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Forecast Model for Return Quality in Reverse Logistics Networks

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By

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ABSTRACT

Giving rise to the field of reverse logistics are the governmental legislations mandating used electronics take-backs and sustainable recovery, which often burden manufacturers with the challenge of high implementation costs but no guaranteed profitability. One way to tackle this challenge is to demystify the multi-faceted uncertainties of product returns, namely timing, quantity and quality, that currently inhibit optimal design and operations of reverse logistics networks (RLN). In recognition of the limitations particularly caused by uncertainty of returns' quality in the strategic, tactical and operational planning of the RLN, this research seeks to develop a forecast model for the prediction of the returns' quality of future electronics returns. The proposed forecast model comprehensively incorporates three major factors that affect quality decisions which are usage, technological age and remaining economic value of expected product returns to predict its quality grade. While technological age and economic trends can readily be established, the main complexity lies in modeling of usage-dependent reliability distribution of returned electronics. The novelty of the proposed forecast model lies in deducing usage distributions through segmentation of the consumer base by socioeconomic factors such as age, income, educational status and location. These usage distributions are then used to estimate remaining useful life of returned products and their components, the associated repair costs and the subsequent profitability of reprocessing based on economic value in the market. This research develops analytical models of expected return quality based on empirical usage distributions and pricing trends. The analytical models are then applied in Monte Carlo simulations to forecast expected returns' quality from different urban and rural areas in Canada.

DEDICATION

To Farhatulaain Jaleel Shaikh,

my mother, friend and pillar of strength

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LIST OF ABBREVIATIONS/SYMBOLS

Abbreviation	Full-Form
CWTA	Canadian Wireless and Telecommunications Association
EPR	Extended Producer Responsibility
FSC	Forward Supply Chain
RLN	Reverse Logistics Network
WEEE	Waste Electrical and Electronics Equipment
d	Daily usage in hours
Component $Price_i(t)$	Price of component i at time t needed for replacement
EP_PartH(u,t)	Expected profits from part harvest from an individual end-of-use unit
EP_Recycle(u,t)	Expected profits from recycling from an individual end-of-use unit
EP_Remanf(u,t)	Expected profits from remanufacturing from an individual end-of-use unit
EP_Reuse(u,t)	Expected profits from direct reuse of an individual end-of-use unit
np_product(t)	New selling price of the product at time t
$np_i(t)$	Selling price of a new component i at time t
Pi	Bernoulli trial, probability of failure of component
Pi(u)	Probability of failure of component i after being used for u hours
Remanf Cost(u,t)	Cost of remanufacturing an individual unit that has being used for u hours, at time t
$R_i(u)$	Reliability of component i in used product after u hours
rp_product(t)	Market price for refurbished version of the product at time t

Si	Bernoulli trial, probability of survival of component
Sp(t)	Direst reuse selling price of product at time t
t	Length of ownership
u	Total usage of a product in hours
v	Value of material recycling per unit
$X_i(t)$	Selling price of used component i at time t
up_product(t)	Market price for used version of the product at time t
$up_i(t)$	Selling price/salvage value of a used component i at time t
λ_i	Constant value of failure rate of component i

NOMENCLATURE

Consumer returns of-use	Products returned by customers to collection centers at end-
Daily Usage Hours daily	Number of hours an individual spends on their smartphone
End-of-life decline stage	Products returned by customers after hardware failure or in
End-of-use	Products returned by customers due to failure or new purchases, and before decline stage in product life-cycle
Forecast	Quantitative estimation of a parameter trend in the future time periods
Length of Usage	Number of months an individual uses their smartphone before next purchase
Parts harvest	Extraction of used but functional parts from used products and selling them as-is
Quality grade	Categorization of a used product as good, moderate or bad based on degradation
Recovery decision	Selection of optimum recovery process from reuse, remanufacture, parts-harvest or recycle
Recycle	Recovering materials from used product
Refurbish	Replacing failed components in a used product to restore functionality
Remanufacture	Replacing all components in a used product to reset its usage life to zero
Return quality	Quality grade of a used product at the time when a customer returns it
Returned batch	Consolidation of many units of consumer returns into one shipment or lot
Reuse	To resell an end-of-use product after basic cleaning and repackaging, without need for any repairs or component replacements

Reverse logistics	Process planning and all activities pertaining to the collection and sustainable disposition of used products
Technological age consumer market	Time lapse after release of a product or model in the
Total usage hours	Total accumulated usage or runtime of a device in hours at the time of return. It is a product of the daily usage hours and the length of usage
Uncertainty	The risk associated with incomplete information about parameters that are taken into account during supply chain planning and execution

CHAPTER 1
INTRODUCTION

1.1 Birth of Sustainable Development

The digital revolution, also known as the third industrial evolution, of the late 1950's set the tone for the boom in the electronics industry which is still prevalent today. It began with the gradual shift of analogue systems into digital ones, ushering in the rapid adoption and proliferation of rapid computers for those who were able to afford it at that time. As the demand for this technology grew, so did the manufacturing capabilities of the industries which found themselves able to mass produce the digital products. With mass production, came the decrease in prices which meant that more people could afford it, further fueling the infiltration as well as the dependence of activities on these devices.

The opportunities for financial gain were too lucrative for businesses to ignore. Very soon, the electronics industry began to seem like a race for rapid technological advances and new product launches that furthered mass sales. At the height of financial euphoria, no one was paying attention to the key enabler of such technological advances: the raw materials, metals and semiconductors, that were being depleted into making these electronics. All this mass production was only possible because of the readily available natural resources. But what would happen when these ran out? This realization gave birth to the concept of sustainable development.

Sustainable development means using the natural resources available to satisfy the needs of this generation without diminishing the ability of the future generations to satisfy theirs. In the electronics industry, the adoption of sustainable development is the circulation of the resources from the old products that are no longer in use, to produce new products so that the net mining of virgin natural sources is reduced and the resources are conserved for the needs of the future generations. Under this concern, companies have adopted multiple product recovery management options such as repairing remanufacturing, or recycling (Ramani et al., 2010). In the words of Thierry et al., (1995), the term product recovery management means salvaging as much of the economical (and ecological) value as sensibly possible in order to reduce the residual waste.

In addition to conservation of non-renewable sources, concept of sustainable development extends to environmentally friendly disposal of the electronics that consumers no longer use, after they purchase a replacement. Electronics contain metals, chemical batteries, silicon chips and other materials, which if sent to landfills, can release toxic chemicals into the environment. This disposal issue is major concern today due to the rapid rate at which consumers are disposing electronics today. In Canada alone, nearly 40,000 mobile phone units are returned for recycling each day. This rapid generation of electronics waste is a byproduct of the same factors that incite sales of new purchases. In the smartphone industry for example, rapid technological advances, new functionality and designs, and pressure from marketing and sales incite consumers to replace their devices with new ones. At most times, their current devices are still functional but, because of the factors mentioned earlier, the consumers feel entitled to a new purchase. This has led to a shortened life cycle for smartphones. In the case for Canada, the average life of a phone is 30.6 months which means consumers are likely to upgrade their device in less than three years (Communcations Monitoring Report 2017).

In addition to the factors that affect consumer behavior, tactics such as designed-for-obsolescence also ensure new sales for the manufacturers. Smartphones today are not only less reliable in terms of functionality, but are also more difficult to repair. When a device fails due to malfunction of one component such as the microphone or speaker, consumers find it easier to buy a new device than repair it. The costs of repair have increased due to the sleek designs and intricate assembly and disassembly of the current generation of smartphones which require skilled labour (Ait-Kadi et al., 2012). This has contributed to an increasing sales and an even larger and more frequent rate of mobile phone returns reaching their end of use, thereby magnifying the disposal issue mentioned earlier. The implementation of recovery options such as remanufacturing, repairing and recycling can ensure the safe disposal of these electronics as well. In order to enforce effective compliance of industries with the product recovery practices that facilitate sustainable development, government regulatory bodies in various countries have implemented strict legislations with regards to the recovery management of electronics and electrical wastes.

Under one such regulatory policy, the Extended Producer Responsibility (EPR) legislation was put into practice in Canada in 2009. Under the EPR, all original equipment manufacturers (OEMs) of electronics, electrical supplies, automobiles and parts, or any other product which has toxic materials, are mandatorily responsible for taking back their products from the consumers at the end of use, and performing product recovery operations in an eco-friendly way. Under the government policy, the OEM is usually responsible for funding any activities that are required to implement the EPR legislation.

With the pressures of complying with EPR, OEMs were grappling with the difficult task of not only collecting their end-of-use products from their country-wide consumer base, but also with finding economic viability of the product recovery processes. This gave rise to the entire field of product recovery management which has gained exponential interest from both- industrial partners and academia. The common objective of this interest has been in maximizing the efficiency and profitability of all activities that fall under EPR compliance. Under the umbrella of sustainable development, these activities entailing product-take back schemes and recovery operations are collectively addressed under the term “reverse logistics”.

1.1.1 Reverse Logistics: Challenges and Decisions

Reverse logistics consists of a series of activities required to (1) collect used product from a consumer and (2) reprocess the used product using the recovery decisions available, in such a way so as to recover its leftover market value or dispose it in an environmentally friendly manner. Based on this definition, the activities in reverse logistics can be split into 2 groups: product take-back and product reprocessing (or recovery). Within these two groups, there are many sub-activities that may overlap or directly affect the activities of the other. In literature, the term reverse logistics has been used interchangeably with reverse supply chains, where “logistics” is limited to the activities only pertaining to group 1 which is product take-backs, collection and transportation and “reverse supply chain” is comprehensive of all activities in both groups mentioned above.

A typical reverse logistics network (RLN) consists of collection centers which accept used products from customers, reprocessing facilities and secondary markets, where customers buy reprocessed products. It may seem that this RLN structure is analogous to the forward supply chain structure that consists of suppliers, manufacturers and demand markets but there is far more dissimilarity between the two types of networks than meets the eye. The stark differences in the two networks are adequately described by (Fleischmann, Krikke, Dekker, & Flapper, 2000) who addresses reverse and forward chains as “converging” and “divergent” networks respectively.

The first difference arises from the supplier sources which, in the reverse supply chain context, are the consumers themselves. The consumers are located in large area spread out across cities and countries. In fact, in FSC, manufacturers actually try to expand their installed consumer base by gaining market share in as large an area as possible. However, during the collection of used product, the burden of collecting products from the large consumer base poses a logistics challenge because it requires large amounts of resources. The fact that the suppliers are located in so many places and the stream of goods is towards fewer reprocessing facilities is why Fleischmann (2001) addresses reverse supply chains as “convergent” networks. The issue of optimizing collection networks, schemes, routing and many other issues are addressed in a large body of literary work (Aras et al., 2008; Min & Ko, 2006).

The second, and more complex part of reverse logistics is the profit maximization of the recovery processes. There are generally three levels of recovery that are currently in practice: direct reuse, refurbish or remanufacturing, and materials recycling. In order to recover the costs of the product collections and sustain further profits from product recovery, companies must exercise acumen in the design and allocation of their reprocessing facilities.

It goes without saying that recovery business manufacturers and remanufacturers are not only driven by environmental regulations, but mainly motivated by potential profits from product or component recovery (Zikopoulos and Tagaras, 2007). Two critical issues that heavily impact maximizing profits from recovery are: designing of the reprocessing network, and selecting the optimal configuration of recovery strategies. Selection of optimal configuration means assigning the most economically viable recovery strategy from all possible alternatives for the product as a whole and for each component as well.

This process of assigning an appropriate recovery decision is complex, and varies from one unit of product to the other. To understand this complexity, it is first important to explain the three recovery processes.

1.1.2 Recovery Processes

Reuse: The first option, reuse, means to directly retail the returned product after some cleaning and repackaging. According to Geyer and Blass (2010), direct reuse of mobile electronics generates the highest profit margins. This is because it doesn't require any reprocessing operations. Meng et al., 2017 also claim that reusing is also the most environmentally-friendly option. However, for a returned product to be eligible for direct reuse, it must satisfy two conditions (1) It should be completely functional with very little cosmetic wear, and (2) there must be a demand for that model in the market.

For the purpose of this study, the term reusability is defined as the probability that a product that has been returned by the customer is found to be excellent functional status with only minor cosmetic wear such that it can be directly resold without any repairs. The product may require some cleaning and repackaging but it does not require any replacement of components and has not water damage.

Refurbishing/Remanufacturing: The second recovery option is remanufacturing. Compared to recycling, this solution requires lesser resources and energy and is increasingly gaining attention because of its value-added potential and environment-friendly features (Guide and Wassenhove, 2009; Deng et al., 2017; Ji et al., 2017). As one link of reverse logistics, remanufacturing is less dependent on virgin materials and more profitable compared with manufacturing. In remanufacturing of cellphones, the failed components, or the ones that do not meet the industry standards are replaced with new components. Thus, remanufacturing incurs the costs of disassembly, new components and the subsequent reassembly of the product, which are not applicable to direct reuse. However, the selling price of a remanufactured or refurbished product is usually more than the price of a reused product because the product has been reset to manufacturer's quality. In such a case, the increase in revenue is generally large enough to offset the cost of remanufacturing. Having said that, not all returned products are eligible for remanufacturing. Similar to establishing reusability, it is important to gauge the quality of the returned product and the current market trends before making a decision of whether to remanufacture or not.

Part Harvesting: Sometimes, the activity of removing used components from a used device and selling them is more profitable than the process of remanufacturing. If the costs of remanufacturing are too high due to bad return quality, then part harvesting can be considered as a recovery option.

Recycling: If the quality of the returned product is so bad that it requires extensive repairs, or, if the market value of the product has reached a point where the costs of remanufacturing outweigh the profits, then the appropriate recovery decision for it will be materials recycling. According to Geyer and Blass (2010), recycling is the least profitable recovery decision. However, it is an enabler for natural resource conservation and more environmentally friendly than mining of new materials. Therefore, even though an OEM may not find recycling to be compatible with their economic objectives, they must adhere to it due to environmental concerns.

When would recycling be feasible?

Sometimes the product returns can be of such low quality that the cost of repair or remanufacturing is too high and cannot be matched with the possible value on a secondary market (Ostlin et al., 2009). The recovery option that is slightly more favorable than recycling is directly selling used components by harvesting them from returned devices. Usually this is a low cost option that generates good profits as it requires no repairs, replacement with new parts or even reassembly (as is needed in remanufacturing). However, sometimes the revenue or demand of the used components may not justify the disassembly costs needed for extraction of the components. In such a case, the device would be assigned to recycling instead.

As seen from the above discussion, the recovery decision of a product is highly dependent on two factors: the return quality, and the market value of the product. The dynamics of these two factors inject high level of complexity in the product recovery process and make the planning and management of reverse logistics highly challenging (Ondemir and Gupta, 2014).

The returns come with different qualities. Uncertainty in quality can impact various aspects of the reverse logistics process (Pochampally et al., 2008). When the quality of returned products is incorporated in the decision process, it is possible to develop more intelligent remanufacturing and disposal policies.

1.2 Motivation

The operational viability of any supply chain network depends on how well it was designed to sustain surplus in a multi-period setting. A supply chain surplus is defined as the net profit from all the supply chain activities which include planning, manufacturing, distributing, marketing and logistics (Chopra & Meindl, 2006) In reverse logistics the complexity of designing a network that is robust in the face of multi-dimensional uncertainties is challenging. The main uncertainties that hinder RLN planning are related to the volume, quality and timing of consumer product returns. These uncertainties arise from the randomness of consumer behaviour with regards to their usage patterns, their willingness to return the used product and at what point of time they decide to return.

Several works in literature have attempted to quantify the uncertainties of return timing and return volumes using a wide range of optimization and simulation tools including stochastic programming, robust optimization, fuzzy techniques and forecasting methods. The most effective way of dispelling the impact of uncertainties on network design is through forecasting methods. Several works in literature attempt to forecast the timing of consumer returns such as Krikke et al., (1999), Kelle and Silver (1989) and Toktay (2001). Similarly, there have been several literary publications that effectively forecast the volume of consumer returns that can be expected to enter the reverse supply chain stream in a multi-period setting across a variety of product types (Marx-Gomez (2002), Hanafi (2008), Kannan et al., (2014), Temur and Bolat (2014), Ugurlu (2012)). A recent thesis by Pillai (2017) also addresses forecast of remanufacturing cores in a time-series analysis. Evidently, there is a plethora of substantial research dated as early as 1989 that can be used practically to optimize reverse logistics network decisions against risks that accompany the uncertainties in return timing and return quantities. Unfortunately, there is no presence of such a body of research on forecasting return quality although this factor plays a crucial part in network profitability.

Return quality is basically the quality grade of a product when it is returned by the consumer post-use. The random and individualistic consumer usage patterns induce a large variance in the return quality. The effect of return quality on the structure and operations of a reverse supply chain have been elaborated in many publications (Guide et al., (2006), Zikopoulos and Tagaras (2007), Ferguson et al., (2009), Ondemir and Gupta (2014), Liang et al., (2014), Meng et al., (2017)).While the importance of the effect of return quality has been well established, there is a lack of literature pertaining to forecasting of return quality of highly volatile and short-lived electronics products such as smartphones. Considering the vast tonnage of wastes that smartphones create all over the world, it is important to dedicate research that optimizes their reprocessing for faster and more efficient of product and materials recovery. This research is motivated by the need to demystify the volatility of return quality of end-of-use mobile electronics in order to facilitate the managerial decisions in the design and operations of their reverse supply chain.

The sections that follow elaborate on what return quality means in the context of reverse logistics, what areas of management are impacted by its volatility, existing gaps in literature and finally, the objective this research attempts to fulfill.

1.2.1 Return Quality Uncertainty

Exploitation of the remaining useful value in consumer returns has been identified as a promising source of revenues. In reverse logistics and product recovery, the term “useful value” is a transient quantity that is subjective to the product type, industry and the concerned stakeholder (OEM, third-party remanufacturer, government or consumer). In their book, Pochampally et al., (2008) mention that the definition of “value” must encompass all aspects of environmental, social and economic opportunities. The remaining value of any product will directly depend of the cost of repairs that it needs, and the potential profit it will generate when resold in the market. There is an inherent nexus between the cost of repairs and the quality of the used product when it is returned by the customer. While this correlation has been acknowledged in many literary works, there is very little literature available on trying to dispel the uncertainty of return quality.

Return quality, in the context of RL, is defined as the condition of a product unit when it is returned by a consumer at the end of its use. Based on the assessment of the quality of the product, it is assigned to an appropriate recovery decision. Authors in RL literature refer to return quality using various terms such as: input quality in remanufacturing (Denizel et al., 2004), condition of used product (Galberth and Blackburn, 2010), heterogeneity of input (Ferguson et al., 2009), or core quality (Teunter and Flapper 2011). Return quality ratios, or simply quality ratios refers to the fraction of the total volume of returns that can be subjected to one of the recovery processes: direct reuse, remanufacturing or recycling. In most of the literature present, it is assumed that this quality ratio is deterministic (Zikopoulos and Tagaras, 2015). However, in reality the quality of returns is stochastic and random (Aras et al., 2004).

The uncertainty in these quality ratios arises from the randomness that characterizes consumer behaviour (Ferguson et al., 2009). In the case of electronics, consumer purchasing frequency and daily usage behaviour largely depends on their income, social status and age. There is a nexus between these usage patterns and the product wear at the end of its use. Moreover, Zikopoulos and Tagaras (2015) mention that, in addition to these socioeconomic end-user characteristics, factors such as an individual's motivation for returning product and the characteristics of the location of use (temperature and humidity) also affect the return quality of the product. Thus, it is established that return quality of each unit of returned product varies according to its length and intensity of usage and the environment in which it was used. This creates a huge uncertainty in return quality which greatly impacts profitability and decision making in reverse logistics on strategic, tactical and operational level of reverse supply chain management.

A successful supply chain network is one that can sustain favorable surplus in a multi-period setting, and ensure profit margins withstanding all the various possible uncertainties. In the field of reverse supply chains, this is no easy feat due to the uncertainties involved concerning timing, quantity and quality of returns. The variations in the return quality of products make it difficult to plan an optimal network. This inhibits maximization of profitability. In fact, the large variations in return quality can sometimes offset the profitability of the recovery process, as explained by Denizel et al., (2010) in their case study on the IBM remanufacturing facility.

This research is highly motivated by the roadblocks in reverse supply chain management that are caused by lack of return quality forecasting. The next section elucidates on these hindrances.

1.2.2 Problem Description: Challenges under Quality Uncertainty

This section describes the problems that arise in strategic and tactical management of reverse supply chain due to the uncertainty of return quality.

Strategic Planning

Designing supply chain networks is an exhaustive process that requires extensive research across a range of diverse areas from consumer behaviour and demand to location selection and in some case, even legislative measures.

A central issue in strategic phase of SCM is the configuration of network design. The facilities and equipment required can incur large fixed costs which can only be justified if the network layout is optimized for profitability over long periods. The major aspects of network design are:

1. Location decisions for facilities
2. Number of facilities
3. Capacity allocation

A major determinant of the optimal number and capacity of the facilities is the forecasted demand for manufactured goods (Lambert, Riopel and Abdul-Kader, 2011). In forward logistics, demand forecasting is accepted as the most fundamental step in strategic planning. The decision to invest in facilities and the manufacturing equipment is dependent on this demand. In fact, 80% of a product value comes from its design stage which includes the fixed cost of its supply chain network (Pochampally et al., 2008). Forward chains have the advantage of robust forecast models that accurately predict demand trends, allowing economically justified investment in equipment and facilities network with assured profit margins. However, this is not the case in reverse supply chains. Due to the unknown quality distribution, ‘traditional expectation-based optimization” which are generally adequate for forward supply chains, become completely incompetent in reverse supply chain planning (Jiang, Netessine, and Savin, 2011).

In the reverse supply chain, the conventional “demand for volume of goods” is replaced by “volume of returned goods”. The manufacturing equipment is replaced by more specialized reprocessing equipment essential for recovery processes such as machines for automatic disassembly, remanufacturing or cleaning of returned products. While forward chains need only one type of equipment which performs manufacturing and assembly, reverse supply chains need multiple types of specialized equipment based on the recovery methods. The returned products exhibit varying levels of wear and tear and thus, require tailored recovery operations. This is because consumer behaviour of electronics is not consistent. For e.g. a user who might be prone to overheating the device due to excessive usage, will return their phone with a much lower grade quality than another user who only uses the same type of device for basic functions. This gives rise to randomness in the quality of the returned products collected.

It is usually unknown what volumes of the different quality grades are going to enter the reverse chain. As Ait-Kadi et al., (2012) mention, the efforts and resources needed to justify and support this type of uncertain returns are much more significant as compared to returns that would just fit one type of reprocessing option. To this end, investment in the rather expensive equipment required for reprocessing carries high levels of risk. It is necessary to take into account what type of specialized reprocessing equipment and what capacity is required for a viable network design. Similar to forward chains where decision makers have forecasts of demands to assist them in deciding the number and capacity of manufacturing plants, the decision makers in reverse supply chains are also in need of forecasts of return volumes pertaining to variant quality grades. This information will enable them to generate higher profit margins by optimizing their fixed costs.

The above problem is acknowledged by Pochampally et al., (2008) in their book, where they mention that in current network design, some predefined configurations of what volumes will go for specific recovery options is used in the planning stages. They list "possible processing options" as one of the network constraints. They mention literature works that suggest directing products towards processing options by assuming proportions or fixed amounts for each recovery process. Other approaches can also configure a lower proportion of products to be cleanly disposed of whereas the remaining products are sent for remanufacturing. A higher proportion of repair, remanufacturing, updating or upgrading and a smaller portion for recycling is used for designing a network with a desired level of flexibility. They say that these "proportions" are decided so that they take into account technical, commercial, and environmental constraints. Such a practice leads to an overly conservative network design, which has a lot of scope for optimization with accurate quality ratio forecasts so that "predefined recovery configurations" do not have to be assumed. Moreover, this existing practice does not necessarily sustain profitability in multi-periods.

Tactical Planning

On a tactical and operational level, there are two major issues that can be addressed through the forecast model proposed in this research. These are deciding on used product acquisition policy, and planning the production lines for the recovery options that are available.

Most reprocessing facilities purchase batches of returned products in fixed lots from informal or formal collectors. Usually these batches are aggregates of consumer returns across multiple collection points in an area and then consolidated into one larger batch for the collector. It is most often unknown what the functional state of the products in any given batch are. While some phones may be good enough for direct reuse after general cleaning, others might be completely malfunctioned and need costly repairs. Denizel, Ferguson and Souza (2010) identify this issue that, since a returned shipment vary in the quality of the cores, some cores will need more capacity to restore the unit to standard quality than others. These batches, regardless of how many bad phones are inside them, are quoted at a fixed selling price to the reprocessing facilities. While the batches are randomly tested and labeled with an expected quality ratio based on expertise, their precision cannot be reported. This concept of testing a sample of a returned batch, and the inherent errors of the statistical sample are discussed by Panagiotidou, Nenes and

Zikopoulos (2013). Earlier than that, Nikolaidis (2009) had developed a model to find the optimal acquisition and remanufacturing quantities under the effect of sampling inspection of the returned batches. Sometimes, a batch can have many malfunctioned devices or models that are aged and no longer have any market value. In such cases, it does not justify for the reprocessor to spend in their repairs as they do not generate any profitability from future sales. However, a reprocessor cannot demand a device-by-device test of each unit in a batch before purchasing, nor can they return a batch if they find it to be unprofitable. Thus the cost incurred of buying such a low quality batch is often a hefty financial loss for the reprocessor. The impact that overestimation of the quality of the returned batch on the profitability of remanufacturing is acknowledged by Van Wassenhove and Zikopoulos (2010). It would be financially beneficial for reprocessing facilities if they could get a quote for a batch based on an accurate estimation of the quality ratio of each batch rather than an estimate applied across all batches, a fact that is asserted by Denizel, Ferguson and Souza (2010) who mention that the acquisition price of used cores should be lower for lower quality grades. When the quote is based on the quality ratio, they know precisely what to expect from the box and can then decide if the cost of the box is justified against the potential profit it will generate for them. Since collections are aggregated into batches by region, this research avails the opportunity to estimate quality ratio of batches by accounting for regional differences through socioeconomic factors (See 3.2 Socioeconomic Usage Model).

The first four steps for products that enter the value recovery stream are: gatekeeping, collection, inspection and sorting (Lambert, Riopel and Abdul-Kader, 2011). When a batch of returned products arrives at a reprocessing facility from collectors, it is standard inspection to perform functional tests on each unit in the batch in order to determine which reprocessing option is most feasible, and then sends them to the appropriate reprocessing department. This process is a fail-proof method of ensuring that each device generates maximum profit. However, this real-time method of incrementing the lot size that arrives at the different reprocessing production lines can induce extreme inefficiencies and variabilities in the production planning. Having uncertain knowledge of how much inflow of raw material (in this case, returned products) to expect for their production lines put the production planners at a disadvantage.

Moreover, variations in production input can reduce overall equipment efficiency of the line by causing increasing change over frequency and suboptimal utilization of the line capacity. Guide and Srivastava (1997) list unknown conditions of recovered parts and probabilistic recovery rate of parts among other factors that add complexity to inventory control and production planning. This is a contingency due to the random quality ratios of the batches fed into the line. For e.g. a remanufacturing line has a capacity of x units per day. A reprocessor purchases a batch of x units with an estimated quality ratio of 0.6 and another of 0.3 to make a day's production. However, after sorting the devices from the batches, it is found that the quality ratios reported were significantly different. Then, in this case, the remanufacturing line capacity will not be optimized. If the quality ratios are lower, then the line will have excess capacity. If the quality ratios are found to be higher, then the reprocessor will incur an opportunity cost and will be at a loss. This loss is due to the fact that, for each day the remanufacturable units spend in the facility, they lose time value. Pochampally et al., (2008) name this as "loss of sale" cost. Since the secondary market value of electronics is highly sensitive to time, it is not profitable for the remanufacturer to incur a profit loss by decaying good quality cores at its facility. This dilemma is acknowledged by Ait-Kadi et al., (2012) where they state that companies must strike a balance between the acquisition price of the returned product-whether that is batch purchasing from collectors or incentives paid to the customers, and the resale value. Inherently, to gauge the resale value, they must also consider the various reprocessing paths that the recovered product may take (Pochampally et al., 2008). While the above mentioned example is for a remanufacturing line, the same concept applies to repairing or recycling equipment and lines.

To conclude from the above discussion, equipping reprocessing facilities with accurate forecasts of the quality ratios empowers them to configure their batch purchases, plan their production lines efficiently and sustain favorable economic profits.

1.2.3 Value of Prior Information on Return Quality

From the above discussion it is clear that the return quality affects not only strategic decisions of network design, but also affects the tactical and operational decisions. From network design to capacity planning of reprocessing facilities, to acquisition policies and production schedules, all of these activities are affected by the quality of the returned products. In order to enable effective managerial decisions at the correct time, it is important to have knowledge of the return quality forecasts based on the customer zones for a multi-period setting.

<u>What positive impact can a return quality forecast have on strategic planning?</u>

A forecast of return quality will empower the decision makers in reverse supply chains with the expected volume of returns that will be of good, moderate or bad quality in any given time period. This will allow them to make the following strategic decisions:

1. Optimal location for reprocessing facilities
2. Optimal number and capacity of reprocessing facilities based on the expected volume of returns in multi-period network
3. Optimal supplier zones: In the case of RLN, the end-users are the suppliers (Fleischmann, 2001). Since consumers exhibit variability in device usage, they produce end products of different quality, which can be attributed as "suppliers with different return quality". It is possible to assign nominal quality ratios to returned batches based on area of collection if a pattern between these two variables in established. some consumer areas will generate high quality of used products than others e.g. urban vs. rural. One way to correlate return quality by region is to characterize returned products based on the demographic profile of that region. This study attempts to achieve this through the proposed socioeconomic forecast model.

By optimizing the fixed costs of the RLN, forecasts of return quality can greatly increase the reverse supply chain surplus.

<u>What positive impact can a return quality forecast have on tactical planning?</u>

Confidence in the quality ratio of returned batches through forecasts will enable more profit-based acquisition policies. Based on current market trends and the remanufacturers own production capacities, they will be able to configure how many batches to acquire, of what quality ratios and at what frequency. This added sense of control over their inputs will allow them to efficiently plan their production schedules, comply with delivery times (due to better throughput management) and enhance their overall line efficiency. All this cannot be planned if the information of quality ratios is made available to the planners only after a batch enters the facility's doors.

1.3 Research Objective and Expected Contribution

As seen from the above discussion, the random nature of the return quality of electronics can significantly reduce the surplus of sustainable supply chains. It is critical to accurately quantify what quality ratios to expect from returned products a priori to the strategical planning stage so that decision makers can design robust networks that can successfully generate financial profits in a multi-period setting. As a solution to this problem this research proposes a forecast model to predict the quality ratios of returned electronics. The main objective of this research is to:

1. Create smartphones usage distributions by categorizing consumers by socioeconomic factors namely, age income, education and region.
2. Use the categorization of products by socioeconomic factors to formulate probability distributions for the quality of end-of-use consumer returns
3. Combine these formulated return quality distributions with economic trends to formulate a forecast model that will predict quality ratios of the future returns that will be subjected to direct reuse, remanufacturing or recycling.

1.4 Description of Methodology

The first step will be to use available data on smartphone usage characterized by age, income, gender, education and region to identify which of these factors play a significant part in determining smartphone usage and purchase behaviour. The independent variable will be the socioeconomic factors and the dependent variables will be (1) number of usage hours per day and (2) length of ownership of one smartphone device. Next step will be to identify the statistical distributions that govern the relationship between the input factors and the outputs.

After the usage distributions have been established, the usage model will be used to calculate the functional status, or survival probability, of the used devices at the end-of-use. The usage distributions will be used in reliability calculations to determine the probability distribution of returned products that will survive at the time of their return. This survival probability will also be calculated for the crucial components of the device based on component selection.

In the formulation of the forecast model, the survival distributions will be used in conjunction with economic depreciation trends of mobile devices and their components to predict the most suitable recovery option. To this end, the expected cost of repairs needed will be calculated based on the survival probabilities, and the expected revenues will be calculated based on the market price of the product in the current period. Then the difference of costs and revenue will be used to calculate the expected profit for each recovery option. The recovery option with the highest profit will be assigned to the used product.

1.5 Scope and Limitations

This section lists the assumptions and limitations of the proposed forecast model.

Assumptions

1. The phones were not stored for any period of time after their end of use.
2. The year of release of the phone coincides with the start of the usage time
3. One phone unit has not been reused by more than one age group.
4. The usage intensity of the phone (such as the type of application: games, graphic content versus office usage) have not been taken into consideration.
5. Probability of water damage and physical fall are the same across all age groups
6. No lead time for reprocessing is taken into account. It is assumed that the time value of the product at the time of return stays the same while it’s being reprocessed
7. At t=0, the quality of all phones is uniform with usage hours=0.

Limitations

This research provides an aggregate forecast model to predict future quality of returns. This information is intended to be useful in network design and production planning phases. The model does not eliminate the need for the gatekeeping and inspection steps that are characteristic of the reverse logistic process and are instrumental in assigning the appropriate recovery decision to each device on an disaggregate level.

1.6 Industry Selection

The electronics waste generated from smartphones all over the world is a growing issue. The catalysts to this problem are the growing sales and the shortening life-cycle of smartphone devices. In 2017 alone, 1.5 billion units of mobile phones were sold worldwide, generating nearly US $500 billion in revenue. In North America, the smartphone penetration has peaked, and most of the smartphone sales are from replacement purchases i.e. consumers replacing their existing smartphone with a new one. Technological advancements, marketing activities, hardware obsolescence and the adoption of latest technology as a status symbol are all contributors to what spurs consumers to in the race to acquire the latest phone models, even when their old ones are perfectly functional. This phenomenon has led to shortening of the life-cycle of mobile phones. In Canada, the average length of ownership is about 30.6 months (CWTA, 2016). This means that the more sales, the more electronic waste accumulates. Thus, even though mobile phones are small, light in weight and use lesser materials than bigger electronics, they are contributing tonnes to the growing problem of WEEE management by virtue of their short life-cycles.

In recognition of the criticality of managing wastes from smartphones, this study has chosen the smartphone industry for the numerical application of the proposed forecast model for return quality.

CHAPTER 2

LITERATURE REVIEW

Following the theme of return quality in reverse logistics, this section attempts to compile existing literature that establishes the inevitable existence of this uncertainty in RL. It also discusses relevant work which brings to light the various management issues which are impacted by the uncertainty in return quality, and how it is currently being addressed through qualitative methods that rely on human expertise and data-driven methods that employ electronic data logging systems. Lastly, it provides an overture of the forecasting method and the Monte Carlo simulation technique that will be used in this study.

2.1 Quality Grades and Recovery Decisions

Most of the work in literature classifies the quality of returned product in three discrete groups: good, moderate and bad. Literature in which quality grades are treated as discrete variables include Teunter and Flapper (2011). However, in some literature, quality grade is also treated as a continuous variable (Galberth and Blackburn, 2010). Regardless of whether return quality is modeled as a discrete or continuous variable, it is almost always assumed to be deterministic.

In Zikopoulos and Tagaras (2015), the remanufacturability (a measure of quality) of a returned product is modeled as a continuous variable but with a known distribution. Regardless of the type of variable, the quality ratios have almost always been treated as deterministic parameters.

Golany et al., (2001) assume a single quality grade for all returns, while Robotis et al., (2005) assume two distinct return qualities, each sourced from a separate supplier with no correlation. Zikopoulus and Tagaras also assume two quality grades: refurbishable and non-refurbishable. However, they upgrade the model presented by Robotis et al., (2005) by assuming that there is correlation between the stochastic distribution quality of returns collected from each of the two separate suppliers.

Aras et al., (2004) also use two quality grades: high quality and low quality in their Markov Chain model to optimize inventory management of hybrid manufacturing systems. They assume that the probability distribution of the products being of either high or low quality is already known. Similarly, Galberth and Blackburn (2010) considered the uncertainty in the quality condition of the returns and assumed that the quality grade followed a binomial distribution, the parameters of which are assumed to be known.

