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Forecasting of Core Returns for Remanufacture: A Time Series Analysis

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FORECASTING OF CORE RETURNS FOR REMANUFACTURE: A TIME SERIES ANALYSIS

by

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ABSTRACT

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Over centuries, consumption of natural resources has been on a steady increase in response to the increasing global population. Increased and unsustainable use of natural resources in addition to increased manufacturing is affecting the environment adversely. Hence, governments and environmental protection agencies are implementing firm regulations for industries to reduce their footprint on environmental pollution, for instance by ensuring that their waste products are not only disposed sustainably but also reduced. In response to these regulations, industries have embraced product end-of-life management strategies. These include reverse logistic, material and product recovery, reusing, recyling and remanufacturing.

This Thesis addresses one of the major challenges in remanufacturing which is uncertainties in the number of core returns for remanufacture. Specifically, we propose a time series model that uses real data from a partner International OEM company that manufactures aswell as remanufactures electronic products. A unique aspect of the data that was obtained was the fact that specific distinctions were made delineating billable return products from warranty return products for remanufacture. It is with this uniqueness that we sort to construct three time series model that is (a) Overall product core return; (b) Warranty return and (c) Billable return.

The forecast for the overall product core return and billable return was calculated using the Seasonal ARIMA (autoregressive integrated moving average) model, whereas the warranty return forecast was calulated using the ARIMA model. The best model was selected on the basis of akaike information criterion. ARIMA(0,1,1)(0,1,0)[12] was selected as the best model for overall returns; ARIMA(0,1,1) was selected as the best model for warranty return

and ARIMA(0,1,0)(0,1,0)[12] was selected as the best model for billable return. The selected models were proven to be appropriate by means of residual diagnostics which includes Box-Ljung test, residuals of ACF, ARCH effect and Jarque Bera test. Two-thirds of the data was used to build the models. After verification, this models were used to forecast the remaining one-third of the data. The accuracy of these forecasting results were determined with ME, RMSE, MAE, MPE, MAPE, MASE and ACF1. Overall, though not generizable to all companies, our model proved that for our partner company the overall returns were largely driven by the billable returns hence making it a profitable venture.

Dedicated to my parents, sisters and Joel

for their unconditional love, support and motivation

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1 Introduction

1.1 Motivation

Over centuries, the consumption of natural resources has been on a steady increase in response to the increasing global population. Increased and unsustainable use of natural resources in addition to increased manufacturing is affecting the environment adversely. Hence, governments and environmental protection agencies are implementing firm regulations for industries to reduce their footprint on environmental pollution, for instance, by ensuring that their waste products are not only disposed sustainably but also reduced.

In the United States, there are many new regulations which industries need to follow such as the Clean Air Act, National Ambient Air Quality Standards, Toxic Substances Control Act, and Resource Conservation and Recovery Act, among others. Correspondingly, today's manufacturers are encouraged to take back and reprocess their end of life products. Most of the industries view these new legislations as a threat to their current business models. Moreover, the customers also prefer products which are environmentally friendly. Industries need to address both governmental and customer demands to stay in the business, hence the emergence of research in the fields of reverse logistics, one of which is remanufacturing.

Industries mainly enter into remanufacturing for various reasons, some of which are listed below (*Yoruk, 2004*):

1. *Environmental protection*: Most of the companies get into remanufacturing considering the environment as an important factor. Remanufacturing processes return used products to as-new condition, thereby reducing the use of natural resources in the form of virgin material. Remanufacturing also plays an important role in sustainable manufacturing. Less waste is generated by reusing the materials. According to the US Environmental Protection Agency (USEPA), over 12 billion tons of industrial waste is generated in the US every year (*U.S. Environmental Protection Agency (E.P.A),*

1988a,b; Allen and Jain, 1992). This rate is expected to increase significantly. In addition, the number of landfill sites reduced from 18,000 in 1985 (*Pohlen and Farris, 1992*) to 3,581 in 1995 (*Rogers and Tibben-Lembke, 1990*). Moreover, there are stricter regulations put into effect on limiting materials which can be thrown away. For instance, companies are allowed to discard only a certain amount of materials to environment every year.

2. *Consumer awareness*: People have now realized the environmental effects of products which they are using. Many consumers have started purchasing products from manufacturers who are ready to take back their products after the end of life (*Gungor and Gupta, 1999*). Other communities refuse the development of dumpsites in their neighborhood.

3. *Competitiveness*: If the Original Equipment Manufacturers (OEMs) do not have a recovery program for their manufactured products, third-party remanufacturers may collect the manufacturer's used products, on which reverse engineering is applied. Such a strategy by third parties pose threats design and process information leakage to competitors, allowing them to make the needful modifications and sell the same product at a cheaper price.

4. *Reduced manufacturing cost*: It is generally possible to restore the product to their operating condition by replacing only the faulty parts, thus reducing the overall manufacturing cost of the product.

5. *Shortened product life cycle*: Many technologies come with short product life cycles which in turn increase their disposal rate. This is particularly true for mobile phones; forcing phone companies to devise better product recovery systems to extend the life of their products through reuse.

1.2 Remanufacturing

Remanufacturing which is also known as 'Reman', is an industrial process wherein used products which are also known as cores are restored to a useful life (*E.Sundin, 2004*). Remanufacturing, according to Fortune Magazine (*2007*) is a process which is carried out by the Independent Remanufacturers (also known as IRs) and the Original Equipment Manufacturer (also known as OEMs). Independent remanufacturers are companies which do not have the details of the manufacturing process of the product and hence the products are re-engineered by applying reverse logistics. Original equipment manufacturers are the ones who originally manufactured the products and make the needful changes either to extend their lives or to upgrade them into better products.

In remanufacturing, the products are recovered, processed and sold as like new products for a cheaper cost in the same or separate market (*Clottey, 2012*). According to the reports of Hauser and Lund, it has been found that remanufacturing operations accounted for total sales in excess of $53 billion per year (*Hauser W.M, Lund, 2003*). Many industries are adopting sustainability as the environment is being affected by the increasing rate of virgin material consumption. The five basic principles of sustainability include decreasing the amount of resources used in the manufacturing of products, usage of less virgin materials so that there will be a decrease in the transportation, less assembly, less packaging and reduced tooling, choosing the appropriately environmentally benign materials needed to avoid harmful substances, long life span of a product and including strategies that ease recycling and reuse such as easing the process of disassembly (*The HAG Movement, n.d.*). Hence, the companies have started taking up these principles which can actually be profitable.

Remanufactured products are those that are returned back to the manufacturer or the third party remanufacturer when their initial useful life is about to end or when it comes to an end. Products are also returned from the customers whenever an upgrade is required. Certain companies make the needful changes and return the same products i.e.

same serial numbers whereas other companies replace them with new products at discounted prices.

According to a survey which was carried out by US and European executives, there is high business value in remanufacturing (*A.D.Little, 1998*). There are several studies which have proven that remanufacturing is profitable for OEMs (*R.Hammond, 1998; B.K.Thorn, April 2002; D.Guide, 2003*). Many companies such as Honda, Goldman Sachs, Continental Airlines are adopting remanufacturing in an environmentally responsible way as was reported by Fortune Magazine 19 (*Chen, Changrong, 2016*)

Remanufacturing is the out most mode of recycling assuring the raw material content while continuing much of the value added in the course of product's manufacture. The important benefit of remanufacturing is the ecological benefits since less of waste is created which includes the waste which needs to be scrapped and waste which needs to be recycled. Remanufacturing is a method wherein the products are dismantled, cleaned, repaired and then reassembled again back to their operating condition. Remanufacturing is applicable in most of the areas today which includes automobiles, automotive parts, electric motors, tires, cameras, computers, industrial equipment, furniture, compressors, telephones, televisions, electrical parts, vending machines, photocopiers, gaming machines, musical instruments, robots, aircraft parts, bakery equipment. The industry so far leads, accounting for two third of the total remanufacturing products globally (*Statham, 2006*).

1.3 Remanufacturing across the globe

The European Remanufacturing Network provides the global remanufacturing outlook which we will briefly present in this section (*Parker et al.,2015*). Mostly, remanufacturing is observed more in the United States and the United Kingdom.

Remanufacturing in Brazil is centralized in the aerospace, motor vehicle parts, heavy-duty and off-road equipment industries. There are thousands of remanufacturing organizations employing 20 or fewer workers. There is an existence of both Original

Equipment Manufacturers and Independent Remanufacturers. Companies like ZF Sachs Automotive, Eaton Corp. and Siemens Inc. account for 3/4th of the total value of Brazil's remanufactured engines and parts. In the IT sector, remanufacturing of printer catridge also takes place in Brazil.

In China's automotive sector, there are hardly 15 remanufacturers which were approved for pilot program. There is a lack of an official definition which is seen as a significant barrier because regulators find it confusing to deal with firms seeking approval for their remanufacturing operations. In China, there is an import ban on used goods to be remanufactured domestically. Remanufactured mechanical and electronic products are considered used products for import purposes and are prohibited, restricted or freely imported. China's customs service does not have a separate classification for remanufactured goods, hence it is difficult to apply correct import duty (*Remanufactured goods: An overview of the US and Global Markets and Trade, 2012*).

The scope of remanufacturing in Denmark is constrained. The products keep modifying so much that the old products cannot be used for remanufacturing, making them expensive. There is less of demand of remanufactured products for fear that remanufactured products have an inferior quality. It's a costly affair to assure the quality of remanufactured products. According to Danish laws, import and export of remanufactured product is banned (*Parker, 2015*).

In India, unlike repair, which is mostly practiced, remanufacturing is yet to have a strong hold in the market of used products. However, the remanufacture of printer cartridges has been in practice for several decades. Whereas the import of used goods to be remanufactured and sold in the local market is banned, import of goods for remanufacturing in order to fulfill the export market is allowed.

Remanufacturing in Japan is observed in the automotive sector, tires retread, photocopiers and toner cartridges. This increase in the remanufacturing industry is as a result government mandates for reduction of pollutants and waste generation. The government has for a while focused on the 3R's which include reduced waste generation; reuse of parts and recycling used products. To implement the 3R strategy, companies such as Fuji Xerox, Ricoh and Canon do remanufacture their products. In fact, Fuji Xerox used remanufactured parts in their new products. Remanufacturing in the automotive and printer cartridge industry is being carried out mostly by Independent Remanufacturers when compared to the Original Equipment Manufacturers. The automotive sector in remanufacturing is seeing a growth as the average age of passenger vehicles in Japan increases and their repair industry is deregulated (*U.S. Department of Commerce, 2014*).

Automotive parts and printer cartridges are mostly remanufactured in South Korea, representing 80% and 17% of all remanufactured products respectively. Other remanufactured products include heavy-duty equipment, IT products, medical devices and defense sectors.

