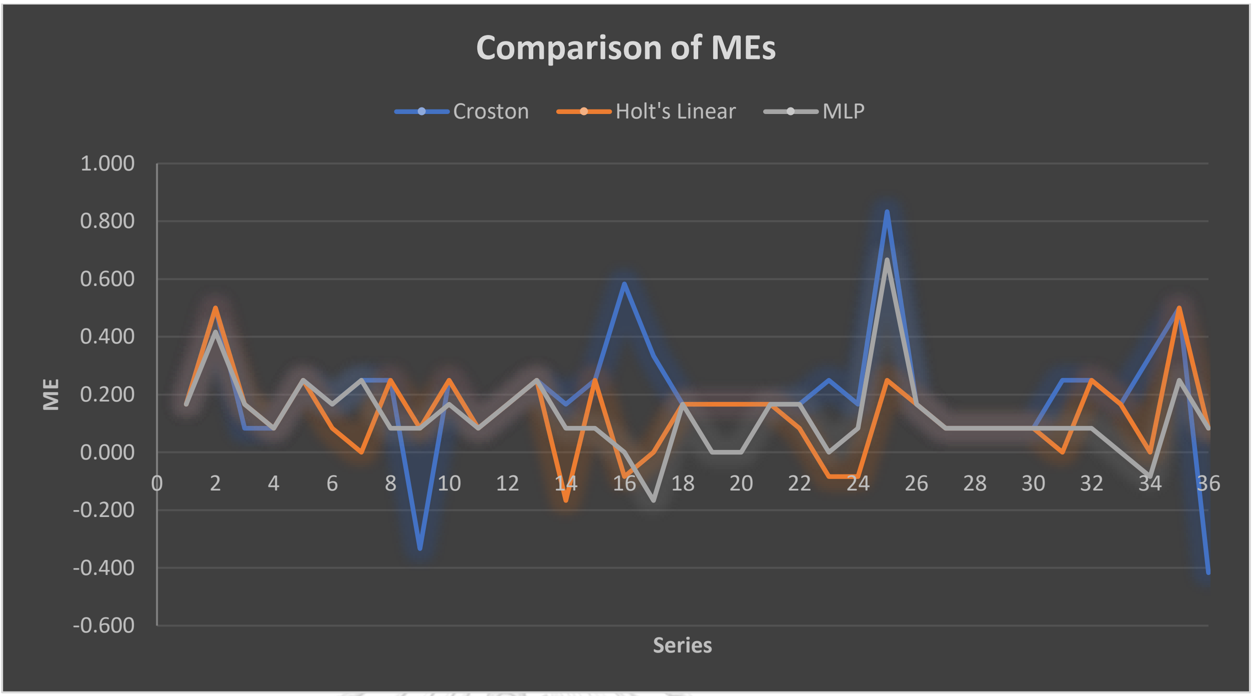

Figure 4.4: Comparison of MEs

In conclusion of ME accuracy measurement, all 3 methods generally forecast too low values for the spare parts demand of Company A. But the most unbiased method is MLP approach of Neural Network method which generate the lowest forecast bias values over the sampling data series and also generate the lowest sum and average of overall data. Somehow, the positive and negative errors from MEs result will cancel out one another and providing the mean error (ME) results close to zero and finally approximately unbiased but in fact, the positive and negative errors of each individual item should not cancel one another out by different signs in order to measure the performance of forecasting method because of the different, important and implication on each item so that a small value of mean or sum of ME are not guarantee that the performance of that method is the best. So that, to capture the degree of error, regardless of the sign, other error measurements are then required.

4.4.2 Mean Absolute Error (MAE)

Table 4.8 and Figure 4.5 show the performance of the methods by considering the MAE measurement. It is obviously that almost all these data series, MLP approach has either the lowest MAE value among all 3 forecasting methods or even has the same lowest MAE value same as other methods except series 9, 17 and 34 in which the performance of MLP approach are inferior than Croston's Method and series 6 is inferior than Holt's Linear Method.

