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A SOCIO-ECONOMIC FORECAST MODEL FOR RETURN QUALITY OF SMARTPHONES: A CASE STUDY FOR CANADA

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ABSTRACT

Strategic planning of Reverse Logistics Networks (RLN) is necessary to ensure economic viability of the network. One of the critical issues hindering profit maximization and efficient planning of RLNs is the scarce information available on the quality grades of future returns. Effective planning of capacities for repair, refurbish and recycling for smartphones requires predictive data on incoming return quality grades of used phones. This makes it vital to have a forecast model for return quality, which is not available in the literature for the case of short-lived electronics such as smartphones. The proposed research work attempts to address this gap by developing a forecast model for return quality using artificial neural network (ANN). The novelty of this paper lies in using socio-economic factors to segment the smartphones consumer base by socio-economic factors and find smartphones usage and purchasing trends to predict return quality. The methodology begins with the selection of relevant socioeconomic factors through the collection of empirical smartphone usage data and performing hypotheses testing. A random sample is generated to represent the consumer base using Monte Carlo simulation methods. Each dataset in the sample is characterized by the parametric distribution that models the smartphones usage and purchasing behavior of the population. The dataset is then used to train the ANN model, the output of which can be used to predict expected future amounts that can be reused, refurbished, or recycled. The findings of this study suggest that age groups and region of location are valid factors that can be used to predict the return behavior and return quality of smartphones. Stakeholders along the e-waste RLN can use this data to optimize their profitability. The paper concludes with recommendations for future enhancement of this research work.

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Keywords- Reverse Logistics, Cellphone Return Quality, Socio-Economic Factors, Monte-Carlo Simulation, Artificial Neural Network, Forecast Model

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INTRODUCTION

A rising global issue is the sustainable recovery of waste of electrical and electronic equipment (WEEE). This waste is generated in large amounts every year. And cellphones are one category that contributes majorly to this waste. The rapid generation of WEEE from cellphones is a derivative of the same elements that favor frequent sales: fast technological improvements, new functionality and models, and marketing strategy and sales that lure consumers to change their cellphones with recent ones more frequently. This situation has caused a short lifecycle for cellphones. The average life of a cellphone in Canada is 30.6 months. This leads consumers to replace their device in less than three years [1] (Communications Monitoring Report, 2017). To assure sustainable use of natural resources and reduce toxic waste, governmental regulatory authorities in several countries have implemented stringent regulations, which bind original equipment manufacturers (OEMs) to be responsible for recovering their products from the consumers and reprocessing them in an environmentally friendly method. The most common recovery operations in the context of returned cellphones are direct reselling, repairing, and refurbishing, before being scrapped for materials/components harvesting and recycling.

Reverse logistics implementation is a cost intensive investment for manufacturers. It is challenging to design a robust network due to three major uncertainties: the volume, the quality, and the timing of end-of-use (EOU) returns. These uncertainties are attributed to the randomness of consumer behavior about their purchase frequencies of a product, their usage intensities, and their willingness to either return, or store the product at the end of its life. One way of enhancing reverse logistics network (RLN) designs against these uncertainties is to develop quantitative forecast models for the volume, quality grade, and timing of product returns. In the literature, several works have addressed the issue of forecasting product returns ([2], [3], [4], [5]). Additionally, forecast models for the timing of returns have been developed such as that by [6]. However, while there is a well-developed body of forecasting of return volume and timing, there is insufficient literature that presents a practical model to forecast the quality of returned products, especially in the context of short-lived consumer products, such as cellphones. To address this gap, the objective of this paper is to develop a forecast model to predict the return quality of end-of-use cellphones. The outcomes of this forecast model can enhance the reprocessing of used phones.

The novelty of this study lies in using consumer behaviors based on socio-economic factors to gauge cellphone purchasing and return behaviors. Relevant data is collected from existing surveys about how often consumers, from different socio-economic groups, purchase new phones, and how often they dispose their old phones ([7] Forum

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Research, 2018; [8] CWTA, 2016). A second dataset is collected on the average number of hours these consumers spend using their phones daily. These two datasets are amalgamated and analyzed to find trends in timing of return of a cellphone and its cumulative lifespan in hours. Since the quality of a returned phone is directly dependent on its lifespan and timing of return, these trends are used to formulate a forecast model to predict the return quality of the product.