Ferguson et al., (2009) use three quality grades: fit-for-scrap, fit-for-part-harvest and fit-for-remanufacturing in their case study on an electronics company for evaluating the effect of quality grading before remanufacturing operations.

In all the studies mentioned above, it is clear that the quality of the product has been used as an indicator to assign it to the appropriate recovery decision. However, none of the studies above mention the data source that forms the basis of their assumptions of choosing a distribution to model the quality ratios. All the studies mention that their stochastic modeling of the return quality is based off of expert opinion or historical data. While both of these may be a reliable source in electronics with long life cycles such as household appliances, they cannot be used as reliable sources with fast moving consumer electronics with short life cycle. This is because the trends pertaining to usage and returns of these electronics is constantly changing, which automatically reflects in the quality distribution of these products when they are returned at the post-consumer stage.

2.2 Impact of Uncertainty of Return Quality (Economics/ Recovery Decisions)

There is a large body of work that emphasizes the impact of uncertainty of return quality on various aspects of reverse logistics and its profitability (Zikopoukos and Tagaras 2007; Aras et al., 2004; Teunter and Flapper 2011). A recent review by Ondemir and Gupta (2014) showed that quality was incorporated into a wide range of decision models for reverse logistics, which further proves that return quality is an important parameter in reverse supply chain planning.

This section discusses relevant literature on how return quality can impact three main areas in RL: network configuration, procurement decisions and remanufacturing profits. The reason these three areas have been specifically chosen is because these are the areas where profitability can largely be enhanced with prior information on the quality ratios of future returns by means of forecasts. However, due to lack of forecasting models of return quality, all the existing academic research resorts to assumptive probability distributions and scenario analysis for their optimization models (Aras et al., (2004); Zikopoulos & Tagaras (2007); Panagiotidou et al., (2017)).

2.2.1 On Strategic Planning

There is ample research which shows that the uncertainty of the return quality can have impact on network design, especially in a multi-period setting. In a reverse supply chain, network decisions include location, number and capacity of collection and disassembly centers, remanufacturing and recycling facilities. One may ask, how can return quality affect these decisions? The answer to this is analogous to the planning of manufacturing centers in the forward supply chain where it is common practice to study demand forecasts of different zones before selecting facility locations and deciding their capacity. Similar to that, in reverse supply chain it is important to forecast how many returned products will be arriving at the facility, the zones where they will be arriving from, and what kind of reprocessing capacity will be required. The decision-making with regards to reprocessing capacity is where the complexity of return quality has a large influence. Reprocessing capacity encompasses decisions such as capacity to repair, disassemble, remanufacture and parts inventory. In order to exploit economies of scale in a multi-period setting, the remanufacturers must have enough knowledge of what kind of processing the future returns will need so that they can adjust their investments in their reprocessing production lines. By providing them with forecasts of return qualities, they will have information on what fractions of the returns will be expected to undergo repairs or what fraction will need refurbishing and what fraction of the arrival will only be fit for recycling. With this knowledge, they can optimize on their investments of facilities and equipment capacities as well. Some relevant literature with results that explore the effect of uncertainty in quality on strategic planning of the reverse supply chain are discussed in this section.

Zikopoulus and Tagaras (2007) argue that a single-period problem is sufficient in the strategic planning of the RLN. However, this is inadequate for OEMs where the lifecycle of the product may be too short for example, cellphones. In other electronics where a single period can be of ten years or more, this model would be more suitable. In another study, Zikopoulus and Tagaras (2015) attempt to study the impact of sorting by quality on the network design, especially the location of the sorting centers in the reverse logistics network. Their results suggest that when there is early classification of return quality in the reverse logistics network, poor quality does not affect profitability as compared to sorting in the later stages. This means that the network design is economically competent even if the returns are of very low quality and only fit for recycling. This is an important result because usually recycling of mobile electronics leads to economic losses (Geyer and Blass, 2010). On the contrary, this study by Zikopoulos and Tagaras shows that if the uncertainty of the return quality is reduced in the network design stage, then even low quality of returns can be profitable. Thus, it can be seen that quality information in the strategic stage is highly useful in profitability of network operations. The results of this study can be extrapolated to conclude that the earlier the information is collected on the expected quality ratios in network design and implementation stage, the more robust the profit margins will be to any future uncertainties in quality of returns.

2.2.2 Procurement Decisions

In supply chain management, procurement decisions involve lot sizing, frequency of delivery and supply selection. In the reverse supply chain, when procuring batches of returned products from third-party or informal collectors, the quality ratio of the batch plays a crucial part in pricing and procurement decisions, especially if the collection was not carried out by the OEM itself. Accurate information of the quality ratios of the batch can affect all three decisions of the procurement process. According to Panagiotidou et al., (2017), the most efficient practice of dealing with uncertain quality is to "quantify, reduce or even eliminate it before making procurement and disposition decisions". This can only be done through forecasting of return quality. However, as per the discussion below, all the research that study procurement decisions in reverse logistics do so by optimizing against this uncertainty, rather than attempting to quantify or predict it.

Procurement decisions under uncertain return quality have been addressed in multiple works including Robotis et al., (2005), Zikopoulos and Tagaras (2007) and Amin and Zhang (2013). A recent study that addresses this issue is by Yang, Ma and Talluri (2018). They devise an acquisition decision model with partial random yield information to identify the impact it has on the remanufacturing process. They use robust optimization technique to model a remanufacturing system that is unaffected by the lack of prior information regarding the return quality of the batch.

Several studies that acknowledge the importance of uncertainty in quality of returns often assume simplifications in their model for convenience. For example, Robotis et al., (2005) assume two distinct return qualities, each sourced exclusively from a separate supplier with no correlation. Zikopoulus and Tagaras (2007) also assume two quality grades: refurbishable and non refurbishable. They upgrade the above mentioned model by assuming that the quantity of refurbishables in a batch follow a continuous random variable distribution and that there is correlation between the quality of returns collected from each of the two separate suppliers. However, they assume that the quality distributions of the two sources are already known. The problem with these two assumptions is that, if the collection centers are open to the general public with random usage behaviors. As such, the quality that accumulates at any given collection center is extremely heterogeneous. At least in the consumer electronics field, it is error-some to assume that the quality from each source is homogenous as assumed by Robotis (2005).

Other studies that follow a similar concept are by Davey et al., (2005) for printers and Debo and Van Wassenhove (2005) for tires. They also optimize network under the assumption that each collection location will give them one consistent type of quality grade.

The frequency of procurement as well as the lot size decisions of returned products is linked to the return quality. While Ferrer (1997) highlights the impact of uncertain quality on the timing of procurement, Panagiotidou et al., (2017) devise a model for the optimal lot sizing decisions of returned cores under the effect of return quality uncertainty. More specifically, in their model, they examine the procurement and production decisions in a hybrid system that exploits usage data to assess the quality condition of returned units. Under the assumption that both demand and returns quality are stochastic, they model two alternatives regarding the timing of new-products lot size determination relative to the actual returns quality realization (Panagiotidou et al., 2017). From the results of this study, it is seen that the acquisition policy can vary based on the quality ratio of the returned batches. Based on the remanufacturability ratio of the batches available, and the production capacity of the OEM's remanufacturing line, the OEM can make tactical decisions relating to economic order quantity to maximize throughput at reduced cost. It must be pointed out that the stochastic distribution for return quality used by the authors is based on expert opinion, a practice which is unreliable for the consumer electronics industry due to unpredictable and rapidly changing consumer trends.

On the same subject of procurement under quality uncertainty, Aras et al., (2004) show that incorporation of returned product quality in the remanufacturing and disposal decisions can directly have significant impact on cost savings. Further, the results of their study suggest that prioritizing higher quality returns in remanufacturing is a better policy because the revenue generation from the sales of these remanufactured products will be higher. This emphasizes on the need for the OEMs to know, with reasonable accuracy, the quality ratios of the batches before they purchase them.

In relation to the acquisition price of used products, Denizel, Ferguson and Souza (2010) state that "any unused cores may be salvaged at a value that increases with their quality level". This can be extrapolated to mean that if the quality ratio of the cores is higher, they can be allowed to be sold at a higher price. Bakal and Akcali (2006) also studied the impact of random quality in remanufacturing on pricing decisions in reverse supply chains. A batch of returns is always a mix of used products of all quality grades. While making procurement decisions, it would be in the best interest of the OEM to know if the price they are paying for a batch is worthwhile for them and will generate sufficient revenue to at least cover the acquisition price. Accurate pricing of these batches is only possible if the information on their return quality of the products is known before the purchase is made. While it is possible to test and grade each and every unit in the batch to find the quality ratio, this is a time-consuming and expensive method. Thus, it can be seen that accurate information on quality ratios is needed for accurate pricing of returned batches.

Another interesting issue with procurement decisions is that the acquisition policy that an OEM adopts will change based on the lifecycle stage of the product. In other words, the quality ratio of batches that firm seeks to acquire will depend on the secondary market value for that particular product. An illustration of this concept can be through the smartphone market. In the early stages of a smartphones release, there is higher demand for remanufactured versions of the product as compared to the demand in the declining stages of the phones lifecycle. Based on the demand, the revenues for the remanufactured product will be much higher in the early stages than in the decline stages. Therefore, a firm may find it justified to pay a higher price for a batch with a high quality of returns in the early stages because the profits are higher. In the declining stages of the product cycle, the firm may rather procure batches with lower quality grades as those will cost cheaper. In the declining stage, it will make no sense for the firm to buy batches of high quality returns when there is no longer any avenue for the sale of the remanufactured product. Thus it can be seen that the acquisition policy of returned batches will vary based on the life cycle of the product. This concept is covered in literature by Ostlin et al., (2009).

Yang, Ma and Talluri (2018) propose a low-cost and high-reliability approach that can assist remanufacturers in making effective acquisition decisions when a small sample size is provided. However, sampling is still necessary in this case and must be postponed until the collection of the batch. In a multi-period setting with dynamic consumer trends, this practice does not provide any benefit for advanced tactical planning because the historical data becomes irrelevant with changing consumer behavior.

Any decisions of procurement, as discussed above, will directly be linked to the profitability of the recovery processes that follow the acquisition. The next sub-section discusses literature that highlights the impact of uncertainty of quality on remanufacturing profits.

2.2.3 On Remanufacturing Profits

Two of the main characteristics that differentiate remanufacturing from new product production are uncertainty in the number of returned products and uncertainty in the quality of the returns (Denizel, Ferguson and Souza, 2010).Since cores are collected from various sources, such as customer returns and cancelled orders, demonstration and trial units, overstocks, products damaged during shipping, and lease returns, the quality of acquirable cores is highly variable, which impacts the design and cost savings of remanufacturing processes (Yang, Ma and Talluri, 2018). The logic behind varying remanufacturing costs is that different quality of returns will require different processing times and resources. The lower the quality, the higher the remanufacturing costs, which means lower profit margins. One of the earlier research work that address profitability of reuse operations under uncertain quality is by Zikopoulus and Tagaras (2007). They study lot-sizing decisions and the optimal number of returns that must be remanufactured for a single-period case.

In addition to remanufacturing costs, inherent high uncertainty and variability of acquirable cores, hinders effective production planning and efficient control of remanufacturing systems as well (Guide and Jayaraman, 2000; Guide and Van Wassenhove, 2001). Inefficient planning can have a direct impact on the throughput and profitability of the production line. Unlike the forward supply chain where cycle time for the production of each unit remains constant, the cycle time in reprocessing of units varies depending on the level of repairs required for each unit. This uncertainty hinders effective production planning and foresight of throughput. Especially in the electronics field where the price of remanufactured products is highly sensitive to time and untimely delivery to secondary markets can incur penalty costs, the uncertainty in return quality plays a major part in dictating profitability. This area can greatly be optimized with forecasts of return quality.

This issue of optimizing production planning under different and uncertain quality levels, has also been studied by (Denizel, Ferguson and Souza, 2010). They identify the issue that some cores will need more production capacity to restore the unit to standard quality than others. This will affect remanufacturing profits- a batch with much lower quality will yield higher labour costs. In a period where demand may not be high enough or the product value is not favourable, the revenues may not be able to offset the high remanufacturing costs. For this reason, confidence in return quality before acquisition can be considered as a significant player in ensuring profit margins.

Uncertainty of the quality of returned products translates into high variabilities in remanufacturing costs and lead times which can be disruptive to the production line and impact throughput efficiency and production costs. To this end, Aras et al., (2004) study how inventory management and how cost savings of hybrid remanufacturing systems can be maximized under the impact of the uncertainty of return quality.

In remanufacturing, the final state of all products is reset to the same standard, and is independent of the quality level of the cores that they originated from (Ferguson et al., 2009). The revenue from all remanufactured products will be the same, regardless of what the input quality of the core was. However, the cost to remanufacture them will directly depend on the quality of the core. The worse the quality of the core, the higher the remanufacturing cost. In order to maximize the remanufacturing profit, the company must make an effort to acquire cores of higher quality. This can only be done through an accurate estimation of return quality through forecasts.

Liao, Deng and Shen (2018) further contribute to the research on quality-dependent remanufacturing costs by formulating a functional relationship between a continuous quality condition distribution and unit remanufacturing cost based on discrete data and substituted it into the profit equation for further optimization analysis.

As can be seen from the above discussion, the return quality spectrum affects many strategic and tactical decisions in reverse supply chain management. The research available today uses return quality distributions based on expert opinions or historical data. While these sources can be a reliable source for equipment and electronics with stable life-cycles and predicted usage behaviors such as household goods, construction machinery, automobiles etc., they are hardly reliable for fast moving consumer electronics such as mobile electronics. The primary reason for this is the spontaneity in the consumer purchase and return behavior as well as the differences in usage behavior of each consumer. For reverse supply chains of these industries, there has been no academic work that seeks to address how the uncertainty in return quality can be addressed. One might argue that the quality data can be obtained from inspection and testing of the returned products. While this practice helps in operational decisions, it does not help in advanced managerial decisions that are required for design and implementation of the network in the first place. To enable these, return quality forecasts are a crucial tool.

2.3 Methods of Forecasting Return Quality in Present Literature

On the value of prior information of return quality, many companies have implemented tailored techniques that can provide them with historical data in lieu of return quality forecasts. These techniques can be classified into two broad categories: sorting data and usage data.

2.3.1 Historical Sorting Data as Predictor of Quality

Sorting data is basically the historical record of how many returned units were assigned to reuse, refurbish or recycling. Based on these records, the companies can generate trends or estimate quality ratios, which can help them predict the future quality of returns. This method is a time dependent method because, in order to generate reliable quality trends, the companies will have to collect data over many periods. An additional drawback of this method is that, any change in consumer behaviours will create a ripple effect in the characteristics of the returned products. This will deem a historical data irrelevant. For this reason, the sorting method is limited to products that will not show alternating trends in consumer purchasing, usage and return behaviour over multiple periods. Only in such a case would it be worthwhile to generate return quality forecasts based on historical data.

In addition to that sorting criteria changes with time based on changing life cycle of product, user perception and marketing value. For example, ReCellular relies on its suppliers of used products to classify returned cell phones in different quality categories based on a number of technical and visual criteria. While the technical and visual criteria will remain the same over time, the market value of the product, which plays a key role in the recovery decision (and hence the quality grade), will not remain the same. Thus, the overall sorting criteria will change. So even though the historical data from sorting can be used to establish expert ratios, it cannot help in long term multi-period planning where the decision factors influencing quality grades are themselves constantly changing. Therefore, sorting data cannot help in reliable quality forecasts in dynamic products.

2.3.2 Data-Driven Predictors of Return Quality

One of the most common methods of data-driven usage monitoring is through installing electronic data loggers, sensors or RFID into an electronic system. Once a consumer returns the product, the usage data generated from these components is read to categorize the residual quality returned product. This method is widely practiced in many industries including Hewlett-Packard for computers and Bosch for power-tools. Simon et al., (2001) recorded the full life histories of washing machines using a life cycle data acquisition (LCDA) system. Guide et al., (2008) proposed a two-step disposition policy based on 'data from US Navy depots, under the command of Naval Industrial Capabilities NAVAIR 4.0D'. Mashhadi and Behdad (2017) reported that the remanufacturer 'records the return date for each computer and retrieves the Self-Monitoring Analysis and Reporting Technology data of the hard drives' which can help in calculation of the reusability level of the hard disk drives.

To same effect, RFID technology has also found an application in determining quality of used products. For example, Kim and Glock (2014) examine the benefits of RFID-tagged returnable containers in order to reduce uncertainty in timing of returns. Several publications consider the implementation of RFID in reverse logistics for improving the visibility of returns quality (Asif, 2011).

Drawbacks of data-driven systems

1. Firstly, it must be remembered that the usage data can only be read after a device is returned. Thus, while the usage monitoring system reduces the time of physical sorting and testing, it does not provide any assistance in strategic planning of the reverse supply chain unless large amounts of data are collected which is similar to the issue discussed earlier with regards to sorting-based quality estimates. On the same note, Meng et al., (2017) use condition monitoring data to create a distribution of remaining useful life in the planning of component recovery.
2. The infrastructure needed for data-driven methods may be too expensive for remanufacturers. From the cost of the extra sensory components, the equipment required to read the data from the sensors to the large data processing and storage that maybe required for meaningful usage of historical data to generate quality forecasts, the costs of such a method may not be justified, especially if the life span of the product is short.

3. For short life-cycle products, it is redundant to spend resources on life-cycle and usage data collection.
4. The usage data cannot be the sole parameter in forecasting the return quality. It fails to take into account the market demand, economic trends and the profitability. Ultimately, it must be used in conjunction with other parameters. This inaccuracy of employing usage data to ascertain true quality of the product is defined as "rather loose" by Panagiotidou et al., (2017).
5. In order to generate meaningful forecast trends of return quality, storage of large amounts of life time data from a large number of users is needed. This can provide a huge economic strain.

From the above discussion it is seen that for short life-cycle electronics, there must be a faster way to generate quality forecasts which are flexible enough to factor in not only usage data, but also market trends and economic viability of the various recovery options. Such forecast models are lacking in present literature. Two studies that come very close to devising such forecasts models are by Sabagghi et al., (2015) for the case of laptop batteries, Mashhadi and Behdad (2017) for hard disk drives and Liang et al., (2014) for the remanufacturing of electric vehicle batteries. These studies effectively use empirical usage data based on aggregate consumer behavior to predict return quality.

2.3.3 Empirical Data Models

The reusability model devised by Mashhadi and Behdad (2017) uses empirical laptop usage data from a sample population of students from a school which is used to generate probability distributions for the remaining useful life of the batteries. This data is then used with the exponential reliability distribution of the batteries and a linear cost model for remanufacturing to calculate the expected profits from three possible recovery options: refurbishing, remanufacturing and recycling. A similar reusability model is developed by the authors in which empirical usage data of hard disk drive is used in conjunction with remaining useful life and economic value to generate a reusability index value. The reusability index value of all the returned products is then used in K-means clustering to find out the total number of returns assigned to each recovery option.

Another study that successfully incorporates empirical data on consumer usage with economic trends to predict return quality is by Liang et al., (2014) for the case of lithium batteries in electric vehicles. They model consumer usage based on historical data and model consumer return behaviour using inverse Gaussian distribution to create a joint probability distribution for the remaining useful life of the battery. By coupling this with the time-dependent economic viability of the remanufacturing process, they formulate a distribution for the return quality of vehicle batteries.

One commonality in the studies by Sabaghhi et al., (2015), Mashhadi and Behdad (2017) and Liang et al., (2014) is that their choice of product is one with a reliable and stable usage pattern. Both laptop computers and automobiles also have long life-cycles and relatively stable and predictable market trends as compared to the volatility of the mobile phone market. The consumer behaviour in the laptop and automobile industry is less spontaneous because these are expensive purchases and people are not likely to buy or replace them within a few months. New product launches, feature upgrades, or marketing strategies do not incite consumers to replace their cars or laptops as easily as smartphones. The vulnerability of the smartphone consumerism creates a challenge in predicting consumer usage and hence, predicting return quality.

Since this research seeks to establish return quality as a dependent variable of socio-economic factors, the next section discusses literature that has previously taken these factors into account for modeling of consumer behaviour.

2.4 Consumer Behaviour and Socioeconomic Factors

This section discusses relevant literature which has demonstrated a correlation between socioeconomic factors and the recycling and smartphone usage behaviours of a particular region.

2.4.1 Reverse Logistics Context

This section discusses literature that involves socioeconomic factors in studying consumer behavior in commercial returns, recycling in general, and recycling WEEE.

Socioeconomic factors used to study commercial returns

Pei (2015) studies the consumers' motivation behind commercial returns. He classifies commercial returns into two categories: legitimate returns and illegitimate returns. Legitimate returns are defined as returns with valid reasons such as product defects, product not meeting expectations or any other valid reason. Illegitimate returns are defined as buyers' remorse, unethical returns after short term usage, or other opportunistic return reasons. Pei makes an effort to study the trends in legitimate and illegitimate return behaviours by grouping the participants in his study based on their age, gender, income, education and race.

His results suggest that age is a positive influencer, meaning that as people get older they are more likely to exhibit legitimate return behavior as opposed to illegitimate returns. As age increases, older consumers have higher expectations for the products than do younger consumers, thus they are more likely to make legitimate returns. Similarly, gender plays a part as well as it was found that women are more likely to behave legitimately than men. Income and education was also a strong influencer. Consumers with higher incomes are more likely to return the product, legitimately and opportunistically. Additionally, people with higher education levels were found to indulge lesser in illegitimate returns. Thus, Pei (2015) concluded in his thesis that socioeconomic factors are a valid determinant of commercial returns.

Socioeconomic factors used to study recycling rates

In her report to the Waste Diversion Committee in Ontario, Brock (2012) studies the impact of socioeconomic factors of the different municipalities in Ontario, and the subsequent recycling rates of these regions. She uses recycling tonnage report published by Waste Diversion Ontario (WDO) in 2006 based on the collections from the 196 municipalities in Ontario.Specific socioeconomic factors that were considered in this study include: the percentage of rented households in the municipality, the percentage of individuals who hold a university degree, population density and the region in which the municipality is located. The main contribution of this study was that among all the factors considered, the education level of a society was a very strong variable in determining recycling behavior the rate of waste diversion of a specific region.

Socioeconomic factors used to forecast WEEE returns in RLN

Similar results that show strong relation between education and recycling participation were found through a pilot mobile collection program in Malaysia by Hanafi et al., (2013). In their study, mobile collection booths were set up in a university and two office buildings. Their study found that educational level of the participant, their awareness of the benefits of the program as well as the level of corporate involvement shown by their employer were all positive influencers of a person's willingness to recycle their electronics. Thus, both studies by Pei (2015) and Hanafi et al., (2013) suggest that educational level is a strong input variable to judge recycling behaviours.

In a prior study by Hanafi (2008) in the context of Australia, socioeconomic factors particularly age, income, population density and education level, have been successfully used as input variables to forecast the return quantities of mobile phones. The proposed fuzzy model was trained based on prior collections from all the cities in Australia, and they tested against another set of data. The mean square error of the results was found to be less that 20%. Another similar study by Temur and Bolat (2014) uses the same socio-economic factors in a fuzzy expert system to create a forecast model for the expected return quantities from unknown cities by training the fuzzy system based on a data set of known cities in Turkey. A prior study by Ugurlu (2012) proposed a multiple linear regression model with socio-economic factors as input variables to predict the return rate of white goods in Turkey. Thus, these three studies corroborate the relevance of using socio-economic factors to study consumer behaviour, particularly return quantities of electronics, in reverse logistics. However, there is no present literature on how socioeconomic factors can be used in reverse logistics to create similar forecasts for return quality.

This study proposes such a socioeconomic forecast for return quality by exploiting the link between return quality and product usage. Since return quality is predetermined by product usage, it would be necessary to study the usage behaviour patterns of the public. This can easily be done on an aggregate level if the consumers are categorized by socioeconomic factors, and their usage behaviours are studied.

The next section validates the logic behind formulating usage behaviours based on socioeconomic factors by presenting relevant publications.

2.4.2 Smartphone Usage Behaviour Context

A study by Pew Internet Research (2004) on the effect of demographic factors on length of internet usage per day establishes that there is indeed a strong correlation between the two. They found that, in addition to age, regional differences have a large influence on the total time that users spend browsing the internet. On the note that previous literature proposed as a general concept that young Internet users tended to use the Internet as a communications device whereas older (30 and up) tended to use the Internet as a device for information retrieval, this study attempted to gauge if the purpose of usage was reflected in the number of hours spent on the internet. To this end, it was found that older individuals — as defined by 30–49 years of age did in fact have a statistically significant difference in usage of the Internet. Moreover, the younger group used the Internet only about 25 percent of the time whereas the older group used it about 50 percent of the time.

A study was conducted by University of California Los Angeles in collaboration with Microsoft which correlates smartphone usage based on different consumer groups to model rate of energy drainage and use the data for resource optimization (Falaki et al., 2010). The main segmentation in this study that was driven by socio-economic factors was occupation namely student vs. knowledge worker. Three metrics that were used to measure smartphone usage of the different users are: session lengths, inter-arrival time between sessions, and application popularity. The results of this study found that, while the statistical models for usage were common across users they were governed by different parameter values depending on the characteristics of the user group.

In a similar light, Biljon and Kotze (2008) Studied the impact of cultural background on mobile phone usage and adoption. They categorized the participants in their study by two factors: age and ethnic group. Through the results of this study it was found that there is a distinct difference in the usage of mobiles between people above 30, and people below 30. This difference is strongly motivated by the fact that people below 30 use mobiles diligently for communication where as people above 30 do not solely rely on mobile phones for communication. Thus, this study corroborates a dependence of mobile usage on the users' age.

2.4.4 Conclusion: Applicability of Socioeconomic factors in this study

From the above section of the literature review, it has been established that socioeconomic factors not only affect consumers' participation in reverse logistics activities, but are also a strong indicator of product usage patterns.

Combining this information forms the rationale that socioeconomic factors can be used successfully to determine the usage of mobile phones, which can then be used to predict their return quality when these phones are returned into the reverse logistics stream. The proposed forecast model for return quality is developed on the basis of this logic.

2.5 Thesis Contribution

From the discussion so far, specific issues have been identified as missing from the RL literature which this thesis aims to resolve.

2.5.1 Gap in Literature

The following issues have been identified as missing from the RL literature

1. There is no cost-effective and stand-a-lone tool to simulate usage data of the population. Present practices of using historical data or condition monitoring to generate usage behavior take a lot of time and require extensive infrastructure which may not be justified for short life-cycle electronics.
2. There is no forecast model that predicts usage-dependent end-of-use quality for mobile devices based on socio-economic factors.
3. Present literature uses fixed probability distributions, regardless of the characteristics of each consumer and zone for modeling return quality. This issue of trying to have different probability distributions based on the unique socio-economic profile of different zones has not been used to forecast return quality.
4. The probability distributions for quality used in literature are inadequate because they fail to incorporate the multi-dimensional factors that affect recovery decisions. This issue has only been addressed by Liang et al., (2014) for the case of batteries.

2.5.2 Thesis Contribution

The gaps in literature helped develop the research objectives that have been outlined in Section 1.3 Research Objective and Expected Contribution.

The main contribution of this thesis will be a socioeconomic forecast model for return quality that can add value of information and reduce uncertainty of quality in the planning and execution of a reverse logistics networks. By using aggregate consumer behaviour based on socioeconomic factors to formulate usage distributions, the model will prove to be an inexpensive tool that can provide quick results, as compared to existing data-driven methods of generating return quality data. Additionally, the superposition of economic trends with the usage model will increase the relevance and applicability of the model.

2.6 Background on Methodology/Techniques used in the Model

This section elaborates on the techniques that will be employed in the formulation of the forecast model that will be presented in this thesis. The main idea is to create an aggregate forecast model for return quality using socio-economic factors as input variables. Monte Carlo Simulation will be used to create a population scenario. The forecast model will then be applied to the population scenario to generate meaningful results.

2.6.1 Aggregate Forecast Models

In order to sustain a competitive edge, successful companies are always planning ahead. Aggregate forecasts models of future trends play a crucial part in allowing them to do so.

In conventional forward supply chains, aggregate forecasts usually include demand for the company's products over a long period of time. Exceptional forecasts will be comprehensive of impact of the companies' own marketing strategies on their demand as well the impact of their competitors' activities. Factors that enable these forecasts include backorders, marketing information, seasonal trends and pricing strategies. Additionally, the company needs to factor in the impact that future innovations in its industry could have on its products. All of these factors come under aggregate demand forecasts.

In forward supply chain, aggregate forecasting has widespread applications. The mathematical technique has also been applied in reverse logistics to predict the forecasts of the volumes of returned products from different cities. Hanafi (2008) devises a fuzzy-based aggregate forecast based on socioeconomic factors to predict the quantity of mobile returns from different cities in Australia. Temur and Bolat (2014) use fuzzy expert systems to predict return quantities of electronics on an aggregate level from the cities in Turkey. Similary, Ugurlu (2012) used SAA method to forecast city-based collections of household appliance wastes in Turkey.

Thus, aggregate forecasting has been established as a useful technique in regional based forecasting. This thesis uses aggregate forecasting to predict return quality of mobile electronics from different regions. The population samples from each region are modeled using Monte Carlo methods.

2.6.2 Monte Carlo Simulations

Monte Carlo simulations are computation methods that use repeated random sampling in order to obtain final results (Liang et al., 2014). In order to deal with uncertainties, it is necessary to resort to stochastic programming techniques. Usually in stochastic programming, it is necessary to create a scenario based on known probability distributions of the events that are being modeled. A scenario is a plausible occurrence of events in a system. One way of generating scenarios is using Monte Carlo Simulations.

Monte Carlo Methods can be used to generate samples of a given number of equiprobable and independent events. The scenarios are created using known probability distributions of the concerned parameters. The reliability of the results of a Monte Carlo simulation are limited by the accuracy of the probability distributions that are used in the scenario generation.

In relation to management of risk and uncertainty in supply chain management, many published works have used Monte Carlo simulations as a reliable means of scenario modeling. Some recent examples include Heidary and Aghaie (2018) who use is it in a simulation-optimization case of the newsvendor problem, Mangla et al., (2014) use it to model risks in the operation of green supply chains, Liang et al., (2014) use Monte Carlo for forecasting quality of lithium batteries in remanufacturing, and Schaefer et al., (2019) who use a hybrid Monte Carlo method with Analytical Hierarchy Process (AHP) to model water risks in supply chains.

CHAPTER 3

MATHEMATICAL MODELS

3.1 Model Description/Metrics for Recovery Decisions

Recovery decision depends on the quality of the returned product, the costs of the recovery operations and the profit that each of the recovery operations are expected to generate based on market demand. It is necessary to make quality-driven decisions to achieve effective and efficient recovery. It is even more crucial to have information on prior forecasts of the expected ratios for each recovery process. In order to make forecasts of return quality, the same factors that affect recovery decisions must be used to predict what quality of returns will arrive.

The proposed forecast model addresses the issue of quality grading by incorporating three major factors listed below:

1. Quality of the used product
2. Cost of recovery operations
3. Economic value of the product and its parts

These factors have been explained in further detail below.

Firstly, the quality of the used product will depend on the intensity of usage. While each customer uses their device in unique ways, there is sufficient literature to establish that fact that general usage trends can be deduced based on clustering of consumers by their socioeconomic factors. The forecast model devised in this research categorizes product returns based on the socio-economic factors governing the consumer base. By analyzing the differences in product usage patterns, purchase and recycling behaviours based on the age, income, education of a consumer, this model attempts to forecast what the quality of their returned product might be.

The second factor is the cost of recovery. The level of usage, and hence product wear and tear, will automatically dictate the cost of the recovery operations. Products with heavy usage, and thus more wear, will have a higher probability of component failure and bad cosmetic conditions than products with lower usage. This impact of usage on recovery costs has been mentioned diligently in literature as one of the primary variables in reverse logistics process (Geyer et al., 2007; Zikopoulos and Tagaras, 2007; Panagiotidou et al., 2017). The recovery costs will also be affected by the costs of replacement parts, which in turn will change in time. Since the recovery costs vary per individual unit with time, the profitability will also vary in every period. Therefore, pros and cons of all recovery options must be weighed before a recovery decision is predicted.

This leads us to the third factor which is economic trends. The repair cost is not the only factor that determines profitability. In fact, the time-dependent market pricing and demand for the product also contribute to the profitability. Therefore, it is important to formulate time-dependent economic value of products in order to calculate expected profits from recovery operations accurately. For this reason, this model also takes into account various economic trends that can impact the profitability of recovery decisions. The variations in the selling price of refurbished goods with time determine the profitability of remanufacturing decisions. Market value is influenced by many factors including new releases, technological age, popularity of a model, and marketing strategies of both new and remanufactured products. In recent times, part harvesting is gaining momentum in the smartphone industry. For some smartphone models, the market demand for its components may outlive the demand for that whole product. To enhance the practical relevance of the forecast model, economic trends of used parts have also been taken into account.

Figure 1 aptly summarizes how the two factors mentioned above, cost of recovery and market value, change with the usage level and the life cycle stage of the product.

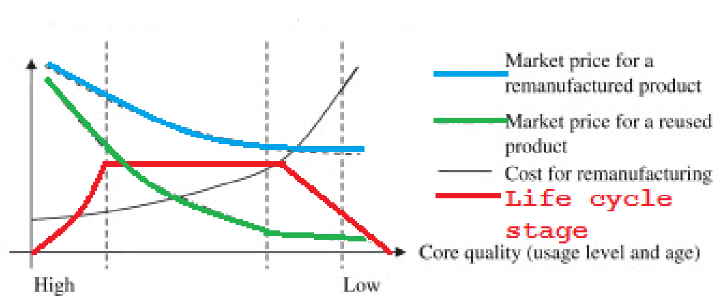


Figure 1 Quality-dependent costs of recovery. Adapted from Ostlin et al., (2009)

Figure 2 in the next section attempts to illustrate the above description of the dynamics at play when deciding profit-based recovery decisions for used electronics.

3.1.1 Schematic for Influencers of Recovery Decisions

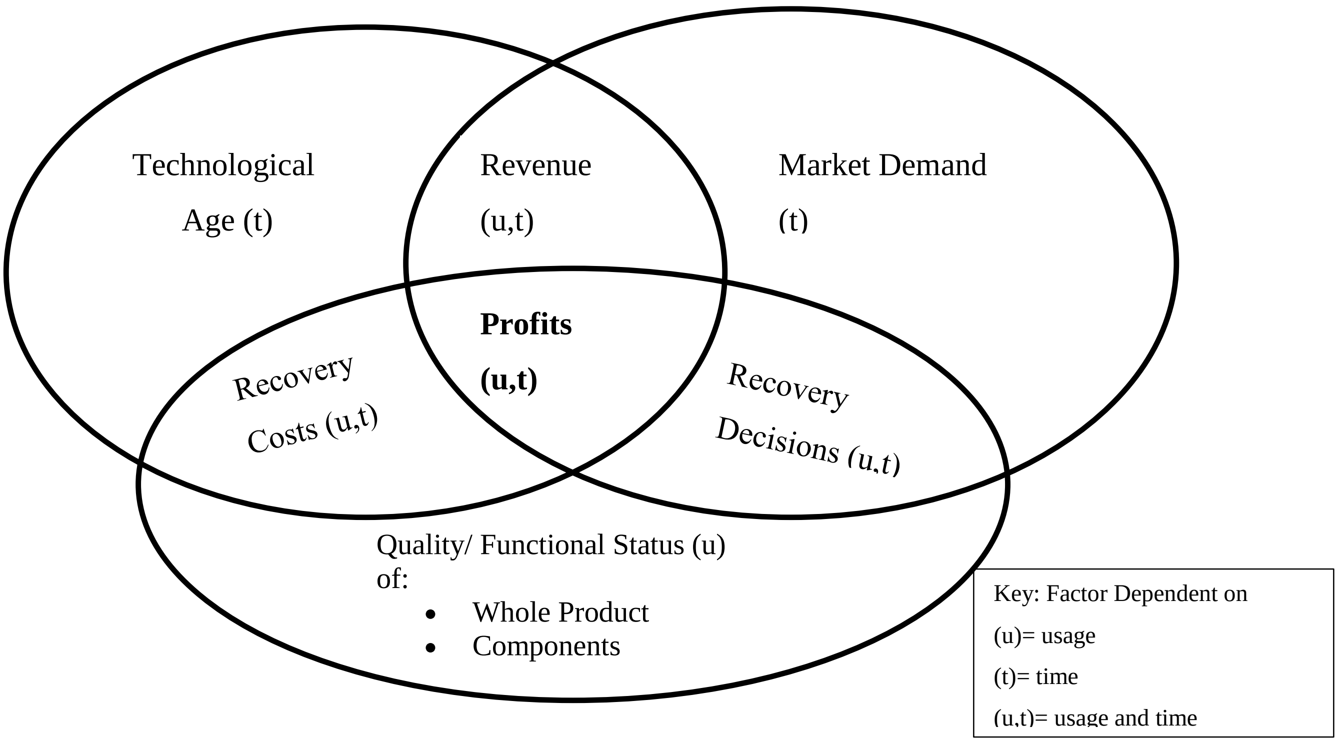


Figure 2 Interplay of factors that affect recovery decisions in RLN

3.2 Socioeconomic Usage Model

In their book, Pochampally et al., (2008) mention that product wear and end quality can be estimated from consumer specificities amongst other things like date of marketing, environment of use and sensors and gauges.