Table 4.8: MAE values of different forecasting methods

Series	Croston	Holt's Linear	MLP
1	0.167	0.167	0.167
2	0.833	0.833	0.750
3	0.250	0.167	0.167
4	0.083	0.083	0.083
5	0.250	0.250	0.250
6	0.167	0.083	0.167
7	0.250	0.333	0.250
8	0.250	0.250	0.250
9	0.333	0.583	0.417
10	0.250	0.250	0.167
11	0.083	0.083	0.083
12	0.167	0.167	0.167
13	0.250	0.250	0.250
14	0.167	0.500	0.083
15	0.250	0.250	0.250
16	0.583	0.750	0.000
17	0.500	0.833	0.667
18	0.167	0.167	0.167
19	0.167	0.167	0.000
20	0.167	0.167	0.167
21	0.167	0.167	0.167
22	0.167	0.250	0.167
23	0.250	0.417	0.167
24	0.167	0.417	0.083
25	0.833	0.917	0.667
26	0.167	0.167	0.167
27	0.083	0.083	0.083
28	0.083	0.083	0.083
29	0.083	0.083	0.083
30	0.083	0.083	0.083
31	0.250	0.500	0.250
32	0.250	0.250	0.083
33	0.167	0.167	0.000
34	0.333	0.667	0.417
35	0.500	0.500	0.250
36	0.750	0.750	0.250
SUM	**9.667**	**11.833**	**7.500**
MEAN	**0.269**	**0.329**	**0.208**

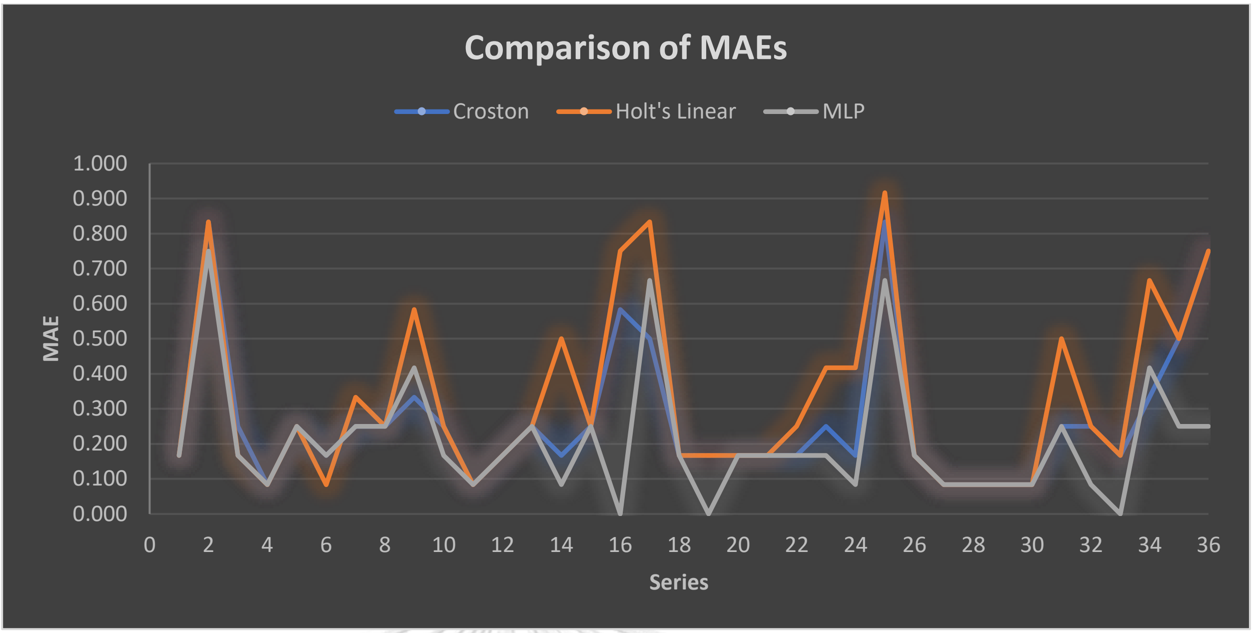

Figure 4.5: Comparison of MAEs

In term of the measurement of overall data series, MLP gives the lowest values both sum and average MAE of overall data 36 series which are 7.5 and 0.208 respectively. While, the second rank is Croston's Method which its sum MAEs is 9.667 and average MAEs is 0.269 and the last method is Holt's Linear Method which its sum MAEs is 11.833 and average MAEs is 0.329. From the results, it can be concluded that if evaluate by MAE forecast accuracy measurement, MLP approach of Neural Network Method is the best performing method.

4.4.3 Adjusted Mean Absolute Percentage Error (A-MAPE)

Table 4.9 and Figure 4.6 report A-MAPE for the 3 selected forecasting methods. It can be seen that almost all of these data series, MLP approach has always obtained the lowest A-MAPE value or even the same lowest value as other methods except series 9, 17, 34 which are inferior than Croston's Method and series 6 that is inferior than Holt's Linear Method which are the same result as measured by MAE measurement.