LITERATURE REVIEW

The functional condition at the time of return defines the return quality of a product. Return quality can be modeled as a direct function of the total lifetime, i.e., total hours of usage of a device. The quality of returns is stochastic and random due to the randomness of consumer behavior [9]. Total lifetime and hence the return quality of any returned product depend on user-specific variables such as the number of daily usage hours, the total length of ownership, intensity of usage and the environment in which it was used. Because these variables are unique to every individual, there is a large variance in the return quality spectrum of cellphones. The resulting uncertainty hinders effective planning of many strategic, tactical, and operational aspects of the RLN, which in effect, leads to reduced profitability.

To understand the significance of forecasts of return quality, the paragraphs below present a review of relevant literature, which highlights the influence of return quality on several RLN decisions, and how these decisions can be improved with prior knowledge of return quality through the proposed forecast model. Recent literature on reverse logistics seems to be focusing on the latest trends of Industry 4.0 and circular economy ([10], [11], [12]). Another set of studies investigates the economics of RLN ([13], [14]). However, many of the major concerns on uncertainty of return quality in RLN remain a main issue, but they have not been investigated in the literature. The focus of this section is to conduct an exhaustive review of models dealing with return quality and forecast models in RLN.

Return Quality and its importance in RLN

Quality has always been a critical concern in forward logistics and manufacturing of new products.
Giovanni and Zaccour (2018), [15] consider the impact of return quality on pricing strategies in the case of active and passive returns. Their study finds that for products with passive returns, manufacturers should establish a flexible pricing strategy according to the improvements in quality. On the contrary, for products where the returns are active and dependent on quality and price, either the manufacturer can afford to have a rigid, or flexible pricing strategy

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based on its business interest. This way, the manufacturers can avoid the sub-optimality that can result from over pricing in non-conducive sales markets.

To plan the investments and capacities of the processes of repair, refurbish and recycling, it is necessary to have prior information of the estimated number of returns for each type of the recovery options (with return quality categories: good, moderate, and bad). Pochampally et al. (2008), [16] acknowledge the above problem by indicating that in network design, some predefined ratios of volumes that will proceed to specific recovery options, are used in the planning phases. They cite papers that propose directing returned products to processing options by supposing proportions or fixed quantities for each recovery process.

In tactical and operational supply chain management, knowledge of return quality of the products affects pricing of returned batches and acquisition policies in cases where the OEM is not directly involved in the collection of end-of-use (EOU) products. When buying batches of returned products from third-party or informal collectors, the quality ratio of the batch is the determinant factor in pricing decisions for the seller and the buyer (recycler). Precise information of the quality ratios of the batch can lead to fair pricing, which is profitable for not only the seller, but the buyer as well ([17], and [18]). Thus, we see that predicting return quality is important in the context of RLN. However, very few existing studies address this topic. The next paragraphs present a review of these studies.

Forecast Models for Return Quality based on Empirical Data

Lu et al. (2020), [19] devises an optimization model that includes uncertainties in quantities of return flows, but with no consideration to uncertainty of return quality. In addition, another study by Trochu et al. (2020), [20] attempts to model early separation of wood waste by factoring in the difference in return quality of wood. However, the factors that can be considered to predict return quality of wood cannot be applied to electronics, which contribute to excessive amounts of waste every year.

Mashhadi and Behdad (2017), [21] considers empirical data on laptop usage from a sample of students to generate probability distributions for the remaining useful life of laptop batteries. This data is used with the exponential distribution of the batteries and a linear cost model for remanufacturing to calculate the expected profits from the three possible recovery options: refurbishing, remanufacturing, and recycling. Another study that successfully incorporates consumer usage data with economic trends to predict return quality is by Liang et al. (2014), [22], for the case of lithium-ion batteries in electric vehicles. They model consumer usage based on historical data, and consumer return

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behavior using inverse Gaussian distribution to create a joint probability distribution for the remaining useful life of the battery. Xia et al. (2022), [23] presents a comprehensive review evaluating end-of-life automobile-quantity forecasting methodologies. Huster et al. (2023), [24] addresses various forecasting assumptions and their effects on remanufacturing capacity planning of EV lithium-ion batteries. The common aspect in the above-mentioned papers is that the selected product by the authors has a reliable and stable usage pattern. All automobiles, electric vehicle batteries, and laptop computers, are characterized by long lifecycles and balanced and expected market trends in comparison to a volatile cellphone market. The vulnerability of cellphone consumerism creates a challenge in predicting consumer usage and hence, predicting return quality.