Remanufacturing in Malaysia takes place in the aerospace, motor vehicle parts, Information and Communication Technology (ICT) equipment and ink and toner cartridge sectors. Importantly, previously remanufacturing used to take place for airframes and other aerospace components. However, the most significant challenge is the lack of skilled labor for the remanufacturing industry.

According to Parker and Riley (*2015*), HDOR equipment, automotive parts, medical devices, electrical apparatus and marine equipment are remanufactured in Singapore. The government does not differentiate between new, used or remanufactured products nor does it have any kind of special labeling particular to remanufactured products. Goods to be remanufactured can be easily imported, remanufactured and sold in the local markets. Caterpillar, a leading remanufacturing company, remanufactures equipment for trucking and mining work which consists of transmissions, drives and torque converters. 80% of the remanufactured products in Singapore are exported to Indonesia and Australia.

44,300 full-time jobs exist in the remanufacturing industry in the UK, mostly in the ink and toner cartridge industry. There is also remanufacturing of mechanical or powered machinery. In recent years, there has been a decline in the remanufacturing sector due to the availability of low-cost products, cost of labor, low awareness of remanufactured products among consumers, economic recession, longer product lifetimes, quantity of cores available further increasing cost and complexity of remanufactured products (*Parker, 2004*).

Remanufacturing is carried out on a large-scale in the United States, in various fields which include aerospace, automotive components, consumer products, electrical apparatus, HDOR equipment, IT products, locomotives machinery, medical devices, office furniture, restaurant equipment and retreaded tire. According to the USITC (United States International Commission, 2012) report, the USA is the largest remanufacturer in the world (*Remanufactured goods: An overview of the US and Global Markets and Trade, 2012*). US exports most of it's remanufactured products to Canada, Europe and Mexico. The Figure 1 and Table 1 indicate products that are mostly remanufactured in the US using the data mentioned below (*Remanufactured goods: An overview of the US and Global Markets and Trade 2012, USITC*).

Sector*	Production (US$m)	Investment (US$m)	Employed ('000 FTE)	Exports (US$m)	Imports (US$m)	Intensity (%)
Aerospace	13,046	90	35.2	2,590	1,870	2.6
Automotive parts	6,212	106	30.7	582	1,482	1.1
Consumer Products	659	5	7.6	21	360	0.1
HDOR Equipments	7,771	163	20.8	2,542	1,489	3.8
IT Products	2,682	18	15.4	260	2,756	0.4
Machinery	5,795	711	26.8	1,349	268	1.0
Medical Devices	1,463	31	4.1	488	111	0.5
Retreaded tyres	1,399	24	4.9	19	11	2.9
All other	3,974	68	23.0	225	41	1.3
Wholesalers		8	10.9	3,752	1,874	
Total	43,000	1,223	179.5	11,736	10,263	2.0

Table 1: US REMANUFACTURING STATISTICS, 2011

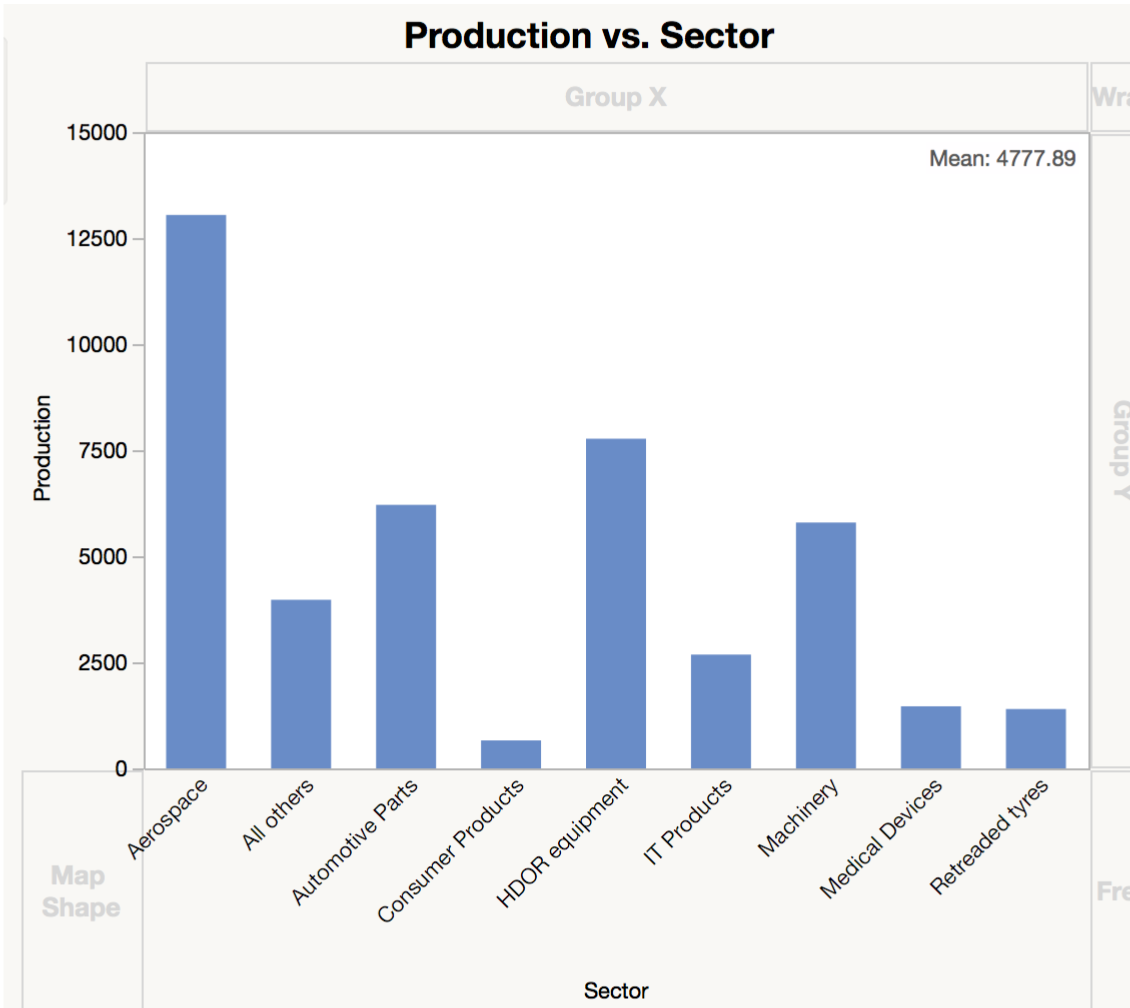


Figure 1: GRAPHICAL REPRESENTATION OF US REMANUFACTURING STATISTIC, 2011

1.4 Challenges in Remanufacturing

Today, remanufacturing face challenges due to the limited product and information flow from upstream product life-cycle stakeholders, precisely product development, manufacturing, customers or user and service (*Steinhilper, 1998; Sundin, 2006; Lundmark et al., 2011*). The remanufacturing process is way more erratic and unpredictable in terms of the timing, quantity and quality of incoming cores than the traditional manufacturing process itself (*Guide, 2000; Steihilper, 1998*). Hence, the remanufacturing operations results in longer lead times.

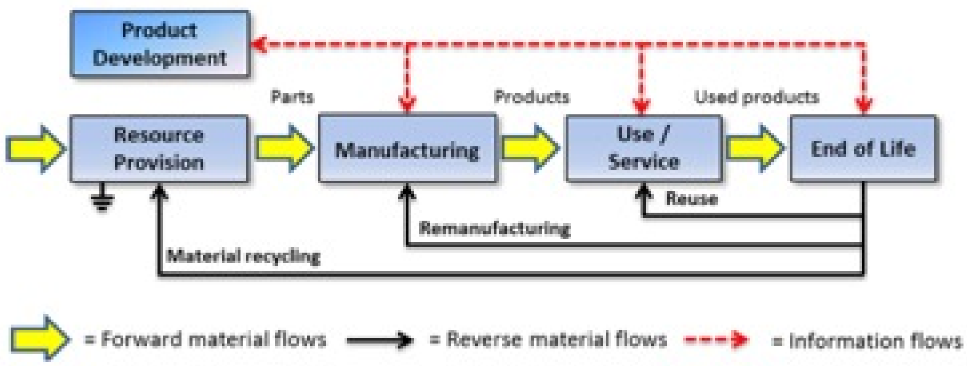


Figure 2: PRODUCT LIFE-CYCLE (*ADAPTED FROM LINDKVIST AND SUNDIN, 2013*)

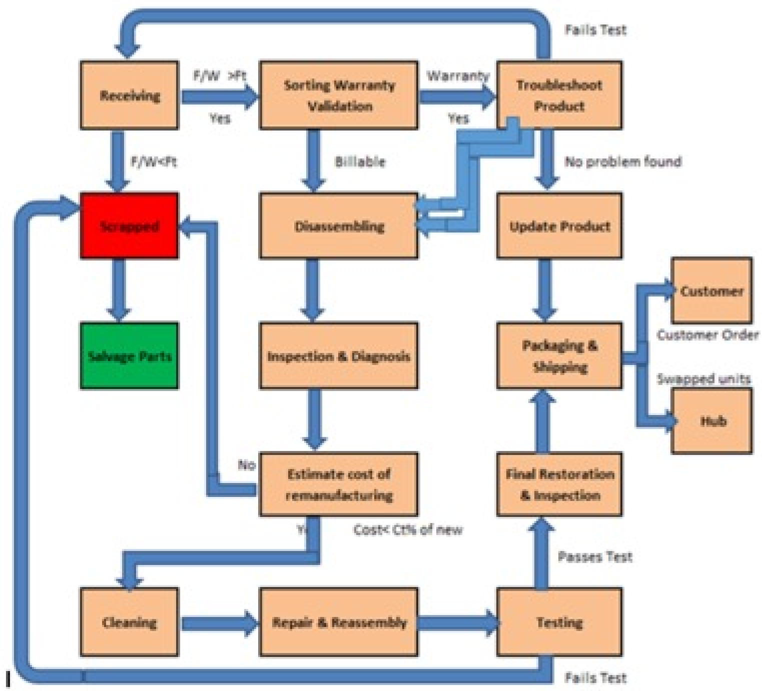


Figure 3: REMANUFACTURING PROCESS, *(OMWANDO 2016)*

Guide (*2000*) listed seven characteristics complicating the production planning and controlling activities in remanufacturing. There is an uncertainty in the timing and quality of cores being returned. It is difficult to predict when the customers will return the products. However, using a forecasting model, taking the past data into account, we can predict the return, despite the fact that predicting the quality of the product may be nearly impossible. Moreover, there is an uncertainty in materials recovered from cores. Figure 2 is a schematic representation of a typical product end-of-life. In addition, Figure 3 provides a detailed flow diagram of the remanufacturing process *Omwando, 2016*. This specific remanufacturing process will be discussed in detail in Section 3.10. In the disassembly of returned products, an inspection is carried out on all of the parts to determine whether they can be used or if they need to be scrapped. The parts which can be used are sent for further processing and the other parts are either repaired or replaced.