Following that logic, in this study it is assumed that return quality of end-of-use mobile devices can also be gauged by consumer specific demographic data. The logic behind is that much of the usage behaviours of a consumer's device is governed by their social factors like their age, income and social status. In addition to the daily usage, the rate at which consumers replace their devices, and how they choose to dispose their devices is also determined by these factors. A report by CWTA (2016) clearly defines these differences in behaviour. In addition, according to a research published by Pews Internet Research (2016), there is statistical correlation between the internet usage of the population based on these social factors.

Since the usage of a device varies based on consumer attributes, an attempt is made to characterize returned products based on the socioeconomic factors that govern consumer behaviours on an attribute level. This section contains a description of how relevant socioeconomic factors have been selected for calculating smartphone usage in particular. Then, a model is developed for usage distributions based on the selected factors. This usage model will be used as a tool to forecast the functional quality, in other words survival probability, of the expected end-of-use returns.

3.2.1 Factor Selection using Statistical Methods

The following sections describe how age, income, education level and region influence the number of hours a consumer spends on their mobile device daily.

Based on relevant literature, the socioeconomic factors that tend to affect the behaviour of consumers in the realm of internet usage are: age, income status, type of occupation, gender, geographical location and educational level.

In order to find which of these have high statistical significance on a user's daily device usage, a chi square test of association with an alpha level of 5% has been performed. The data used in the analysis was gathered from a survey conducted by Forum Research Poll in January 2018 in Canada. The data was collected through telephonic and online polls. The survey asked members of the population questions pertaining to their age, income group, highest level of education, gender, province of residence and how many hours they spend on their smartphones on a daily basis. The results of the survey were published in a two-way table for each factor separately, in which the columns represented the different groups of each factor, and the rows represented intervals of daily hours of usage, ranging from 0 to 5 hours per day. The age groups used in the study were from 18-34, 35-44, 45-54, 55-63 and 64+. Similarly, the household income groups used in the study were: <$20K, $20K-$40K, $40K-$80K, $80K-$100K, $100K-$250K and $250K+. The education levels used in the study ranged from below secondary schooling all the way to post graduate studies. The permissions for the use of the data published by the Forum survey in this can be found in Appendix B.

Below, is an illustration of the hypothesis setup for the chi-square tests followed by tabulated results. This test for independence was carried on the survey data using Minitab 18® with a significant level of 95%. The full results obtained from the software can be found in Appendix C.

Results Conclusions from Statistical Analysis

Through the above statistical analysis in this research, it has been proven that the main socio-economic factors that influence the daily hours spent on smartphones by an individual are age and income. All other factors namely gender, region of location and education have not shown statistical correlation with daily usage. This is because the p-value for age and income was found to be 0.000 and 0.001, which is significantly less than the alpha value of 0.05. Therefore, the null hypothesis is rejected and it is concluded that daily usage of smartphones is **not independent** of age and income. The p-value for all other factors is greater than the alpha value, therefore the null hypothesis for these factors is accepted.

Chi-Square Test of Independence

H_0: Age and daily usage are independent

H_a: Age and daily usage are not independent

$\alpha = 5\%$

If p-value< 0.05, reject null hypothesis

Table 1 Hypothesis testing results for association between socioeconomic factors and daily usage

	Category	Null Hypothesis	Chi Score	P-Value	Result
AGE	18 to 65+	Age and daily usage are independent	75.066	0.000	**Rejected**
	55 to 65, 65+	Age and daily usage after 55 are independent	3.259	0.353	Accepted
INCOME	<$20K to $80K	Income and daily usage are independent	38.080	0.001	**Rejected**
	$80K to $100K+	Income and daily usage after $80K are independent	1.931	0.587	Accepted
EDUCATION	High school to Post grad	Education and daily usage are independent	11.373	0.251	Accepted
GENDER	Male or Female	Gender and daily usage are independent	1.593	0.661	Accepted
REGION/ PROVINCE	Atlantic, ON, BC and MB	Geographic location and daily usage are independent	11.813	0.224	Accepted
	Atlantic & ON	Provincial region and daily usage are independent	6.771	0.080	Accepted
	ON & MB	Provincial region and daily usage are independent	5.058	0.168	Accepted

Intergroup-Correlation

The chi-test square test of independence was also carried out between two consecutive groups under the same factor. Based on these results, it was found that all age groups are characterized by statistically distinct distributions except for the two age groups 55-64 and 65+. The p-value of this test was found to be 0.353, which is larger than the alpha value of 0.05. This means that the members of these two age groups have statistically similar daily usage distributions. The conclusion of this test is that, after the age of 55 years, the daily usage becomes independent of age. Therefore, in the usage model developed in this study, one single usage distribution will be used to represent mobile users of both age groups.

In addition to that, similar analysis was performed for the income groups. The results of these tests suggest that the two income groups of $100K-$250K and $250K+ have similar daily device usage behaviours. The p-value for this test was 0.587 which is larger than 0.05. Thus it was concluded that after the $80K income bracket, daily device usage becomes independent of income status.

Going forward in this research, this section has established that the two dominant socioeconomic factors that affect smartphone usage, and hence the return quality, are age and income.

In the next section, the usage distributions for each age group and income group will be shown.

3.2.2 Usage Distribution Based on Age

The following distributions show the smartphone usage behavior of people from different age groups. The graphs from Figure 3 to Figure 5 show the probability distributions for 18-35, 35-54 and above 55 years of age. Since the age groups 55-64 and 65+ have similar usage distributions, they have been superimposed on a single histogram, clearly showing an overlap of more than 90% See Figure 5. This further signifies the argument that daily usage becomes independent of age after 55 years.

For the age group 18-34, the daily usage hours have been modeled as normal instead of uniform distribution. This is because using the uniform distribution leads to equal usage probabilities for up to 24 hours a day. This is inaccurate as the probability of using a phone for 24 hours cannot be the same as the probability of using it for 5 hours a day, which is more likely for the given age group. This introduces anomalies in the results of the forecast model that deviate from an accurate representation of return quality ratios.

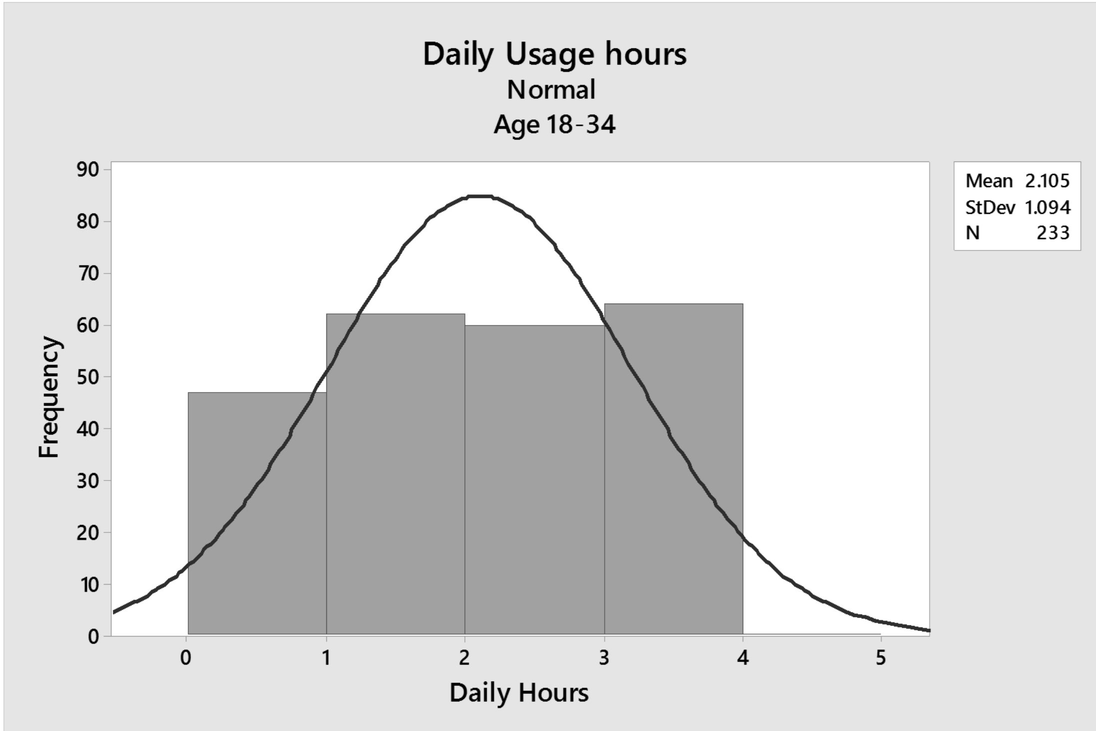


Figure 3 Daily usage for Age 18-34

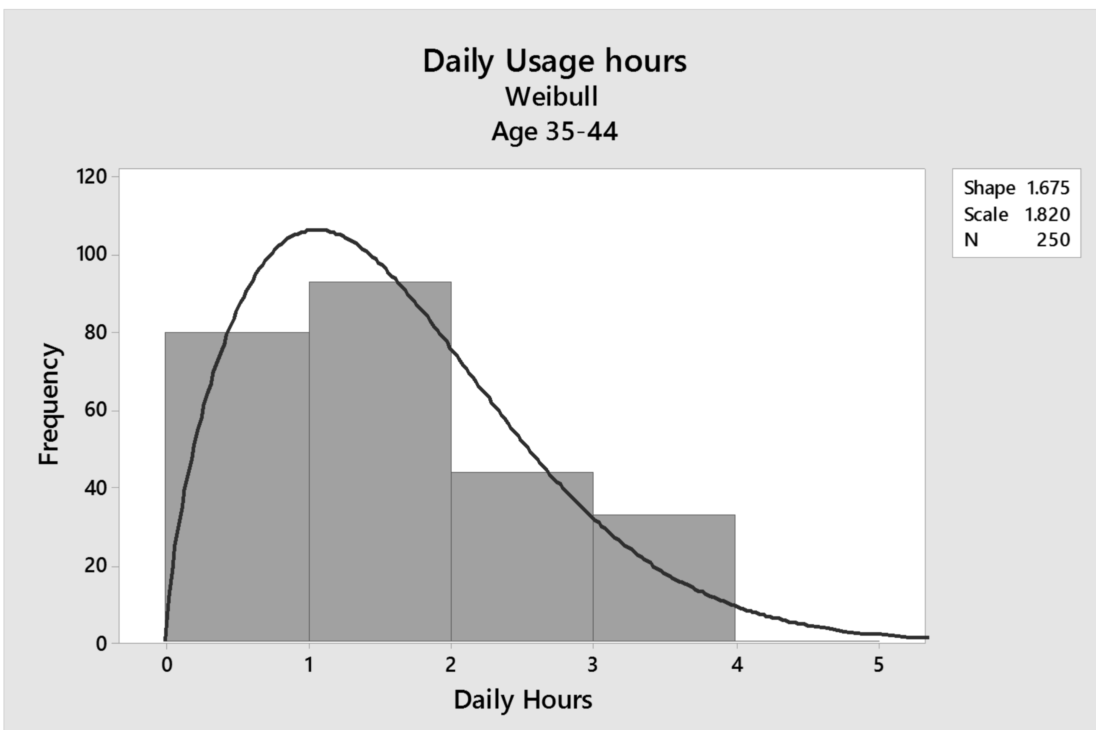


Figure 4 Daily usage for Age 35-44

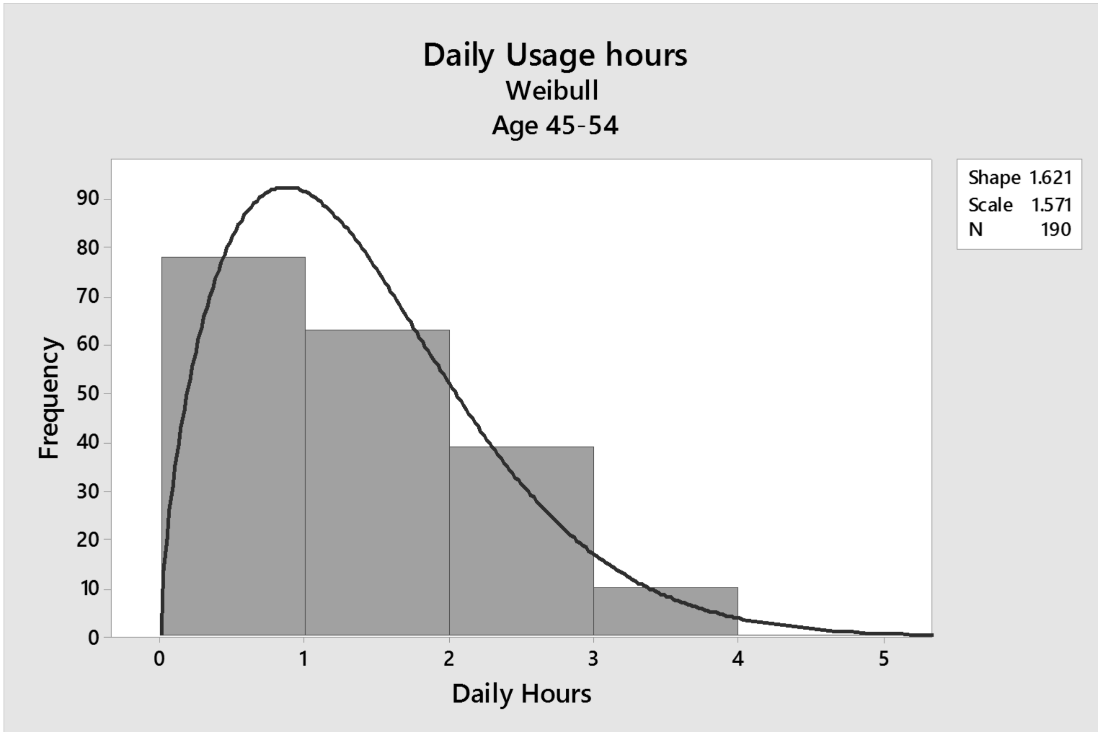
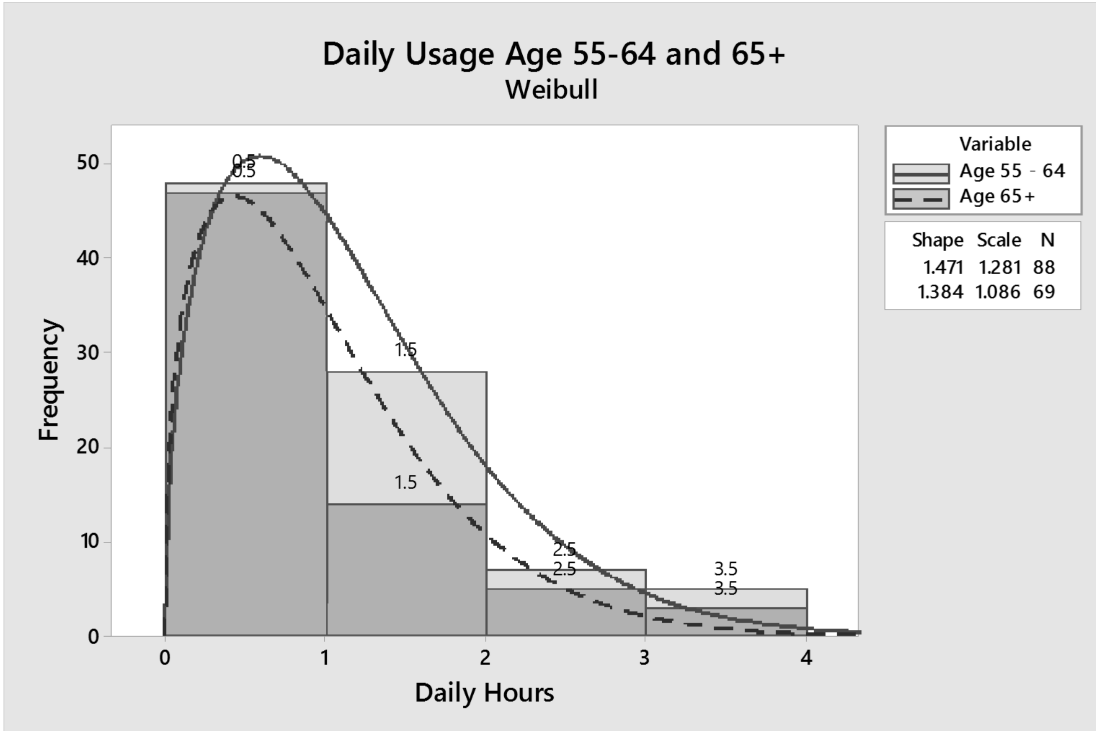


Figure 5 Daily Usage for Age 45-54

Length of Ownership versus Age

The distributions below show the probability distribution of length of usage of one device with respect to time. In other words, the distributions below depict the length of time a user will hold on to their device before returning it. According to the data collected, it has been found that the parameters of these distributions are different depending on the concerned age groups. The graphs from Figure 7 to Figure 9 show the probability distributions for 18-35, 35-54 and above 55 years of age. The data used in this analysis was collected in a survey by Canadian Wireless Telecommunications Association through a dual mode telephonic and online survey in Canada in 2017. The permissions to use the data from the concerned study can be found in Appendix B. However, reprinting of data tables is not possible.



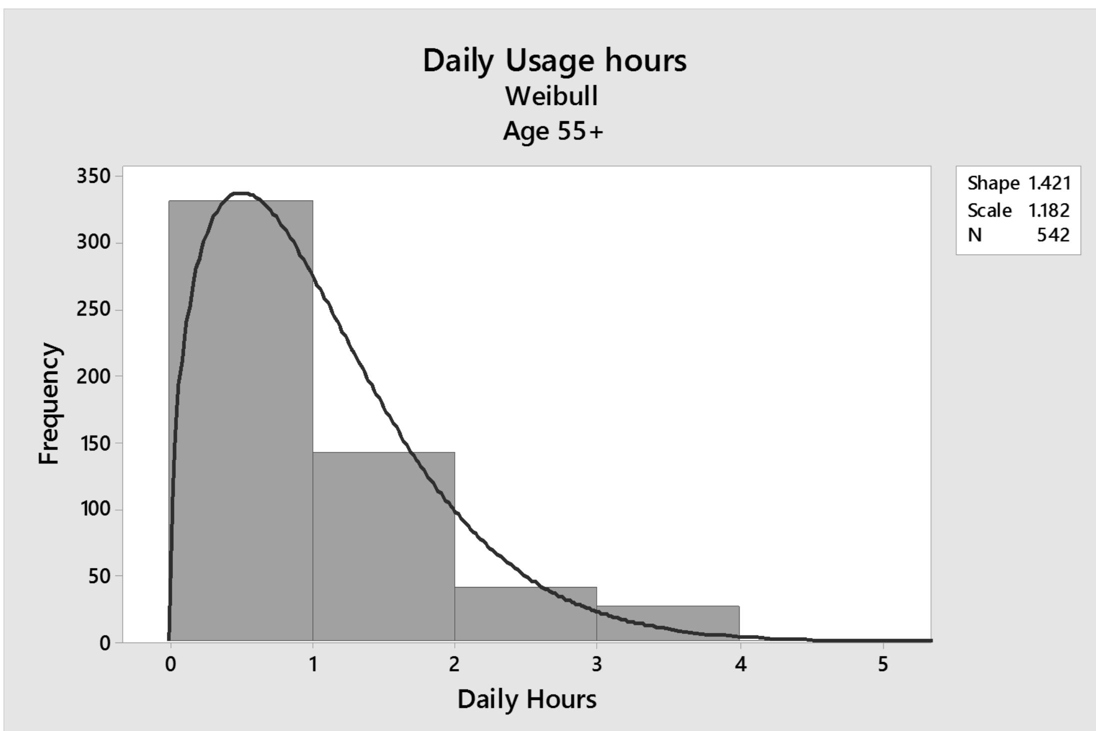


Figure 6 Daily usage for ages 55 and above

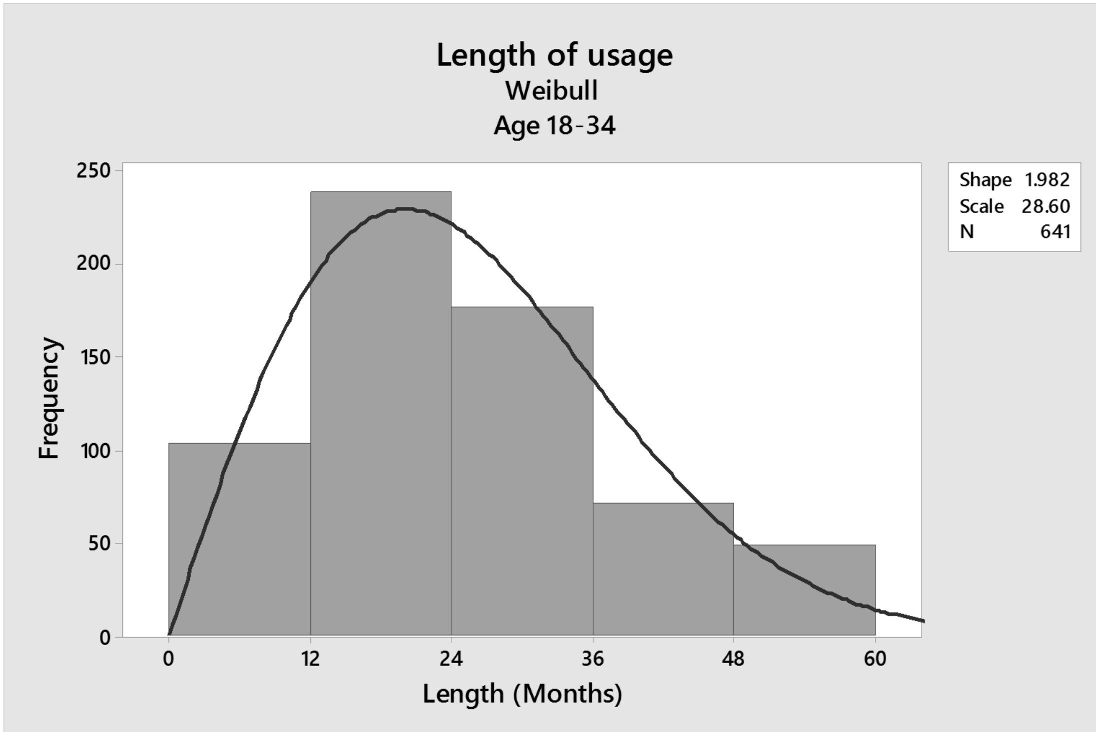


Figure 7 Length of usage for 18-34

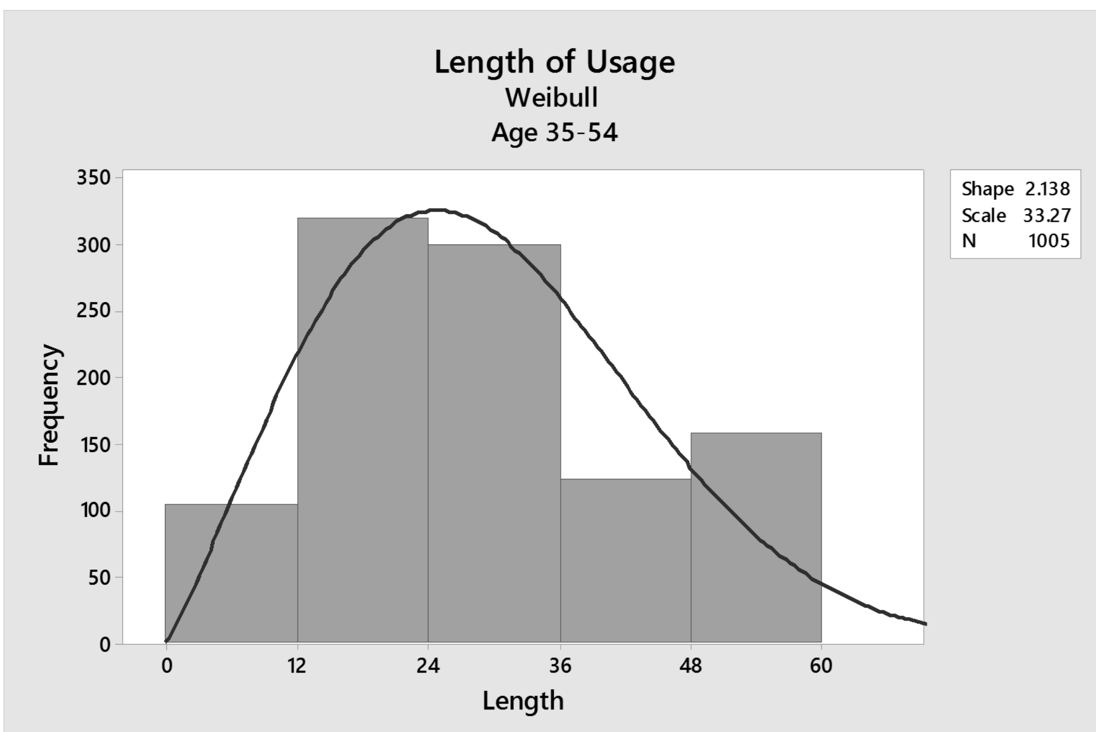


Figure 8 Length of usage for ages 35 to 54

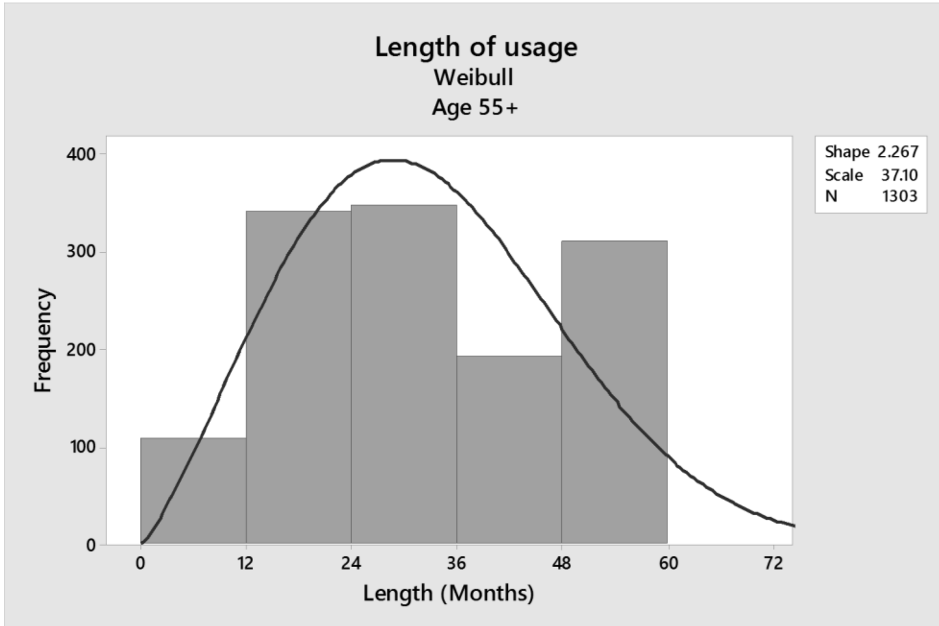


Figure 9 Length of usage for ages 55 and above

3.2.3 *Usage Distribution Based on Income*

The following distributions show the smartphone usage behaviour of people from different income groups.

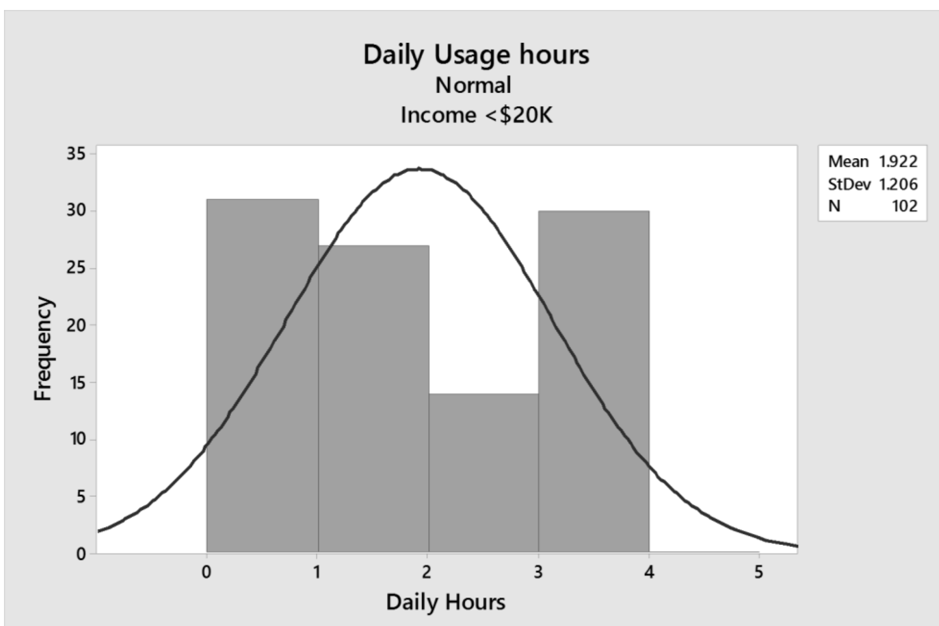


Figure 10 Daily Usage for income below $20K

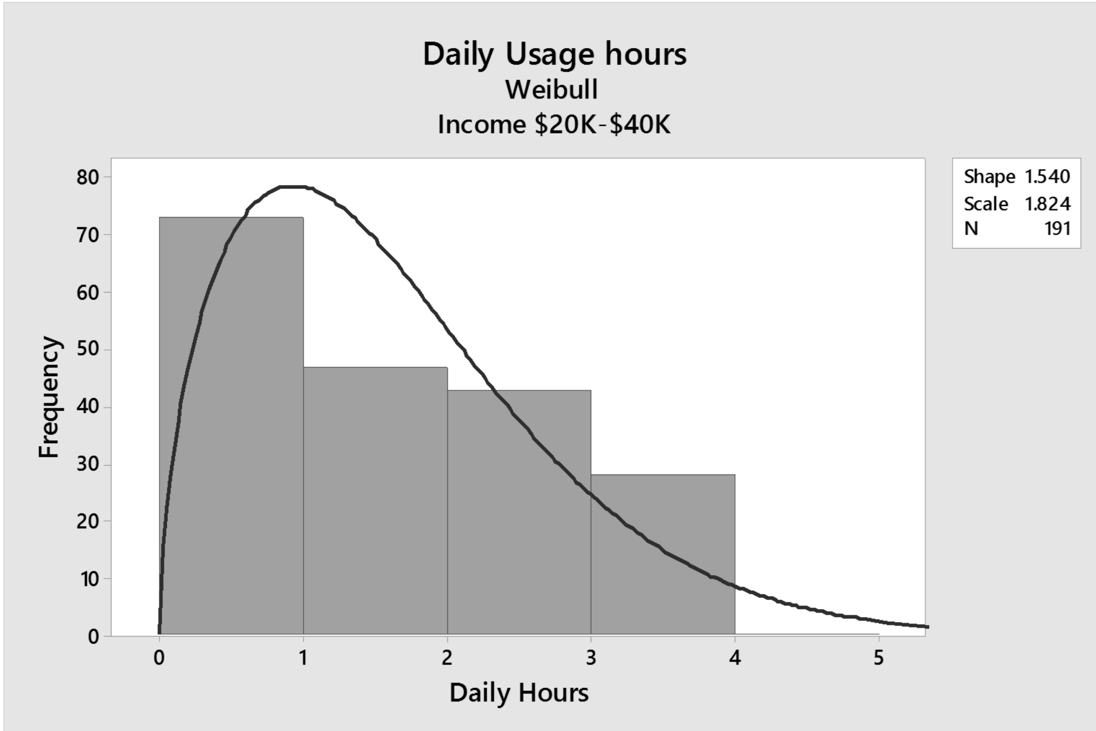


Figure 11 Daily usage for income $20K to $40K

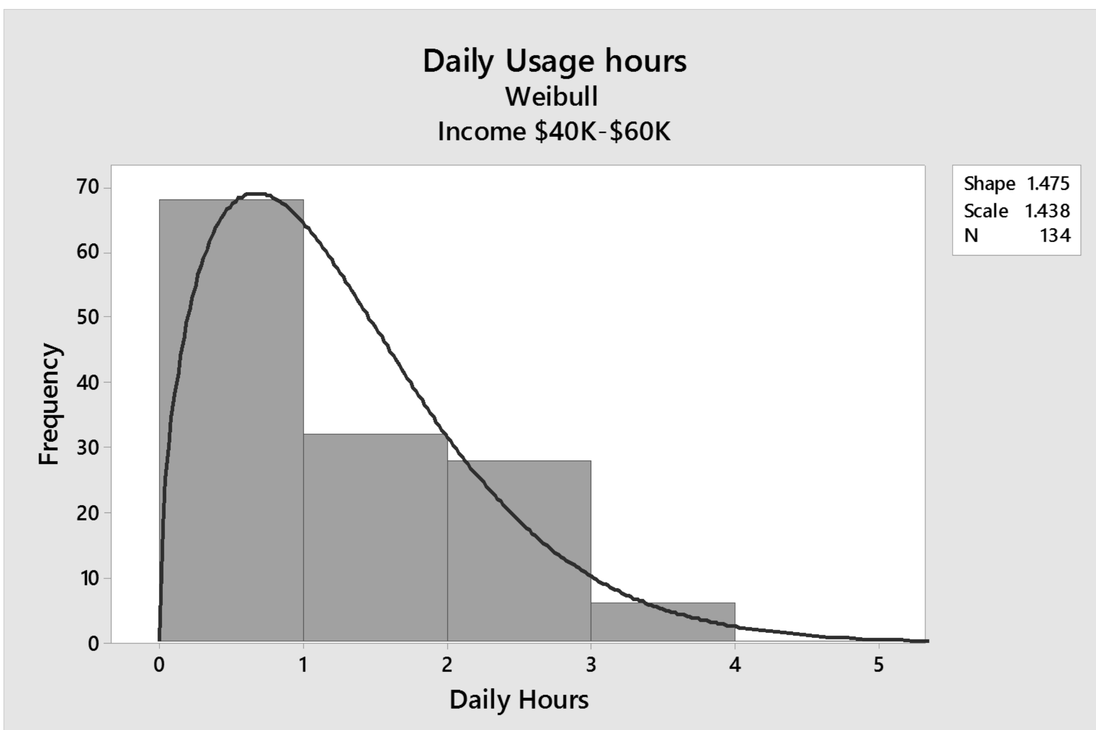


Figure 12 Daily Usage of income from $40K to $60K

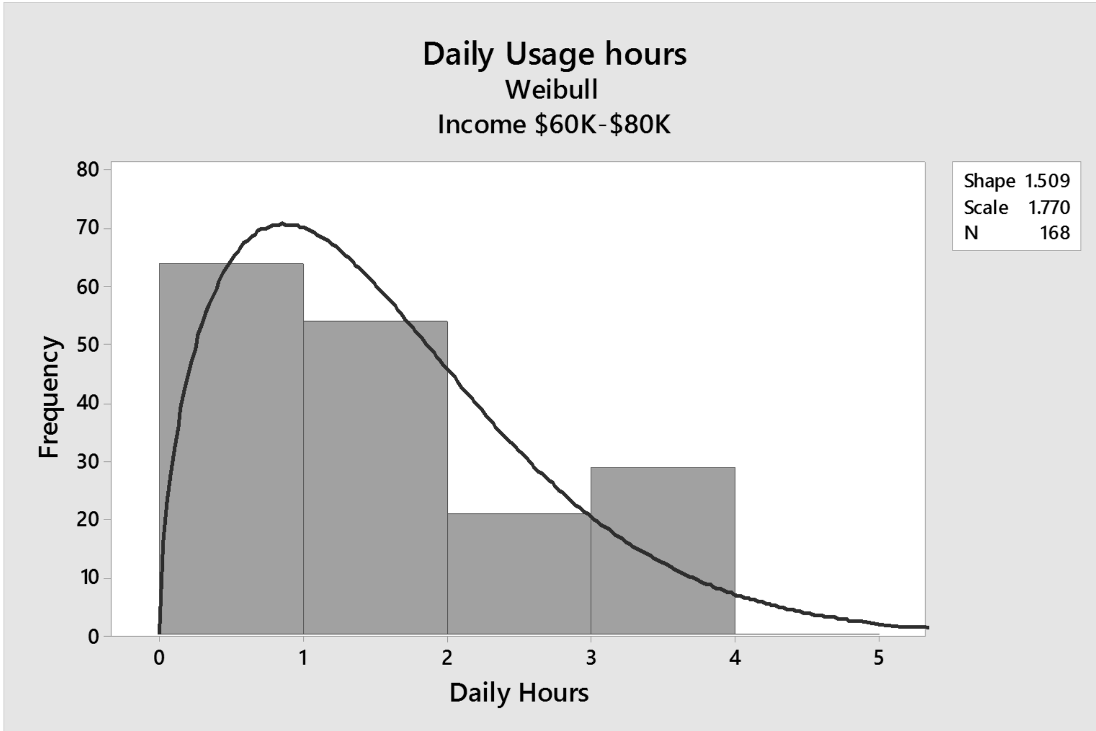


Figure 13 Daily usage for income $60K to $80K

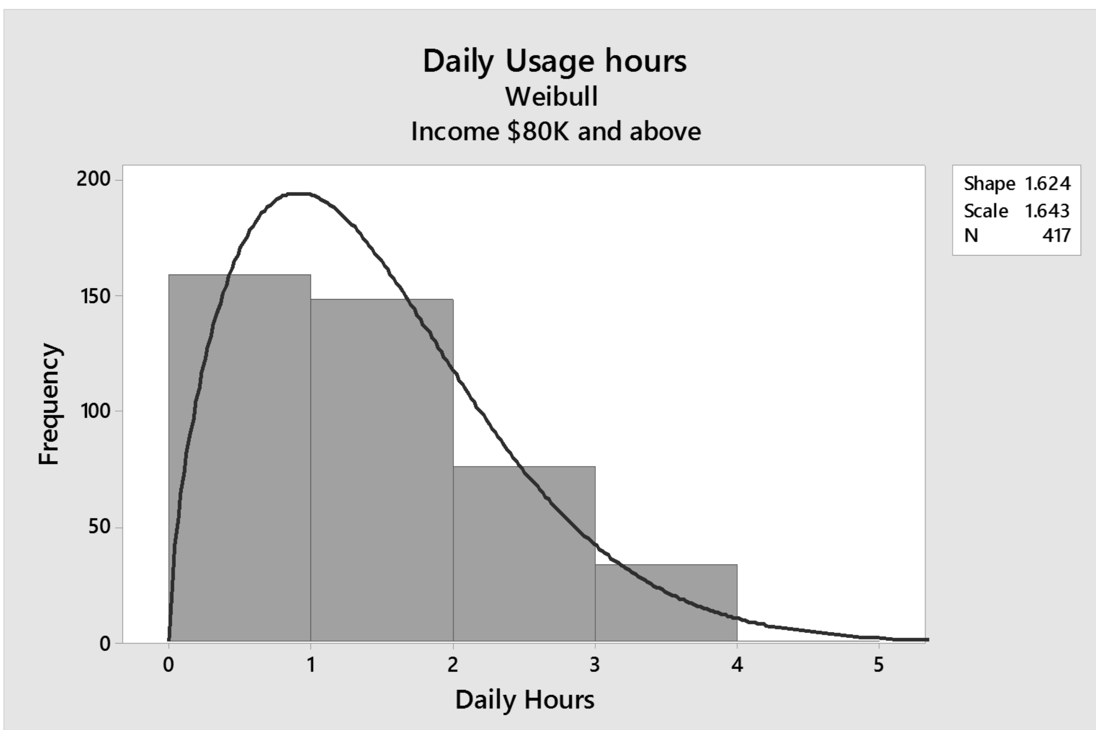


Figure 14 Daily usage of income $80K and above

3.2.4 Social Factors Selection: Conclusion

From the hypothesis testing, it is clear that the two main factors that have significant impact on daily usage of mobile devices are: age and income. The p-values for these tests were 0.00 and 0.001 respectively, both of which are much lower than the alpha value of 0.05. This strengthens the argument that daily device usage is strongly dependent on age and income of its user.