Research Gap

The above-mentioned studies recognize the impact of return quality in supply chain planning, but there are no studies to quantify the accurate return quality of incoming products. So far, they have been assumed either deterministic or stochastic following a probability distribution chosen based on opinion. There has been no effort to find the probability distribution of return quality based on the actual consumer return behavior, or to predict expected return qualities in a multi-period setting for short lifecycle consumer electronics.

Most of the existing RLN models use predefined return quality ratios that are either deterministic or are drawn from historical data. However, both these sources can be misleading in the context of cellphones. Firstly, return quality of cellphones cannot be deterministic due to the random nature of consumer usage behavior. Secondly, any conclusion drawn from historical data cannot be expected to hold reliability in the end due to the rapid technological advancements and the short lifecycle of cellphones. Historical data needs large data collected over a considerable time. For the cellphone market, this method is unreliable because of the lack of stability of sales or return trends, along with other factors that affect the dynamics of the market. This information can be made available through a forecast model for return quality.

To summarize, the aim of this paper is to contribute to the literature on reverse logistics by addressing one of the key concerns, which is to reduce the uncertainty of return quality. This research attempts to address this issue by developing a forecast model to predict the quality of future cellphone returns.

The novelty of this model lies in finding which socio-economic factors hold enough statistical significance to influence consumer cellphones behavior, and subsequently using those factors to make a prediction of the end-of-use quality of

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cellphones. The methodology uses Monte Carlo (MC) simulation methods to generate a random sample that can represent cellphone users. The model then inputs the random sample into an ANN, which is trained to forecast the return quality of individual returns. The use of ANN model is motivated by the fact that while there is enough data to train an ANN model, there is not enough historical data to warrant the use of the well-established or traditional forecasting methods. Moreover, the use of an ANN model is flexible and could learn by itself. The model would also produce output that is not constrained by the input initially given or introduced in the model.

The remainder of this paper is organized as follows: The section below provides a detailed explanation of the methodology of the forecast model. Subsequently, an analysis of the ANN model along with discussions on how to apply the results in practice is presented. Finally, the paper concludes with recommendations for future extension of this research work.

METHODOLOGY

The proposed method begins with gathering and analyzing data on how consumers purchase and use their cellphones, with the socio-economic factors being the independent variables. The two dependent variables for this step are daily usage in number of hours and purchase frequency in number of months. The flowchart in figure 1 presents the adopted methodology. We first provide detailed explanations of steps 1 to 4. Then, we tackle steps 5 to 8.