Table 4.9: A-MAPE values of different forecasting methods

Series	Croston	Holt's Linear	MLP
1	1.000	1.000	1.000
2	0.556	0.556	0.500
3	1.500	1.000	1.000
4	1.000	1.000	1.000
5	1.000	1.000	1.000
6	1.000	0.500	1.000
7	1.000	1.333	1.000
8	1.000	1.000	1.000
9	0.500	0.875	0.625
10	1.000	1.000	0.667
11	1.000	1.000	1.000
12	1.000	1.000	1.000
13	1.000	1.000	1.000
14	1.000	3.000	0.500
15	1.000	1.000	1.000
16	1.000	1.286	0.000
17	1.200	2.000	1.600
18	1.000	1.000	1.000
19	1.000	1.000	0.000
20	1.000	1.000	1.000
21	1.000	1.000	1.000
22	1.000	1.500	1.000
23	1.000	1.667	0.667
24	1.000	2.500	0.500
25	1.000	1.100	0.800
26	1.000	1.000	1.000
27	1.000	1.000	1.000
28	1.000	1.000	1.000
29	1.000	1.000	1.000
30	1.000	1.000	1.000
31	1.000	2.000	1.000
32	1.000	1.000	0.333
33	1.000	1.000	0.000
34	1.000	2.000	1.250
35	1.000	1.000	0.500
36	1.286	1.286	0.429
SUM	**36.041**	**43.602**	**29.370**
MEAN	**1.001**	**1.211**	**0.816**

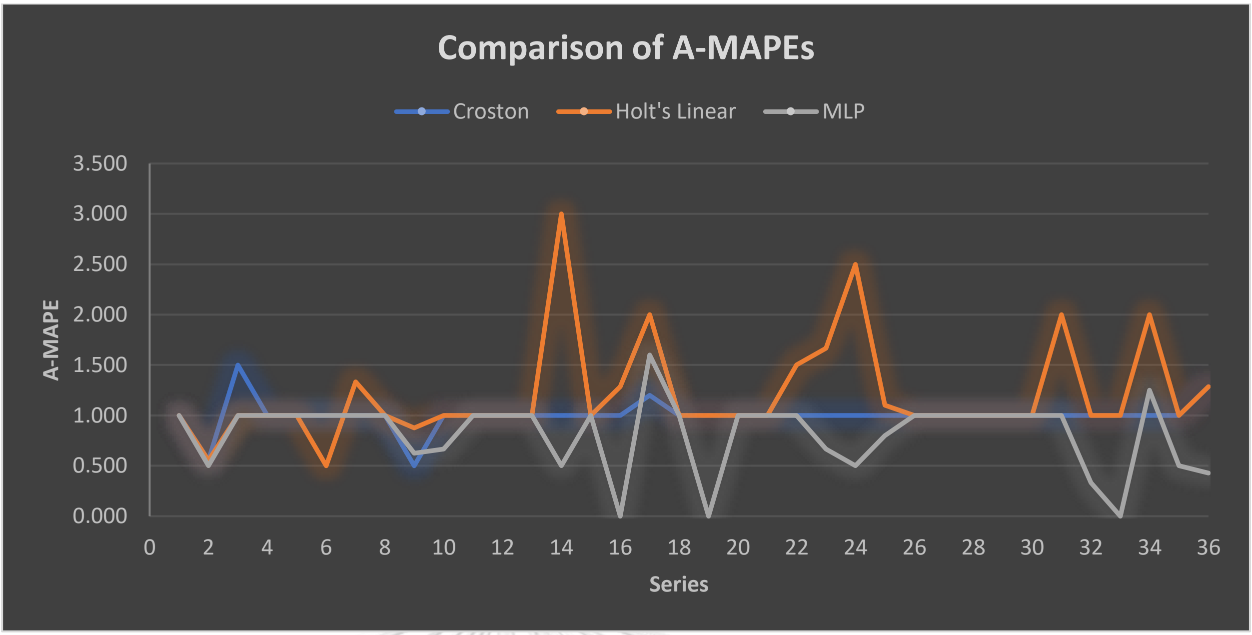

Figure 4.6: Comparison of A-MAPEs

In term of the measurement of overall data series, MLP gives the lowest values both sum and average A-MAPEs of overall data 36 series which are 29.37 and 0.816 respectively. While, the second rank is Croston's Method which its sum A-MAPEs is 36.041 and average A-MAPEs is 1.001 and the last method is Holt's Linear Method which its sum A-MAPEs is 43.602 and average A-MAPEs is 1.211. From this result, it is obviously seen that the performance of MLP approach forecasting method is the best performing from the evaluation of A-MAPEs forecasting accuracy measurement.