Although other socio-economic factors such as education level also show variations in usage behaviour, their differences do not hold as much significance as age and income. Based on the data available in this study, the p-value for these variables were much larger than the significance level chosen for this study, thereby validating the null hypothesis. Therefore, they shall not be considered for the purpose of this research.

Going forward in the research, the two main socio-economic factors that will be used in the forecast model are age and income distributions of the population.

3.2.5 Usage Model Formulation

This research attempts to develop a usage model based on social factors in order to determine the total hours that a device has been used at the time of its return. The objective of such a model is to predict the functional reliability of the electronic devices. To collect the historical quality data effectively, the variable can be represented by sensors that record running time of the entire machine lifetime (Simon et al., 2001)

How is Usage Model defined in this study?

For the purpose of this study, a usage model is defined as mathematical modelling of how many total hours a particular device has been used for at the time of its return. Mathematically, the 'total hours' is calculated as the product of two input variables: daily hours of usage d and total length of ownership t. The usage model can simply be represented as:

$$Total\ hours(u, t) = daily\ hours\ usage\ (d)\ x\ length\ of\ ownership\ in\ months\ (t)\ x\ 30\frac{days}{month}$$

Since the daily hours of usage, d, and the length of ownership t vary across each age group, it is obvious that the 'total hours' distribution will also be different for each age group

What is the importance of the usage model in this study?

When determining return quality, the most important factor is the functional status of the device (Mashaddi and Behdad, 2017). If the device has been used for longer total hours, the probability of having a lower functional status is higher. Conversely, if a product has been used for relatively lesser hours, the overall failure probability of the components and the product will be higher. In order to forecast the functional status, or in other words, the reliability, of the product, it is crucial to quantify and plot the distribution for total usage in hours. Since the total usage profiles are different for each age group, then the functional reliability of the returned devices will also be different.

3.3 Usage-based Reliability Model

Reliability is the probability that a product achieves the function for which it has been designed in a given period of time and in given conditions. To be able to forecast the end quality of a used product, before the testing and inspection stage, failure rate and reliability calculations can give a good idea of whether a mobile unit will be functional or not, thereby playing a part in quality determination (Ostlin et al., 2009). Since reliability depends on usage hours, the usage model described in the above section will be used in the reliability calculations. Additionally, the reliability of the individual components can also be calculated if their failure rate is known. Since the mobile phone is an electronic, the modeling of its reliability is more complex than that of mechanical devices. The following sections address how the reliability calculations for the whole mobile product and the reliability of its individual components have been addressed for the case presented in this research.

3.3.1 Usage-based Product Reliability

The calculation of an entire product's reliability is a complex process which requires data of the failure rate on each of its constituting components and also information of the arrangement of the components- whether they are in series or parallel. Regardless of whether the components of electronic devices are arranged in series or parallel, the overall reliability is always limited by the component with the highest failure rate.

In order to accurately predict the reliability of used phones at the end-of-use stage, it is necessary to carry out a systems reliability assessment by mapping out the component arrangement inside the cellular phone, and conducting fault mode analysis. However, this detailed assessment of reliability falls outside the scope of this study. In order to simplify the reliability calculations of smartphones, an attempt has been made to study existing literature that can provide close enough estimates for the system reliability of smartphones.

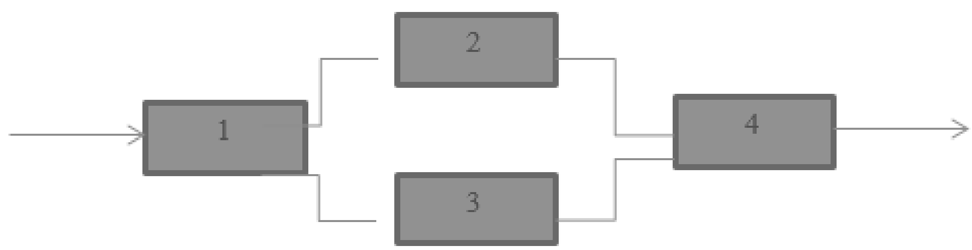


Figure 15 Example of reliability block diagram

According to the literature survey on this subject, two studies were found which collect field failure data of smartphones, censor the data, and fit the data to parametric distributions to find a suitable failure rate distribution for smartphone systems. Two main studies that follow this method are by Tiwari and Roy (2013) and Wang and Huang (2011). While Tiwari proposes a cox proportional hazard distribution to model the survival function of smartphones, Wang et al., have found that lognormal distribution is the most appropriate distribution to model failure rate of the smartphones. The solution methodology in this research uses the methods defined by Wang and Huang (2011).

In this study, the field return data was input into Minitab and arbitrary censoring was used to calculate the lognormal parameters for the distribution that would estimate the failure rate of smartphones. The data set consisted of number of days and number of failures in the specified number of days. Data set was collected for a period of 360 days.

Table 2 Example of the data table format used to generate failure distribution

Start	End	Censored Units	Failure Units
0	30		
31	60		
…	….		
331	360		

According to the results, the parameters for the log normal distribution for modeling the failure of smartphones was found to have a location of 11.07 and scale of 2.49. The log normal plot for the specified parameters is shown in **Error! Reference source not found.**. From this plot, it can be seen that the survival probability gradually decreases as the number of days of usage increases. Therefore, this distribution has been used to calculate the probability that a phone survives for a given length of time without any type of failure.

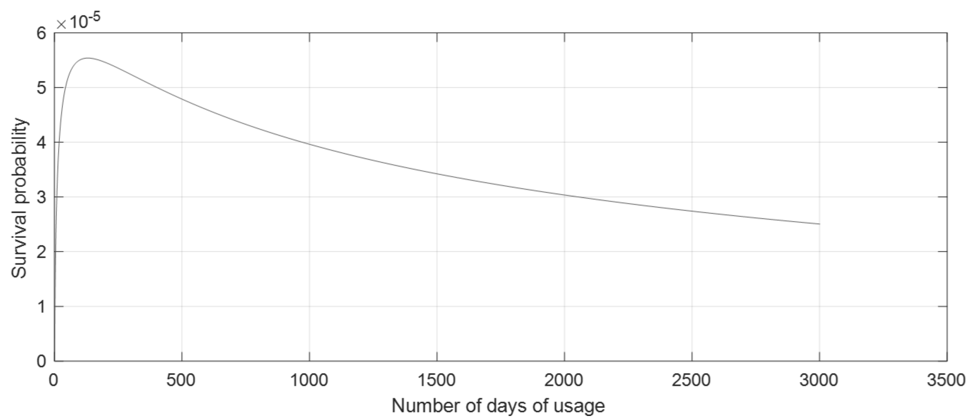


Figure 16 Product survival function

3.3.2 Usage-based Component Reliability

It is crucial to pursue quality-driven decision-making for component recovery because quality is a dominant factor for component salvage value and its recoverability (Meng et al., 2017). Since quality depends on functional reliability, it is important to calculate reliability of the components in advance, to predict which components are more likely to fail. This forecast of component quality can help production planners with spare parts inventories.

One of the main problems with calculating the reliability of electronic components is that they follow a random failure pattern. Unlike mechanical components that fail with respect to how the product has been used, electronic components usually don't follow the same failure curve (Ostlin et al., 2009). Their model also attempts to calculate marginal reusability of components.

Usually for mechanical components or even lithium batteries, remaining useful life (RUL) serves as a useful measure of quality. However, for electronic components present in mobile phones such as microphones, speakers, cameras, home buttons or touch screens, there is no way to calculate RUL. In this study, it has been assumed that the electronic components have a constant failure rate with respect to time or usage. The failure probability and reliability of relevant components are then calculated using the exponential distribution. This method is used for LCD and battery failure probabilities.

For components that do not have time-based failure rates, it is not feasible to model their failure reliability calculations. For these components, failure probabilities have been calculated using the Bernoulli trial method.

<u>Component selection and failure modes</u>

Based on a report by Blancco (2017), it was found that some of the most common failure reasons which cause customers to return their phones are:

- Display damage
- Water damage
- Home button failure
- Battery life reduction (capacity and discharge rate)

Based on these failure reasons, a research was carried out to find what spare parts were available in the market, and whether the spare part availability coincided with the most common failure reasons. The list of the most common spare parts listed online for sale was found to be:

- LCD screens
- Home buttons with flex (which includes microphone and speaker)

- Volume buttons
- Back cameras
- Front Cameras
- Charging port

Based on the internet price listing, these components were the ones that sustained the highest prices over a long period of time. It was also found that these components have a market for both used and brand new parts.

Calculation of failure probabilities of used components

In this study, it is assumed that failure rate of components can either be calculated through exponential failure probability calculations, or through Bernoulli trial probabilities. Specifically, exponential reliability calculations are carried out for batteries and LCD modules. For other components namely, home button, charging port, and camera, individual failure probabilities from returned batches have been calculated as per data in a report from Square Trade (2010). Table 3 summarizes how the failure probabilities chosen for each component that has been included in this study.

Table 3 Failure probabilities for different components

Component/ Damage type	**Symbol**	**Probability taken from:**	**Failure Probability**
LCD accident damage	λ_{DROP}	SquareTrade (2010) and local repair shop	Bernoulli trial
Water Damage	λ_{W}	SquareTrade (2010) and local repair shop	Bernoulli trial
LCD functional damage (LCD)	λ_{LCD}	Manufacturer's quality assurance reports show mean number of hours to failure of screen functionality	Exponential

Home button (HB)	λ_{HB}	Local repair shop data on average probability of home button repairs	Bernoulli trial
Charging port (CP)	λ_{CP}	Local repair shop	Bernoulli trial
Back Camera (BC)	λ_{BC}	Local repair shop data on average probability of camera failures	Bernoulli trial
Battery (B)	λ_{B}	Average life span of 1000 cycles are used to calculate mean time to failure	Exponential

<u>Calculation of the failure probabilities for components with Bernoulli failure probabilities</u>

From Table 3, it can be seen that accidental damage and water damage have been assumed to follow Bernoulli trial failure probabilities. The reason that a Bernoulli distribution was chosen to represent these failures is because these values of failure probabilities were taken from a report by Square Trade which reports them for the failed phone batches that they collected. Therefore, time-based reliability calculations for them are redundant. To exemplify, consider the probability that a screen of a phone cracks because a person dropped it, or the phone gets damaged through water; these are not events whose probability increases or decreases with time. Therefore, the event of these two failures cannot have exponential probabilities. However, it can be a discrete probability such that there is a probability of success (failure event happening) or probability of failure (accident event not happening). Similar analogy applies to the failures of home buttons and cameras. The data to establish these probabilities has been collected from a report published by Square Trade (2010).

Based on the data collected from the local repair shop it has been found that: out of every 30 phones that come for repair, 20 are from accidental cracks in screen, around 4 are for charging port replacement. Thus the probabilities have been taken as 0.66 for accidental screen damage and for failure of charging port where a replacement was required, the probability is 4/30= 13%. Probability where charging port just needed cleaning is 15% for the repair shop. Similar failure probabilities have been calculated based on a report published by Square Trade (2010).

Table 4 lists the failure probabilities that will be used in this research. While only the values found by Square Trade (2010) will be used, the local repair shop data has also been included in the table, where possible, for comparison. The reason that the local repair shop values will not be used is that these values are biased and not random, as compared to Square Trade.

For the components that are assumed to follow a Bernoulli trial, the probability of survival will be:

$$Si = 1 - p_i$$

Where p_i is the probability that the event of failure has occurred.

Table 4 Bernoulli probabilities for failure of components

Damage Type/ Component	**Local Repair Shop Data**	**Square Trade (2010)**	**Bernoulli probability of failure event Pi**
Cracked display	20/30= 66%	18.24%	0.1824
Water damage	20%	4.8%	.048
Home button	N/A	11%	.11
Charging port	13%	4%	.04
Camera	N/A	1.8%	.018

Calculation of the failure rates of components with exponential failure distributions

Battery life and LCD failure probabilities have been modeled with exponential distributions based on the logic that total runtime does in fact increase the probability of their failure. This means that their failure probability (or survival probability) is a function of total usage hours.

For the components that are assumed to follow an exponential distribution, the probability of survival will depend on the total usage hours, u. The survival will be calculated in the following way:

$$R(u) = e^{-\lambda u}$$

Since it is assumed that the lifetime distributions of phone battery and LCD each follow an exponential distribution, it is important to first calculate their constant failure rate λ. $1/\lambda$ is defined as the mean time to failure of a component in hours.

The next sections detail the parameters and calculations for the failure probabilities of batteries and LCDs.

3.3.3 Usage based Reliability Calculations for Batteries

Parameters and Variables:

u= total usage in (hrs)

b= no of hours the battery can run on a single charge cycle. In other words, it is the usage time taken to go from 100% charge to below 20%.

c= cycles

noc= total number of battery cycles consumed

Ω= maximum number of cycles for smartphone battery

Mean Cycles to Failure (MCTF)= manufacturer's specified life span of battery

λ_B= constant failure rate for battery (/cycle) = 1/MCTF

$P_B(u)$= probability of dead battery after u hours of total usage

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Assumptions and Constants:

b= 9 hours 48 mins= 9.8 (hrs/cycle) (assumed to remain constant throughout battery life, and for all usage intensities)

Ω= 1000 cycles

MCTF= 500 cycles

Calculations

1. Number of remaining cycles after u hours of usage

$$\boldsymbol{noc = \frac{u}{b} = \frac{hrs}{\frac{hrs}{cycle}} = \#\ of\ cycles}$$

2. Probability of failure of battery after u total usage hours

$$P_B(u) => F(noc) = \int_0^{noc} \lambda e^{-\lambda c}\ dc$$

$$Therefore, F(noc) = 1 - e^{-\lambda noc}$$

3. Reliability of battery after u total usage hours

$$R_B(u) = 1 - Probability\ of\ failure$$

$$R_B(u) = 1 - P_B(u)$$

$$R_B(u) = 1 - \left[1 - e^{-\lambda noc}\right] = e^{-\lambda noc}$$

3.3.4 Usage-based Reliability Calculations for LCD

The LCD failure mode used for this study is the reduction of backlight luminescence by 50 percent. Each LCD backlight comes with a half-life which dictates the total runtime at which the backlight will reduce to 50%. At this point, the LCD does not pass the quality control for refurbished quality grade and therefore, must be replaced.

Half life for backlight= 3500 hours with exponential decay

λ_{LCD}= constant failure rate for LCD = 1/MCTF

Calculations

To calculate the depreciation constant k (also known as constant failure rate) of the backlight based on half-life value:

$$\ln\left(\frac{N(t_{0.5})}{N(t=0)}\right) = -kt_{0.5}$$

$$\frac{\ln(0.5)}{-3500} = k = 0.000194$$

3.4. Economic Factors

In addition to the usage and reliability of the product, other factors also play a part in recovery decisions. According to Guide and Jayaraman (1999), product life-cycle along with the technical and economic issues that are linked to the product life cycle play a crucial part in optimum recovery decisions in remanufacturing. Ait-Kadi et al., (2012) also mention that reprocessing option depends on product age at the time of return.

In order to incorporate the life-cycle of the product and the effect it has on the economic trends, the following section discusses secondary market dynamics in the context of both, used products as well as used mobile phone components.

3.4.1 Product Life Cycle

The life-cycle of a product and the consequent disposal rate, for both products and components, has a great impact on the profitability of remanufacturing (Ostlin et al., 2009; Ait-Kadi et al., 2012; Meng et al., 2017). The life cycle of a product consists of the many stages: design, production, distribution, use and end of life. Some literature in business and marketing management also describes the life cycle stages as: introduction, growth, maturity and decline stages. The definition of product life-cycle that is most relevant to this thesis is the one that describes the evolution of a product, measured by its sales over time (Ostlin et al., 2009).

During each life-cycle stage, a different set of stakeholders will be involved. For example, in the early design stages, it is mainly the manufacturers that are involved. In the later production and distribution stages, consumers and distributors have more involvement. As shown in Figure 17 below, the cost of the product on the society begins to rise right from the production stage and reaches its height towards the end of use. Therefore, in the end-of-life, stages, recyclers, remanufacturers and other parties related to sustainable development may find more involvement.

The applicability of reverse logistics exists in each of the product life cycle stages and leads to three different types of returns. The characteristics of the life-cycle and its effects on the reversed supply chain have been discussed by Rogers and Tibben-Lembke, (2001). In the early stages of production and distribution, the returns are classified as commercial returns due to defects or buyers' remorse (Potdar, 2010). The returns in the early stages are usually of high quality and suitable for remanufacturing without the need for sorting decisions (Ostlin et al., 2009). Returns during the Use stage of the cycle are usually due to customers replacing their phones with newer purchases due to one of many reasons such as software failure, accidental damage or other component failures. Additionally, returns in this stage can simply be because the user decided to upgrade their phone to a newer specification available in the market.

Finally, in the end of life stage, the returns are primarily due to loss of functionality of complete phone failure or technological obsolescence. According to Ostlin et al., (2009) who studied the relation between supply and demand curves of cores for remanufacturing, there is a high number of returns in this stage but since the demand for the remanufactured product is very low, it makes remanufacturing less economically viable.

It can be deduced that the greatest uncertainty in the return quality will be for the returns in the Use stage. This is because the reasons for returns are a mix, and largely vary from one customer to the other. It is also in this stage of the product lifecycle where recovery processes will yield more profitability.

Why is life cycle important in recovery decisions?

Depending on the stage of the life cycle, the rate of product return and the demand for remanufactured product will also vary. This shift in demand will dictate the market value of the product and thus, influence the profitability of the remanufacturing decision. Therefore, in each stage, the optimal fraction of returned product that will classify for remanufacturing will vary on both, the quality of the returns and the market value of the product.

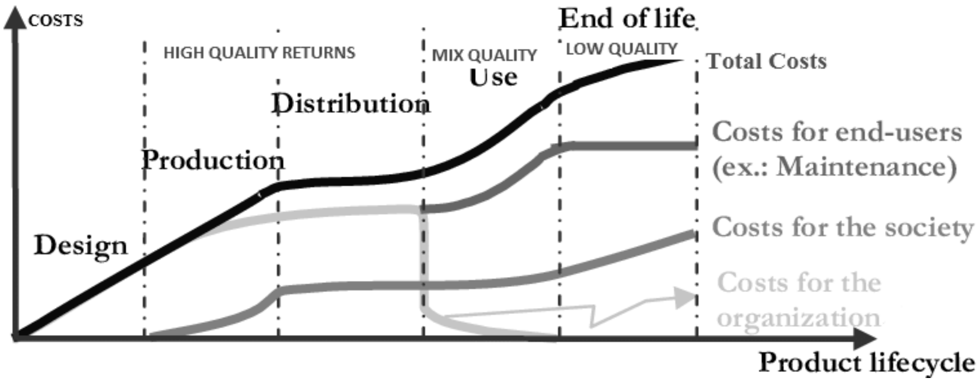


Figure 17 Costs on product life cycle. Originally by Alting (1993), adapted from the version by Chouinard et al (2008).

There are two studies, by Aydin et al., (2015) and Ostlin et al., (2009), which model the demand of remanufactured product with respect to its life cycle stage. Comparison of these two studies establishes that the demand for remanufactured products has the following key characteristics:

1. Right from the introductory stage of the product, there is demand for remanufactured product
2. The remanufactured product demand continues to increase even during declining stage up to a certain point. It peaks during this decline phase then starts to decrease.
3. While the number of remanufactured products decreases, the demand for them is sustained for a long time, well beyond the death of the new product sales.

The only difference in the two studies is that Aydin et al., (2015) assumes there is a lag between the first period when initial product launch happens, and the second period in which demand for remanufactured product picks up. On the other hand, Ostlin et al., (2009) shows that the demand for both- new and remanufactured units begins simultaneously. The applicability of either model will vary based on the product type that is chosen and the pricing strategies at play.

For example, in the early stages of a new model smartphone launch, a company may experience frequent returns due to infantile failures. The company will refurbish these products and sell them in the same primary market as refurbish-grade. However, they may or may not reduce the price of the refurbished product. If the demand for this new model is high, they may capitalize on that by selling their refurbished phones at a price that is almost the same as the price of a new unit. Customers on the other hand, may not find it worthwhile to save just $15-$20 for a refurbished phone and will opt for a new unit instead. This way, the company is regulating their product value in the market by controlling the disparity between the price of a new and refurbished unit. In such a case, Aydin et al.'s (2015) model will be a more precise representation.

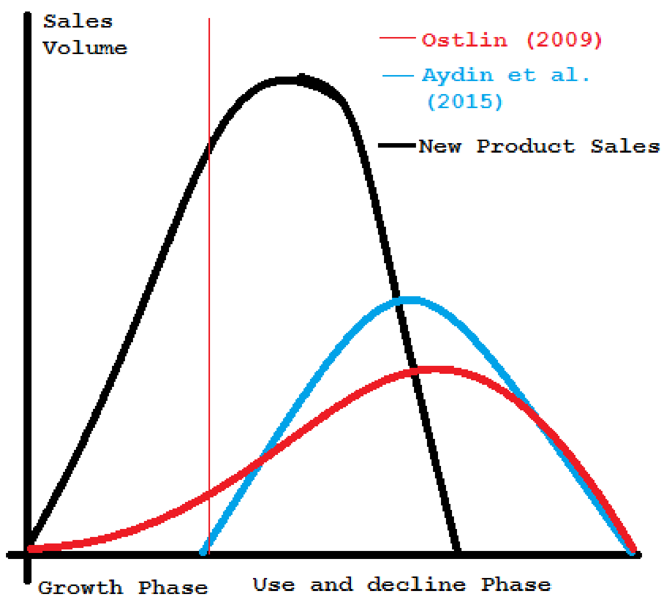


Figure 18 New and remanufactured product sales based on Aydin et al., (2015) and Ostlin et al., (2009)

The above discussion reinforces the dependence of recovery decisions on the market value of the product. Through market demand segmentation for remanufactured products, many studies including Aydin et al., (2015) and Ostlin et al., (2009) have found that the demand and sales price for remanufactured products are time dependent. Since the market value will establish profit margins, it must be taken into account when forecasting the recovery decisions of future returns. In order to reflect market value of products and their constituting components in the proposed forecast model, the next section studies current value trends using real-time pricing data from e-commerce price lists. Through curve fitting, these trends are used in the formulation of equations that will be used in the forecast model to incorporate time-dependent economic value in the recovery decision process.

3.4.2 Secondary Value for Product

The market value of any product in the market is never stagnant. It is affected by new releases, technological advancements, marketing activities of competitors and consumer demand. In fact, Ostlin et al., (2009) uses an exponential price function on, stating that once a new product is launched, its price is always decreasing over time, especially for consumer products such as smartphones and computers. Exponential modeling of product prices is also prevalent in other works (Ferrer, 1997; Kwak and Kim (2012); Liao, Deng and Shen (2018); Bayus, 1993; Pazoki and Abdul-Kader, 2016).

In the proposed model, we firstly corroborate the exponential pricing trends by collecting pricing data of used and new products from 2013 and 2019 from e-commerce websites. The plots for the pricing of trends of refurbished phones are shown in Figure 19.

The pricing data for the smartphone was collected from the website and tabulated in Microsoft Excel. Through curve fitting, it was found that 4^{th} degree polynomial curve and the exponential curve offer the best fits for the data points, with R-square values of 0.91 and 0.8368 respectively. For the case of this study, the exponential equation was chosen to represent the market value of the refurbished/remanufactured smartphone. Although the polynomial curve offers greater R-square value, which means greater accuracy, it was discarded so that the model aligns better with the literature that establishes exponential distributions as the general form for modeling price depreciations.

3.4.3 Secondary Value for Used Parts

The concept of reusing modules of components is not novel for larger machinery and computer electronics. However, in the field of mobile phones, this concept is relatively new and very little published work exists on the market for used phone parts. According to Ferguson et al., (2009), parts that have been salvaged from used products can also be used to fill "spares and warranty part vectors".

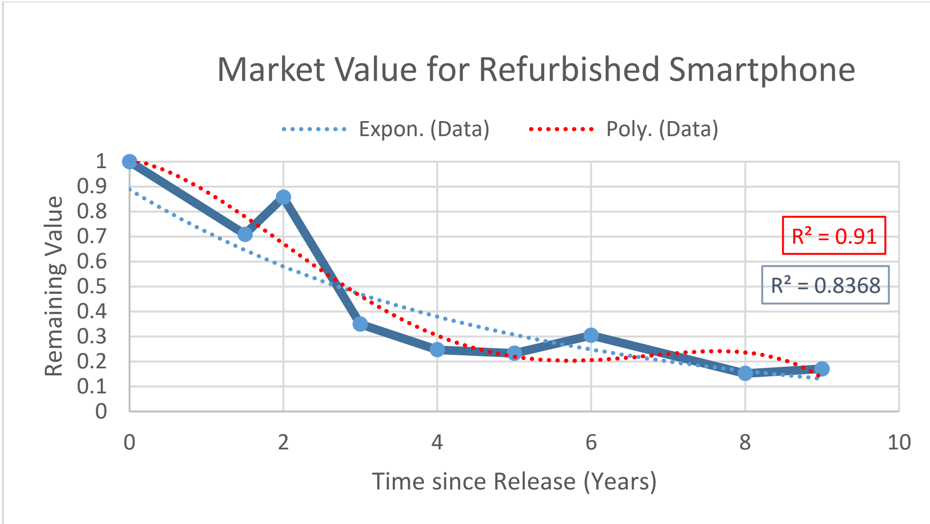


Figure 19 Market value for refurbished phone from online pricing data

Is parts harvesting a justified recovery option for smartphones?

Used parts sold through e-commerce are usually not certified by any quality standards such as ISO. In spite of this, there is a high demand for parts of both, new and older models. The lack of quality assurance certificates is replaced by the high level of confidence that the e-commerce websites have instilled through features likes “seller ratings” and “customer reviews” for both the sold parts and the seller. Moreover, features like easy returns enhance the comfort that customers feel when committing to purchase of these used parts online. The motivation for this do-it-yourself mindset is further fueled by numerous videos and visual material online that thoroughly demonstrate how to open your device, replace common parts and reassemble the device. The strong support for this practice is clearly visible through the recent movement on the internet supporting the “Right to Repair’. The movement gained momentum after a high-end phone brand recently called for its refurbished products to be listed on the world’s largest e-commerce website (Amazon), only if they were being sold by brand-certified refurbish sellers.

Explanation for demand of used parts belonging to older models

Usually demand for used parts gain momentum when manufacturers stop production of spare parts belonging to older models. This is because manufacturers don’t want to make inventories of parts that might not be needed as the product enters the decline stage and the risk of obsolescence is too high for them to invest in production of these parts. This creates a market for remanufactured components or possibly reused components (Ostlin et al., 2009). Usually a popular phone model even if it is a few years old, still remains in use by the customers, an example of this is iPhone 6. It is usually common to see popular models directly reused through adults passing the device down to younger children. When such phones fail, the customer seeks to repair them. However, the replacement parts needed for the repair are no longer in the market because of the technological obsolescence of the phone. In such cases, there is a demand for components of a very old model but no supply from the OEMs, who have stopped production of those older part families (Ait-Kadi et al., 2012). This demand for parts of older models can then be satisfied, rather successfully, through used component market. A good example of this is the iPhone 5, which in spite of being over 6 years old, shows an upward trend for pricing of its used LCD parts in the online market. Figure 20 shows a rise in component prices at the 6th year. This corroborates the study by Ostlin et al., (2009) that suggests that part harvest can have great potential late in the product life-cycle.

Explanation for demand of used parts belonging to newer models

The costs of spare parts for latest phone models are very high during the first year or so. One of the most sought after part is the LCD screen of phones. For high end models, the cost of a replacement screen manufactured by the OEM starts at $300, which is usually one third of the price of the phone. In fact, in the early phases of the release, even refurbished display screens are valued at high prices. In such cases, customers may find cheaper options for the replacement if they opt for parts that were extracted from used phones. If the extracted part is from the original manufacturer, then even as a used part, it sells at a higher price. Thus, it can be seen that reprocessors can exercise great profitability by extracting used parts from returned phones if they find that other recovery options are not profitable enough.

Equation formulation of price of used components

From the literature, the price of components has usually been shown to follow an exponential decay trend (Ostlin et al., 2009; Guide et al., 2006; Ferrer, 1997). The general form of the equation proposed by Ferrer (1993) is:

$$V(t) = V(o) * t^{-a}$$

Where, V(t) is the time dependent component price, V(o) is the initial price, t= time since release and *a* is a component-specific parameter obtained by regression analysis of the retail prices of the new components.

For the purpose of this study, the exponential equations for each component are formulated based on the pricing data of the components collected from online stores. The data is then plotted and fitted to the exponential curve to derive the time-based price trend. The pricing for used parts was taken primarily for ebay and Mobile Sentrix.

The following Figure 20 exemplifies how the equations have been formulated by illustrating the market value of used LCDs for two models of the iPhone. Display Type A represents that 4.7" display screens present in the recent iPhone 7 model, and Display Type B represents screens from iPhone 5 which is a much older model. It was found that exponential curve offers the best fit for Display A, with an R-square value of 0.9691. However, for Display Type B it was found that fourth degree polynomial offers a better fit that exponential trend, yielding an R-square value of 0.8393 (See Figure 20, Display Type B). From this analysis, the question arises, why does polynomial fit better, when, in general, exponential is the most widely accepted distribution for pricing trends? The next section seeks to answer this question.

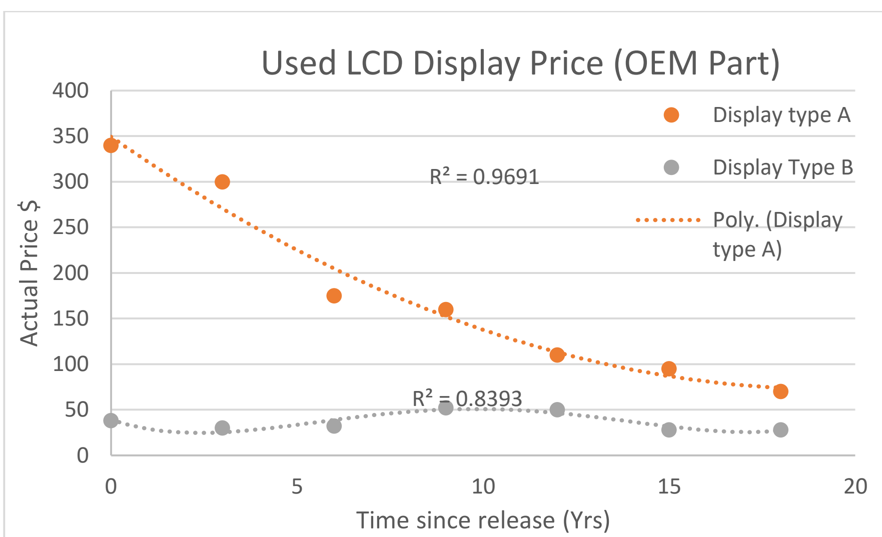


Figure 20 Market value for used LCDs from pricing data on e-commerce sites

<u>Why does price of used LCD increase for Display Type B?</u>

At a glance of Figure 19, it is clear that the price for Display A is constantly decreasing but the price for Display B increases for some time after the 5th year. To understand this, it must be kept in mind that Display B corresponds to model iPhone 5, whose LCD has not been used in any other product families in the years that follow. On the contrary, the 4.7" display represented in Display Type A is common across three products: the iPhone 6,7,8. This means that over the years, the OEM has sustained production and distribution of Display Type A as opposed to Display Type B. Following with the logic, it can be said that used parts pricing is influenced by who the manufacturers for those parts are. If the OEMs are still producing those parts, the prices will be lower as compared to when they stop producing them (Ostlin et al., 2009). The dynamic dependence of spare parts pricing on OEM manufacturing has been demonstrated through an automotive case study involving Volvo. Spare parts pricing also fluctuates based on the manufacturing capabilities of third party parts suppliers as well (Ostlin et al., 2009).