For increasing profit, the demand need to match with supply. In remanufacturing, supply and demand do not have a simple connection. The quantity of cores depends to the demand which was met previously. Imperfect correlation between demands and returns may lead to excess stocks of remanufactured products. This problem generally arises when there are different needs for components of the same product as those components that are disassembled at the same time.

Remanufactured products are generally sold at a cheaper price (30 to 70 percent less) when compared to similar new products (*LeBlanc, 2016*). There are customers who do not prefer buying remanufactured products because they consider them as second-hand and they have a mind-set that the products are of low quality. Ultimately, such customers generally end up buying cheaper new products having low quality, thereby undermining remanufactured products which may have similar or better quality than new low quality products. Getting good prices for remanufactured products will result in more companies adopting a remanufacturing strategies. Setting competitive prices, warranties and quality levels will encourage customer's confidence in remanufactured products.

The quality of remanufactured product needs to meet the set standards or requirements. There are countries where these quality standard are not enforced seriously, hence making their customers hesitant to purchase the remanufactured products. It is always important to have supportive legislation to establish an industry in the economy. Currently, there is not enough support for the remanufacturing industry from a legislative perspective even in the United States. There should be laws and incentives that will encourage companies to use remanufacturing friendly design, public supply chain architecture and proper end-of-life product acquisition approaching to higher volume of remanufacturing (*LeBlanc,2016*).

The challenge specifically in remanufacturing electronic drives components is that many times there is a misalignment between Original Equipment (OE) divisions, on product design needs for remanufacturing, resulting in wasted efforts during remanufacturing (*R.Hammond, 1998; Huisingh and Chinnam, 2009*). Moreover, there is a lack of proper technical, environmental and quality data to convince customers to use the remanufactured products. Mass production mentality does not fit well with the low remanufacturing requirements for replacement parts. Additionally, remanufacturing is not being addressed as product value stream approach but as a service which is a need after OE production.

With the accelerated pace of new technologies, people tend to throw away their old products to buy new ones bringing an astonishing glut of electronic waste resulting in serious issues to the environment. In its January issue, National Geographic reported that much of the worlds electronic waste ends up in poor countries like Ghana and Nigeria, where children are paid pennies a day to salvage the choice commodities exposing themselves to dioxins, lead and other poisons. The rest of the waste, spanning everything from dot-matrix printers to surge protectors, end up scattered in open dumps or washed out to sea (Lu, 2009).

Most of the electronic waste is in functionally good condition. In Business Week

(Farzad, Roben, 2008), the author reported a Greenwish CT based private equity firm which sensed opportunity in discarded computers and invested \$50 million in TechTurn (e-recycler). It refurbishes the waste from companies and sells it to schools, NGOs and poor countries. In 2007, the company recorded \$40 million in sales.

1.5 Research Objectives and Outline

Currently, there are many industries developing product recovery, remanufacturing and recycling strategies in order to reduce their environmental impact. In the United States alone, there are more than 73,000 firms engaged in remanufacturing employing over 350,000 people accounting for total sales in excess of $53 billion annually (*Shirazi, 2011*).

There is no universally accepted definition of remanufacturing and many people confuse it with repairing, refurbishment, reuse and recycle. Hence, it becomes difficult for many people to understand the periphery of remanufacturing. Lack of knowledge in the remanufacturing affects the international trade of remanufactured goods are they are often considered as used products (*LeBlanc, 2016*).

Supply chain communities are another barrier to remanufacturing. When there is no efficient communication between parties including aspects such as product design, the assembly process, testing and subcomponent sourcing and disassembly, remanufacturing of products gets complicated and less efficient. Even lack of customer information about the products during their service phase affects their remanufacturability.

In particular, the Thesis focusses on the forecasting of remanufactured products using the data from previous years/months/weeks. The data used in this Thesis was obtained from a partner EOM that produces electronic control drives. Forecasting demand is an important aspect since it allows an organization to accurately and efficiently allocate resources to a level of production that meets anticipated demand. Incorrect forecasts, either too high or low are economically inefficient and unprofitable. Therefore, the objectives of this paper are:

1. To build a forecasting model for the supply of used control drives for remanufacture

2. To analyze the effect of warranty versus billable attributes on the forecast models

2 Literature Review

This chapter provides a review of the existing literature related to forecasting of remanufactured products. Over the last few years, with the increase in demand for remanufactured products, several prior studies have been carried out which emphasize that Original Equipment Manufacturers (OEMs) have various advantages in remanufacturing when compared to the Independent Remanufacturers (IRs). Lund and Skeels (*1983*) and Lund (*1984*) emphasize on the advantages of OEMs which include:-

- Feedback on product reliability and durability
- Competition from lower priced markets
- Manufacturer's reputation for quality
- Advantage over IRs in data, tooling and accessing to suppliers

Haynsworth and Lyons (*1987*), anticipated the way OEMs could become aware of the potential for remanufacturing through correct marketing and product design and by developing a product distribution and return system. There are many studies which have concluded that remanufacturing in OEM is profitable (*Hammond, Amezquita, Bras, 1998; Guide, Harrison, Van, 2003*). Despite the profits, OEMs are not shielded from the obstacles within the remanufacturing process. For instance, remanufacturing may decrease sales of new goods. There is generally more profit in the selling of new products when compared to the remanufactured product. Therefore, increasing companies' bottom line is not the primary motive for remanufacturing, especially for OEMs. There are other considerations such as ethical responsibility (*de Brito, Dekker, 2004*), corporate brand protection (*Seitz, 2007*), intellectual property protection (*Pagell, Wu, Murthy, 2007*) and among others.

Broadly, there were other obstacles in creating a remanufacturing business. Lund and Skeels (*1983*) point out the following challenges:

1. Product selection
2. Marketing strategy
3. Remanufacturing technology
4. Financial aspects
5. Organizational factors
6. Legal consideration

Steinhilper (*2001*) submitted eight criteria to be assessed in establishing the suitability of products for remanufacturing:

1. Technical basis (type or variety of materials and parts, suitability for disassembly, cleaning, testing, reconditioning)
2. Quantitative basis (amount of returned products, timely and regional availability)
3. Value basis (value added from material/production/assembly)
4. Time basis (maximum product lifetime, single-use cycle time)
5. Innovation basis (technical progress regarding new products and remanufactured products)
6. Disposal basis (efforts and cost of alternative processes to recycle the products and possible hazardous components)
7. Point of comparison regarding interference with new manufacturing (competition or cooperation with OEMs)
8. Other basis (market behavior, liabilities, patents, intellectual property rights)

2.1 Forecast Models

In this section, we will discuss forecast models which have been studied in the past and applied to the remanufacturing industry. Prior to the advent of sophisticated software, the methods used for forecasting were very basic such as the use of the likelihood of the ratio between cumulative returns to cumulative sales. For instance, if a vendor sells 'A' number of products over the time and 'B' is the average of the percentage of the product that comes back as returns; it is assumed that 'B' is the probability of the product returns for future time bucket (*Potdar, 2009*). Accurate forecasting methods rather than this basic methodology are needed for better decision making in strategic, tactical and operational areas of the remanufacturing organization (*Potdar, 2009*).

Goh and Varaprasad (1986), were among the first people to study the statistical way of handling product returns. Their research was on soft drink reusable containers. Using data spanning 4 years, they studied the product demand and product returns for these products. They used the product life cycle parameters and basic time series techniques to develop the methodology. Their main target was to study the effectiveness of recycling the containers and evaluate the cost over the container life cycle. The model evaluated return probability by proportion of total product returns. According to their results, they observed that a number of returns from a single issue was statistically significant only in the first three months, with close to two-thirds of the containers being returned in the same month of the issue. It was focused towards inventory management and examining effectiveness of the recycling process of containers.

Kelle and Silver (1989) did research on reusable containers which are used in the industry to sell or store liquids. There is a chance those containers are never returned either due to loss or damage. Their study focused on forecasting return containers to estimate net demand. Their work was an extension of the model that was earlier developed by Goh and Varaprasad. Using the estimation of return proportions for forecasting, Kelle and Silver calculated variability of various factors. Method 1 included the probability that all containers were returned. Method 2 used the more detailed information where each time bucket analyzed separately to find probabiliy of returns in each time bucket. Method 3 involved method 2 in addition to conditional probabilities between each time bucket. Method 4 was method 2 plus aggregated return data. The authors evaluated the forecasting methods taking the most-informed method as a benchmark. However, it is applicable only when there is perfect information and limits itself to relative forecasting performance without considering costs.

Panniset (1998) described the importance of remanufacturing and proposed that alteration in Material Requirement Planning (MRP) systems are needed to plan and control remanufacturing. *Krupp (1992)* developed a model detailing the role of forecasting in the planning of replacement components. The objectives of his models were to estimate the number of new cores needed to meet the demand, to measure and monitor high core demand in order to prepare for potential control problems, to provide a technique to predict core obsolescence and update this information as acquired to utilize a weighted average approach to evaluate core obsolescence.

Srivatasva and Guide (1997) were the initial researchers to propose the idea of applying intrinsic forecasting method based on a time series approach for estimating return quantities and the rate of returns. They developed a model for product recovery rate. Based on this recovery rate of the product, planning capacity was designed. The relationship between the product recovery rate, time for which product is in service and total sales for the product was shown. The model was based on simple time series analysis.

Guide et al (2000) conducted a research study on the management of recoverable manufacturing systems. He restated that correct estimation of return quantity allows manufacturers to use these parts in manufacturing thereby decreasing the consumption of new materials. However, the estimation process is made more challenging due to data unavailability and uncertainty of return time.

Hess and Mayhew (1997) developed a direct marketing model which was different from all the above traditional methods. They developed a statistical model where direct marketing companies collect information from the returned products and use it to forecast the returns. Their model focussed on the timing of the returns and probability of return. They modeled time to return by using simple linear regression method which depends on the past returns and factors affecting the returns. In their paper, they showed that when larger amount of money is at stake, the customers tend to react quickly if they wish to return the product for a given price. The probability of returns can be calculated as a return rate of a product. *Hess and Mayhew* used a variable called product fit as a category in the logit hazard model. A dummy variable was defined for product fit. They concluded that for some clothing items, product fit was unimportant when compared to others. For instance, socks versus suits. Logit model showed the impact of product category and product fit on product returns. According to them, both the regression and logit models uses the data for products that have been returned and does not use the information for the products which are not returned yet will be returned eventually. Basically, an event will happen and the timing would have some statistical distribution. It's a ratio of probabilities that is purely a function of time. This model calculates the probabilities of the two events such as return will occur and return has not occurred yet. The probabilities are calculated from the previous data which has been classified by the effect of product category, price, among other factors on return quantities with one factor at a time.