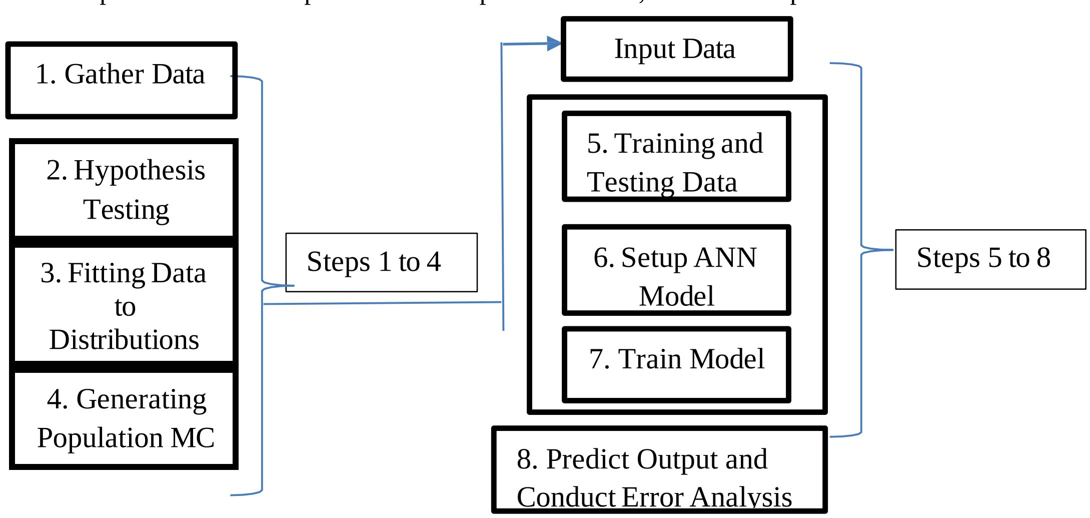

Fig. 1: flowchart of the methodology to forecast return quality

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Random Sample Generation Using Monte Carlo (MC) Methods

The first step is to perform a statistical analysis to find which of the five socio-economic factors influence the daily use and duration or length of ownership of cellphones. The five socio-economic factors initially chosen for the statistical analysis are age, income, gender, education level, and region (province of residence, urban, rural). The procedure to find which of these factors are of the highest relevance, is as follows:

1) Gather data on daily usage and frequency of purchase from individual users along with their age, income group and region. This can be collected either through retail points where new phones are purchased, used phones are returned, or through surveys. For the case of this study, the data is extracted from existing surveys, after obtaining rightful permissions from the owners ([7], [8]). The obtained data is for the consumers in Canada, and is presented in the form of two-way tables, with age groups as columns and the variable "number of daily usage hours" in the form of rows. The age groups presented in this work are 18-24, 24-34, 34-44, and 55 years and above. Similarly, two-way tables are provided for income groups and provinces. The five income groups presented in the study are: below \$20K, \$20K-\$40K, \$40K- \$80K, \$80K - \$100K, and above \$100K. The stated income is in Canadian dollars before tax deductions. For the case of region, the data collected in the survey was for each province separately, except for the group of Atlantic provinces, which were considered collectively.

2) Perform hypothesis testing to test dependence of daily usage on each of the five socio-economic factors separately. Repeat the statistical analysis to find the dependence of the second output variable, which is purchase frequency, with all five socio-economic factors. Select the relevant input variables based on the p-value criterion for the hypothesis testing. In the case of this study, this test of association was performed using the chi-square test of independence in Minitab 18, with a significance level, $\alpha = 5\%$. The p-value of this hypothesis testing is shown in table 1. The results of the test suggest that age is the most statistically significant input variable in determining both output variables: daily usage, and purchase frequency, with a p-value less than 0.05. According to the results, regional differences do affect the purchase frequency of cellphones. The provinces of Quebec (QC), Ontario (ON), British Columbia (BC), and Alberta (AB) have statistically similar consumer behavior about cellphones usage and length of ownership. However, compared to the consumers from the province of Manitoba (MB) and the Atlantic provinces, there was a large difference. Similarly, there was a statistically large difference in the behaviors of consumers from Manitoba as compared with the Atlantic provinces. Manitoba and Saskatchewan have statistically similar consumer behavior. The results further suggest that the factors gender and education level do not have enough statistical significance. Hence,

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statistically similar provinces have been represented by one single province. For example, since Manitoba and Saskatchewan do not exhibit significant variation in cellphone usage behavior, the ANN model shown below on page 257, will consider both provinces as one, Manitoba.

Table-1: hypothesis test results to find relevant socio-economic factors

	Category	Null Hypothesis	P-Value	Result
AGE	18 to 65+	Daily usage and age are independent	0.000	Reject
INCOME	<$20K to $250K	Daily usage and income are independent	0.001	Reject
EDUCATION	High school to post-graduate	Daily usage and education are independent	0.251	Fail to Reject
GENDER	Male or Female	Daily usage and gender are independent	0.661	Fail to Reject
REGION/ PROVINCE	Atlantic, ON, AB, SK, BC, QC and MB	Daily usage and geographic location are independent	0.015	Reject

From the above discussion, it is apparent that age, household income and region are the most relevant socio-economic factors to gauge cellphone usage behaviors and cellphone length of ownership (i.e., purchase frequency).