Additionally, it can be seen that the rise in the value of the used OEM LCD happens around the 6th year, which corresponds to the time when after-market copies of the display enter the market (See Figure 21). The presence of third party spare parts increases the value of the LCD parts that were manufactured by the OEM regardless of whether they are used parts.

Conclusion of Parts Harvesting

From the discussion above, it can be affirmed that the secondary market for used parts is a viable market for the smartphone industry and strong enough to receive consideration in scientific work. The value of the used part will be influenced by the market value of the product family, its life-cycle stage and the production suppliers. To this end, "part harvesting" has been included in this research as a recovery option to sustain optimum profitability in the later stages of the life cycle where both returns quality and remanufacturing revenue are unfavourably low.

The next section tabulates the pricing equations that will be used in this study. As discussed above, the equations have been formulated from pricing data collected from online shops that sell used and new OEM parts.

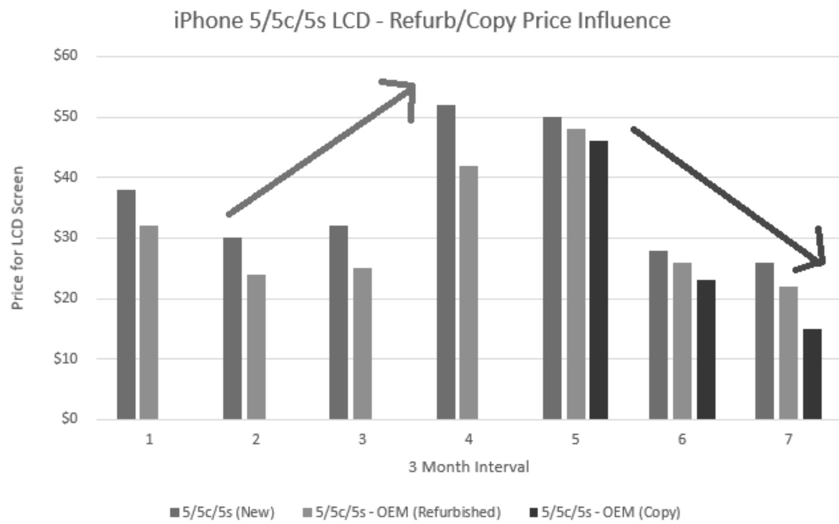


Figure 21 Value trend for refurbished LCD part. Harvestcellular, Jones (2017)

3.5 Equations for Pricing of New and Used OEM Components

This section compiles the equations used to model the pricing of the used and new components. The data from which these trends were derived is available in Appendix E.

Table 5 Equations for pricing of new spare components

	New OEM Part		
Component	**Distribution**	**Equation**	R-Square
Home button	Linear	= -1.82t+11.385	0.9038
Charging Port	Linear	(-1.7882t)+12.59	0.9886
Back camera	Linear	= -9.016t+52.632	0.9151
Battery	Exponential	=28.39*exp(-0.276*t)	0.8477
LCD	Exponential	=344.99*exp(-0.089*t)	.9776

Table 6 Equations for pricing of used parts from parts harvest

	Used OEM Part		
Component	**Distribution**	**Equation**	R-Square
Home button	Constant	Averaged at $20	-
Charging Port	Linear	-4.1657t+34.571	=0.5309
Back camera	Exponential	129.52*(exp(-0.539*t))	0.8556
Battery	Constant	Averaged at $18.5	-
LCD	3rd Order polynomial	$= -3.178t^3 + 48.295t^2 - 237.09t + 412.42$	1.00

The next chapter outlines the methodology for the proposed forecast using the usage model and the pricing equations formulated in this section.

CHAPTER 4

SOLUTION METHODOLOGY

4.1 Proposed Forecast Model: Description and Algorithm

1. Create scenario using Monte Carlo simulation for population using age or income distributions for a specific region
2. Generate daily device usage data using probability distribution for each age group
3. Generate length of ownership in months using probability distribution for each age group
4. Calculate total usage hours from daily usage and length of ownership
5. Calculate length of ownership in years by dividing it by 12
6. Calculate probability of smartphone survival at time of return t based on usage data
7. Calculate failure rate of components based on the exponential probabilities or Bernoulli trials, depending on the component.
8. Calculate expected profit from reuse option
9. Calculate expected profit from remanufacture option
10. Calculate expected profit from parts harvest option
11. Calculate maximum profit from recycling
12. Assign quality grade based on maximum profit
13. Accumulate counts for each recovery decision
14. Calculate quality ratios for each option: reuse, remanufacture, parts harvest and recycling.
15. Repeat simulation for another region with region specific demographic data as described in 1. above
16. Discuss differences in trends form the results generated for different regions and the applicability of the results

4.2 Profit-based Recovery Decisions

Profit model is a maximization of expected profit generated from four value recovery processes namely: direct reuse, remanufacture, parts harvest and material recycling. Based on the usage and timing of return, expected profits for the four value recovery processes are calculated. Then, the returned product is categorized based on recovery option with the largest profit margin.

In order to assign the most profitable recovery option to the predicted return, all the possible profit values are calculated from each recovery option. Then, the recovery option with the highest profit is assigned to that unit.

Equation 1: Profit-based recovery decision

Recovery Option_j = maxprofit{Reuse, Remanufacture, Parts-Harvest, Recycling} for all j

Where j= a unit product from a batch of returns

The proposed set of equations for the calculation of the profits from the four recovery processes is listed below.

Equation 2: Expected Profit from Reuse

$$\text{EP\_Reuse}(\text{u},\text{t}) = \text{P}(\text{R}|\text{u}) * \text{Sp}(\text{t}) - (\text{Cost of Trans} + \text{Insp} + \text{Clean} + \text{Repackage})$$

Where P(R|u) is the conditional probability that a product is eligible for reuse, and Sp(t) is the selling price of the product with used condition at time t

Equation 3: Expected Profit from Remanufacturing

$$\text{EP\_Remanf}(\text{u},\text{t}) = \text{Remanf. Product Selling Price}(\text{t}) - \text{Remanf Cost}(\text{u},\text{t})$$

Where selling price is derived from the economic trends and the usage-dependent Remanf Cost(u,t) is calculated using **Equation 4** shown below.

Equation 4: Usage-dependent Remanufacturing Cost

$$\text{Remanf Cost}(u,t) = \text{Trans}+..+\sum_i P_i(u) * \text{Component Price}_i(t)$$

Where Pi(u) is the probability of failure of the component after being used for *u* hours

Component Price(t) is the current market value of the required component.

Equation 5: Expected Profit from Parts Harvest

$$\text{EP\_PartsHarvest} = \sum_i X_i(t) * (1 - P_i(u))$$

Where $X_i(t)$ is the selling price of a used component *i* in the market at time *t*, $(1\text{-}P_i(u))$ is the probability that the component *i* is still functional after *u* hours of usage, since Pi(u) represents the probability of failure of the component.

Equation 6: Expected Profit for Materials Recycling

$$\text{EP\_Recycling} = \$v \text{ per unit device}$$

In this study, the value of v is assumed to be constant at $5.66 based on the metal retrieval value for all iPhone models from Movaluate.com (Movaluate, 2019).

4.3 Development of the Profit Equations

This section elaborates on the logic of how Equations 2 to 6 were formulated

4.3.1 Reusability Profit Function

This section explains formulation of Equation 1.

This definition of reuse has been adapted from Kwak and Kim (2012), further adapted by Pandian and Abdul-Kader (2017), who define the functional condition for reuse as follows:

1. Product can turn on, dial and receive calls and messages.
2. No screen damage.
3. No water damage

4. Good cosmetic condition.

The goal of this section is to probabilistically predict how many incoming products in a given batch will be eligible for direct reuse without the need for disassembly or part repairs.

Reusability requires that all the components of the device are in functional state. Based on that, the first step is to calculate the probability that a phone that is returned after t years has no failures. This is done in the following way.

P(R|t)= Probability that a phone fails after t years of ownership

The following is a description of the logic used in the calculation of P(R|u).

By definition, for a phone to be eligible for reuse, all its components should be functional. This means that even if one component has mal-functioned; the product is directly not eligible for reuse. The functional status of the components can be assessed from their probability of survival. Since the probability of failure of all components is not the same, each of them need to be analyzed separately.

This essentially means that there should be no failures for the device at the time of return. In order to calculate this probability, the proposed forecast model uses the empirical failure distribution devised by Wang and Huang (2013) who propose a log normal distribution for survival function of phones. The method of finding the parameters for the distribution has been discussed in Section 3.3.1 on page 54.

<u>Profit Calculation from Reuse</u>

Although the costs for reuse option are minimal, the expected profits will directly be dependent on the selling price of the phone in the secondary market at the time of return t. Thus the time-dependent profit from Reuse can be calculated in the following way:

$$\mathrm{EP\_Reuse(u,t)} = \mathrm{P(R|u)} * \mathrm{Sp(t)} - (\mathrm{Cost\ of\ Trans} + \mathrm{Insp} + \mathrm{Clean} + \mathrm{Repackage})$$

Where Sp(t) is the selling price of the product with used condition at time t

For modelling purposes, the costs of transportation, inspection, cleaning and repackaging can be eliminated because these costs do not depend on usage u or the time of return t and also because they will usually be constant for all returns in a single period.

4.2.2 Remanufacturability: Profit Function

Remanufacturing cost for each returned product is different because it depends on two factors: the usage condition of the product (Panagiotidou et al., 2017; Liao, Deng & Shen, 2018) and the time-dependent cost of the replacement components. The following steps are assessed for calculations of remanufacturing costs:

1. What is the cumulative usage hours of the device?

2. At the given usage, what is the probability of failure of each component?

3. If one component fails, it needs to be replaced. How much would it cost to buy the replacement component at the present market value?

4. The total expected cost would be depended on failure probability and cost to replace a specific component.

In previous work, Ferrer (1997) developed a model for calculating the cost of remanufacturing a computer. The drawback of Ferrer's equation is that it does not consider a usage-dependent failure probability, thereby leading to a cost equation that is unrealistically constant over time. Ferrer's equation is as follows:

$$\text{Remanufacturing Cost} = \text{Transport} + \cdots + \text{required components}$$

Where the cost of required components depends of the probability of failure and the price of the new component needed for replacement:

$$\text{Cost of required Components} = \sum_{I} \{(\text{Pi}) * \text{Component Price}\} \text{ , for all i}$$

Where i = component number, Pi = probability that a component fails.

Another example of a remanufacturing cost equation is proposed by Panagiotidou et al., (2017). In this study, they calculate the remanufacturing cost as a function of the quality grade only. Similarly, Liao, Deng and Shen (2018) also assume that “cores of the same rank are considered to have the same unit remanufacturing cost”. They do not consider the probabilities of which components will have failed, and what the cost of their replacements will be. Their calculation of the remanufacturing cost equation is shown below:

$$\text{Expected Remanufacturing Cost of batch} = \sum_{q=0}^{Ql} cr(q) * p(q)$$

Where, as per their equation they use the following notations:

q= quality grade

p(q)= probability that a product with quality q is remanufacturable, with known distribution

cr(q)= cost of remanufacturing based on quality q

Ql= Number of remanufacturable units available after inspection

This equation is lacking because:

1. The probability distribution for quality p(q), is assumed to be known, and is not calculated empirically from usage data.
2. The cost of remanufacturing is not calculated from the cost of the components that required replacement. It is possible that 2 products that fall under the same quality grade need different sets of component replacements. In such a case, the remanufacturing cost of the two products will be different because the cost of the different components is not all the same.

Thus, it can be seen that the equations proposed previously in literature fall short of representing totally accurate remanufacturing costs. These equations have been improved in this study to represent a more time and usage-dependent model for remanufacturing cost as described hereon.

Proposed Equation for Remanufacturing Cost

In order to present a more relevant version of Ferrer's (1997) and Panagiotidou et al.'s (2017) equations for remanufacturing cost, this research proposes an updated version of the equation which comprehensively takes into account the total usage of the device to calculate the probability of component failure and also the age of the components to calculate their price. This method provides a more precise estimate of the remanufacturing costs. The proposed equation which is developed in this study is as below:

$$\text{Remanf Cost}(u, t) = \text{Trans}+..+\sum_{i} P_i(u) * \text{Component Price}_i(t)$$

Where Pi(u) is the probability of failure of the component after being used for *u* hours, Component Price_i (t) is the current market value of the component required, N is the batch size, x is number of successes.

Calculation of Remanufacturing Profit

Just as remanufacturing cost is a function of time, remanufacturing profit is also not constant throughout the secondary life of the product. Although remanufactured products are renowned for yielding high revenues, their profit margins are not constant over time. The main reason for this is that the selling price of a remanufactured product is largely governed by the consumer behaviour in the secondary market.

$$\text{Remanf. Profit}(t) = \text{Remanufactured Product Selling Price}(t) - \text{Remanufacturing Cost}(u, t)$$

An interesting observation from the above equation is that the profit generated from any single device will actually depend on the usage of the returned device, or rather, its original state. Thus, if a production planner sees a batch of returns with a bad quality ratio that will not generate enough profits due to high costs, they can choose a more profitable recovery option. Similarly, if a planner sees a batch of bad quality returns but knows the particular model is highly in demand in the secondary market, they will find those same higher remanufacturing costs to be financially viable. This, once again, emphasizes the need for accurate estimates for quality ratios.

4.2.3 Part Harvesting Profit Function

For the case of mobile phones, part harvesting is a relatively new practice which is usually applicable exclusively to the high-end smartphone market. The recovery value of parts harvesting is positively associated with component quality (Meng et al., 2017). This means that devices with less usage will generally have components with high quality and thus, yield higher profits.

The proposed equation for expected profits from used parts comprehensively takes into account the probability that a component is alive after being used for u hours, and the revenue that will be generated based on its time-dependent selling price. For simplicity in calculation, the disassembly costs associated with parts harvest are discarded.

$$\text{Expected Profit from Used Parts} = \sum_{i} X_i(t) * (1 - P_i(u))$$

Where: $X_i(t)$ is the selling price of a used component *i* in the market at time *t*, $P_i(u)$ is the probability that the component *i* fails after *u* hours of usage.

The model in this study includes the major components namely: battery, LCD, home button, camera, and charging port. In reality, the reprocessor can actually harvest many more parts from a device and gain higher profits. However, since the listed components are the ones that retain highest economic value with time, the other components have not been included. Parts that are found to not be profitable through direct selling can be sent to materials recycling and still generate value.

4.2.4 Material Recycling Profit Function

There are many useful materials in a mobile phone including gold, copper and aluminum, that can be separated and reprocessed to replace the mining of new metal resources.

For the purpose of this study, the profit from recycling is modelled as a fixed constant value, modeled after the study by Mashhadi and Behdad (2017). Recycling profit is independent of the functional state or the product age because it is only linked with material recovery. Geyer and Blass (2010) claim recycling as the least profitable recovery option for smartphones. However, this is subjective to the life-cycle stage of the product.

For this study, we will work under the assumption that, at any given time or life-cycle stage, the profit from recycling is far lesser than the profit from reuse, remanufacturing or part harvesting. The value of v is taken as $5.66. The proposed equation is

$$Recycling\ profit = \$v\ per\ unit\ device$$

4.4 Summary

This chapter outlined the algorithm that will be used in the forecast model and related the profit equations for all the possible recovery operations. For each expected return, the expected profits will be calculated based on the usage of the used product and the time of the return. The product will then be assigned to recovery option with the highest profit margin.

The next chapter describes the data collection and setup for the scenario generation. The scenarios designed in the next chapter will be simulated using Monte Carlo methods and then the forecast model algorithm will be applied to these scenarios to generate expected return quality from various regions.

CHAPTER 5

NUMERICAL EXAMPLE FOR FUTURE RESULTS

5.1 Data Collection

In order to simulate the results of the forecast model in the Canadian context, rural and urban communities from 5 provinces in Canada have been chosen. To gain a good representation of the country, provinces have been chosen based on their location. Beginning from the west coast, British Columbia was chosen. For the representation of the east, Quebec was chosen. To cover the Atlantic provinces separately and better analyze their unique trends Newfoundland and Labrador was chosen from the east coast. To represent central regions in Canada, Manitoba has been selected. Ontario, being the most populated province has been included for obvious reasons.

From each province, an urban population center and rural population center has been chosen. For the case of Ontario, rural communities have further been separated as Rural-North and Rural-South to gain a better insight into the product returns across the provinces. The age and income distributions of the chosen regions have been tabulated in Table 7. It must be noted that the income represents total household income before tax. The data for these distributions is available through Statistics Canada (Statistics Canada, 2016).

The consumer behaviour pertaining to daily usage hours and length of ownership has been categorized by the user's age, income, community type and province of location. The empirical distributions for these have been deduced from the survey data published by Forum Research (See 3.2 Socioeconomic Usage Model) and are presented below in Table 8. For space conservation, Weibull notation has been trimmed to X~W(scale, shape). The normal distribution is denoted using the standard notation X~N(mean, standard deviation).

Table 7 Age and income distributions of cities for scenario development

Province	City	Population Density /km^2 (2016)	Community Type	Age Distribution Profile (%)	Income Distribution Profile (CAD$) (%)
Ontario	Toronto	4334.4	Urban	18-34:29.81 35-44: 17.31 45-54: 17.98 55+: 34.90	<20k: 13.22 20-40k: 16.97 40-60k: 15.74 60-80k: 13.0 Above 80k: 41.1
Ontario	Kingston	274.4	Rural	18-34: 27.21 35-44: 14.39 45-54: 17.17 55+: 41.24	<20k: 10.48 20-40k: 17.39 40-60k: 16.55 60-80k: 14.144 Above 80k: 41.42
Ontario	Algonquin Highlands	2.3	Rural-South	18-34: 10.47 35-44: 7.85 45-54: 15.23 55+: 66.39	<20k: 8.597 20-40k: 19.09 40-60k: 20.361 60-80k: 18.55 Above 80k: 32.12
Ontario	Windsor	1483.8	Urban	18-34: 25.87 35-44: 15.658 45-54: 18.50 55+: 39.96	<20k: 14.55 20-40k: 20.57 40-60k: 18.61 60-80k: 13.72 Above 80k: 32.55
Ontario	City of Sault Ste. Marie	328.6	Medium Urban	18-34: 21.64 35-44: 13.56 45-54: 17.07 55+: 47.75	<20k: 11.23 20-40k: 20.50 40-60k: 17.47 60-80k: 13.24 Above 80k: 37.54
British Columbia	Vancouver	5492.6	Urban	18-34: 31.79 35-44: 17.42 45-54: 17.59 55+: 33.19	<20k: 14.96 20-40k: 16.05 40-60k: 15.32 60-80k: 12.87 Above 80k:40.80
British Columbia	Okanagan Falls	649.4	Rural	18-34: 9.564 35-44: 11.158 45-54: 17.003 55+: 61.63	<20k: 11.79 20-40k: 23.58 40-60k: 19.81 60-80k: 14.62 Above 80k:29.72
British Columbia	Fort-St. John	1040.3	Rural	18-34: 41.519 35-44: 21.087 45-54: 16.324 55+: 21.053	<20k: 4.94 20-40k: 9.75 40-60k: 10.70 60-80k: 10.95 Above 80k: 63.73

Province	City	Population Density /km^2 (2016)	Community Type	Age Distribution Profile (%)	Income Distribution Profile (CAD$) (%)
Quebec	Montreal	4662.1	Urban	18-34: 30.05 35-44: 18.384 45-54: 16.41 55+: 35.15	<20k: 16.809 20-40k: 22.42 40-60k: 19.66 60-80k: 13.47 Above 80k:22.64
Quebec	Alma	156.6	Rural	18-34: 20.0 35-44: 14.085 45-54: 17.021 55+: 48.89	<20k: 12.19 20-40k: 21.02 40-60k: 19.81 60-80k: 14.65 Above 80k: 32.33
Manitoba	Winnipeg	1518.8	Urban	18-34: 28.32 35-44: 17.24 45-54: 17.56 55+: 36.88	<20k: 9.735 20-40k: 16.57 40-60k: 17.10 60-80k: 14.86 Above 80k: 41.74
Manitoba	East St. Paul	223.2	Rural	18-34: 18.24 35-44: 14.202 45-54: 21.44 55+: 46.09	<20k: 1.69 20-40k: 5.368 40-60k: 8.44 60-80k: 9.66 Above 80k: 74.85
ATL (NF)	St. John's		Urban	18-34: 29.38 35-44: 15.90 45-54: 17.39 55+: 37.325	<20k: 11.48 20-40k: 17.78 40-60k: 14.51 60-80k: 12.68 Above 80k: 43.55
ATL (NF)	Bay Bulls		Rural	18-34: 23.1 35-44: 22.22 45-54: 18.22 55+: 37.78	<20k: 7.08 20-40k: 12.39 40-60k: 11.50 60-80k: 10.62 Above 80k: 60.18

Table 8 Distributions for consumer behavior based on socio-economic factors

Factor	Sub-Groups	Daily Usage in Hours	Length of Ownership in Months
Age	18-34, N=233	X~N(2.106,1.100)	X~W(28.50, 1.982)
	35-44, N=250	X~W(1.820, 1.675)	X~W(33.27, 2.138)
	45-54, N=190	X~W(1.571,1.621)	X~W(33.27, 2.138)
	55+, N=542	X~W(1.182, 1.421)	X~W(37.10, 2.267)
Income	Below $20K, N=102	X~N (1.922,1.206)	N/A
	$20K-$40K, N=191	X~W(1.824, 1.540)	N/A
	$40K-$60K, N=134	X~W(1.438, 1.475)	N/A

Factor	Sub-Groups	Daily Usage in Hours	Length of Ownership in Months
Income	$60K-$80K, N=168	X~W(1.770, 1.509)	N/A
	$80K+, N=417	X~W(1.643, 1.624)	N/A
Community Type	Urban, N=2208	N/A	X~N(29.62,14.82)
	Rural, N=736	N/A	LogN(0.6399, 3.184)
Province	Ontario, N=274	X~W(1.756,1.514)	X~W(33.81, 2.087)
	British Columbia	X~W(1.750,1.577)	X~N(30.35, 15.02)
	Manitoba, N=110	X~N (1.7,1.090)	X~W(31.17,1.948)
	Quebec, N=237	X~W(1.587,1.543)	LogN(.6113, 3.192)
	Atlantic Region, N=171	X~W(2.039,1.696)	X~N(31.19, 14.59)

5.2 Scenario Development

This section shows how the various scenarios have been developed for the simulation.

Table 9 Scenario development

		Age	**Income**	**Community**	**Province**
	Age	x	x	x	Scenario 1
	Income	x	x	x	Scenario 2
	Community	x	x	x	Scenario 3
	Province	x	x	x	Scenario 4

Scenario 1: In this scenario, the forecast model will be used to draw a comparison (1) between different regions of Ontario and (2) among major cities across provinces. In this scenario, only the effect of the age distribution and the provincial distributions on daily usage and length of ownership will be tests.

For testing between different regions of Ontario, the daily usage distribution and the length of ownership distribution will be generated based on the age group percentages of various places. The results of this test will allow the observation of the different age groups on return quality. The results of this scenario are presented in Section 6.1.1 Comparison of Quality Ratios for Regions in Ontario based on Age.

For comparison of different major cities in Canada based on provincial usage distributions, the simulations are carried out with daily usage and length of ownership distributions based on the province in which the city is located. The results from this analysis are presented in Section 6.1.3 Comparison of Quality Ratios from Major Cities in Canada

Scenario 2: This scenario is created in order to analyse the effect of household income on the return quality ratio. The daily usage distribution is modeled based on the percentage of the population in each income group. The length of ownership is modeled based on the province wide trend. For this scenario, three places in Ontario namely, Toronto, Kingston and Windsor are chosen because they correspond to three different community types: large urban, rural and medium urban respectively. Thus, the aim of this scenario is to study the effect of varying income distributions on the return quality of used smartphones. The results from this scenario are discussed in Section 6.1.2 Comparison of Quality Ratios by Income Distributions.

Scenario 3: In this scenario, the return quality ratios from rural and urban areas are generated based on the daily usage and length of ownership distributions derived specifically for rural and urban areas. This scenario is different from the comparison of rural and urban areas done in Scenario 1, which was based on age distributions. However, in scenario 3, age distributions are kept uniform, and only the effect of rural and urban distributions is studied. Since there's only one model for rural and urban distributions (no data is available for rural behavior based on province or region), it is assumed that the results of this scenario represent the comparison of rural and urban areas throughout Canada. The results of this scenario are presented in Section 6.1.4 Comparison of Quality Ratios from Rural and Urban Areas in Ontario.

Scenario 4: In this scenario, the overall return quality from entire province is compared with that of the return quality from another province. The daily usage and length of ownership distributions are solely based on provincial distributions. The factors age, income and community type are not taken into account.

5.3 Simulation Set-up

To run the Monte Carlo simulation, a random population was generated with a sample size of 10^6. The age distribution and the length of ownership distribution was assigned to the entries in this sample using random numbers. The example below shows how the random population was generated for the specific case of Toronto based on its unique age distribution. Part of the code for the Monte Carlo sample generation is shown in Figure 22.

Step 1: Input Age profile for Toronto:

18-34 = 29.81%

35-44 = 17.31%

45-54 = 17.98%

Step 2: Input Distributions for each age group		
Age Group	Daily Usage	Length of Ownership
18-34	X~N(2.106,1.100)	X~W(28.50, 1.982)
35-44	X~W(1.820, 1.675)	X~W(33.27, 2.138)
45-54	X~W(1.571,1.621)	X~W(33.27, 2.138)
55+	X~W(1.182, 1.421)	X~W(37.10, 2.267)

The corresponding MATLAB code is as shown below:

```
N=1000000;
p1=0.2981;p2=0.1731; p3=0.1798; p4=0.3490; title1= 'Toronto';
%Age proportional for a and l both
a= [abs(normrnd(2.105,1.093,p1*N,1)); wblrnd(1.824, 1.674, p2*N,1);
wblrnd(1.571, 1.621, p3*N,1);wblrnd(1.182, 1.421,p4*N,1)]; %age proportion a
l= [wblrnd(26.60, 1.982, p1*N,1); wblrnd(33.27,2.138,(p2+p3)*N,1);
 wblrnd(37.10,2.267,p4*N,1)];%age proprotion l
```

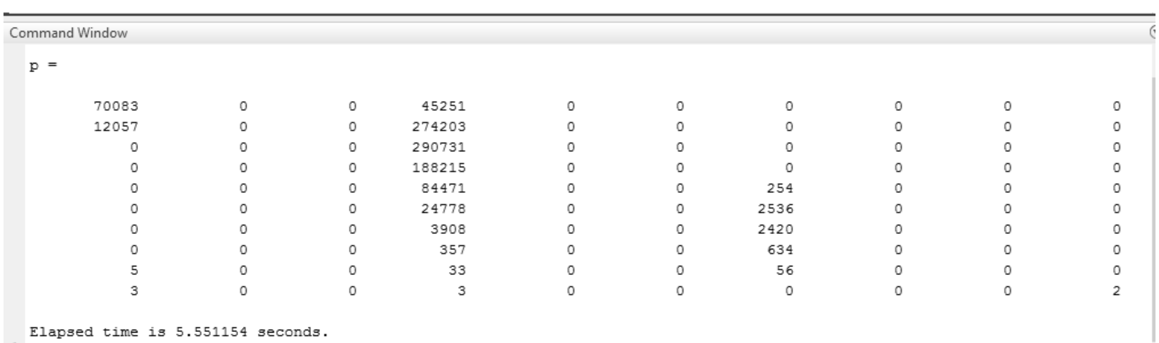
Figure 22 MATLAB code for random sample generation

In the snippet of the code in Figure 22, it can be seen that the variables p1, p2, p3, and p4 denote the percentages in Toronto for each age group. N= 1,000,000 is the number of total samples. The total daily usage distribution was stored in a matrix “a” as shown in line number 4. Thus, the line 4 shows that the daily usage distribution will be randomly generated based on the proportion of age group Figure 22. To explain further, consider the following part of the code in Line 4:

```
a= [abs(normrnd(2.105,1.093, p1*N,1));…..]; %age proportion a
```

This part of the code corresponds to generating the population for the first age group, which is from 18-34. The normrnd function in MATLAB generates random numbers based on the parameters of a normal distribution. The format of the normrnd function is: normrnd(mean, standard deviation, number of rows, number of columns. Since the daily usage distribution is modeled by a normal distribution with mean of 2.105 and standard deviation 1.093, these values are entered in the normrnd function. Since p1 is the percentage of the population which falls under this age group, the total number of samples (or rows) for this age group will be p1*N. The number of columns will be 1. For other age groups, the Weibull random distribution has been used, for which the command follows the format wblrnd(scale, shape).

Similarly, the values for the length of ownership distribution were calculated and stored in a matrix called ‘l”, as shown in Line number 6-7 of the MATLAB code Figure 22. The simulation was run on a system on a 64-bit Windows 10 operating system with 12 GB RAM and a 3.40 GHz i-7 intel core processor.   The time for each simulation run was found using the tic () and toc() command in MATLAB. On average, the time for each Monte Carlo run with 1 million samples was found to be 5.5 seconds, as shown in Figure 23.



```
Command Window

p =

     70083      0      0   45251      0      0      0      0      0      0
     12057      0      0  274203      0      0      0      0      0      0
         0      0      0  290731      0      0      0      0      0      0
         0      0      0  188215      0      0      0      0      0      0
         0      0      0   84471      0      0    254      0      0      0
         0      0      0   24778      0      0   2536      0      0      0
         0      0      0    3908      0      0   2420      0      0      0
         0      0      0     357      0      0    634      0      0      0
         5      0      0      33      0      0     56      0      0      0
         3      0      0       3      0      0      0      0      0      2

Elapsed time is 5.551154 seconds.
```

Figure 23 Elapsed time for single simulation run

CHAPTER 6

RESULTS AND ANALYSIS

6.1 Graphical Results and Analysis

This section discusses the results generated from the forecast model as per the scenarios outlined in Section 5.2.

The results are presented in the form of bar charts and scatter graphs for effective visual analysis. The bar charts have been generated based on the return quality ratios by time period, denoted by the symbol T. Thus, the graph for T=1, depicts the return quality ratios for the first year, T=2 depicts the ratios for the second year and so on.

The **x axis** of the bar charts denote recovery numbers 1,2,3,4. The significance of these numbers is as follows:

Recovery Number 1 = Reuse option

Recovery Number 2 = Remanufacturing option

Recovery Number 3 = Parts harvesting option

Recovery Number 4 = Recycling option

The **y axis** of the bar graphs denotes the quality ratios for each corresponding recovery number.

6.1.1 Comparison of Quality Ratios for Regions in Ontario based on Age

Inputs

The daily usage distributions and length of ownership distributions based on each age group have been used to study the effect of different age profile percentages of different communities in Ontario.

Discussion

The chart in Figure 24 shows the different quality ratios for the four recovery options as generated by different cities in the first year (T=1). The four recovery number 1,2,3,4 correspond to the recovery options reuse, remanufacture, parts harvest and recycle respectively. Thus, the bars above the "number 1" on the x axis can be interpreted as: what ratio of the returns from a given city in year 1 will be eligible for reuse? Similarly, the bars above the "number 2" on the x-axis can be interpreted as: what ratios from a given city can be expected to be sent to remanufacturing in year 1? From Figure 24, it can be seen that all returns in year 1, regardless of total usage, are attributed to either recovery option 1 and 2 only, which correspond to reuse and remanufacturing respectively. The probability of a returned phone being eligible for reuse in the first year is estimated at 0.6 for collections in Kingston and St. Sault Marie, 0.65 for Toronto and Windsor, and 0.69 for Algonquin Highlands. This means that from all returned batches in year 1 from the afore mentioned cities, the quality grade of returns from Algonquin will be the highest. Similarly, reading the bars above "number 2" on the x axis in Figure 24, it can be seen that the remanufacturing probability for Kingston and St. Sault Marie in year 1 is 0.4, 0.35 for Toronto and Windsor and 0.31 for Algonquin Highlands. The figure also shows that there are no significant variations in the quality ratios across different regions. Additionally, it should be noted that no returns seem to be assigned to recovery option 3 and 4 for the first year. This means that regardless of the usage level, whether low of high, reuse and remanufacturing will always be the most profitable recovery options in the first year.

The results in Figure 25 suggest that at T=2 year, 95% of the returns will be eligible for remanufacturing, with the remaining going for reuse.

For T>=3, it can be seen that the remanufacturing ratios of the returned batches decrease with time. The trend for Toronto is unique and it can be seen that the quality ratios are much higher as compared to other regions. This observation is significant because for T=1 and T=2, the ratios from Toronto were the same as those from other regions. However, for T>3, the quality ratios from all other regions continue to be congruent, except for Toronto.

Analysis

Based on the results, there is no significant difference between quality ratios calculated based on age distributions profiles alone, while keeping all other factors (such as community type: rural vs. urban) constant.

Toronto, in spite of being the largest population center cannot be taken as an accurate representation of the entire province of Ontario and its population centers. Even large population centers, such as Windsor, are not similar to Toronto. This is clear in Figure 26 which shows the large variation between the quality ratios from Toronto and other regions within Ontario for T=>3.

The higher quality ratios from Toronto can be attributed to a larger percentage of population between the ages 18-44, which is the age group with lower lengths of ownership. This means that residents of Toronto replace their phones more often, yielding lower cumulative usage hours, thereby generating higher quality grade returns.

Similarly, for the case of Algonquin for T=1, the slightly higher reuse quality ratios are due to the larger percentage of users in the age groups 40 and above, which results in lower daily usage hours and subsequently, higher quality.