Toktay et al. (2003) studied forecasting in managing product returns. Their study was about various factors influencing the return flow of products and influencing the returns and their timings. There were three discussion levels such as strategic, tactical and operational. In the strategic level, decisions related to network design, product launch are made. In the tactical level, decisions regarding the procurement, capacity planning and disposal management are made. In the operational level, decisions are made regarding production planning and inventory management. Their research focussed on the operational level, by calculating the forecast quantity as a function of past sales data. The forecast model is divided into two parts, return delay and estimating parameters to forecast return quantity. This model suggests that factors influencing the returns (take back price, trade in offer, among others) can be used for forecasting returns.

Carrasco-Gallego and Ponce-Cueto (2009) suggested that univariate time series would be helpful when only data available are historic return series in a linear reverse logistics system. Alternatively, *Kumar and Yamaoka (2007)*, show that when available data are in wider range variety, dynamic regression models would be more suitable.

Liang, Jin and Ni (2012) in their journal state the goals of strategic forecasting which is to estimate opportunity and outcome for future business actions, to find what influences and how to influence these outcomes, and to judge the potential risks associated with such business actions. Their research describes the forecasting of product returns or supply of a remanufacturing system by modelling 3 major influential factors which are sales, life expectancy and customer return behavior. The effectiveness and accuracy of the forecasting model developed in their paper were verified and validated with simulations using Monte Carlo simulation.

Jungmok and Harrison (2016) used the results of Goh and Varaprasad and studied further about it. They used three models in their analysis which were ARIMA model, DLM (Dynamic Lag Model) and Mixed model. A mixed model which was their predictive model used both ARIMA and DLM. There were three cases taken into consideration:

1. When sales data were available for returns

2. When sales data were not available for returns

3. When there was a strong and static relationship between return and sales

In the first case, ARIMA model was the best since it generated lowest errors. In the second case, the mixed model was selected the best predictive model. In the third case, the DLM was selected as the best model. The following issues were observed in the predictive models:

1. The required sample size for predictive models: Univariate time series model require more data points as compared to DLM

2. Model appropriateness: Though the mixed model was proven to generally be better than the separate ARIMA and DLM models (*Jungmok and Harrison, 2016*), it however fails when sales data were available for returns

3. Using other variants of ARIMA model: For instance, autoregressive conditional heteroscedastic or generalized autoregressive conditional heteroscedastic can be used for heteroscedastic error in finance

3 Methodology

In this research, all analysis has been carried out in Rstudio (Version 1.0.136 - ©2009-106 R Studio, Inc.). RStudio is a free and open source integrated development environment built for R, a programming language used for wide variety of statistical (linear and nonlinear modelling, classical statistical tests, time-series analysis, classification, clustering) and graphical techniques, and is highly extensible. The founder of RStudio is JJ Allaire, a software engineer and internet entrepreneur (*"Why RStudio?", 2015*). ARIMA and SARIMA models used for our thesis were implemented using R programming.

3.1 ARIMA Time Series Analysis

ARIMA stands for Autoregressive Integrated Moving Average. ARIMA models are mathematical models of endurance of autocorrelation in a time series which was introduced by Box-Jenkins in 1976. ARIMA is a forecasting method which projects the future values of a time series as a linear combination of past values and a series of errors.

Let Y_t be a discrete series which takes different variable over a period of time. The corresponding AR (p) (Autoregressive) model of Y_t series is expressed as:

$$Y_t = \Phi_0 + \Phi_1 Y_{(t-1)} + \Phi_2 Y_{(t-2)} + ...\Phi_p Y_{(t-p)} + \epsilon_t \tag{1}$$

Where Y_t is the response variable at time t;

$Y_{(t-1)}$, $Y_{(t-2)}$,..... $Y_{(t-p)}$ are the respective variables at different time lags;

Φ_0, Φ_1,.....Φ_p are the coefficients and ϵ_t is the error factor

Similarly, the MA (q) (Moving Average) model is expressed as:

$$Y_t = \mu_1 + \epsilon_t + \sigma_1 \epsilon_{(t-1)} + ...\sigma_q \epsilon_{(t-q)} \tag{2}$$

Where μ_t is the constant mean of the series,

$\sigma_1, \sigma_2, ...\sigma_q$ are the coefficients of the estimated error term

ϵ_t is the error term

When Y_t in the data is replaced with $(\Delta Y_t = Y_t - Y_{(t-1)})$, then the ARMA models become ARIMA (p,d,q) models, where 'p' is the number of autoregressive (AR) terms, 'd' is the number of differences and 'q' is the number of moving average (MA) terms. By combining the models in equation (1) and (2), we get:

$$Y_t = \Phi_0 + \Phi_1 Y_{(t-1)} + \Phi_2 Y_{(t-2)} + ...\Phi_p Y_{(t-p)} + \epsilon_t + \sigma_1 \epsilon_{(t-1)} + ...\sigma_q \epsilon_{(t-q)} \tag{3}$$

If Y_t is stationary at level or I(0) or at first difference I(1) then this determines the order of integration. To identify the order of p and q the ACF and PACF is applied.

3.2 Stationarity of time series

The first step is to test the stationarity of time series. We can use scatter plots or line plots to get an initial idea of the problem. After the choice of plotting technique, an Augmented Dickey-Fuller (ADF) unit root test is used to determine the stationarity of the data. If the data is non-stationary, we perform a log transformation or take the higher order difference of the data series which may lead to a stationary time series. This process is continued till stationarity is achieved. The times of differencing of the data are mentioned by the parameter d in the ARIMA (p,d,q) model. Theoretically, differencing the time series repeatedly will eliminate the non-stationarity of the time series. Although it does not imply that more differencing is better since differencing is a procedure of extracting information and processing data. Each time the differencing is performed, it will lead to a loss of information (*Harvey, 1989*).

3.3 Model Identification

The Autocorrelation Function (ACF) plot and the Partial Autocorrelation Function (PACF) plots can help us to determine the properties and number of lags in the models. If the ACF plot shows an exponentially declining trend and the PACF plot shows spikes in the first one or subsequent lags, it denotes the process best fits the AR models. The number of spikes in the PACF plot indicates the number of AR terms (p). If the ACF plot shows spikes in the first one or subsequent lags and the PACF plot shows an exponentially declining trend, it denotes the process best fits the MA models. The number of spikes in the ACF plots indicates the number of MA terms(q). In case, the ACF and PACF plots display exponentially declining trend, it denotes that the process best fits the mixed model i.e. ARMA model (*Robert, 2005*).

3.4 Model Selection Criterion

After identifying the value of p, d and q in the ARIMA (p,d,q) model, the model that best describes the dataset at hand can be constructed using Akaike Information Criterion (AIC) (*Harvey, Lebourne,Newbold, 1998*). The Akaike Information Criterion (AIC) was developed by Hirotugu Akaike (*Akaike, 1974*). The AIC rulde provides the best number of lags and parameters to be estimated in the ARIMA (p,d,q) models. The AIC function can be expressed as:

$$AIC = -2log(L) + 2(p+q) \tag{4}$$

Where L indicates the likelihood of the data with a certain model;

p and q indicate the lag number of AR term and MA term

The AIC rule which is used to determine the best fit model can be expressed as:

$$AIC(p,q) = minAIC(k,l) \tag{5}$$

Where k and l indicate the different choices of lag numbers.

The model with the minimum values of AIC is considered as the best. In addition, RMSE, MAE and MAPE are employed for comparison of the best models selected.

3.5 Model Estimation

Once the values of p, d and q are identified, next step is to specify appropriate regression model and estimate. With the help of R software various order of ARIMA model has been estimated to arrive at the optimal model.

3.6 Model Diagnostics

While we estimate he model parameters; it is important to do model diagnostics in order to check whether the discussed model is appropriate. This is done by checking the residual term obtained from ARIMA model and by applying ACF and PACF functions. In the ACF and PACF plots, if there are lines spiking outside the significant, it means there is autocorrelation and the model is not appropriate. In the Ljung-Box test, if the p-value is greater than 0.05, there is ARCH (autoregressive conditional heteroscedastic) effect and the model is inappropriate. In the Jarque Bera test, if the p-value is greater than 0.05, the residuals are normally distributed and it is not an appropriate model.

3.7 Forecast

Forecasted values are obtained by estimating the appropriate model

3.8 Model Forecast Accuracy Criteria

3.8.1 RMSE (Root Mean Square Error)

measures the mean prediction error. For perfect fit, the value of RMSE is zero. The Root Mean Square Error (RMSE) is also called the Root Mean Square Deviation (RMSD) is used to measure the difference between values predicted by a model and the values actually observed. These individual differences are also known as residuals. RMSE can be mathematically expressed as:

$$RMSE = \sqrt{\frac{ESS}{n}} \tag{6}$$

Where ESS is the error sum of square

n is the total number of observations

3.8.2 MAE (Mean Absolute Error)

measures how close the forecasted values are to the actual values. It's the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight.

$$MAE = \frac{\Sigma_{t=1}^{n} |Y_t - \hat{Y}_t|}{n} \tag{7}$$

3.8.3 MAPE (Mean Absolute Percentage Error)

measures the size of the error in percentage terms. MAPE is the most common measure of forecast error. It functions the best when there are no extremes to the data. MAPE is the average absolute percent error for forecasted values subtracted by the actual values divided by actual values.

$$MAPE = \frac{\Sigma_{t=1}^{n} |\frac{Y_t - \hat{Y}_t}{Y_t}|}{n} * 100 \tag{8}$$

3.9 SARIMA Time Series Analysis

SARIMA stands for Seasonal ARIMA model. SARIMA model takes into account the seasonal characters of the time series data (*Fenyves et al., 2008*). It is used in the analysis of stochastic and non-stationary time series and compliments ARIMA models. This model is useful when the time series data exhibit seasonality; periodic fluctuations that recur with about the same intensity each year (*Martinez, 2011*). The seasonal part of an ARIMA model has the same structure as the non-seasonal part; it may have an AR term, MA term, and/or an order of differencing. A seasonal ARIMA model is classified as an ARIMA (p,d,q)x(P,D,Q)S model where P=number of seasonal autoregressive (SAR) terms, D= number of differences, Q= number of seasonal moving average terms (SMA) terms and S= time span of repreating seasonal pattern.