Once the selection of relevant input factors is completed, the next step is to create a random sample of the consumer base using Monte Carlo simulation methods. To do this, the first step is to find the parametric distributions that best represent the consumer usage and length of ownership behaviors. Histograms were plotted and fitted to distributions as per figure 2. Kolmogorov-Smirnov methods were conducted for testing the goodness-of-fit. The parametric values considered to generate a population whose daily usage hours and purchase frequency depended on the probability distributions, based on the age of each sample in the population. Regional dependencies of usage and length of ownership are factored into the model by means of population density of the associated province. The age distribution of the population in each region is also considered using the percentages of each age group; see [25].

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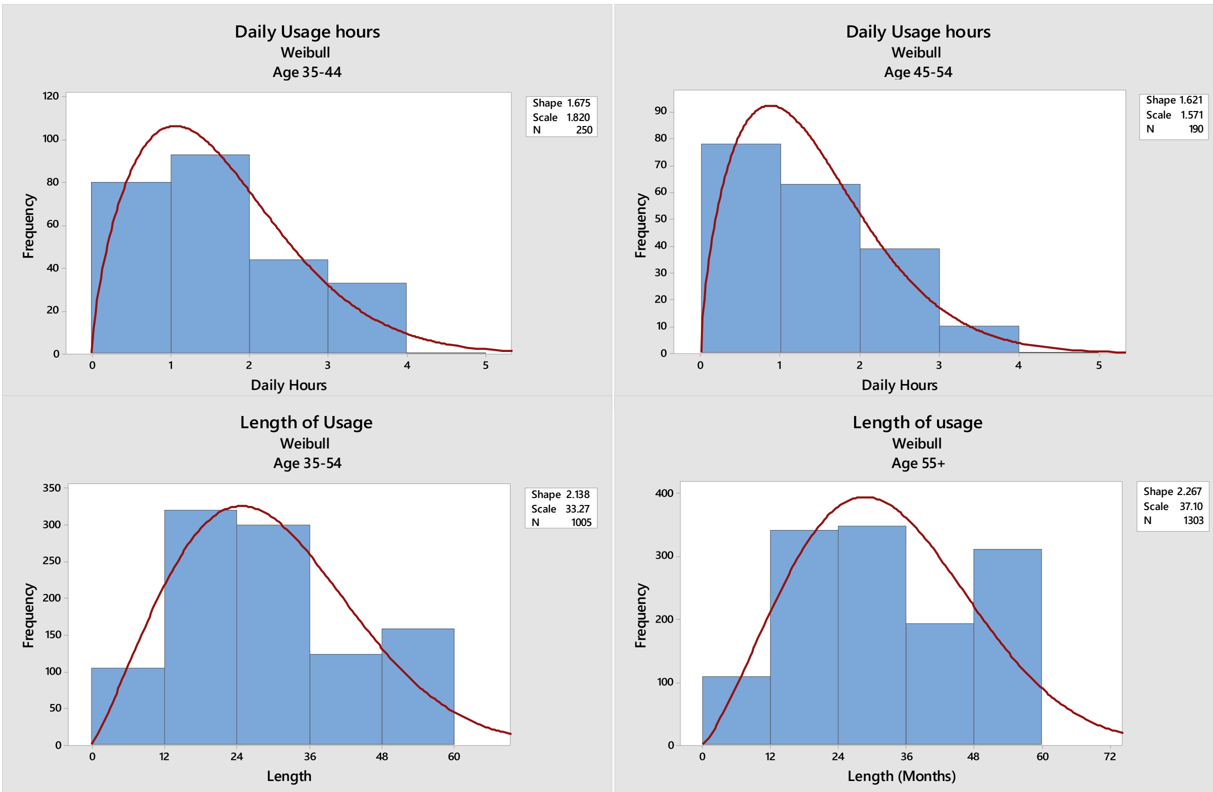

Fig. 2: probability distributions from empirical data for different age groups

Although income is found to be a critical factor, there is insufficient data currently available to plot the probability distributions on the dependence of income on length of ownership. Moreover, because income and age are interrelated, there should be a dataset with information on each specific user's age, income, and usage. Such a dataset would be necessary for accurate training of the model, so that the return quality prediction would be more accurate with respect to age and income. Due to the lack of such data in existing surveys, the income factor has not been included in the study. However, this does not affect the methodology, which is versatile, and can be applied by end-users to predict income-dependent return quality once the appropriate training dataset becomes available.