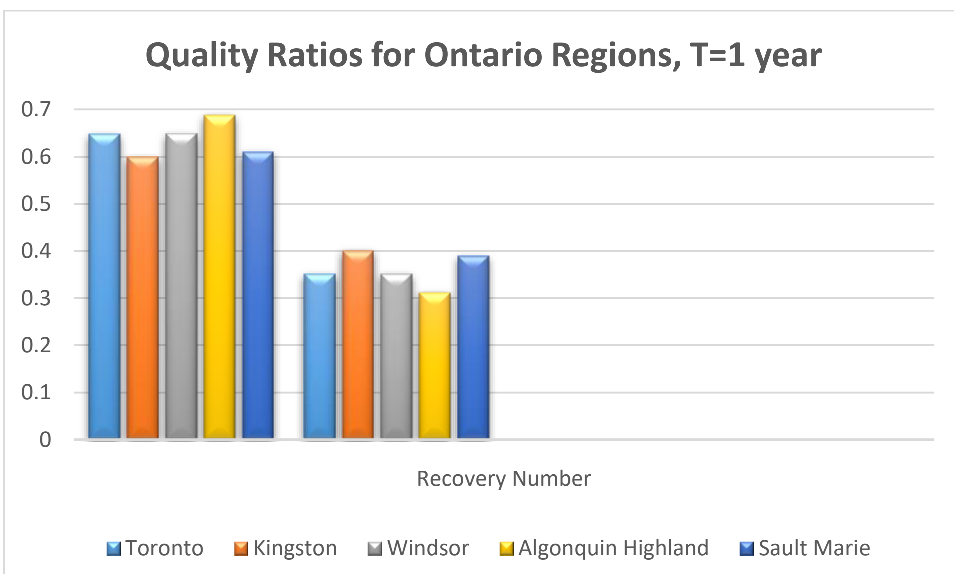


Figure 24 Quality ratios for Ontario Regions, T=1

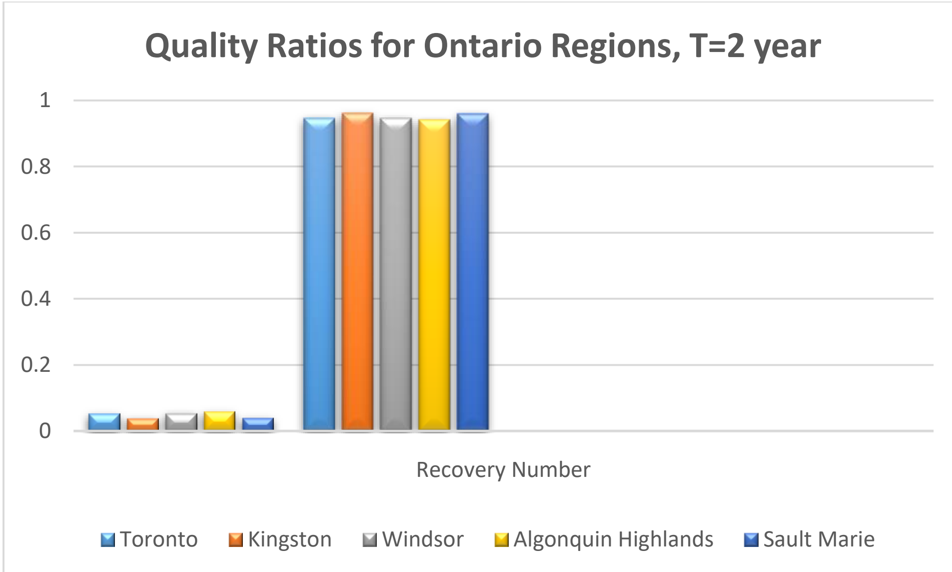


Figure 25 Quality ratios for Ontario regions, T=2

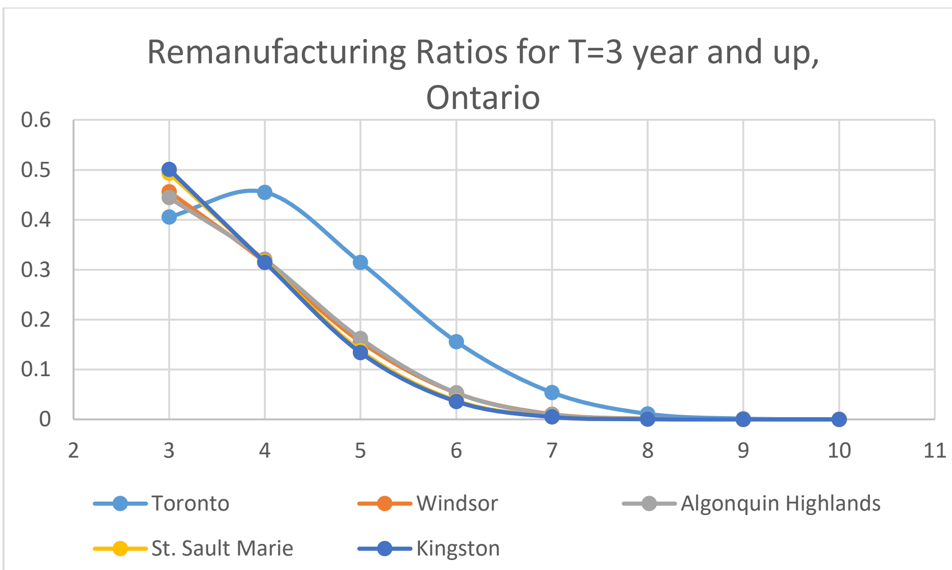


Figure 26 Remanufacturing ratios for Ontario regions

From Figure 27, it can be seen that the recovery option of parts harvest becomes relevant for the regions in Ontario after T=5 (or the fifth year). This is a valid result because the market value of remanufactured phones in the fifth year reaches a lower end, at about 30% of its original value, as shown in Figure 37. Moreover, new model releases in the duration of 5 years means that the particular model may not be able to incur new sales.

Therefore, remanufacturing it would seem less feasible. However, there may still be users of that particular model who already own it. When they need repairs, parts for a release as old as six years may not be available in the market. To satisfy this demand of repairs of old models, the model's results, which suggest parts harvest ratios as profitable recovery options for the fifth year on wards, are justified.

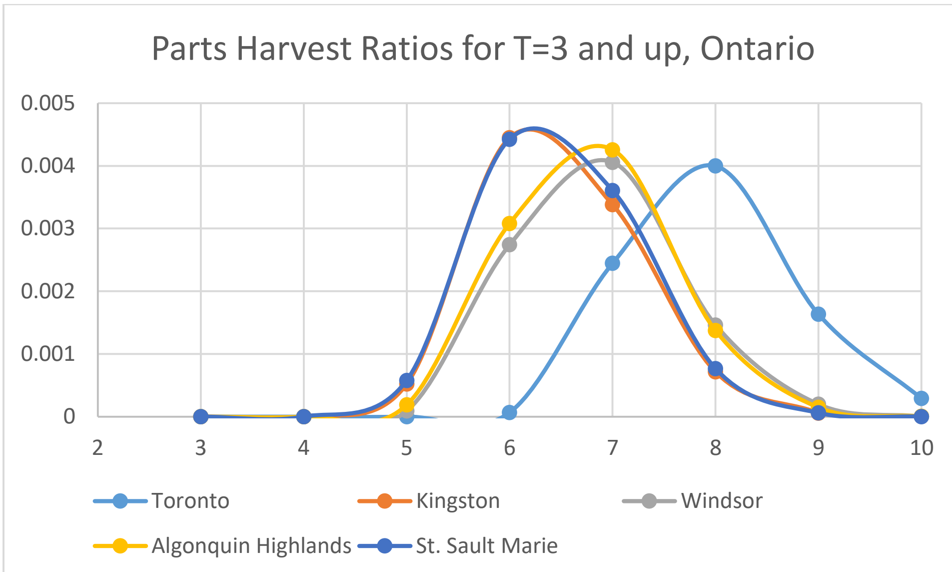


Figure 27 Parts harvest ratios for Ontario regions

Applicability for Ontario

It can be tempting to assume that, since Toronto is the largest population center in Ontario, it would be befitting to assume that all cities in Toronto follow the same quality ratio trend. However, any network design made on this assumption would lead to an overestimation of profitability, and a network configuration that demands more capacity than needed for remanufacturing. The network design may also yield a larger number of facilities to optimize over the large travel distances across consumer zones in a large province such as Ontario, all of which will be error-some. Additionally, since network designs are meant to be designed for a long period of time, one cannot neglect the trends for T=>3 and solely base their strategic planning on T=1 and T=2 which, in fact, do suggest that Toronto is the same as other regions. However, to gain a holistic view for decision-making, it is critical to look at detailed trends beyond the first two years.

In addition to that, it is necessary to take the current collection schemes in Ontario when assessing the usability of these results for the collectors and reprocessors in Ontario. At first glance of Figure 24 and Figure 25 for T=1 and T=2, it would seem that any batch collected in Ontario in the first two years will yield the same quality ratios. However, this is a very error-some assumption. This is because the collection process in Ontario is such that the used phones collected by various third party collectors or even retail shops are first consolidated before being shipped for reprocessing. Consolidation takes place to take advantage of economies of scale and avail cheaper transportation costs. If one whole batch in T=1 was coming from, for e.g., Algonquin Highlands alone, then it could be said with confidence that quality ratio of the batch has 90% units for direct reusability. However, the collections from Algonquin Highlands, like other regions, are combined with collections from neighbouring regions and sent together. This means that the nominal quality of the batch will now be dependent on the qualities from all the regions, and thus, be lower than the individual quality ratios. The results presented in this section make it possible to calculated predicted quality ratios of a batch based on which regions it was collected from. For example, if a batch has collections for Kingston and Sault Marie, then in T=1, the quality ratios of the batch for reuse will be 0.6x0.6= 0.36. The results from this study allow for pricing decisions to be made while taking into consideration the different quality ratios from multiple regions of origins.

In addition to that, it must be kept in mind that consolidation of returns is not always done for the same time period all the time. Keeping in mind the concept of economic order quantity, it is necessary to factor in the longer time that is needed to collect a good volume of returns from smaller population centers, than the time needed to collect the same number of returns from larger population centers. The results can be applied to solve this problem as well. Since the results predict quality ratios based on time period, they allow the effective calculation of quality ratios from different regions based on different time periods. For illustration, an example is presented for the case of Kingston and Algonquin Highlands again for 2 periods.

Assume a batch is ordered every 2 time periods. Assume time value is constant. Kingston collects 40 units in T=1 and T=2. Algonquin Highlands collects 30 units in T=1 and T=2.

R1, R2 represent reuse and remanufacturing ratios respectively. The data is displayed in Table 10.

Total units= 140

Probability of reuse = (0.6*40+ 0.68*30) + (0.03*40+0.05*30)= 47 units/140 = 0.3357
Probability of remanufacture = 1-0.3357 = 0.66

Table 10 Exemplar data for quality calculation

	T=1	T=2
Kingston	40, R1= 0.6, R2=0.4	40, R1=0.03, R2=0.97
Sault Marie	30 R1= 0.68, R2=0.32	30, R1=0.05, R2=0.95

Based on the sample data, a batch with collections from Kingston and Algonquin over 2 time periods would have a reuse quality ratio of 0.33, and a remanufacture quality ratio of approximately 0.66. These ratios are significantly different from the reuse and remanufacture ratios for either region based on T=1 or T=2.

As such, the concerned parties may be able to optimize their shipping frequencies by timing and quantities and even expected quality ratios. It would be more economically viable to ship a batch after two time periods if it has 33% reuse rate, than to ship after every single time period. Thus, results from this model contribute in such acquisition policy decisions especially after the first 2 years.

Thus it can be seen that the results from the solution proposed in this research comply with the research objective of creating a forecast model for return quality ratios such that it can improve profitability and decision making at strategic, tactical and operational stages.

6.1.2 Comparison of Quality Ratios by Income Distributions

According to the Bass Diffusion theory, the purchasing behaviour of consumers can be classified as innovators, early adopters, early majority, late majority, and laggards. The groups from innovators to early majority are the ones with a higher rate of adoption. This essentially means that when a new product is released, they are the first to purchase it, thereby "adopting" it faster. For the context of this study, this "rate of adoption" translates as a factor that can influence the length of ownership. In other words, higher rate of adoption means more frequent purchases and quicker disposal of the previous device. Therefore, the rate of adoption can theoretically have an effect on the quality ratios. Under the assumption that income and consequently, spending power, is a decisive factor in whether a consumer falls under early majority or late majority, an attempt is made to use the forecast model in this study to compare the return quality ratios based on the income distributions of different places in Ontario. Theoretically, communities with larger percentage of people falling in higher income brackets must generate higher quality ratios.

Inputs

The daily usage distribution was based on the individual income groups. The distribution for length of ownership was kept uniform across all income groups. Since the individual length of ownership data is not available for income groups, the provincial distribution was used.

Toronto, Kingston and Windsor have been chosen for this comparison because they represent three different communities: large urban, medium urban and rural, respectively. The percentage of households with an income above $80K are the same for Kingston and Toronto at around 41%. However, they are slightly lower for Windsor at 32%.

Discussion

According to the results it can be seen that the quality ratios of reuse, remanufacturing and parts harvest over a period of T years are similar for Kingston and Toronto. The following observations have been made from the results:

1. Windsor generally follows the same trend as the two other cities but shows some differences.

2. In Figure 28 it can be seen that Windsor generates higher reuse ratios at a faster rate in year 1 compared to Toronto and Kingston. All three cities generate the same maximum

quality ratios for reuse which peaks at 0.35 before year 1. However, after the end of year 1, the reuse quality ratio for Windsor depreciates faster as well, meaning, the quality becomes lower than the other two cities. The same exact trend can be seen for the remanufacturing ratios in Figure 29. However, it must be noted that the peak of the Windsor curve is higher. This means that around the year 2 mark, the quality ratios of returns in Windsor will be higher than Toronto and Kingston.

3. Similarly, for the parts harvest trends, Windsor generates higher ratios at a faster rate and depreciates at to its lowest value by the seventh year, which is much earlier than Toronto and Kingston.

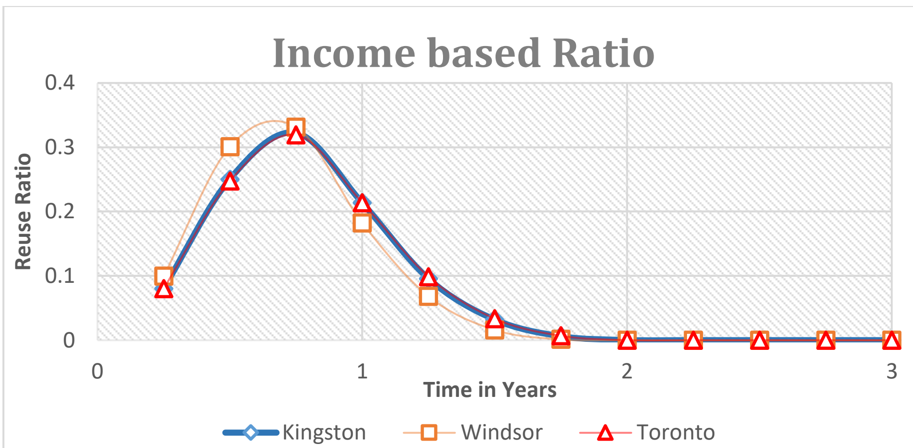


Figure 28 Income based reuse ratios

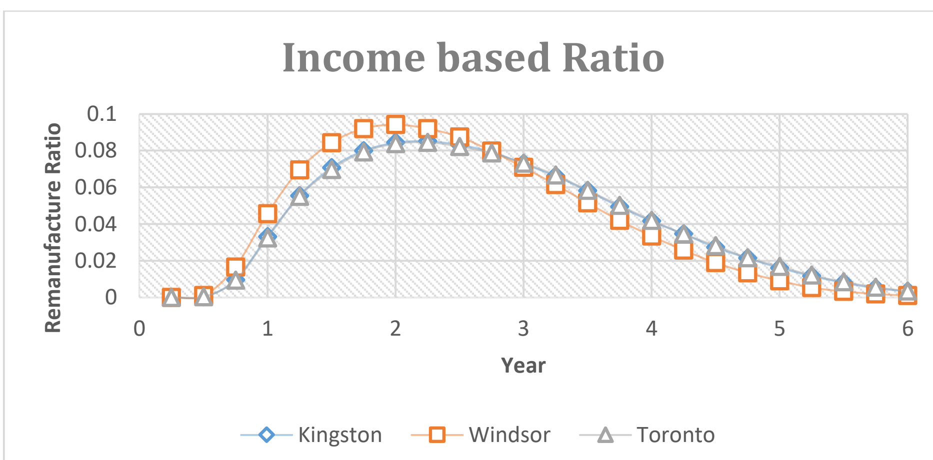


Figure 29 Income based remanufacture ratios

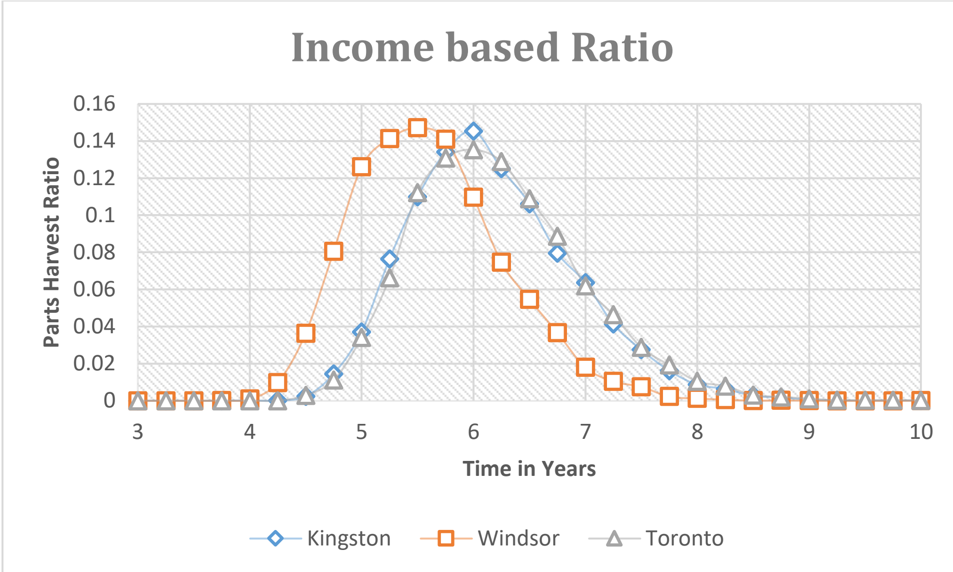


Figure 30 Income based parts harvest ratios

Analysis

Through the analysis of the total usage hours of the cities of Windsor and Toronto it was found that, on a cumulative scale, 90% of users in Windsor use their phones for 3.06 to 3.19 hours per day. Comparatively, in Toronto, 90% of users use their phones for 2.94-2.97 hours per day. This attributes to the higher parts harvest ratios from Windsor, indicating lower quality due to longer usage hours. Toronto has a higher percentage of population in the higher income brackets. Based on the daily usage distribution of the higher income, it can be seen that the mean number of daily usage hours for their age group is lesser. This leads to lower cumulative hours for Toronto and thus, better quality ratios.

Since length of ownership distributions were kept constant, it is safe to say that the results are purely a comparison of the effect of daily usage hours of different income groups. Although the hypothesis testing Table 1 showed that there is a difference in the daily usage hours of different income groups, it can be seen from the results of the forecast model that this does not have a statistically significant effect on quality ratios.

One reason for this is that the length of return has been kept constant. In order to effectively study the impact of Bass Diffusion theory on quality ratios, it would be imperative to have information about the length of ownership, since that is the major factor that discerns between the purchasing behaviours of the different categories of consumers. Since that information is missing, it is unclear how much of an impact income can have on quality ratios. The length of ownership dictates the profitability of reuse and remanufacturing operations and so, the relevant data on that would greatly affect the income based results generated in this study. This can be an area of future analysis when sufficient data is available on income-based length of ownership trends.

6.1.3 Comparison of Quality Ratios from Major Cities in Canada

It can be assumed that the social construct of a large urban city is such that it has a majority of innovators, early adopters and early majority. Other communities such as medium urban and rural areas will have purchasers that fall under the category of late majority and laggards. If the theory that the Bass diffusion model can affect return quality is true, then all cities should generate similar quality ratios. In order to analyze this statement, and whether the behaviour of all urban areas in Canada is uniform, regardless of the geographical (or provincial) location, the results of the model for some major population centers in Canada are compared in Figure 31. By keeping time period in each figure constant (for e.g. T=1, T=2), an attempt is made to study the differences in quality ratios of the cities purely based on daily usage behaviour.

Inputs

The daily usage distribution for each city and the length of ownership was based on the provincial distribution.

Discussion and Analysis

1. For each time period T=1, T=2 and T=>3, as shown in Figure 31, Figure 32, and Figure 33 respectively, it is observed that Toronto, Vancouver and Winnipeg have the same ratios for reuse and remanufacturing. This means that these cities have no difference in return quality, in spite of different geographical locations. Thus, the consumers' usage and return behaviours in these three cities can be described as similar.
2. Figure 31 shows the return quality ratios for the first year (T=1) for major cities in Canada namely, Toronto, Vancouver, Montreal, Winnipeg, and St. John's. In

this figure, it can be seen that all the returns in the first year are either assigned to reuse (recovery number 1), or to remanufacturing (recovery number 2). The ratios of reuse and remanufacturing for Toronto and Vancouver are both the same. When it comes to reuse, St. John's seems to generate the highest quality. Montreal, on the other hand shows lowest reuse quality and highest remanufacturing quality ratio. Analysing the age group distribution of these two places, it is found that Montreal has a larger percentage of population in the ages 18-44 (48 %), than compared to St. John's, which has 44% in the same age group. This means that the users in Montreal have longer daily usage hours than the users in St. John's. This difference in total usage hours leads to higher reuse quality ratios for St. John's as compared to Montreal.

3. Figure 28 shows the return quality ratios for the second year (T=2) for major cities in Canada. From this figure it can be seen that out of all cities, St. John's has the highest reuse ratios for the second year. This is attributed to the explanation that St. John's has a lower percentage of people in the age group 18-44. This means that the daily usage hours in St. John's are comparatively shorter, thus returns are of a higher quality grade which make more of them eligible for reuse. All other cities generate significant ratios for remanufacturing. Once again in the second year it is seen that the model assigns zero returns towards recovery number 3 and 4 (with the exception of Montreal), which correspond to parts harvest and recycling. This is a valid result because in the first two years the economic value of the phone is high enough to make reuse and remanufacturing profitable regardless of the usage level. Once again, the remanufacturing ratios for Toronto and Vancouver are the same. Winnipeg generates higher remanufacturing ratios than other cities because it has lower reuse ratios. This is due to the fact that for the age group of 55+, Winnipeg has a percentage of 36, as compared to Toronto's 34%. This means that the length of ownership for Winnipeg is longer, which means that in T=2, more returns are collected in Winnipeg than in Toronto. Longer length of ownership means longer total usage hours. This means that the quality grade of the returns will be lower, and therefore, the ratio for remanufacturing will be longer.

4. The quality ratios for Montreal are significantly different in each time period compared to the other cities. At T=1, shown in Figure 31, Montreal generates lower reuse ratios, and higher remanufacturing ratios. Since T=1 signifies that length of ownership is fixed at 1 year for this graph, the differences in the ratios must stem from the disparity in the daily usage hours between the residents of Montreal as compared to residents of other cities. Another anomaly with Montreal as compared to other major cities is that for T=>3, it generates larger ratios for parts harvest and recycling, rather than remanufacturing, as shown in Figure 33. The reason for this is that the return distribution for Quebec is a log normal trend. Compared to the Weibull return distributions for Ontario and British Columbia, the lognormal trend signifies that returns will be incoming for much longer years for Quebec as compared to the other two provinces mentioned. Due to the increase in length, the returns are more likely to be suitable for parts harvesting or recycling rather than reuse and remanufacturing. From Figure 34, it can be seen that the remanufacturing ratios rapidly converge to zero for Montreal while they are sustained for up to 7 years for other cities.
5. From Figure 34, it can also be seen that the quality ratios for remanufacturing are not uniform with time but rather follow a decay trend. Additionally, it can be seen that the ratios also vary by the region of location. Once again, the ratio trends of Vancouver and Toronto are exactly congruent. Winnipeg exhibits higher quality for year 3, but that rapidly decays below Toronto's ratios. This can be explained by a comparison of the usage behaviours between Toronto and Winnipeg. The median daily usage hours for Ontario are 1.35 hours, while that of Manitoba are 1.68 hours. Additionally, the median length of ownership for Ontario is 28 months, and that of Manitoba is 25 months, which is around the 2-year mark.
6. Essentially, this means that Manitobans may use their phones for slightly longer per day, but return them much earlier than users in Ontario. That's why, at T=3, the ratio of Winnipeg is higher. However, for T>3, the impact of longer daily usage hours for Manitobans becomes more visible, leading to the decay in remanufacturing ratios as shown in Figure 34. Because Ontarians have a lower

daily usage value, they sustain higher quality ratios as represented by the ratio trend for Toronto.

7. No matter what the total usage hours of any device is, it will always be profitable to reuse or remanufacture it in the first year. This is due to high market value of product.

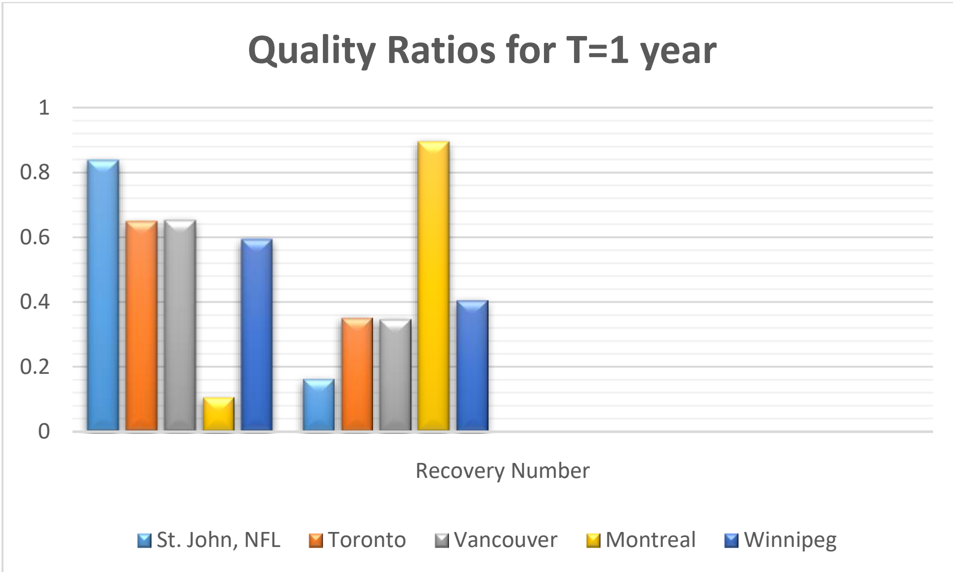


Figure 31 Quality ratios for major cities, T=1

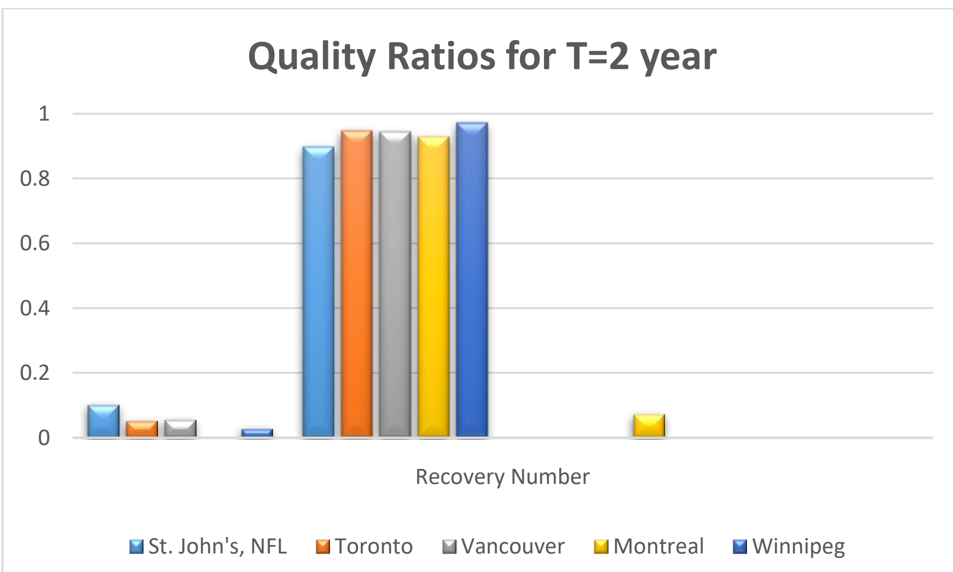


Figure 32 Quality ratios for major cities, T=2

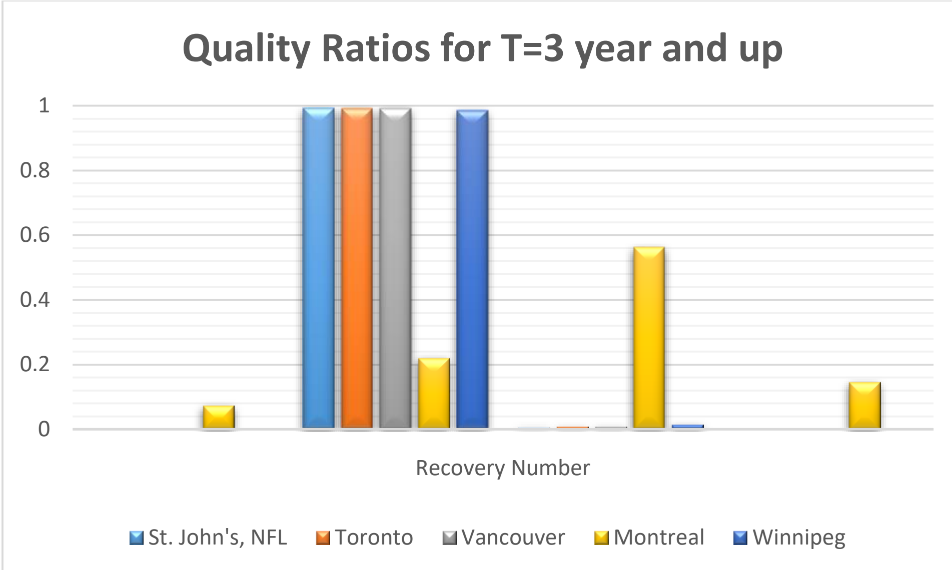


Figure 33 Quality ratios for major cities, T larger than 2

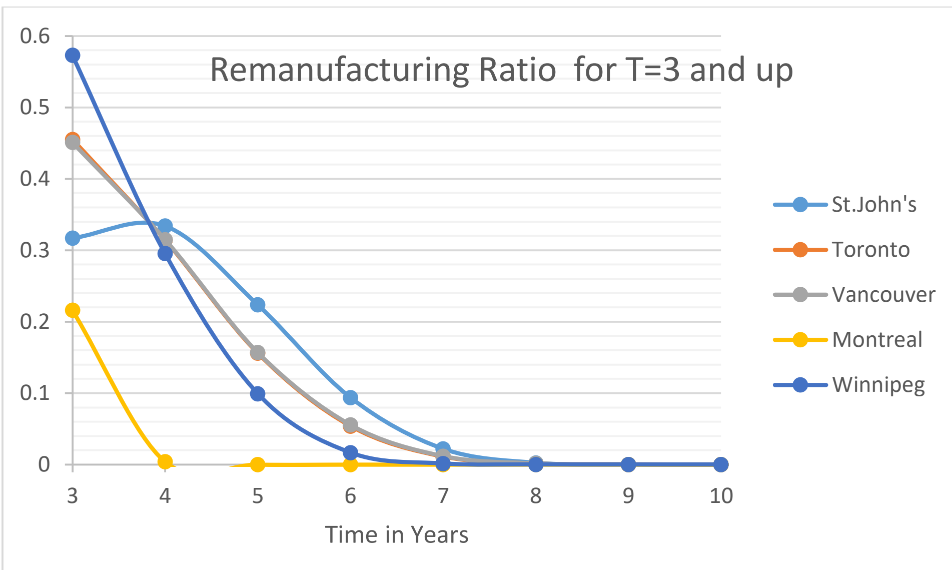


Figure 34 Remanufacturing ratios for major cities

6.1.4 Comparison of Quality Ratios from Rural and Urban Areas in Ontario

Ontario is the fourth largest province in Canada, with an area of 1,076,395 square km, and a population of over 14 million, out of which more than 15% live in rural communities (Statistics Canada, 2016). According to the Waste Diversion Act of Ontario, it is necessary for municipalities with a population of more than 2000 to participate in the

WEEE clean-up act. Thus, when designing the reverse logistics network for a vast area like Ontario it becomes important to make a distinction between rural and urban communities, and incorporate the disparity in strategic planning of a province wide RLN, in order to make sure the network design is sustainable and profitable across all consumer zones.

Inputs

In order to study the quality ratios of returned products from urban and rural, the simulation was run with daily usage distribution for urban from Forum Research, and length of ownership distribution for urban from CWTA, 2016. To generate rural results, the simulation was run with the inputs for the corresponding rural distributions from the same sources.

Discussion of results

The results support the hypothesis that rural and urban areas generated significantly different quality ratios in each year. Through observation of the results it can be deduced that:

1. Rural areas generate very less quantity that is eligible for reuse only in the first year. For remanufacturing, the rural areas generate significant quantities spread out over the first 5 time periods but nothing after that. The highest quality ratio for remanufacturing from rural areas would occur around the first year only. After that, the ratio keeps decreasing.
2. On the contrary, urban areas generate reusable quantities continuously for up to two years. Additionally, the ratios of remanufacturable units generated by urban areas remain considerable higher up to the 5^{th} year (or T=5).

Comparing the results for urban and rural areas, it can be seen that urban areas generate more quantities for Recovery Option 1 & 2, which correspond to reuse and remanufacture. Conversely, rural areas generate more return quantities in latter years, thereby generating higher ratios for parts harvest and recycling.

Another observation is that rural areas generate significant amount of recyclable phones. However, the spectrum for urban ratios does not show any ratios for recycling. This is observed as where there is no scatter line observed corresponding to Recovery Number 4 (which denotes recycling), for urban (

Figure 35) as compared to the scatter line for rural areas (Figure 36).

Analysis of results

The results suggest that urban users generate higher return qualities than rural areas. This can be explained by the fact that urban users have shorter length of ownership. Therefore, they return their phones quicker, with lesser cumulative run time than rural users.

On the contrary, the length of ownership of users in rural areas is modeled by a lognormal distribution. This means that the peak number of returns will occur within the earlier years but the return behaviours of the rest of the people will exhibit an exaggerated delay. In other words, rural users will hold on to their devices for longer before they purchase a new one. This means that at the time of return, their devices will have a larger number of cumulative run time hours. Due to this, the phone will be more prone to failure. Moreover, due to the long time in years, the market value of the phone will deem it unprofitable for remanufacturing. Therefore, it is seen that more returns from rural areas end up as recycling than returns from urban areas.

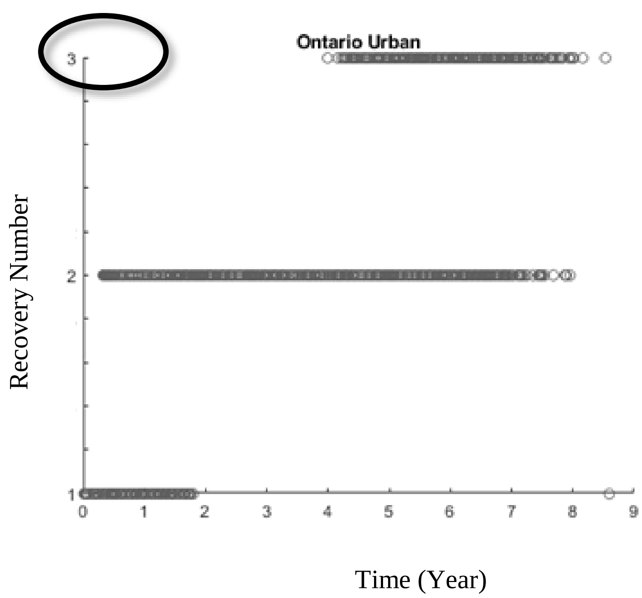


Figure 35 Returns from urban areas

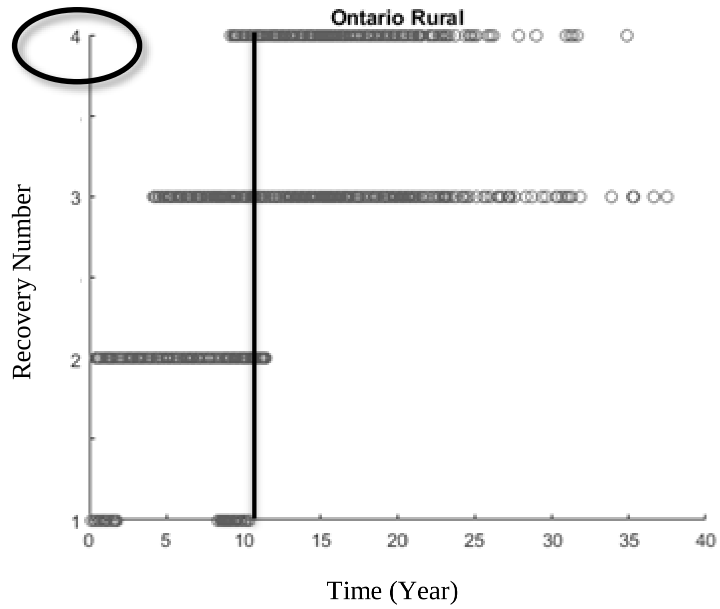


Figure 36 Returns from rural areas

6.1.5 Comparison of Model Trends with Literature

Much of the research that studies the impact of uncertain return quality on network logistics makes the assumption that the quality distribution is:

- Known and deterministic
- Constant with time
- Can be singular to source or area of returns

However, through the analysis of the results generated in this research, it is evident that return quality is not a distribution that can be constant with time, or assigned singularly to a zone. Moreover, the results establish that one distribution, deterministic or stochastic, cannot be chosen as a representation of all other customer zones or cities as in the case of Toronto and other cities in Ontario.