ARIMA (p,d,q)x(P,D,Q)S as written in lag form by Halim and Bisono (*2008*):

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D Y_t = \theta(B)\Theta(B^s)\epsilon_t \tag{9}$$

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - ..... - \phi_p B^p \tag{10}$$

$$\Phi(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - ..... - \Phi_P B^{Ps} \tag{11}$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - ..... - \theta_q B^q \tag{12}$$

$$\Theta(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - ..... - \Theta_Q B^{Qs} \tag{13}$$

Where $p,\ d,\ q$ are the orders of non-seasonal Autoregressive, Differencing and Moving Average respectively;

$P,\ D,\ Q$ are the orders of seasonal AR, differencing and MA respectively;

Y_t represent the time series data at period t;

s represent the seasonal order;

B represent backward shift operator;

ϵ_t represent white noise error at period t.

3.10 Multi-Billion OEM electronic company located in Milwaukee

The partner company from where the data was obtained is a multibillion dollar multinational company that manufactures their products and has a market base in 6 continents. The company has a remanufacturing business that produces more than 500 products daily, covering over 83,000 active and inactive catalog numbers servicing and 23 million products per year throughout the world.

The Figure 3 provides a schematic representation of the remanufacturing process (*Omwando, 2016*).

The remanufacturing process typically involves the following keys: receiving, testing, cleaning, disassembly, reassembly, inspection and diagnosis, testing and packaging. In the final diagnostic testing stage, the products are functionally tested according to their original specification at various loads and operating conditions. In addition, quality control is carried out to ensure that it is equivalent to that of new products. This quality assurance is particularly because remanufactured products are sold with similar warranty offerings as new products. The company provides 12, 18 or 24 months of comprehensive warranty depending on service level. When all the checks are verified, the unit is again visually inspected for cosmetic restoration, product identification and labelling, and proper configuration according to the customer's requirements. Our partner company strives to minimize downtime and production lines runtime by appropriately allocating resources and planning the remanufacturing schedule. It is therefore imperative that the choice of most appropriate model is essential to process the forecasting of incoming cores.

Particular to our partner company, the skill level of the associate working on the remanufactured product depends on whether the incoming cores are under warranty or billable. In addition, forecasts are useful to ensure that the inventory of spare parts is optimized. The objective of this Thesis as mentioned before seeks to fulfill this role by modelling and forecasting incoming cores both under warranty and billable ones.

In this Thesis, we have done the forecasting and data analysis using the data from an electronic drive company considering the returns which were described using *return order creation*, *warranty* and *billable products*. *Return order creation* is the timestamp of the customers' calls to company to place an order for remanufacturing. The products in return order creation can be further classified as warranty products and billable products. The products which come under warranty did not have to pay for getting their product remanufactured. The billable products come under two categories; (1) the remanufactured products, which the customers directly purchase from the company and (2) the products which are returned to the company for remanufacturing when the products become defective, when upgradation is required or when they are purchased from some other company.

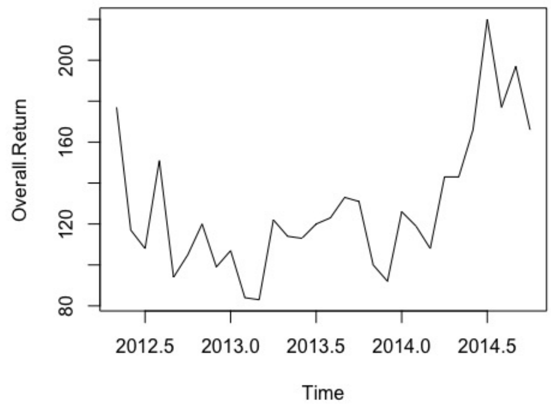
4 Result

4.1 Data Processing:

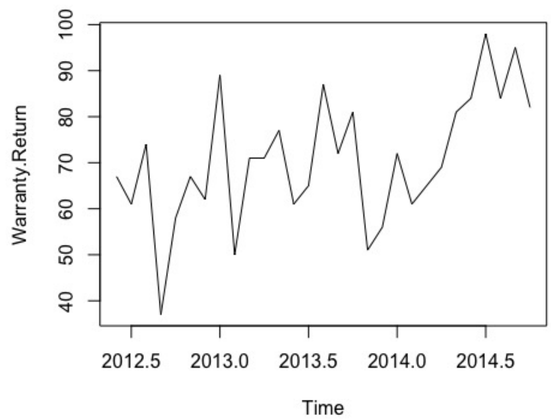
This Thesis used a dataset of return orders for remanufacture that was provided by a multinational electronics company in the United States from May 2012 to April 2015. The dataset of overall return is comprised of 5191 data points, out of which warranty products is comprised of 2877 data points; whereas the dataset of billable products is comprised of 1802 data points. For the purposes of time series analysis, the equipment return order creation (ROC) date was used as the timestamp. The ROC is described as the date a customer calls the company to place an order for remanufacture. There are instances in the data where the equipment was received after the ROC has been created, while other times the ROC is created before the equipment were received. For the analysis in this Thesis, the three-year data was categorized by the number of returned cores that were received each month, for 36 months. Three analyses were carried out, since the returns were categorized as being under warranty or billable. These time series analyses include (1) overall returns, (2) warranty returns and (3) billable returns. A warranty is a type of guarantee that the producer makes regarding the condition of the products, such that if there would be any defect detected within the warranty period, the repairs would be done free of cost to the customer. The billable products can be classified as the remanufactured products which the customers directly purchase from the company and the products which are returned to the company for remanufacturing when the products become defective, when upgradation is required or when they are purchased from some other company. These three analyses were carried out to discern the differences in billable versus warranty returns and particularly if any of the two categories mostly influences the trend and seasonality of the overall returns.

4.2 Time series construction and decomposition:

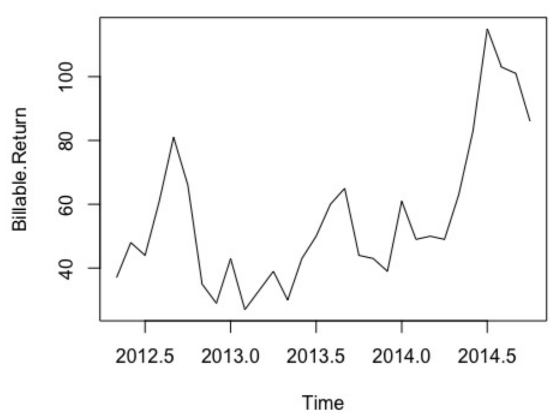
The ts() function available in R library was utilized for construction of time series. The frequency of time series was fixed at 12 months starting from May 2012, and Figure 4 shows the time series plot of the monthly returns of overall returns, warranty returns and billable returns.



(a) OVERALL RETURN



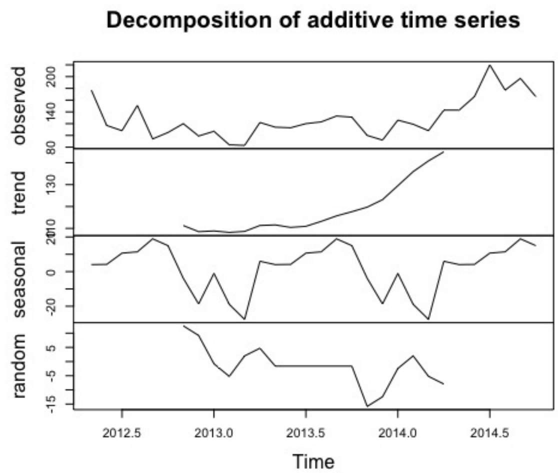
(b) WARRANTY RETURN



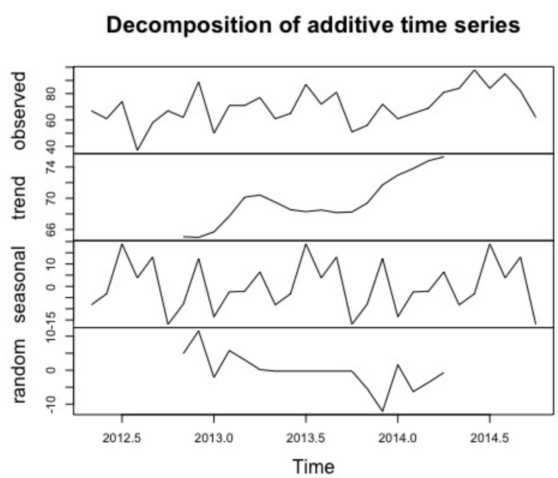
(c) BILLABLE RETURN

Figure 4: TIME SERIES PLOT

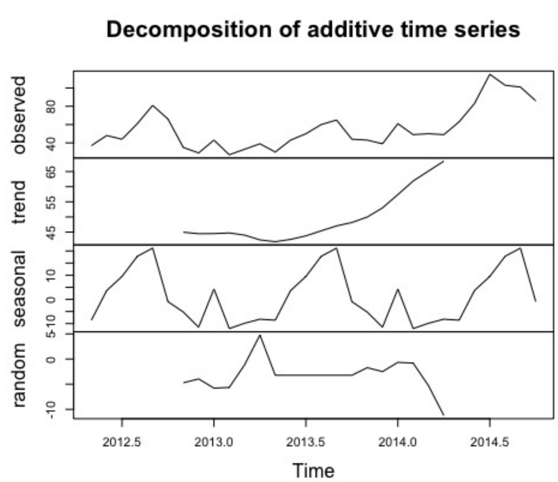
Next, the decompose() function was applied to decompose the time series into the trend, seasonal, cyclic and irregular components, the decompose() function is applied. The graphs in Figure 6 shows the original time series (top), the estimated trend component (second from top), the estimated seasonal component (third from top) and the estimated random component (bottom). The trend component indicates a progressive positive trend over time, while the seasonal component exhibits an annual seasonality.



(a) OVERALL RETURN



(b) WARRANTY RETURN



(c) BILLABLE RETURN

Figure 6: DECOMPOSITION OF TIME SERIES PLOT

Using the auto.arima() function, the best model was selected on the basis of least AIC value from a set of potential of models that were tried following analyses of the Autocorrelation and Partial Autocorrelation Functions (ACF and PACF) of the monthly returns data. These models, with their respective AIC values are shown in Table 2, 3 and 4.