4.5 Summary

Base on the forecasting accuracy measurement, the Multi-Layer Perceptron trained with Backpropagation of Neural Network Model suggested by Gutierrez (2008) generally outperformed than other 2 time series exponential smoothing forecasting methods, Croston's and Holt's Linear Method for all 3 error statistical measurements. In particular, data series 17, 20 and 35 the errors of MLP approach is zero which means that MLP can predict the exact forecasted value both in term of time of occurrence and quantity which is more reinforcing to ensure on the superiority of Neural Network Method.

Chapter 5
Discussion and Conclusion

5.1 Discussion of Research Result

This paper successfully presents that the Multi-Layer Perceptron trained with Backpropagation of Neural Network Model suggested by Gutierrez (2008) outperformed than the conventional Croston's and Holt's Linear method for predicting an intermittent nature of spare parts demand pattern of Company A. From the results of statistical accuracy measurement over the test set data on year 2019, It is clearly showed that the MLP approach mostly performs the best in forecasting for 36 demand series of spare parts. According to the capability of neural network methods, it can generate the better forecasting performance than other models both in term of the demand occurrence and the demand quantity because of it takes nonlinear correlation into account in the data and the capability to deal with both linear and nonlinear data patterns. Therefore, the Neural Network can lead to more accurate forecasting than the conventional method. Although, the study of Gutierrez et al. (2008) stated the superior alternative of MLP trained with Backpropagation approach than the traditional method for modelling and forecasting the lumpy demand pattern. But in this study, it shows that MLP approach with BP algorithm of Neural Network Method is superior for the intermittent demand category in which its time series contain many zero demand values as well.

In term of the variables in each method are summarized in Table 5.1. For Croston's Method and MLP approach have similar variables in order to forecast the future demand which are the demand data at time t and the interval between non-zero demand together with 1 smoothing constant for Croston's Method. Although, the Croston's and MLP approach are using the similar variables in the forecasting process. But the overall performance of MLP approach is superior than Croston's Method which mean that the traditional time-series methods may not capture the nonlinear data pattern like Neural Network since the Neural Network algorithm is like the human brain which comprise of a number of interconnected simple processing elements called neurons or nodes and has ability to find the way to solve the problems. While, Holt's Linear method which is the trend-adjusted smoothing forecasting method (with 2 smoothing values) which use the level of the time series at time t and the slope of the series to forecast the values. From the result, it can be seen that the overall performance of Holt's Linear Method is the worst among all 3 methods except in term of forecasting bias in which Holt's Linear Method is less biased method than Croston's Method. Therefore, it can conclude that the trend-adjusted smoothing forecasting method are not suitable to be the tool for forecasting the irregular and nonlinear demand pattern.

Table 5.1: The variables in each forecasting method

Croston's Method	Holt's Linear Method	Neural Network Method
1. Non-zero demand at time t 2. Interval between non-zero demand at time t 3. 1 smoothing constant	1. An estimate of the level of the series at time t 2. An estimate of the slope of the series at time t 3. 2 smoothing constants	1. The demand at the end of the immediately preceding period 2. The number of periods separating the last 2 non-zero demand transactions as of the end of the immediately preceding period.

The objective of this research as specified earlier has been accomplished through detailed empirical analysis of 3 forecasting methods are applied to 36 real observation demand data series. Based on the result, it concludes that Neural Network model is generally superior to the traditional time-series in forecasting irregular demand especially in intermittent category and Neural Network can be a potential tool for forecasting spare part demand of Company A.

Since Company A have no any tools and methods to predict the future demand occurred from condition-monitoring parts which is an unforeseen defect before. There will be a risk for aircraft flight schedule every time if defect occur, whether there is spare part to replace prior to releasing the flight or not. Unfortunately, if no stock of that specific spare parts available the aircraft can not be returned to operate and resulting to flight delay problem which cost a huge extra cost to the company. However, from the performance of MLP approach of Neural Network Method to predict the spare part demand on year 2019 for 12 months period of 36 sampling spare parts. From Table 4.6

and Figure 5.1, it can be seen that MLP approach can forecast the accurate result in term of demand occurrence and demand quantity for Company accurately about 81% and there are only 15% which is under-forecasting and 4% for over-forecasting.