This section compares some of the analytical trends found in literature with the trends generated from this model with the aim of establishing that the model does align with what has been published in literature so far, and that the formulation of the equations in the model is justified.

Market price for reused and remanufactured product

Firstly, according to Ostlin et al., (2009), it is seen that the market price for the reused and remanufactured products both follow exponential decay trends in Figure 37. However, the decay rate of remanufactured products is slower, which means that it generates higher market value than reused product. A comparison of the same trends based on the equations of the proposed forecast model shows that they align with trends by Ostlin et al., (2009) as shown in Figure 1. It can be seen that the market reuse price of the model is always lesser than the market price for the manufactured product.

Secondly, the same authors also suggest that the remanufacturing cost of the product increases exponentially as the quality of the returned core (or the usage level) goes from high to low. The corresponding trend for this as per the forecast model is shown in Figure 38 . A comparison between Ostlin et al.'s (2009) trend and the forecast model trend leads to the following discussion:

- Both trends suggest that the remanufacturing cost increases as the quality level decreases.
- However, unlike Ostlin et al.'s (2009) suggestion that the remanufacturing cost increases infinitely, the current model suggests that the remanufacturing cost increases until it reaches a peak after which the cost stays the same regardless of the usage level. An attempt is made to explain this difference below.

Explanation for difference in trend

In order to analyze the forecast model's behaviour in reaching a maximum value for remanufacturing cost, it is important to consider the input variables that govern it: the total usage hours (u), and the market value of the components at time (t).

As the total usage hours increase, the component failure rate will increase until it reaches a point where all components have failed. Beyond this point, no matter how much more usage hours the device accumulates, the failure probability will stay the same i.e. all components have failed and thus, all components need to be replaced.

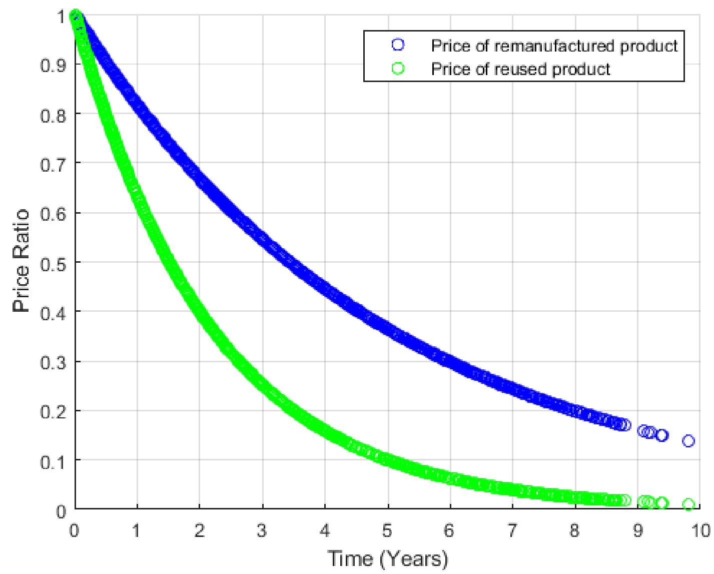


Figure 37 Comparison of reused and remanufactured market value

Similarly, for the time-dependent market value of components, the value follows a depreciation curve which will eventually lead to low values that are negligible.

Thus, both input variables that are used in the calculation of remanufacturing cost hit a limit. The highest remanufacturing cost will occur when all components have failed and need to be replaced. As the market value of these replacement components decreases and stabilizes, the remanufacturing cost will also stabilize. Thus the trend depicted in Figure 38, which suggest that remanufacturing cost will eventually reach a constant value irrespective of usage level is justified and seems more appropriate for this case than Ostlin et al.'s (2009) suggestion that it rises infinitely.

An additional comparison is made between the remanufacturing cost and the remanufacturing profitability with respect to usage level as shown Figure 39. It can be seen that as usage level (or total hours) go from low to high, the remanufacturing cost increases until it reaches the maximum. However, the profits decrease exponentially with the increase in usage until they reach 40% of their initial value. The result suggests that after this, the profitability will depreciate at a lower rate. This is actually in line with the market trend for iPhones that depreciate their value to 37% very rapidly before their value can stabilize. After hitting 37%, the market value of the model usually spends a significant time (in years) between 37% to 25% but it doesn't seem to reach to the value of zero, as evident from the current market price of iPhone 4 even after more than 6 years of release.

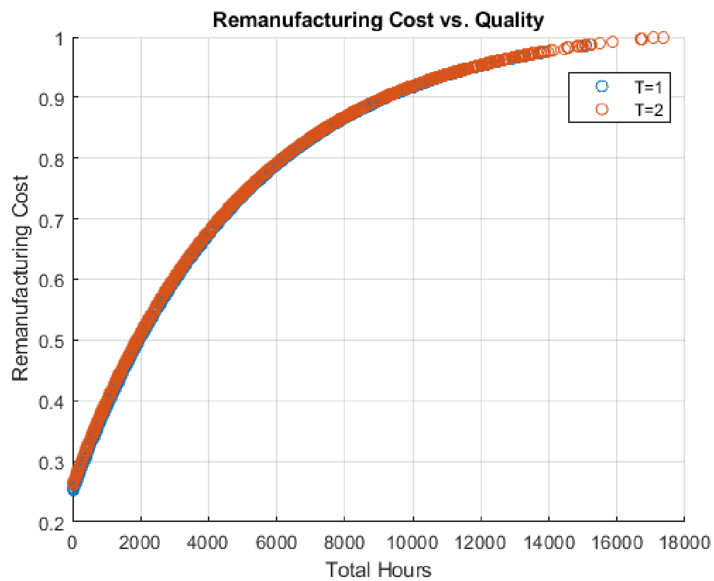


Figure 38 Remanufacturing costs with respect to quality

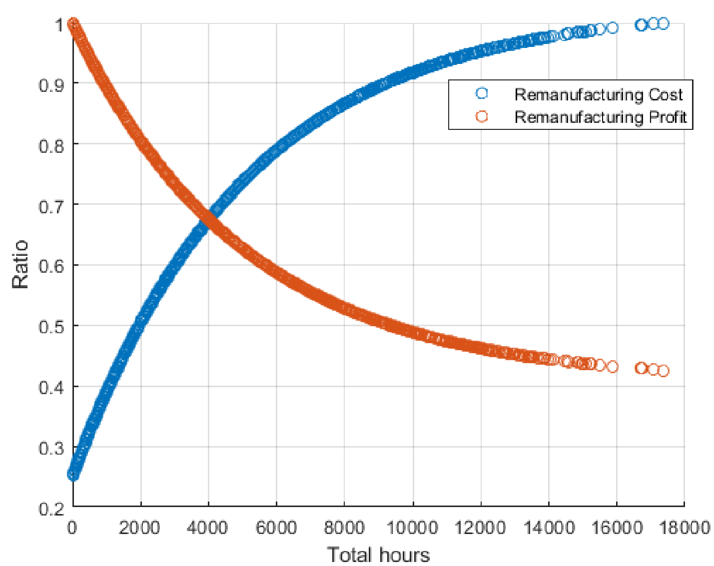


Figure 39 Comparison between remanufacturing costs and profit

6.2 Sources of Error and Sensitivity Analysis

In order to establish the robustness of the forecast model, the sources of errors must be mentioned. Firstly, one source of error is in the statistical reliability of the data which was taken from the Forum Research Survey. This data was published in the form of percentages of people for each age and income group that use their phone for a certain number of hours. The sample size of survey was uniform for all provinces and age groups. This can lead to an inaccuracy due to the larger population of some provinces such as Ontario as compared to other provinces. Moreover, the reliability of the survey data really depends on how accurately the respondents represented themselves in terms of their socioeconomic status, and whether they were reporting their absolute daily usage hours without any bias. Thus it can be seen that the source of errors in the survey can produce some numeric errors into the forecast model. However, this would not affect the overall contribution of the forecast model which asserts the statistical differences in the quality ratios based on age groups and region of location, nor would it change the mathematical formulation of the model.

A second source of error is in the reliability calculations of the LCD module of a smartphone. The LCD module has several failure modes: stuck pixels, backlight failure, backlight brightness reduction, unresponsiveness, delayed response, etc. Due to lack of availability of sufficient literature on the numerical calculations of the LCD reliability that takes into account all the failure modes, this model only considers the backlight brightness reduction in its reliability calculations.

Finally, another source of error stems from the absence of having any empirical or historic information of return quality ratios based on region and age groups. Availability of such data would allow the mean square error calculations which would help to establish the tolerance level of the forecast model.

In order to establish some degree of robustness for the forecast model in the absence of relevant data that would be need for error calculations, sensitivity analysis has been carried out in lieu.

In part 1 of the sensitivity analysis, a comparison is made between the results for different survival functions for LCD module. Since LCD module is the one of the costliest component of the smartphone, its failure probability will highly affect the profitability of recovery decisions. In all the models so far, exponential failure probability has been used for the LCD module, as shown for the case of Toronto in Figure 40 and Figure 42. In Figure 41 and Figure 43, the LCD failure is modeled using the empirical failure distribution devised based on failure data by Wang (2011), who proposes a Burr XII distribution for LCD survival. It can be seen that the change in LCD survival rate has a profound effect on the results of the model. Under the exponential distribution, the model generates sufficient ratios for all three recovery options: reuse, remanufacture and parts harvest. However, under the empirical distribution, there are no ratios for parts harvest. A comparison of the survival probabilities in Figure 44 shows that the exponential failure probabilities decay much faster than the empirical model for the same total usage hours. Therefore, they depict a higher probability of failure. Comparatively, the empirical model shows higher rates of survival for the same total usage hours.

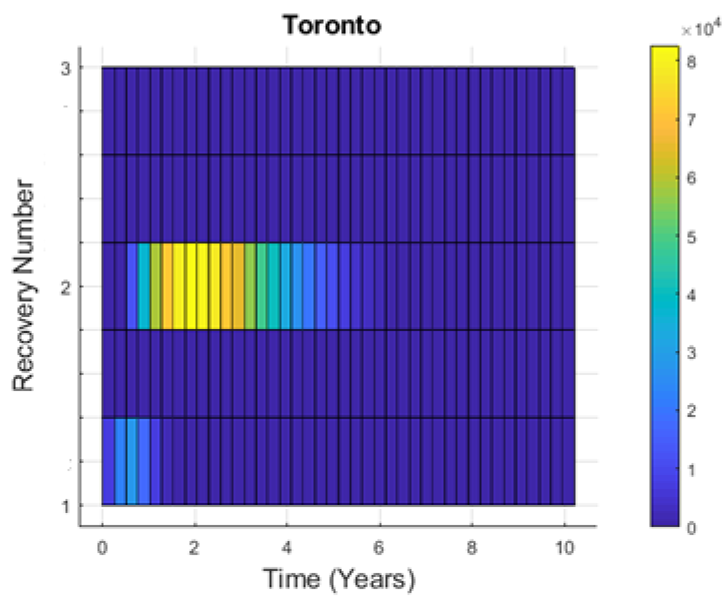


Figure 40 Histogram for Toronto with exponential LCD failure

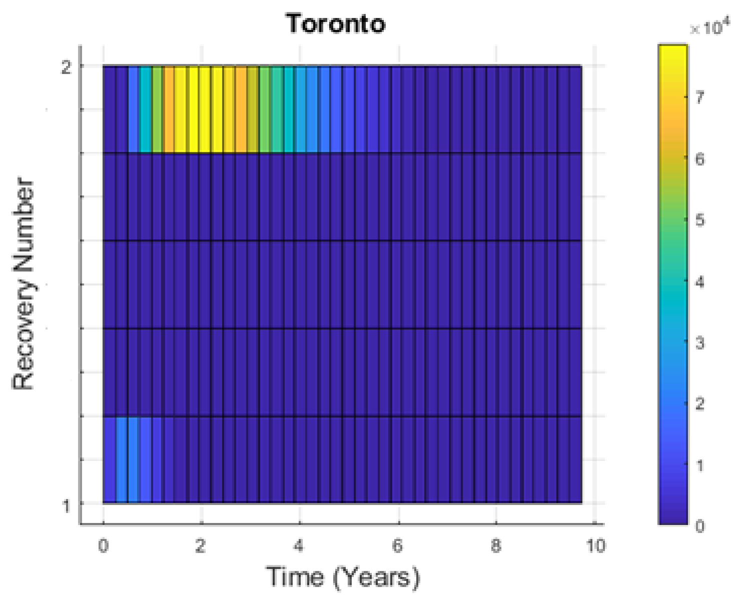


Figure 41 Histogram for Toronto with empirical LCD failure

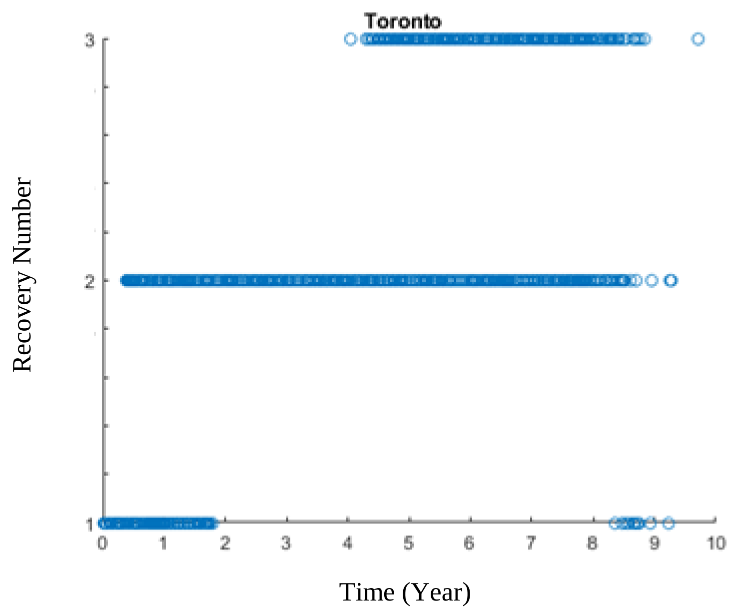


Figure 42 Toronto spectrum with exponential LCD failure

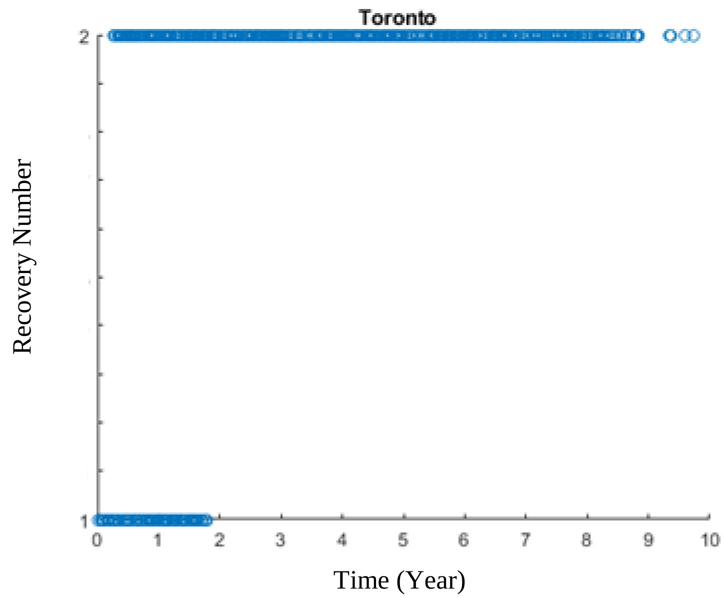


Figure 43 Toronto spectrum with empirical LCD failure distribution

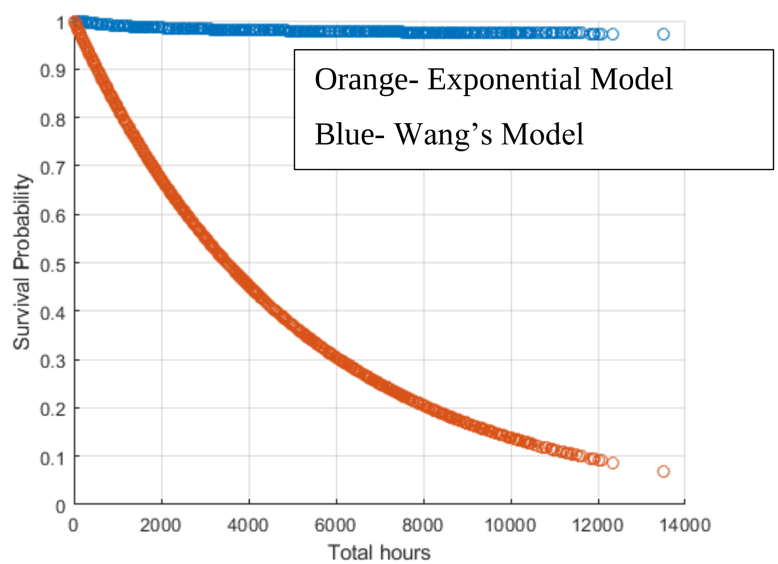


Figure 44 Comparison of LCD survival probabilities from exponential and empirical distributions

Battery reliability

A second sensitivity analysis is carried out to test the effect of the failure rate of smartphone battery on the model. The mean cycles of failure was changed from 500 to 1000, the results of which are shown for the base case of Toronto in Figure 45. Compared with the results in Figure 42 (base case with MCTF=500), it can be seen that lesser returns are allotted to remanufacturing when leads to some feasibility for recycling. However, it can be said that the effect of battery failure rate is not as high as the effect of the LCD failure rate on the results of the model.

6.3 Applicability

This section discusses the applicability of the results from the forecast model for various parties in reverse logistics. It also discusses what kind of products the model can be used for, and its adaptability in the face of dynamic consumer behaviours.

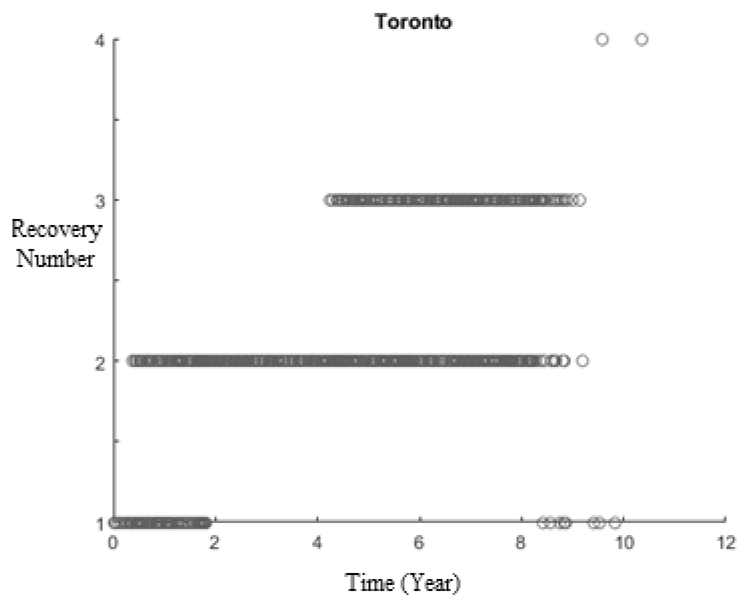


Figure 45 Toronto spectrum with battery mean failure at 1000 cycles

6.3.1 Applicability for OEMs, Retailers, Third Party, and Governmental Reprocessors

OEM's: The results from this model can be used by OEMs to plan their reverse logistics network design, make procurement decisions based on each period, and increase the profitability of their recovery processes overall.

Retailers: The results of the model may not be directly applicable for retailers because they are mainly concerned with collection, and not carrying out reprocessing activities. Therefore, the value that the information this model brings to the network design or operations of reverse logistics network is not directly applicable to retailer. Moreover, retailers usually take part in gatekeeping, which means they assess the device quality at the time of acceptation from the user. This means that they have accurate information of individual units, albeit after they are collected. As such, there is no scope for prior information generated through a forecast model for the retailers. However, if a retailer successfully creates a database for each device collected in terms of its usage level, location of collection, and quality grade, then this data can be used to validate and improve the accuracy of the proposed forecast model.

Third Party Collectors: Through the results of this forecast, one can predict which regions and which time periods will generate high quality ratios. Based on this, third party collectors can allocate their collection efforts wisely and also use the results for forecasting or quoting the price for their collected batches before the physical collection of the used phones or sample testing.

Governmental Reprocessors: Among all the concerned parties in reverse logistics, governmental agencies are the ones that prioritize environmental benefits more than economic profitability. As such, it is in the best interest of the governmental agencies to reduce the overall WEEE from a province, rather than just generate profits. The results of this model can help the government gauge WEEE quality ratios in all areas, rural or urban, of a province or the country at large. Based on these results, the government can perhaps subsidise collection and reprocessing of WEEE from areas that do not seem lucrative enough for other parties in the RLN to initiate reverse logistics activities there. Moreover, the province wide recycling ratios estimation can help effectively plan the number and capacity of the recycling depots required. Results of this model can also be used for governments of different provinces to collaborate and build a more robust country-wide system for WEEE waste reduction. Since Canada is so large area wise, the long travel distances, which ultimately lead to higher transportation costs and carbon emissions, can be ignored if governments collaborate with each other. For e.g. WEEE returns from Kingston might be sent to a reprocessing facility in Montreal instead of one in Southern Ontario so as to save on transportation costs. This is one way through which the results of this may help governmental reprocessing schemes.

6.3.2 Applicability to Product

The forecast model devised in this study is more appropriate for short lived electronic products as compared to large white goods. This is because the purchase behaviour of large white goods is more or less stable and can be forecasted effectively through historic data. In addition to that, the usage distribution of large white goods is deterministic and measured on household level. It does not vary based on individualistic socioeconomic characteristics. Therefore, the applicability of the forecast model is for short-lived consumer electronics, specifically smartphones.

Within the smartphone industry, this model would be more useful for phones which actually sustain appreciable market value over time, and phones for which there is a substantial secondary market for reused and refurbished quality grades. Since the model also considers the concept of selling used parts from the phone through parts harvest, it would be safe to say that the model cannot be applied to smartphone brands whose components do not retain value in the used parts market.

6.3.3 Adaptability of the Model for Future Trends

Since consumer behaviour, especially in the smartphone industry is not known to follow any time series pattern until date, it is safe to say the usage and length of ownership distributions used in this study are bound to change. However, this will not negate the applicability of the model. This is because the model allows the parameters or distribution types of the input variables to easily be changed so as to reflect current distributions changes in customer behavior. On a speculative note, in the future, when the consumer behaviour in the smartphone industry converges or reaches a stable state, the usage distributions may not be subject to changes in parameters. At that point, the parameters in the model would not need to be updated so frequently. Regardless, the changes in parameter do not translate as a need for any changes in the underlying system of equations of the forecast model.

CHAPTER 7

CONCLUSION AND FUTURE RESEARCH

7.1 Conclusion

Return quality is a widely uncertain parameter in reverse logistics that can potentially affect the profitability of product recovery operations. It is caused by the unique and largely varying consumer behavior, especially of short lived electronics. In order to plan a cost-effective reverse supply chain for these electronics, it is crucial to have a quantitative forecast of the return quality ratios over multiple periods.

To this end, this research proposes a forecast model for return quality which can help fill the gap in present literature. Since, the root cause of randomness in return quality is the variations in consumer behavior, this research proposes a model which can gauge consumer behavior by finding usage trends based on socioeconomic factors such as age, income, education and region of location. Based on these consumers' usage trends, the model then assesses usage-based failure rates of used product, market trends and technological age of the product for future returns to predicts the optimum recovery decisions for future returns. The main contribution of this research is in determining the relation between product categorization by socio-economic factors and the return quality.

Through the results generated in the research, it can be seen that return quality ratios are, in fact, dependent on the age group, and the location of the user. A comparison of the return quality ratios for the major cities in Canada showed that provincial location also plays a part in determining the quality distribution. However, some major cities exhibited the same quality ratios regardless of being from different provinces, such as Toronto and Vancouver. In addition, the results suggest that the variations in daily usage hours based on income groups do not affect quality distribution at a significant level. However, it remains to be seen how length of ownership based on income groups alters the results for future work.

Through detailed explanation of the results, it has been established how the results generated by the model can be used by various parties such as OEMs, retailers and informal collectors. An explanation has also been provided as to how the results can be applied to contribute to the process of reverse logistics network design, procurement decisions and improving profitability of the recovery processes.

7.2 Recommendations for Future Research

Future research can work towards quantifying the error of the results, and improving the reliability of the forecast model. In order to achieve this, it would firstly be necessary to record data of the quality level of returned phones along with their date of purchase, daily usage and date of return. Through collection of real life data, it would be possible to calculate an error value for the results of the forecast model.

It is also recommended that future research make an attempt to include cosmetic condition, along with the functional condition, of the phone as part of the failure probabilities as well, and factor in the cost of replacing the outer casings. This model only considers functional condition.

The presented model only concerns passive user returns through consumers' inherent willingness to return. As such, it provides estimates of the base case. In order to forecast overall quality ratios and model the effect of product take-back schemes, the model can be altered to reflect acquisition costs such as constant incentivized returns, or quality-based incentivized returns. Future research can model the effect of such costs on the resulting quality ratios. Additionally, in future models, the costs of disassembly for parts harvest, inventory costs, and also the costs associated with discarding parts that cannot be resold can also be included.

The proposed forecast model, as a first of its kind that predicts future quality ratios, provides a strong mathematical framework that can be further built upon to improve accuracy and reliability of various other phenomenon that affect return quality.

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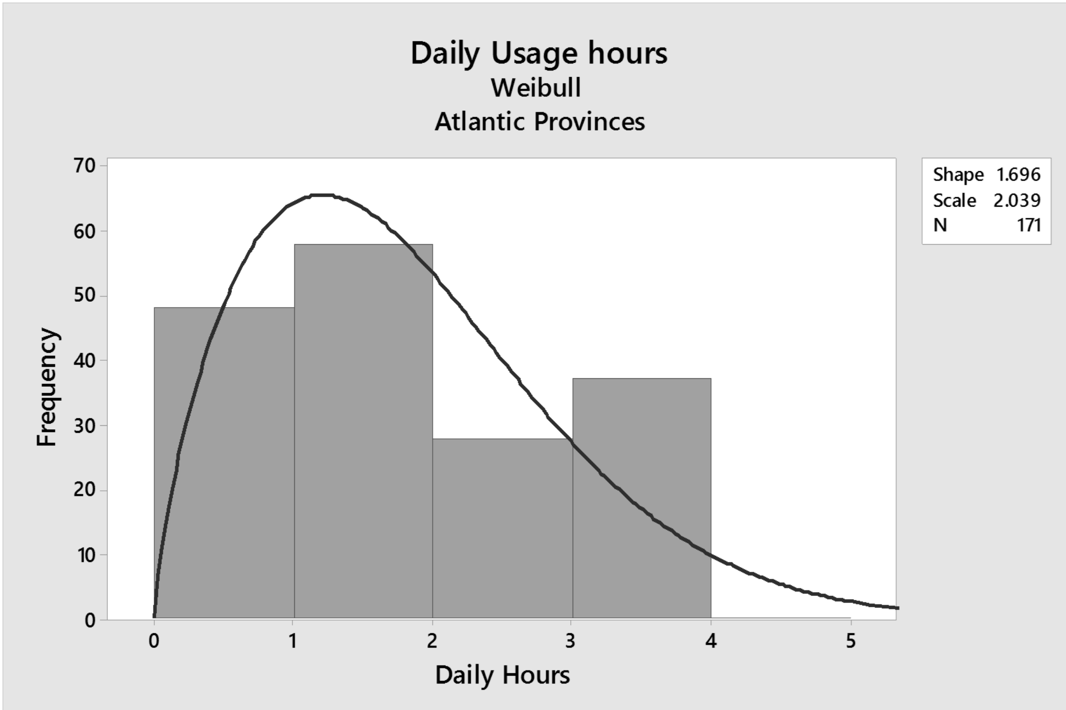
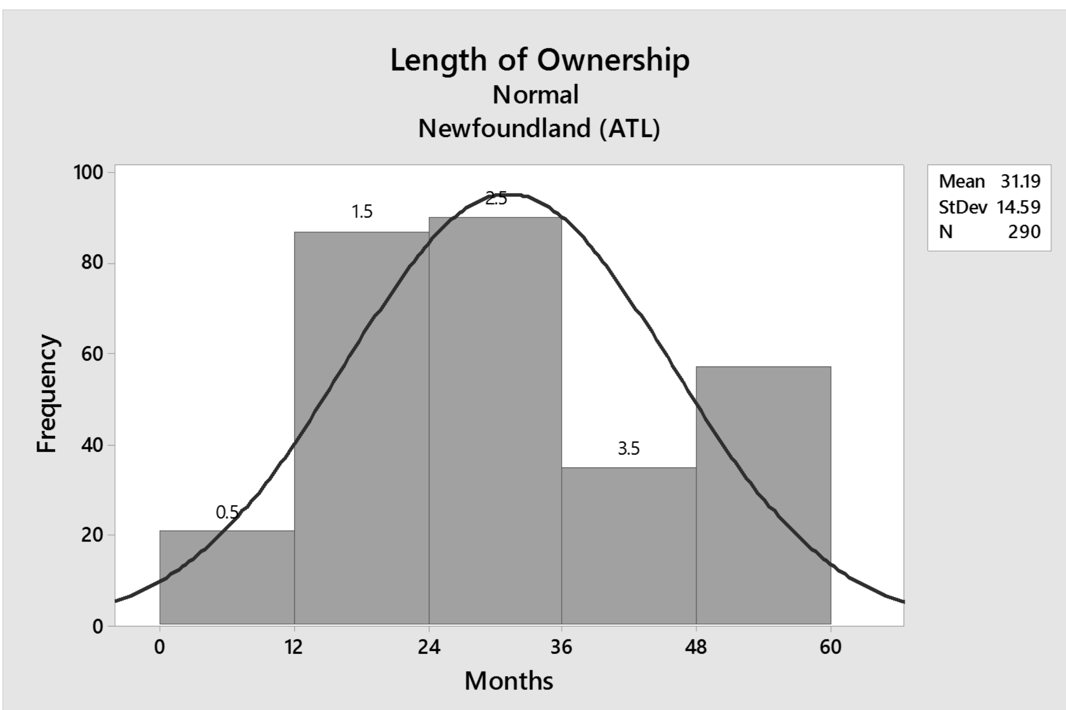
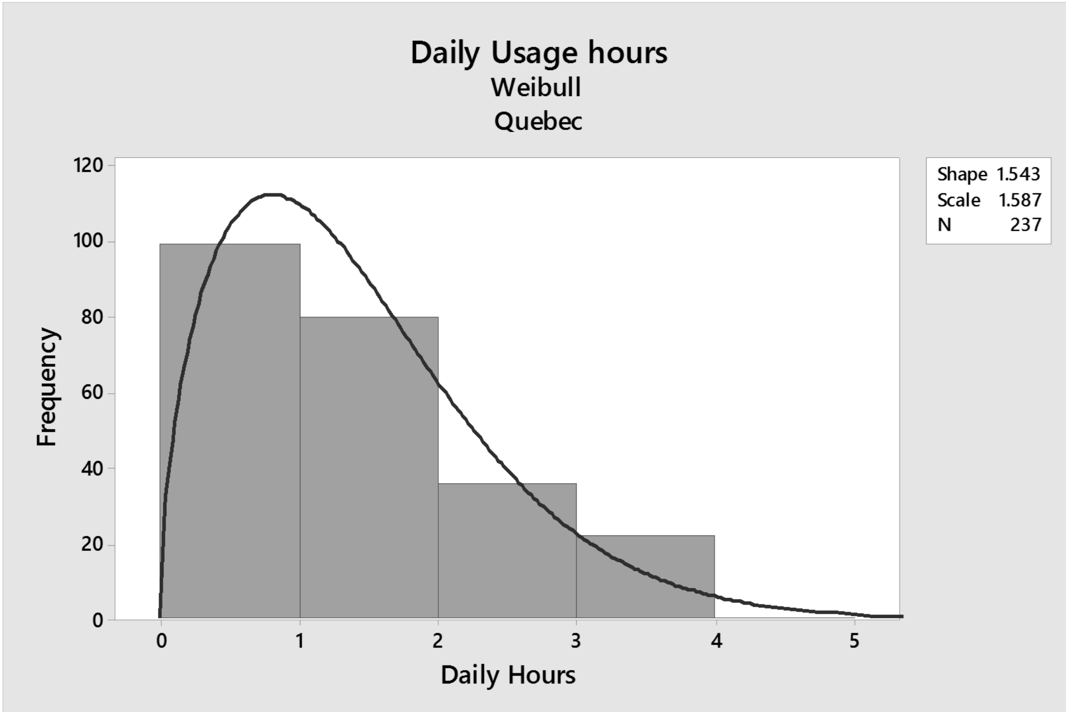
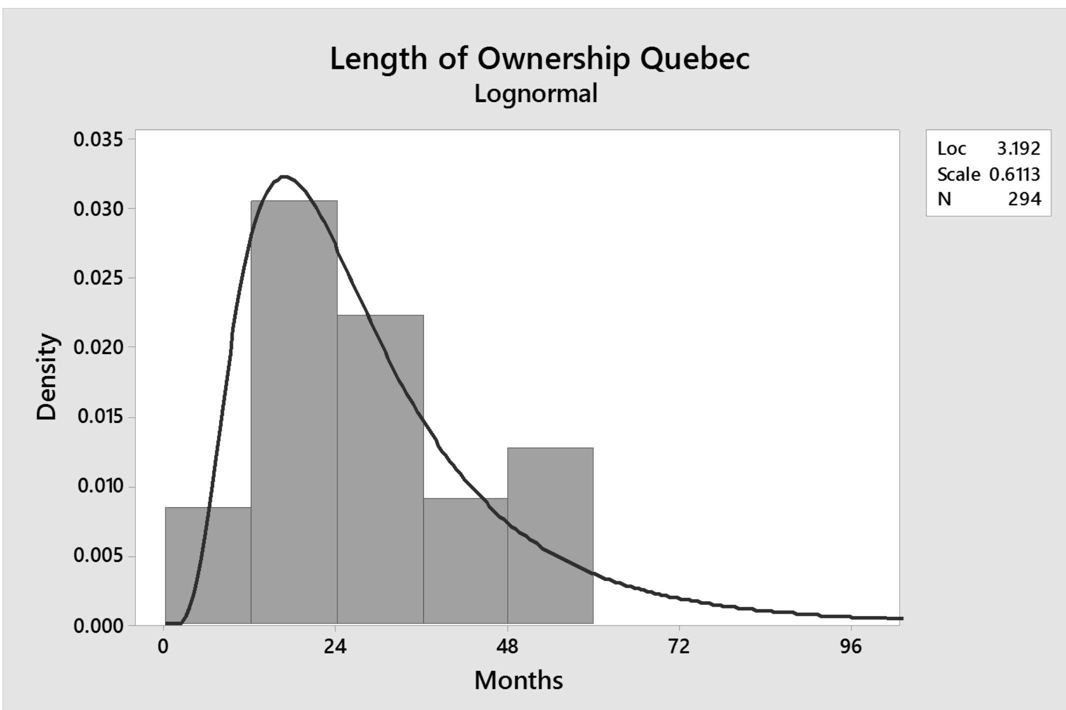
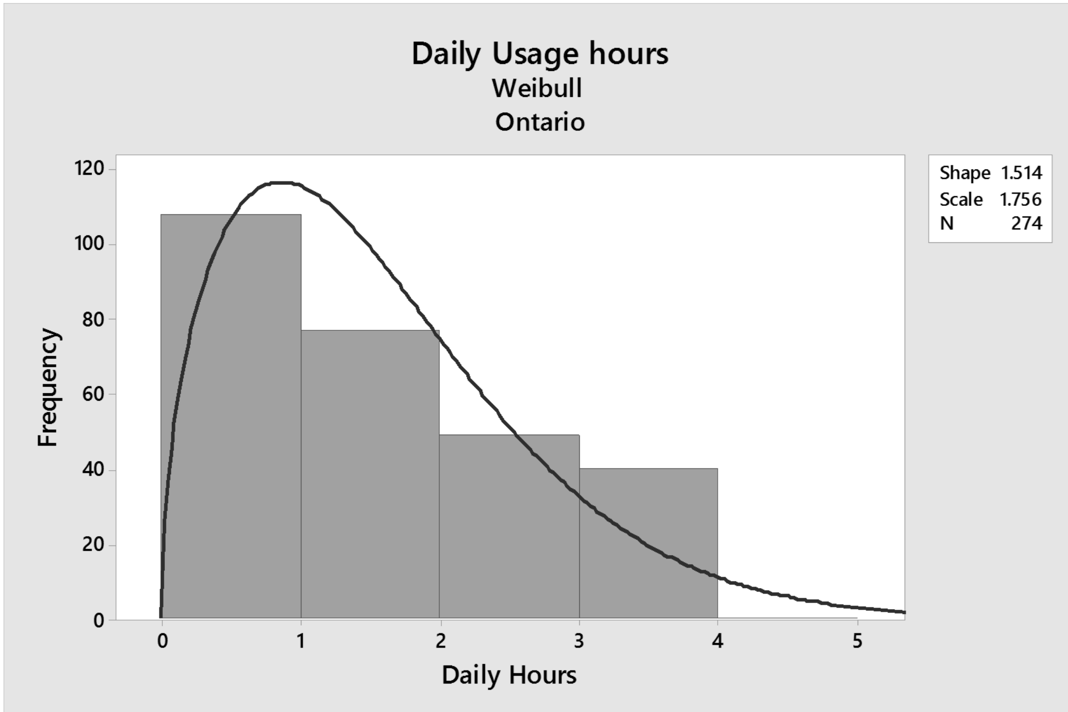
Appendix A Device usage and ownership distributions by provincial