Model	AIC
ARIMA(2,1,2)(0,1,0)[12]	174.0576
ARIMA(0,1,0)(0,1,0)[12]	169.7747
ARIMA(1,1,0)(0,1,0)[12]	170.7538
ARIMA(0,1,1)(0,1,0)[12]	169.4193
ARIMA(1,1,1)(0,1,0)[12]	171.3109
ARIMA(0,1,2)(0,1,0)[12]	171.126
ARIMA(1,1,2)(0,1,0)[12]	172.365

Table 2: ARIMA MODEL FOR OVERALL RETURNS

Model	AIC
ARIMA(2,1,2) with drift	Inf
ARIMA(0,1,0) with drift	242.0476
ARIMA(1,1,0) with drift	232.6442
ARIMA(0,1,1) with drift	Inf
ARIMA(0,1,0)	240.0755
ARIMA(2,1,0) with drift	233.3181
ARIMA(1,1,1) with drift	Inf
ARIMA(2,1,1) with drift	Inf
ARIMA(1,1,0)	230.8735
ARIMA(2,1,0)	231.6589
ARIMA(1,1,1)	230.7175
ARIMA(2,1,2)	233.1115
ARIMA(0,1,1)	229.1192
ARIMA(0,1,2)	230.866

Table 3: ARIMA MODEL FOR WARRANTY RETURNS

Model	AIC
ARIMA(2,1,2)(0,1,0)[12]	Inf
ARIMA(0,1,0)(0,1,0)[12]	139.6265
ARIMA(1,1,0)(0,1,0)[12]	141.5771
ARIMA(0,1,1)(0,1,0)[12]	141.5542
ARIMA(1,1,1)(0,1,0)[12]	143.1197

Table 4: ARIMA MODEL FOR BILLABLE RETURNS

The AIC values show that the best model, with the lowest AIC value was ARIMA(0,1,1)(0,1,0)[12] for overall returns, ARIMA(0,1,1) for warranty returns and ARIMA(0,1,0)(0,1,0)[12] for billable returns. From Table 5, 6 and 7 gives more summary results of the best model, further residual analyses results are presented, verifying how good of a fit the model is for our analysis.

The confidence interval of the selected ARIMA model ranges from -0.9924512 to -0.03754126 in case of overall returns and since the interval does not contain a zero value we can say that this ARIMA model is significant. Similarly, the confidence interval of the selected ARIMA model for warranty returns ranges from -1.003284 to -0.4161898 and the interval does not contain a zero value we can say that this ARIMA model is significant.

$Sigma^2$ estimated as 1028: log likelihood=-82.71
AIC=169.42 AICc=170.28 BIC=171.09
Coefficients:
ma1
-0.5150
s.e. 0.2436

	2.5%	97.5%
ma1	-0.9924512	-0.03754126

Table 5: SUMMARY OF ARIMA MODEL FOR OVERALL RETURNS

$Sigma^2$ estimated as 183.7: log likelihood=-112.56
AIC=229.12 AICc=229.6 BIC=231.78
Coefficients:
ma1
0.7097
s.e. 0.1498

	2.5%	97.5%
ma1	-1.003284	-0.4161898

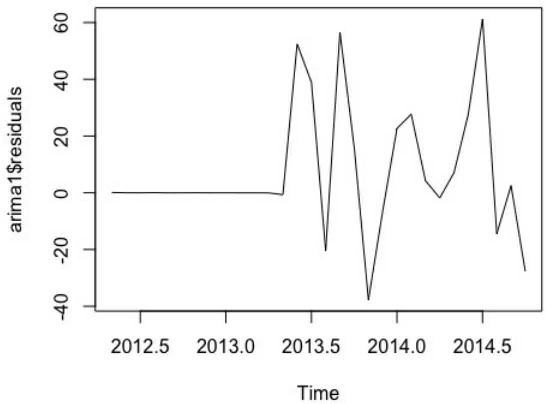
Table 6: SUMMARY OF ARIMA MODEL FOR WARRANTY RETURNS

$Sigma^2$ estimated as 192.1: log likelihood=-68.81
AIC=139.63 AICc=139.89 BIC=140.46

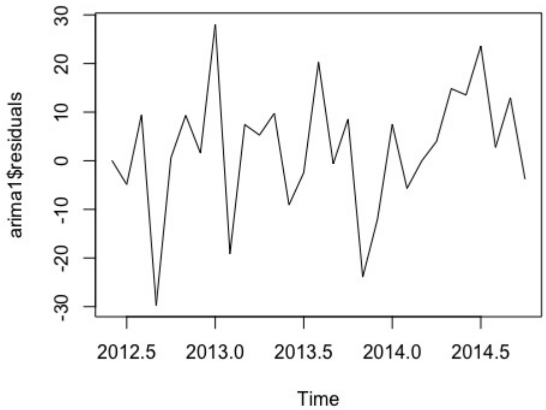
Table 7: SUMMARY OF ARIMA MODEL FOR BILLABLE RETURNS

4.3 Residual Diagnostics:

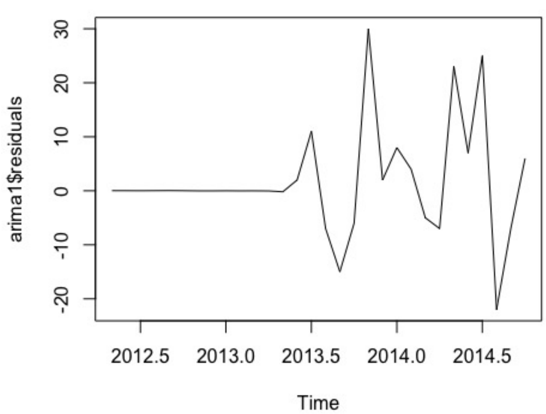
The residual plot which is shown in Figure 7 represents the gap between actual values and fitted (forecasted) values.



(a) OVERALL RETURN



(b) WARRANTY RETURN



(c) BILLABLE RETURN

Figure 7: RESIDUAL DIAGNOSTICS

4.4 Box-Ljung Test:

From the Box-Ljung test, we found that the p-value is greater than 0.05. Hence, there is no autocorrelation which can be further verified by observing the residuals of ACF and PACF graphs.

Overall Returns		
X-squared=7.6479	df=20	p-value=0.994

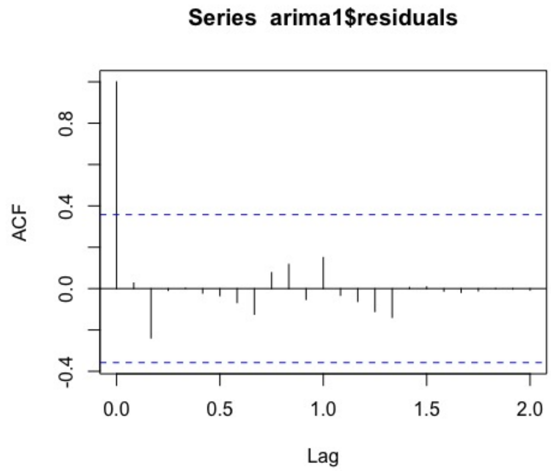
Warranty Returns		
X-squared=18.32	df=20	p-value=0.5663

Billable Returns		
X-squared=18.353	df=20	p-value=0.5641

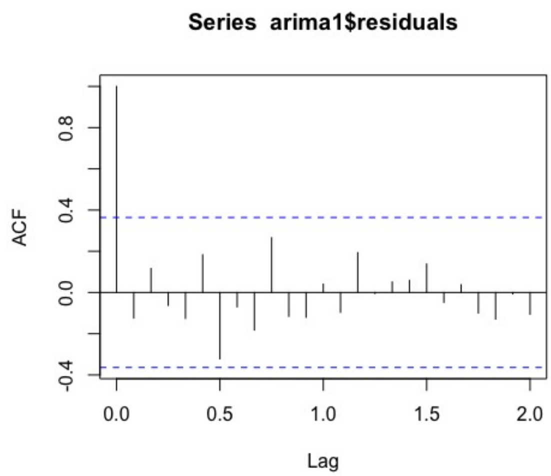
Table 8: BOX-LJUNG TEST

4.5 ACF and PACF:

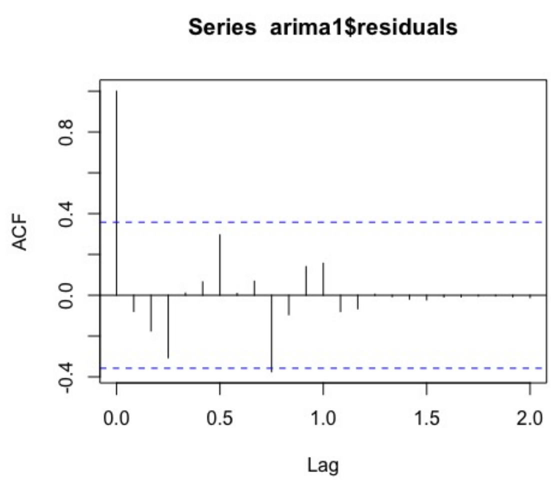
After selecting the best fitted ARIMA model, we check the ACF and PACF values to analyze whether is the model has a good fit. From the below ACF and PACF in Figure 8, we observe that the spikes are within the significant line. Hence, there is no subsequent remaining autocorrelations, making the model a good fit for the returns data.



(a) OVERALL RETURN



(b) WARRANTY RETURN



(c) BILLABLE RETURN

Figure 8: RESIDUALS OF ACF

4.6 ARCH Effect:

Box-Ljung test is done on the square of the residuals to determine whether the model has an ARCH effect. Since, the p-value is greater than 0.05, we resolve that there is no ARCH effect.

Overall Returns		
X-squared=10.37	df=20	p-value=0.961

Warranty Returns		
X-squared=11.505	df=20	p-value=0.9321

Billable Returns		
X-squared=16.549	df=20	p-value=0.682

Table 9: ARCH EFFECT

4.7 Jarque Bera Test:

Jarque Bera test is done to check the normality. Since, the p-value is greater than 0.05, the residuals are normally distributed, though the P-value is not much higher than 0.1, hence it shows that the data points that seem to be outliers should be examined once more before building the ARIMA model.