Table 5.2: Summary of MLP forecasting result in 2019

	No. of occurrence	Accurate forecast	Under-forecasting	Over-forecasting
Jan-19	39	33	5	1
Feb-19	39	33	4	2
Mar-19	39	29	6	4
Apr-19	38	33	5	0
May-19	43	35	7	1
Jun-19	37	32	5	0
Jul-19	40	31	5	4
Aug-19	36	30	4	2
Sep-19	41	31	10	0
Oct-19	37	32	5	0
Nov-19	38	28	9	1
Dec-19	37	27	7	3
Total	464	374	72	18

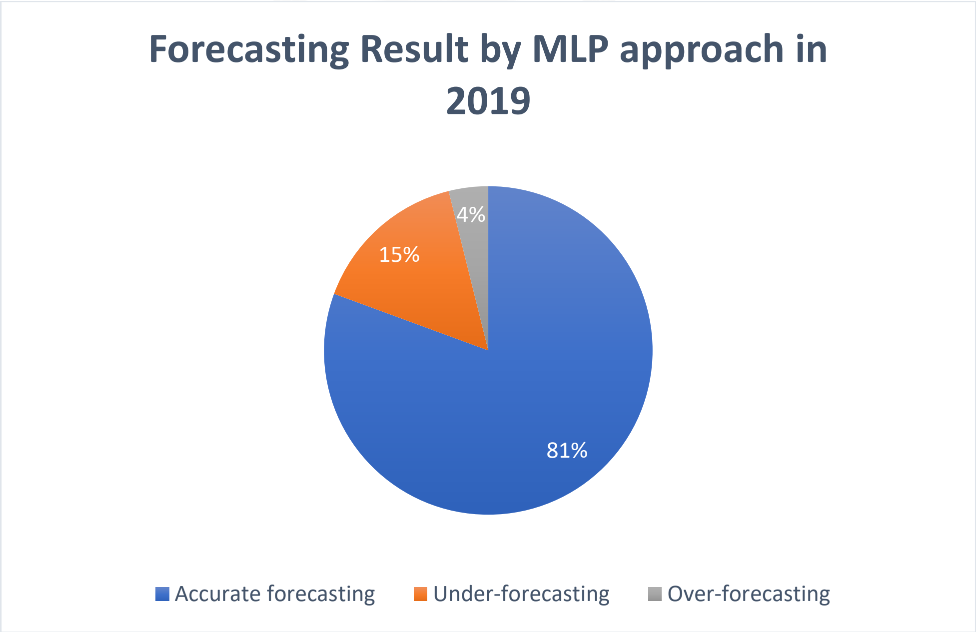

Figure 5.1: Pie chart of Forecasting result by MLP approach in 2019

From this result, it could help company to predict the accurate future demand and reduce the occurrences of unavailability of spare part when the aircraft found defect which could lead consequently effect in the aircraft schedule delay.

5.2 Practical Implication

The best performance forecasting method from this study, can be presented to be the tool for the aircraft maintenance planners use for predicting the unforeseen spare part demand occurrence. The efficient tool can reduce the inaccuracy of spare part forecasting especially for irregular demand pattern group which it is hard to predict its occurrence. Resulting in when the spare part demand occurs, there are no available inventory stock to supply for the demand in time. Vice versa, some spare parts are also kept in inventory stock for long period without the spare part requisition as well. Therefore, the forecasting method can be a tool to reduce a consequent effect in aircraft unavailability due to lack of spare part if defect occurred or else could reduce the inventory holding cost and can procure the right spare part at the right time. It will be more extremely beneficial to the company if this proposed forecasting methodology is applied and integrated with the company's purchasing team to manage developing the company's inventory management system. But due to this study focus only on the intermittent demand pattern. But in fact, it is possible to have the spare part demand occurrence in other categories as well. Therefore, the result from this study is limited only for this kind of demand pattern.