Daily Usage hours
Weibull
Quebec
Shape 1.543
Scale 1.587
N 237
Frequency
120
100
80
60
40
20
0
0
1
2
3
4
5
Daily Hours


Length of Ownership Quebec
Lognormal
Loc 3.192
Scale 0.6113
N 294
Density
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
24
48
72
96
Months


Daily Usage hours
Weibull
Ontario
Shape 1.514
Scale 1.756
N 274
Frequency
120
100
80
60
40
20
0
0
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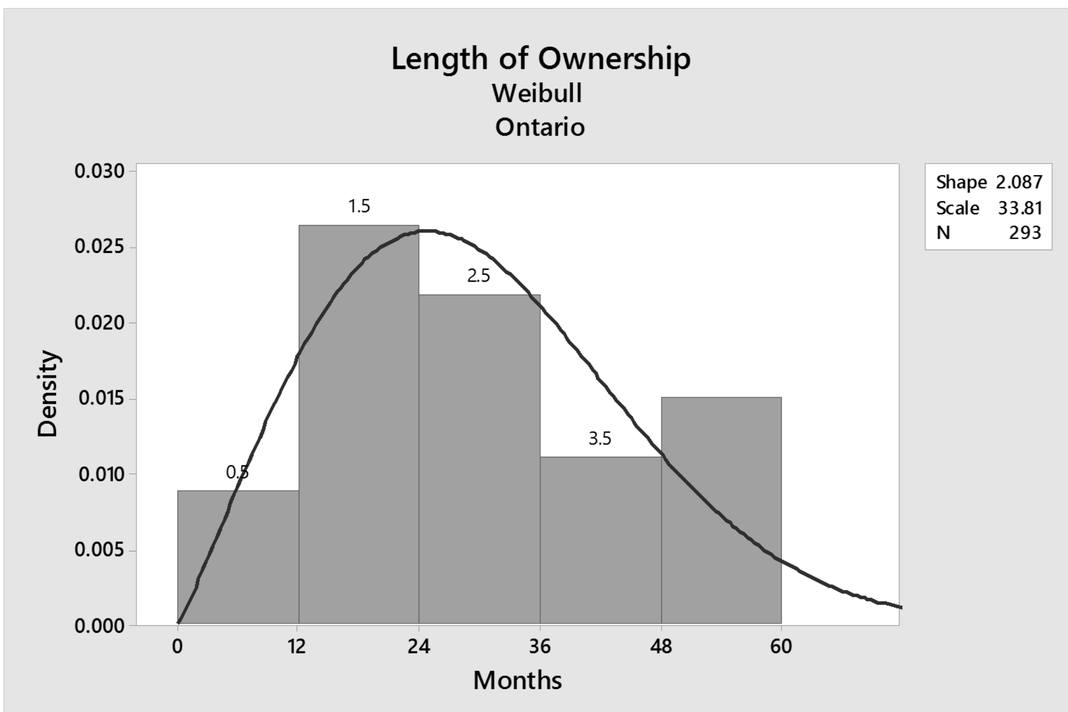
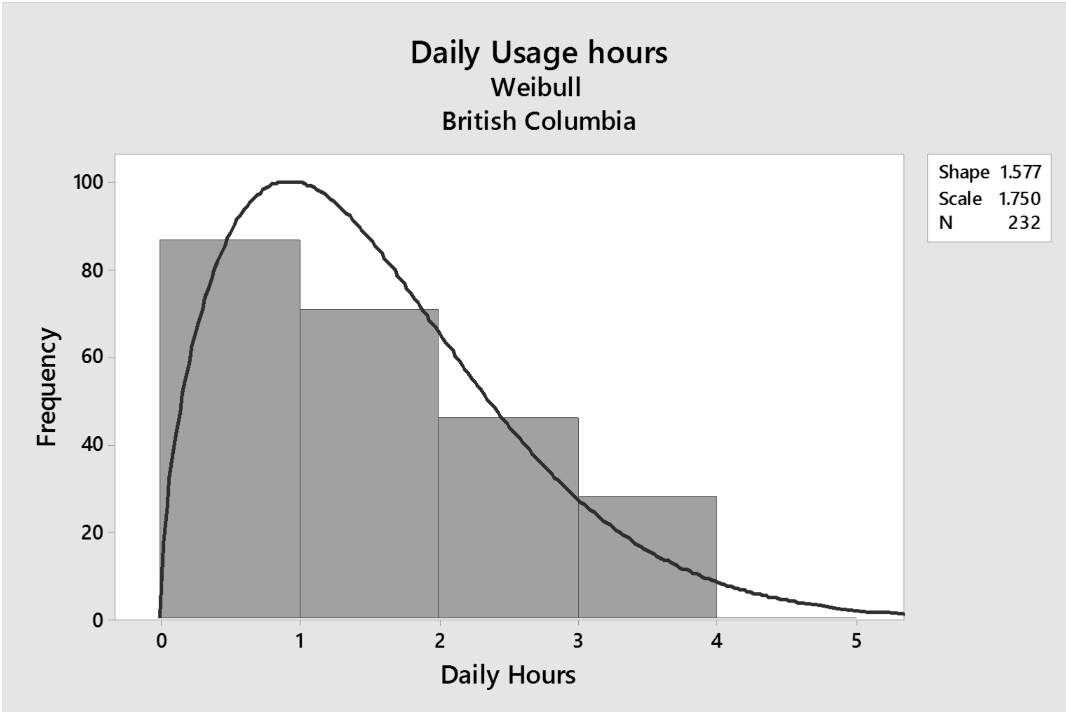
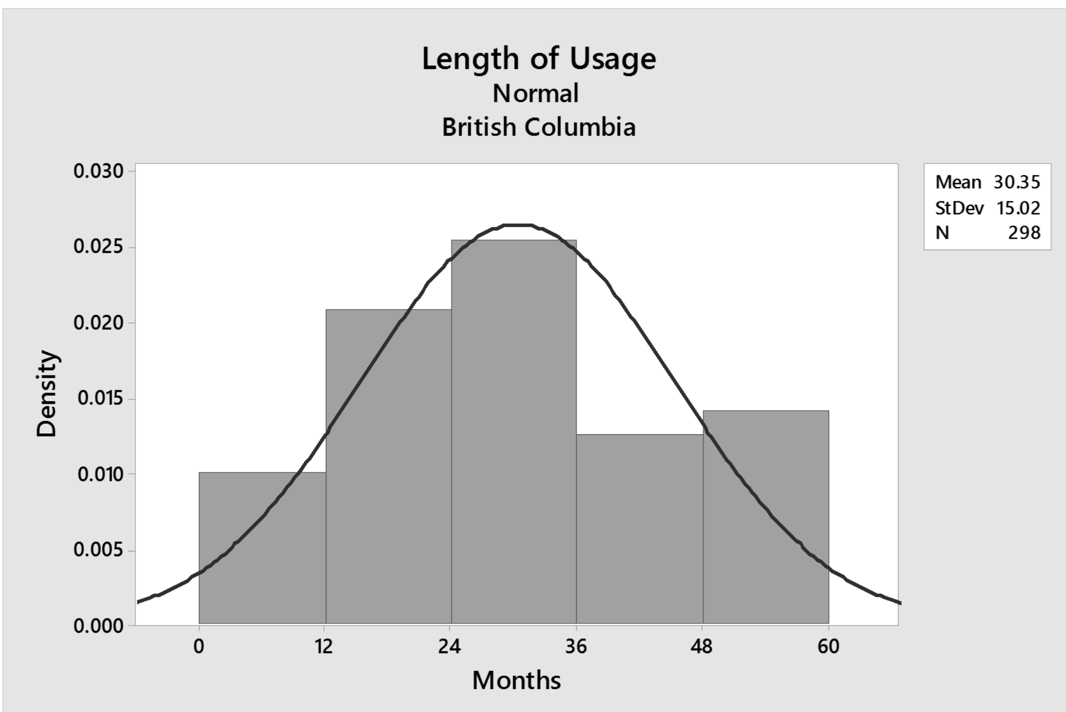
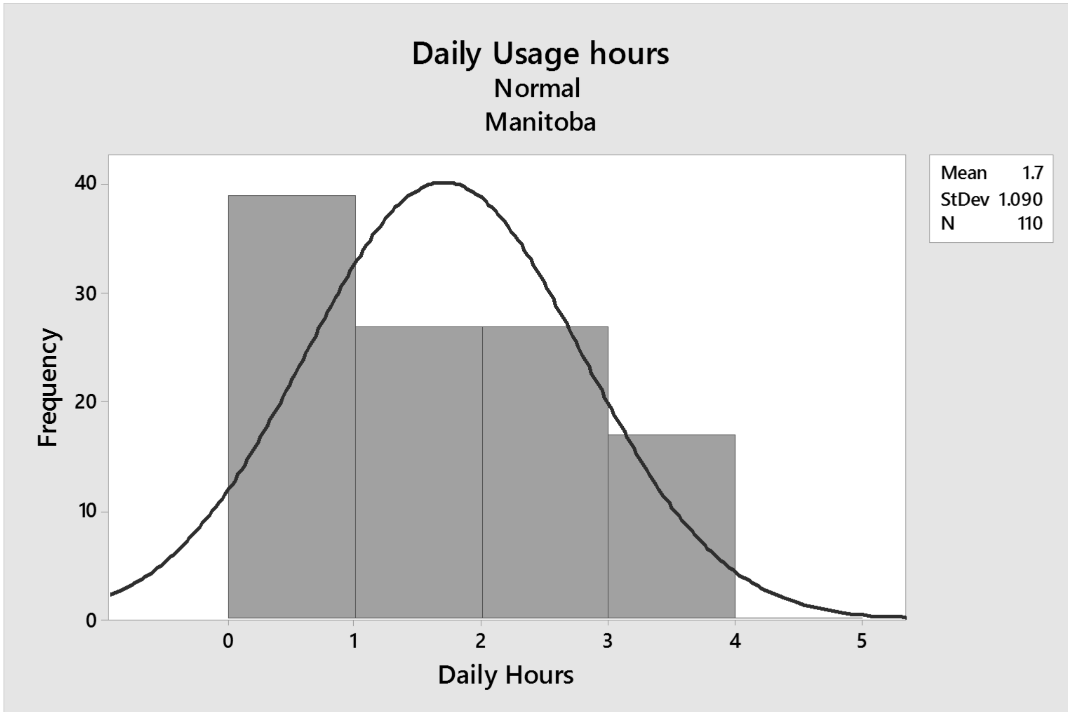
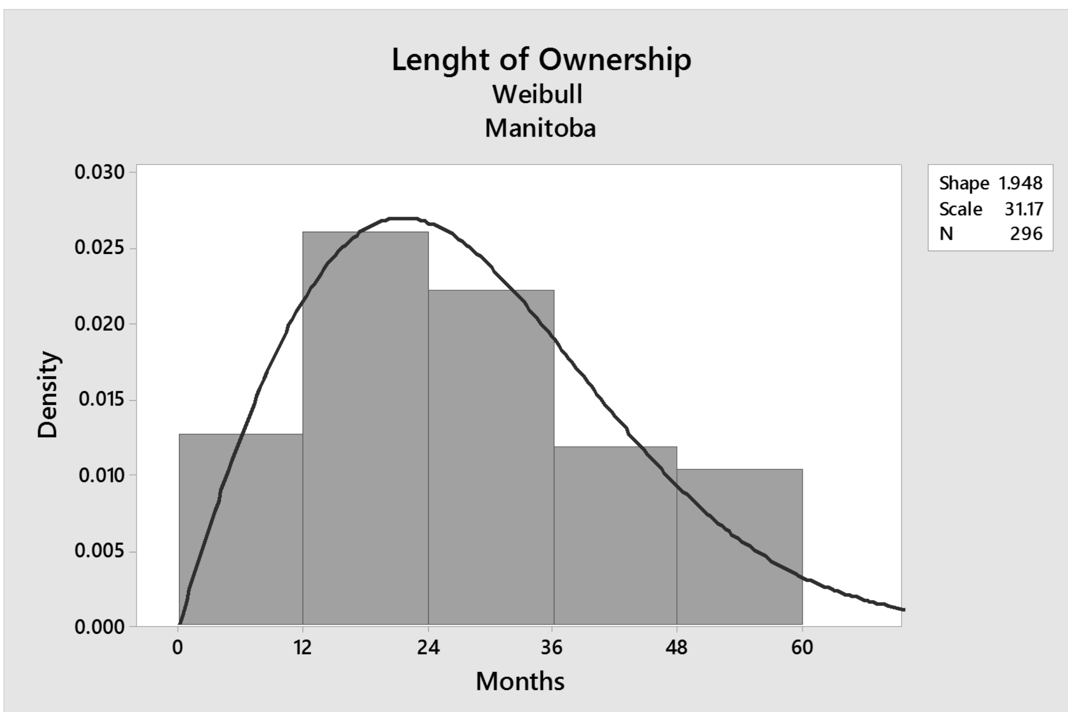
2
3
4
5
Daily Hours

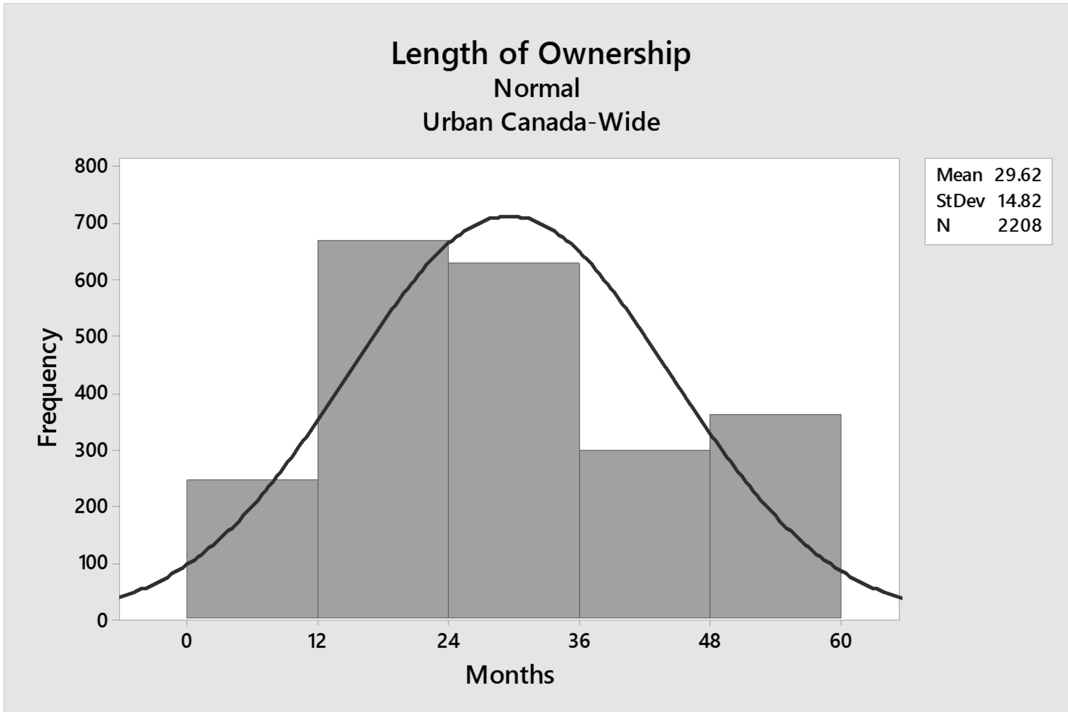

Length of Ownership
Weibull
Ontario
Shape 2.087
Scale 33.81
N 293
Density
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0.5
1.5
2.5
3.5
0
12
24
36
48
60
Months

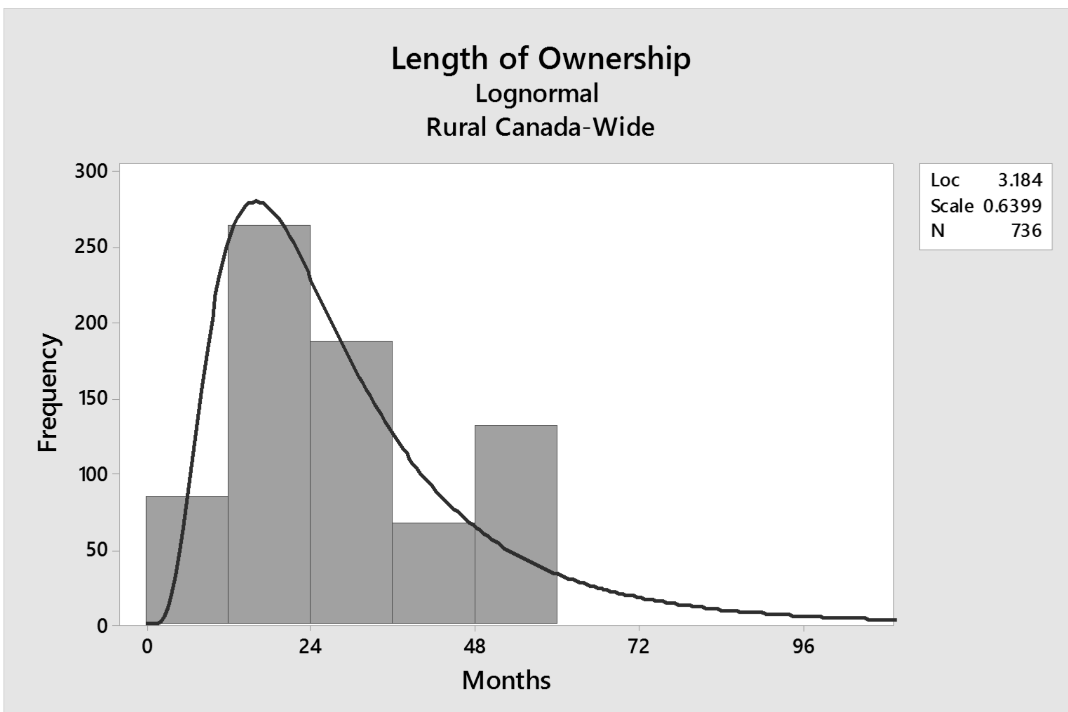

Daily Usage hours
Weibull
British Columbia
Shape 1.577
Scale 1.750
N 232
Frequency
0
20
40
60
80
100
0
1
2
3
4
5
Daily Hours


Length of Usage
Normal
British Columbia
Mean 30.35
StDev 15.02
N 298
Density
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0
12
24
36
48
60
Months


Daily Usage hours
Normal
Manitoba
Mean 1.7
StDev 1.090
N 110
Frequency
0
10
20
30
40
0
1
2
3
4
5
Daily Hours


Lenght of Ownership
Weibull
Manitoba
Shape 1.948
Scale 31.17
N 296
Density
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0
12
24
36
48
60
Months


Length of Ownership
Normal
Urban Canada-Wide
Mean 29.62
StDev 14.82
N 2208
Frequency
Months
800
700
600
500
400
300
200
100
0
0
12
24
36
48
60


Length of Ownership
Lognormal
Rural Canada-Wide
Loc 3.184
Scale 0.6399
N 736
Frequency
Months
300
250
200
150
100
50
0
0
24
48
72
96

Appendix B Copyright permission from CWTA

The data from the report was used to generate the length of ownership distribution for the different age groups and different provinces in Canada.

Ashley Sverdrup-Yap via nanosresearch.onmicrosoft.com May 15, 2019 2:36 PM (44 minutes ago)

to me

Hi Aamirah,

We just confirmed with the Canadian Wireless Telecommunication Association (CWTA who sponsored the study) and you are more than welcome to use the data found in this report:

http://www.nanos.co/wp-content/uploads/2018/06/2017-1097-CWTA-Recycling-Populated-report-Public-Version.pdf

Regards,

Ashley Sverdrup-Yap

Assistant to the President
Telephone 613.234.4666 x237
Skype execassistnr

More information > http://www.nanos.co
Nanos live data portal (ballot, economic sentiment, issues)
> http://www.nanos.co/dataportal/

Appendix C Copyright permission from Forum Research Inc.

The following thread of emails shows approval to use data set published by Forum Research Inc.

>On Tuesday, April 30, 2019, **Gary** Milakovic <**G****@forumresearch.com**> wrote:

Hi Aamirah,

You apply to use the data through the dataverse. You'd request the Federal dataset from Jan 2018 (ensure the codebook has the questions you want) and then you'd be able to use the data in your research.

https://dataverse.scholarsportal.info/dataverse/forumresearch

Gary

From: Aamirah Mohammed Ashraf
Sent: Tuesday, April 30, 2019 10:55
To: Gary Milakovic
Subject: Re: Permission to use Forum Research News Release in Student Research

Hello Gary,

Yes, I had a librarian from the University of Toronto retrieve this news release from data verse for me a while back. I had applied and received access after a few days. So does that mean I'm all set? Do I need any other written authorization?

Once again thank you for prompt help!

Aamirah Mohammed

Gary Milakovic <G****@forumresearch.com> Apr 30, 2019, 11:25 AM

to me

Hi Aamirah,

That's all you need.

Thanks!

Gary

Appendix D Permission to use data through Dataverse Portal

Dataverse portal access received for use of data presented in Forum Reseach Inc.

Dataverse Support <DATAVERSE-SUPPORT-L@listserv.utoronto.ca> Mon, Feb 11, 8:46 AM

to me

Hello,

Access granted for files in dataset: Forum Research Political Poll - Federal Issues (Canada) 2018 (view at https://dataverse.scholarsportal.info/dataset.xhtml?persistentId=doi:10.5683/SP2/FZO8KC).

You may contact us for support at DATAVERSE-SUPPORT-L@LISTSERV.UTORONTO.CA.

Thank you,

Dataverse Support

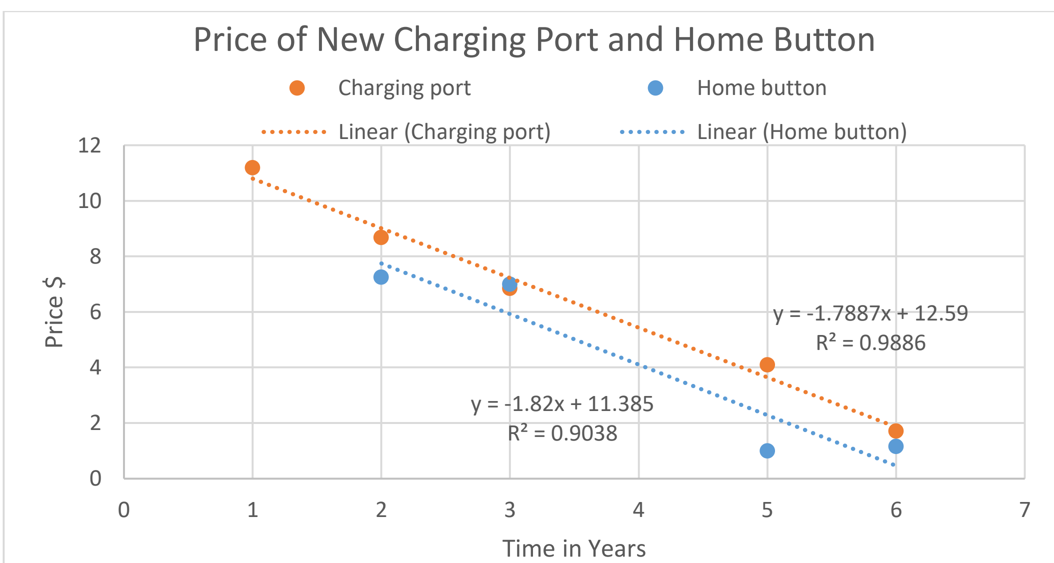
Appendix E Data and trends for New and Used Component Pricing

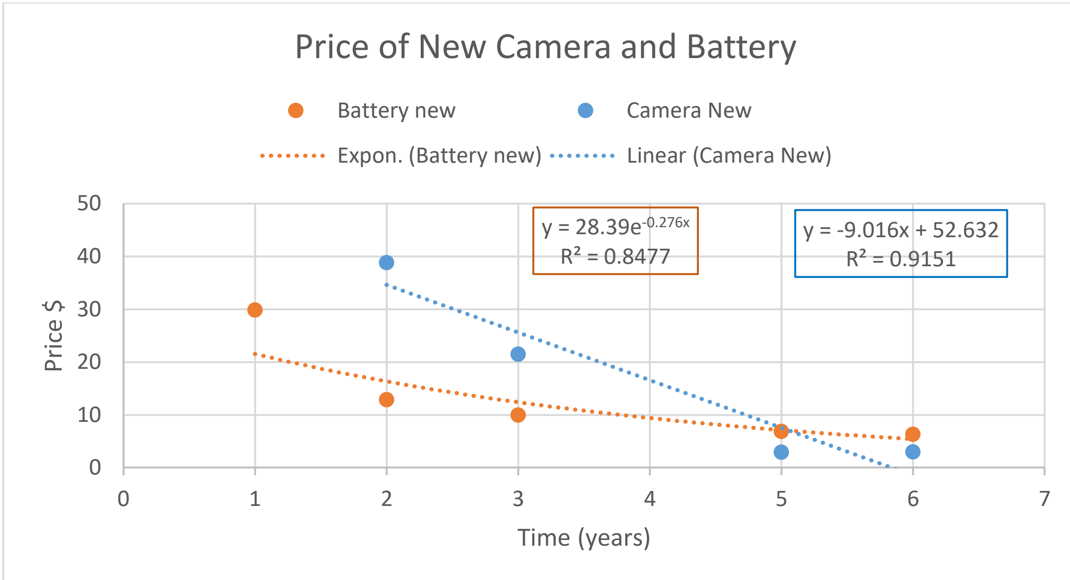
The following table shows pricing for new OEM parts by year. This price data was taken from ebay (2019) and Mobile Sentrix (2019) in April 2019.

Year	2013	2015	2016	2017	2018
t	6	5	3	2	1
Component/Model	5S	6	7	8	XS
Home button	$1.16	$1	$7	$7.26	N/A
Charging port	$1.71	$4.1	$6.85	$8.68	$11.2
Display New	$16.09	$25.76	$47.54	$73.93	$348.88
Camera New	$3	$2.96	$21.5	$38.81	$39.77
Battery	$6.35	$6.89	$9.98	$12.89	$29.83

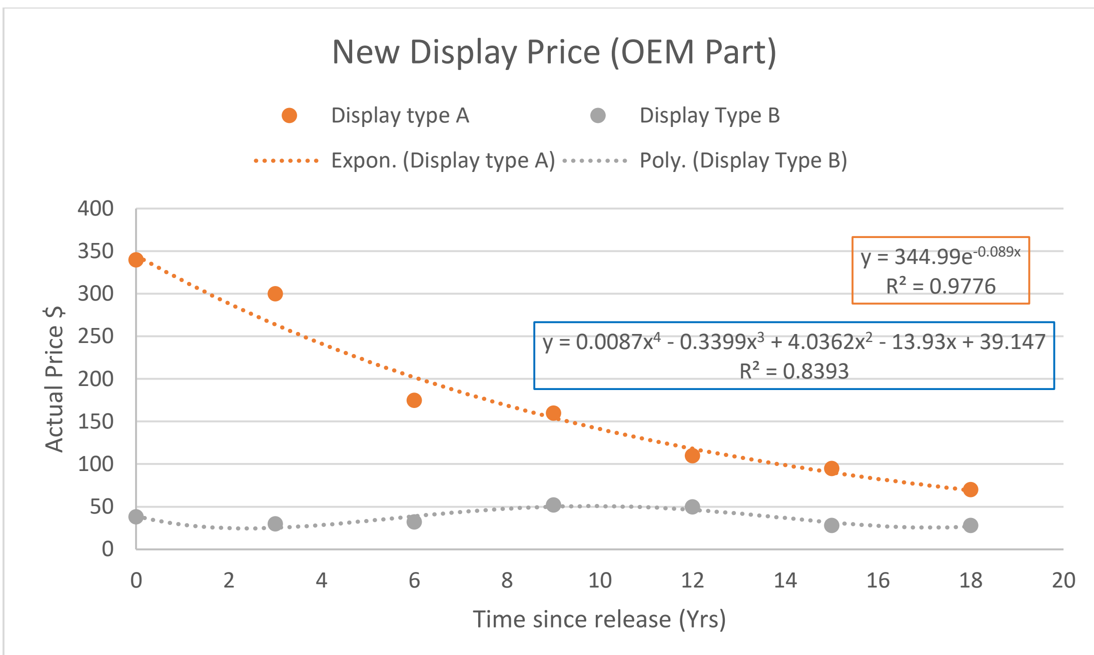
The following table shows pricing for used OEM parts by year.

Model	5S	6	7	8
Year	2013	2015	2016	2017
t	6	4	3	2
Home button	26.69		6.97	20
Charging port	8.8	24	13	30
Display	42	33.38	50	106
Camera Used	6.5	8.52	30	52

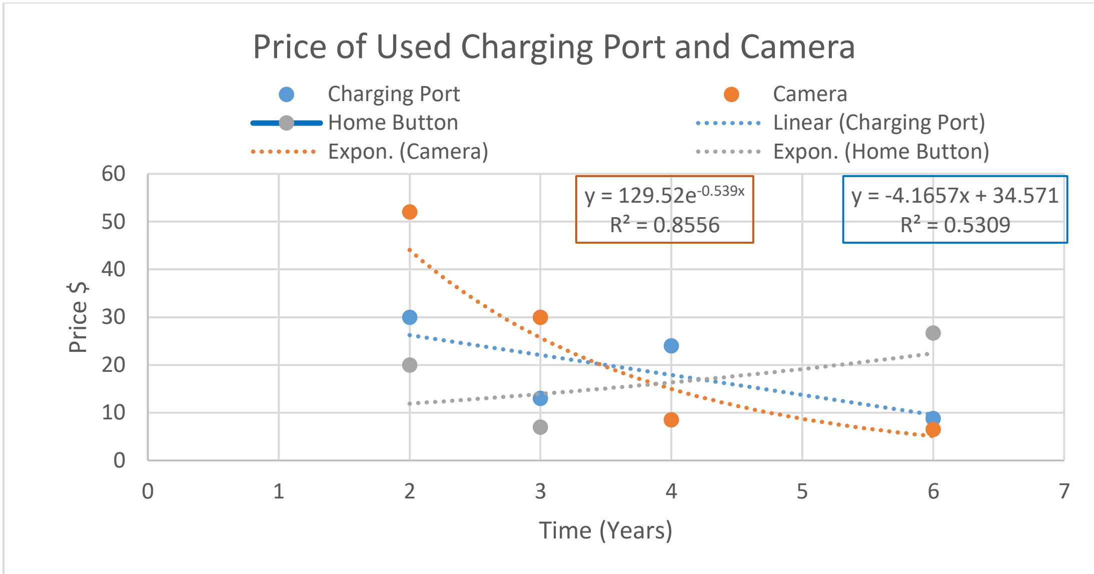


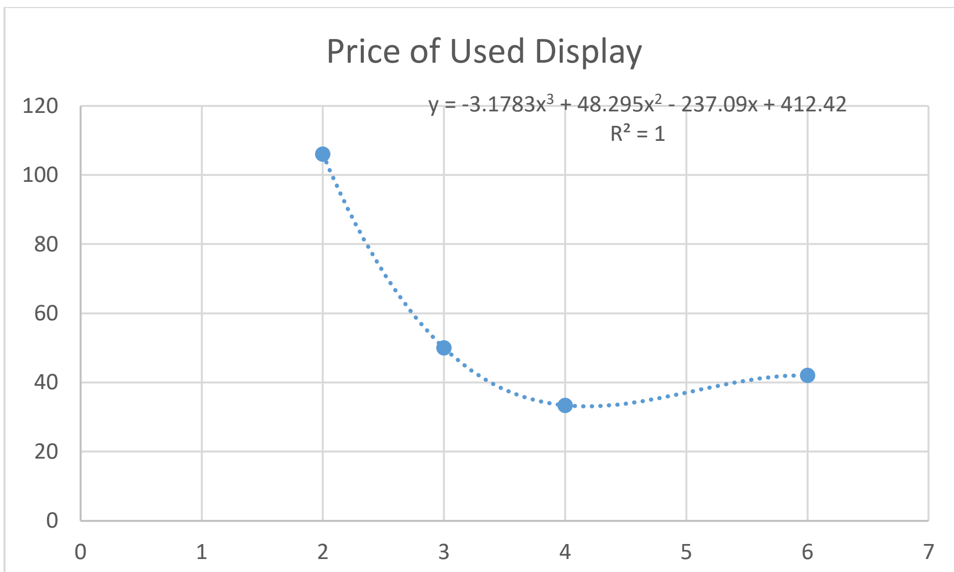


Price of New Camera and Battery
Battery new
Camera New
Expon. (Battery new)
Linear (Camera New)
y = 28.39e-0.276x
R² = 0.8477
y = -9.016x + 52.632
R² = 0.9151
Price $
Time (years)
0
10
20
30
40
50
0
1
2
3
4
5
6
7



New Display Price (OEM Part)
Display type A
Display Type B
Expon. (Display type A)
Poly. (Display Type B)
y = 344.99e-0.089x
R² = 0.9776
y = 0.0087x⁴ - 0.3399x³ + 4.0362x² - 13.93x + 39.147
R² = 0.8393
Actual Price $
Time since release (Yrs)
0
50
100
150
200
250
300
350
400
0
2
4
6
8
10
12
14
16
18
20


Price of Used Charging Port and Camera
Charging Port
Camera
Home Button
Linear (Charging Port)
Expon. (Camera)
Expon. (Home Button)
y = 129.52e^-0.539x
R² = 0.8556
y = -4.1657x + 34.571
R² = 0.5309
Price $
Time (Years)
0
10
20
30
40
50
60
0
1
2
3
4
5
6
7


Price of Used Display
y = -3.1783x³ + 48.295x² - 237.09x + 412.42
R² = 1
0
20
40
60
80
100
120
0
1
2
3
4
5
6
7

VITA AUCTORIS

NAME:	Aamirah Mohammed Ashraf
PLACE OF BIRTH:	Mumbai, India
YEAR OF BIRTH:	1993
EDUCATION:	Ibn Seena High School, Sharjah, United Arab Emirates, 2011
	University of Sharjah, B.Sc., Sharjah, United Arab Emirates, 2016
	University of Windsor, M.A.Sc., Windsor, ON, Expected 2019