Overall Returns		
X-squared=3.4795	df=2	p-value=0.1756

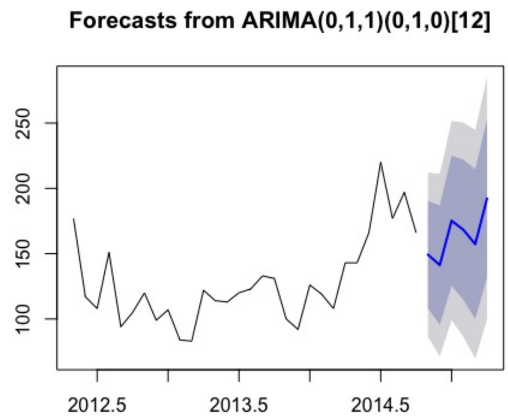
Warranty Returns		
X-squared=1.1319	df=2	p-value=0.5678

Billable Returns		
X-squared=6.6223	df=2	p-value=0.03647

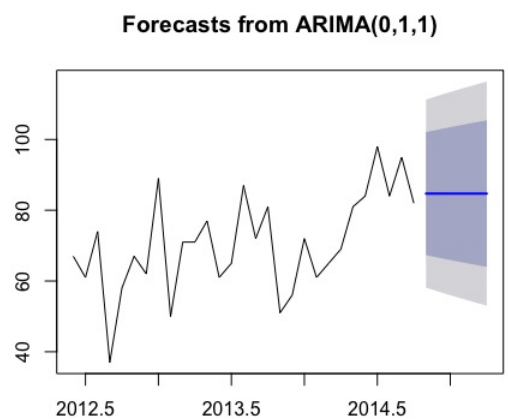
Table 10: JARQUE BERA TEST

4.8 Forecasting with fitted model:

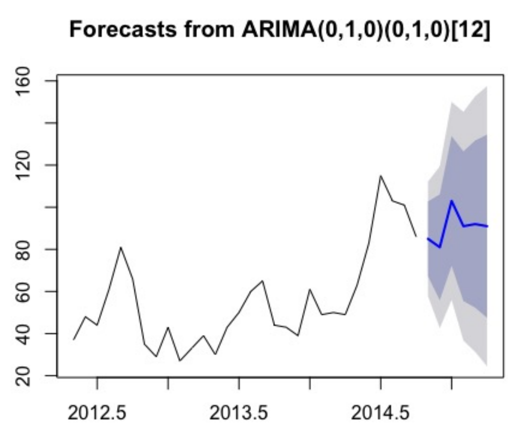
The forecast.Arima() function gives us a forecast of the number of products returned in the next specified number of months (in this study, we forecasted November 2014-April 2015). Figure 9 represents the observed and forecast plots of number of products returned.



(a) OVERALL RETURN



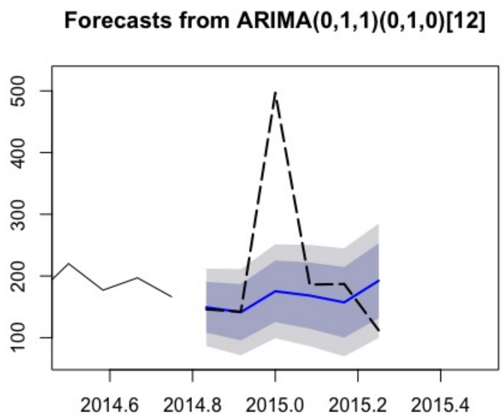
(b) WARRANTY RETURN



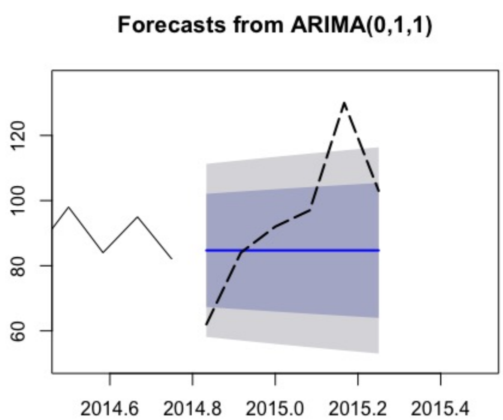
(c) BILLABLE RETURN

Figure 9: FORECAST FROM ARIMA

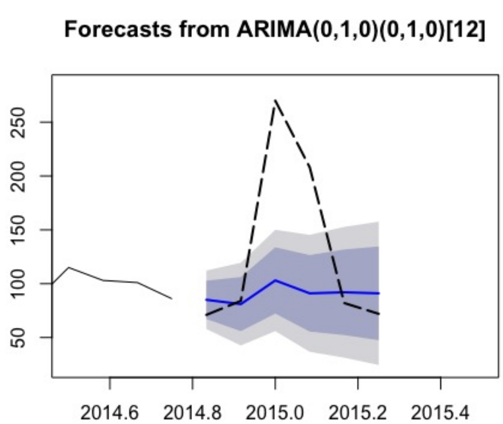
The graph below shows the the forecasted value of products from our analysis which is denoted by the blue line and the actual value of products which is represented by black dotted lines.



(a) OVERALL RETURN



(b) WARRANTY RETURN



(c) BILLABLE RETURN

Figure 10: FORECASTED VALUES (BLUE LINE) WITH THE ACTUAL VALUE (DOTTED LINE)

These forecasts and their 80% confidence interval i.e. lower confidence level (LCL) and upper confidence level (UCL) for 6 months are summarized in Table 11, 12 and 13.

Month	Actual Value	Forecast Value	Low 80	High 80
November 2014	146	149.25	108.17	190.34
December 2014	142	141.25	95.59	186.42
January 2015	497	175.25	125.43	225.08
February 2015	186	168.25	114.59	221.91
March 2015	187	157.25	100.01	214.49
April 2015	112	192.25	131.64	252.86

Table 11: OVERALL RETURNS

Month	Actual Value	Forecast Value	Low 80	High 80
November 2014	62	84.70	67.33	102.07
December 2014	84	84.70	66.61	102.79
January 2015	92	84.70	65.92	103.48
February 2015	97	84.70	65.26	104.14
March 2015	130	84.70	64.61	104.78
April 2015	103	84.70	63.99	105.41

Table 12: WARRANTY RETURNS

Month	Actual Value	Forecast Value	Low 80	High 80
November 2014	71	85	67.23	102.76
December 2014	84	81	55.88	106.11
January 2015	270	103	72.23	133.76
February 2015	208	91	55.47	126.52
March 2015	82	92	52.28	131.71
April 2015	72	91	47.49	134.50

Table 13: BILLABLE RETURNS

4.9 Accuracy of forecasting

Table 14, 15 and 16 shows the accuracy of forecasting that resulted from using the accuracy() function.

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Data	6.93	23.41	14.22	4.72	10.59	0.40	0.03
Actual Value	47.74	136.11	75.58	2.80	27.43	2.14	-0.16

Table 14: ACCURACY OF OVERALL RETURNS

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Data	2.34	13.07	10.02	-0.36	15.39	0.75	-0.12
Actual Values	9.96	22.75	17.76	5.95	18.44	1.33	0.29

Table 15: ACCURACY OF WARRANTY RETURNS

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Data	1.62	10.43	6.24	3.16	9.95	0.28	-0.07
Actual Values	40.66	83.90	55.00	10.56	29.99	2.46	0.18

Table 16: ACCURACY OF BILLABLE RETURNS

5 Discussion and Conclusion

In the preceding chapter, we presented the results of times series analysis that were carried out to test their fitness for forecasting the returns of cores for remanufacture. The data that was used in this research was provided by a multinational remanufacturing company. Though the data indicated when the core was returned for remanufacture, we decided to use the return creation date as the time stamp for the time series models. The return order creation is the timestamp of the customers calls to company to place an order for remanufacturing. The returns were categorized as either warranty or billable. Thus three analyses were done, for warranty returns data, billable returns data and overall returns data. Returns under warranty are remanufactured free of charge to the customer, hence the remanufacturer assumes all the cost. In addition, warranty returns may be remanufactured and returned to the customer or immediately replaced by a new product (if the customer requests), and the remanufactured one added to the outgoing remanufactured products inventory. All remanufactured products are upgraded with the latest software before being sent back to the customer.

From a business point of view, warranty products do not generate direct profits to a company as compares to billable products. This necessitates the need for business strategies to reduce product early failures, thus result in returns for remanufacture that are predominantly billable. It is therefore noted that for the same features and warranty assurance, billable remanufactured products offer a lower cost and sustainable option than new products.

As mentioned earlier, billable products are either returned to the same customer at a fee, or resold as remanufactured products. From a business point of view therefore, billable products are more profitable that warranty returns. For this reason, there is an inherent impetus to forecast the returns of billable products so as to appropriately assign resources such as labor, efficiently plan the remanufacturing process and schedule and align return forecast with inventory and anticipated remanufactured products customer demand.

In addition, billable products often need a major change and additional spare parts. In this case, it is preferable to salvage functional parts from other returned products that are routed for disposal due to the anticipated cost of remanufacture. Thus most companies will keep inventory of used parts that have been salvaged for re-use, to allay additional costs that may result in the use of new parts to remanufacture products.

5.1 Stationarity and Decomposition of Time Series

We initially plotted a time series graph using the overall return data that was provided by the OEM electronic drives company. From Figure 4a, we can see that the time series was not stationary. Normally, time series can be made stationary by differencing and taking a making transformation. In our case, we differenced the data to make it stationary. When the time series was decomposed, we can see from Figure 5a that it had an increase in the trend (supply of returned products for remanufacture) and with graphical evidence that some seasonality exists. The supply of returned products is relatively high in January; however, it decreases till the month of April. We again observe a rise in supply till June and then a steady decrease toward December. The same seasonality was observed from 2012-2015. The increase in January, being the start of the year can be attributed to the fact that most manufacturing companies experience winter shutdown (end of December to mid-January). After the financial year, the supply for products shows an upward trend. The decrease in the supply of returned products for remanufacture is attributable to the heavy season as companies try to fulfil orders before the winter shut-down.

Similarly, in the case of warranty returns, the time series graph as shown in Figure 4b was non-stationary. When the time series was decomposed, we observed that there was seasonality in the product returns (Figure 5b). Like in the case of the overall data analysis, a high supply of return products was exhibited in January being the start of the year and a low manufacturing season due to the winter shut-down. The trend then it drops as the financial year comes to an end as was explained earlier, the companies increase their production to make up for the upcoming winter shut-down. One can observe an increase in new manufactured products and decrease in remanufactured products during the month of December as customers are more comfortable towards purchasing new manufactured products than the remanufactured products can be due to trust deficit. It can probably be due to ensuing holidays in the last week of December, to meet with the completion of the target wherein manufacturing new products can be more in number than remanufactured product. Moreover, customers work overtime to meet the demand of their products before the winter closure and they are not willing to stop the machines to turn in the control drives for remanufacturing.