5.3 Recommendation of Research for Future Development

According to the purpose of the research, it focuses on comparing the different forecasting methods for Rotable Spare Parts demand of Company A and the majority of this sampling parts are fall into 'Intermittent' demand pattern. However, the research can further extend to have a general comparative study for the forecasting methods of the spare parts in other types and more study in other demand patterns. Thus, the results can help in selection of the best forecasting method for any type of the sporadic demand data and also verify the behavior of MLP approach for other demand patterns

Since the result of this study shows that Neural Network outperform rather than the conventional methods. In future research, it could be considered on more factors that lead to a reduction performance of these forecasting models or adding more input variables for Neural Network with the expectation to perform better in demand forecasting.

Also, the possibility to combine the neural network models for building a hybrid approaches for forecasting of the future demands in other group of spare parts might be the way for extension this research further.

5.4 Conclusion

Inventory spare parts managing is becoming more complicated and critical issue in the modern business environment than previous period since it can help the organizations to reduce the inventory costs and ensure the available of spare parts. Also, this inventory management problem can be improved by the demand forecasting technique which have an accuracy. In general, the demand forecasting is difficult, unfortunately the sporadic spare part demands are especially difficult to forecast the spare part demand than usual. Identically, more sophisticated methods are required to forecast the irregular demand pattern in accuracy. The way to build a useful inventory management system is to combine the solid inventory management systems with the efficient demand forecasting methods. The demand forecasting is one of a critical task for inventory management since its results directly affect how to manage the inventory system of the company. Especially in airline industry, the accurate forecasting is so essential as so much cost can incur if the spare parts are unavailable at the right time. If there is an aircraft waiting for spare parts even for an hour, it will cost a lot of money to company up to more than 200k THB for each hour if an aircraft is delay from flight schedule. However, while keeping the huge amount of inventory stock will cost a huge amount of money to company as well. So that, the spare part availability at the right time and right quantity is so important to the company for managing their costs.

The initiation of this research is that no other research has been specially done for the inventory management of aircraft operating in the Company A before. The data used in prediction in the forecasting models came from Rotable spare parts of Airbus A320 spare part consumption of Company A. The most of the demands are classified in intermittent demand pattern and only a few data in lumpy and smooth with no erratic demand pattern. There are 3 forecasting methods implemented in this research which are Croston Method, Holt’s Linear Method and Multi-Layer Perceptron train with Backpropagation of Neural Network Method and then comparing their performance to find the most suitable one for the company’s demand characteristics. From the forecasting aspect, the accurate forecasts can leverage the most recent information for maintenance planning to plan more appropriately. From this study, Neural Network Forecasting Method is much more superior to traditional smoothing methods, Croston and Holt’s Linear Method. The result of this study could be a great benefit to the company to enable them to select the appropriate forecasting methods in which meets their spare part demand characteristics for the company’s inventory management and reduce the unnecessary cost occurred. Even in this study, only one particular airline business, Company A has been used its data to study but these finding may be applicable to any other industrial sectors which have similar in demand patterns to the airlines industry as well.

From this result and analysis of this research are based on intermittent demand pattern only. The forecasting methods that provided the best adjustments for the historical data series is Multi-Layer Perceptron trained with Backpropagation of Neural Network Method, the Croston’s Method is the second rank and Holt’s Linear Method is the worst one. Therefore, from this research, MLP trained with Backpropagation approach of Neural Network method is the most suitable methods and suggested to implement for management of the critical parts for airline operation of Company A. Moreover, it is shown that the irregular demand patterns can be forecasted to a good level of accuracy if the right method is selected as shown in the empirical data, if implement MLP approach method to forecast the demand on year 2019, the MLP approach can forecast the accurate result approximately to 81% which can be beneficially for the company to reduce the inventory cost and reduce the risk of unavailability of specific spare parts when need.

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APPENDIX

A. Ethical Approval Document

Below Figure shows a copy of ethical approval confirmation from the Warwick Overseas Programmes Course Office for the research which the ethical approval reference number is **REGO-2021-WMGOS-0025**.

WARWICK
THE UNIVERSITY OF WARWICK

Ethical Approval Confirmation

Dear Miss Thummathid,

Warwick ID Number: 1737539

Thank you for submitting your Supervisor's Delegated Approval form to the Overseas Programmes Course Office for the project: Development of Rotables Spare Part Inventory Management for Aircraft Maintanance of Low-Cost Airlines in Thailand.

Your reference number is REGO-2021-WMGOS-0025.

You now have the appropriate approval in place to begin your study.

Please ensure you insert a copy of this email into the appendices of your project.

Best Wishes

Mengjiao Han
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Figure A.1: Ethical approval confirmation

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