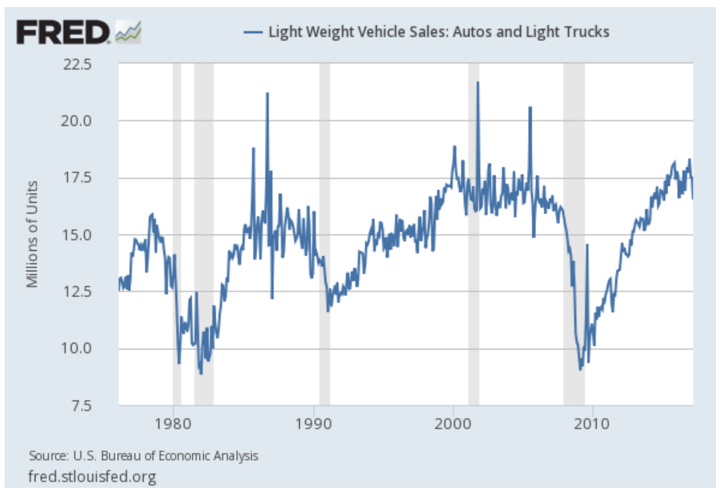


Figure 11: LIGHT WEIGHT VEHICLE SALES

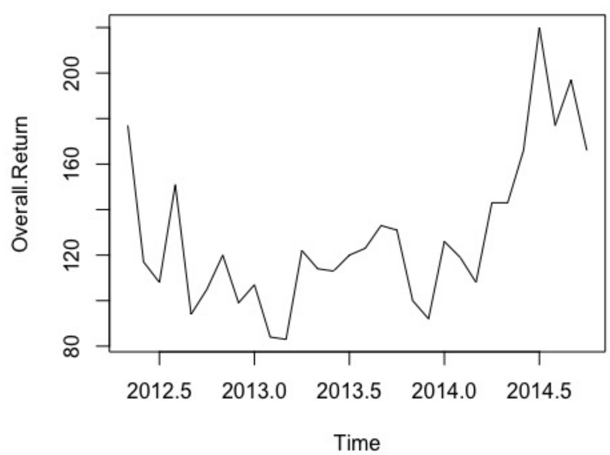


Figure 12: TIME SERIES PLOT FOR OVERALL RETURNS

From Figure 11, we can verify the decrease in sales due to winter shut down (for example in the light weight vehicle sales). Figure 11 is taken from U.S. Bureau of Economic Analysis (April, 2017). It describes the sales of light weight vehicles which includes autos and light trucks. We can see that the sales is down from December end to mid-January because of winter shut down and then it shows an upward trend. Figure 12 which is our overall returns of cores for remanufacture is included here to indicate the increase of returns in the winter times.

The time series plot for the billable products is found to be non-stationary (Figure 4c) and it is made stationary by differencing. When the time series is decomposed, we can see that there is an increase in trend of the number of billable products and it also shows seasonality (Figure 5c). Though the returns in January are not significantly high, they are more than what we have for the closing period of the financial year. It shows a rise after the end of financial year, going upwards until October and then it falls down in November and December due to the increase in manufacture of new products followed by winter shut down.

5.2 Selection of ARIMA model

Next, the best model was selected using the auto.arima() function using R forecasting package. The function conducts a search for the best-fitting ARIMA model according to AIC, AICc or BIC values. The function choses the least AIC value as the criterion for model selection. Especially since we only had 36 data points. If the size of the data was relatively larger than we would have selected the BIC criteria as well, and later compared the models selected following both criteria.

We can see from Table 2 that ARIMA(0, 1, 1)(0, 1, 0)[12] was selected as a best model for overall returns as it had the least value of AIC (169.4193). ARIMA(0, 1, 1)(0, 1, 0)[12] is a seasonal ARIMA model with a combination of simple exponential smoothing and random walk. The simple exponential model uses an exponentially weighted moving average of past values in order to filter out the noise and more accurately estimate the local mean. A random walk model is used when the time series is not stationary as is the case of the data used in this study. FromTable 3 of warranty returns, it can be seen that ARIMA(0, 1, 1) was chosen as the best model since it has the least AIC value (229.1192). ARIMA(0, 1, 1) is a model having one differencing order and one moving average term. ARIMA(0, 1, 1) is a type of the simple exponential smoothing without a constant. It is an approach for correcting auto-correlated errors in a random walk model proposed by simple exponential method. It is better to use an average of the last few observations in order to filter out the noise and more meticulously estimate the local mean. The simple exponential smoothing model accounts for an exponentially weighted moving average of past values to achieve the smoothing effect.

Just as it was in the overall scenario, ARIMA (0, 1, 0)(0, 1, 0)[12] was selected as the best model for billable returns having AIC value as 139.63.ARIMA(0, 1, 0)(0, 1, 0)[12] is a type of seasonal random trend model. Such models assume that the seasonal trend (difference) observed in a given month is a random step away from the trend that was observed in the previous month. In other words, the proposed seasonal difference for a given month is the same as the seasonal difference observed in the previous month. It also assumes that the actual seasonal differences will be subjected to a zero-growth random walk so their values will become very uncertain in the distant future. The seasonal random trend model anticipates next years seasonal cycle will have exactly the same shape (viz. the same relative month to month changes) as current years seasonal cycle. The seasonal random trend model predicts that the future trend will equal the most recent year to year trend. The seasonal random trend model is a peculiar case of an ARIMA model in which there is one order of non-seasonal differencing, one order of seasonal differencing, and no constant or other parameters (like moving average, seasonal autoregression).

5.3 Residual Diagnostics

The confidence interval of the moving average coefficient for overall returns was from -0.993 to 0.0375 and since the interval does not contain a zero value, we can infer that the ARIMA model which we selected was appropriate. Similarly, from Table 6, we observe that the confidence interval of the moving average term for warranty returns ranges from -1.003 to -0.416 and since the interval does not contain a zero value, we can say that the ARIMA model is significant.

Residual diagnostics were carried out to test for model adequacy. The residuals from a regression model were calculated as the difference between the actual values and the fitted values. Box-Ljung test was performed on the ARIMA model to obtain diagnostic information regarding ARIMA model.The Box-Ljung test is used to check whether a series of observations over time are random and independent. If the observations are not independent, one observation can be correlated to another observation, thus making them auto-correlated. Autocorrelation can decrease the accuracy and lead to misinterpretation of data.

From Table 8, we can state that the p-value is greater than 0.05 for overall returns (0.9994), warranty returns (0.5663) and billable returns (0.5641); and hence the residuals are independent which is necessary for model selection.

The ACF and PACF plots of the residuals reveal whether there are any autocorrelation in the residuals thus suggesting that their correlation has not been accounted for in the model. Since there are no spikes in Figure 8, we can conclude that there is no autocorrelation in the residuals.

The ARCH (Autoregressive Conditional Heteroskedasticity) effect is concerned with serial correlation or heteroscedasticity of the residuals. ARCH models are used to characterize an altering, possibly erratic variance. It is often used when there may be short periods of increased variation. Box-Ljung test is carried out on the square of the residuals to check whether it has an ARCH effect. Since the p-value is greater than 0.05, it can be concluded that there is no ARCH effect for overall return (0.961), warranty return (0.9321) and billable return (0.682).

The Jarque-Bera test is a type of Lagrange multiplier test for normality. It is a goodness of fit test used to check whether the sample data have the skewness and kurtosis matching a normal distribution. A data set is symmetric if it looks identical to the left and right of the center point. Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. From Table 10 we get that the p-value is greater than 0.05 in case of overall returns (0.1756) and warranty returns (0.5678), hence the residuals are normally distributed. Whereas, in case of billable returns, the p-value was less than 0.05 i.e. 0.03647, hence the residuals are not normally distributed.

5.4 Forecasting

After the residual diagnostics, if the model is chosen to be significant; forecasting is done to predict the value of products which were returned. The forecast.Arima() function gives us a forecast of the number of products which were returned in the next 6 months (November 2014- April 2015). These forecasts, and their 80% confidence interval is shown in Tables 14, 15 and 16. The foorecasted values were later compared to the actual values.

We can see from Figure 10a and 10c i.e. for overall and billable returns respectively, that there was a high supply for remanufactured products in January 2015. This is because most of the factories often schedule their winter shut-down during this time and therefore choose to return these devices for remanufacture or update. Another reason for high supply in January could be that the warranty period of products was soon ending. Generally, when returned products are under warranty, they are repaired and (or) upgraded free of charge or at a low cost. The supply of remanufactured products is declines in the months of November and December on potentially due to the ensuing holidays where the companies increase their productivity to fulfill the demands during the winter shut down.

In case of warranty returns, we can observe that there are a high number of products which were returned in March which cannot be explained especially since the product has been in the market just for five years. One of the reasons could be that most of the customers' 12 month warranty period is soon coming to an end and they want to get their product upgraded or examined free of cost.

Overall the decomposed time series plots in Figures 5a, 5b and 5c indicate an increasing trend over 3 years. Given this rising supply, we can conclude that consumers are becoming aware of remanufactured products. They are able to understand that the remanufactured products match the quality standards of a newly manufactured product, yet at a lower price. Also, with the increasing global warming, consumers are realizing the importance of remanufacturing as an environmentally friendly approach to production.

5.5 Conclusion

This Thesis addressed the challenge of forecasting product returns in remnaufacturing processes. The objectives of this Thesis were: (1) to build a forecasting model for the supply of used control drives for remanufacture and (2) to analyze the effect of warranty versus billable attributes on the forecast models. We used modeling techniques to fit real data that was obtained from a partner international OEM company. This data showed remarkable variations in returns between warranty and billable products. The overall data fit the ARIMA(0,1,1)(0,1,0)[12], the warranty data fit the ARIMA(0,1,1) whereas the billable returns fit the ARIMA(0,1,0)(0,1,0)[12]. From these selected fitting models we can infer that for the partner company billable returns have a higher influence on the overall returns. In addition, the time series decomposition plots of both overall and billable products indicated an increasing trend unlike the warranty returns which exhibited a negligible increase in the trend.

Though this model may not be generalized, our models indicate that uncertainties within returns for remanufacture can be modelled using Time Series Analysis. In addition, our models show that warranty versus billable status of returns have a potential influence on the returns forecasts and thus should be considered in the model. Lastly, our model shows that there was an overall increasing trend in the returns for remanufacture implying an increase in customers' preferences for remanufactured products. Though this ARIMA model is dependent of the product, in that it was not used to forecast any other products. We envision that ARIMA models can still be used to forecast returns other products keeping in mind the unique attributes such as seasonality, service life, quality and customer expectations.

5.6 Future Research

In this Thesis, we have attempted to construct time series models that can be used to forecast returned cores for remanufacture. To make the forecast as realistic as possible, data from an electronics product remanufacturer was used. For proprietary reasons, we are not able to publish the data neither we are able to name the company. However, the product whose data was used was less than five years in the market; so its long term market trend was yet to be established. It is for this reason that the forecasted returns for March 2015 was not able to present the hike in returns that was observed in the real data. To capture such detail, we propose that the next study should consider the sales of new product data in the model so that the forecast would be dependent on previous returns as well as previous sales. In this Thesis, our data was limited to three years. For the next study, ten years data could be taken to show an improved result. As suggested by Jungmok Ma, distributed lag models (DLMs) can be used to compare the ARIMA models to find the better predictive models in presence of additional product and process unique features such as warranty periods (*Jungmok, 2016*).

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