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The steps of generating the sample data for each province using the parametric values are as follows:

a) Find the age group distribution of a province.
b) Generate a population sample using the age group distribution. The population size is N= 1000.
c) For each data point in the sample, randomly assign a daily usage value to each data point based on the age using the parametric distribution for the appropriate age group and region.
d) For each data point in the sample, randomly assign a length of ownership value to each data point based on the age using the parametric distribution for the appropriate age group and region. And
e) Each data point in the sample is associated with its region by means of the population density of that province.

This completes the formation of the random sample data needed to proceed with the creation of forecast model for return quality. Alternative to using Monte Carlo simulations for dataset creation, empirical data captured at retail points, whenever possible, can also be used going forward with the proposed methods in this study.

The third step of the methodology is to predict the return quality level of each of the returns individually, and it is as follows:

a) Predicting the profit margins from each of the three recovery categories (reuse, refurbish, recycle); and
b) Assigning each returned unit with the return quality grade that corresponds to the maximum profit.

This study assumes return quality as a discrete random variable with values 1, 2, or 3, which linguistically corresponds to good, moderate, or poor quality. Units categorized with return quality 1 are eligible for direct reuse by simple cleaning and repackaging. They represent the lowest reprocessing cost and highest profit margins, depending on the market value of the product. The criteria for a unit being eligible for reuse are that the unit should be fully functional, and in no need of any repairs or parts replacement. Units categorized with return quality 2 are eligible for repairs or refurbishing, depending on the number of repairs or parts replacement they require, and the economic viability of performing these operations based on real-time market value. The last quality grade, return quality 3, corresponds to materials recycling, which may be the most suitable recovery option for returns that are damaged for direct reuse and cannot be refurbished economically. Thus, return quality (RQ) classification is a function of both, functional status, and time-based market value of the returned product, where functional status is dependent on total usage hours of the device, and market value depends on the timing of the return. For the case of this study, the probabilistic failure rate data is derived from a study by Wang & Huang (2013), [26], who use censored field failure data of cellphones and fit

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the data to a parametric distribution to predict the time to failure of a device based on its total usage hours. Through their model, it was found that the lognormal distribution is the most appropriate distribution to model failure rate of

cellphones after n years of usage. For the case of this study, the data presented by [26] was inputted into Minitab's software to replicate their results, and find the parameters of the survival plot, which follows the lognormal distribution as mentioned above. With the help of the probability of survival plot, it becomes possible to determine if a future return will have zero component failures based on its total hours of usage. This makes it possible to determine if a return will be eligible for direct reuse, which is represented by return quality 1.

The second factor that affects return quality has been identified as the market value of the product, a crucial factor for making profitable recovery decisions for short-lived electronics due to their volatile, time-dependent market value. For fixed value of total usage, the quality grading of the returned unit will vary based on the timing of the return. This is because the product lifecycle stage influences the demand for the product in this secondary market, which directly affects the profitability, and hence the individual decision of whether to refurbish the product [27]. Similarly, for a given time or period, the quality grading decisions will also depend on the status of the phone since refurbishing and repairing costs are dependent on the functional status of the phone. If the refurbishing costs are high in comparison to the market value, then the individual unit may not be assigned to return quality 2, but rather to return quality 3, which makes it only fit for recycling. Although recycling is the least favorable recovery option economically [28], sometimes it is the most feasible option from a business model point of view. To incorporate the market value dependence of return quality into the model, pricing data for reused and refurbished phones is collected from e-commerce websites for the period ranging from 2013 to 2019. This helps in obtaining reliable secondary market value trends for reused and refurbished phones separately (Mobile Sentrix, 2019, [29]). Through curve fitting (see figure 3 below) of the generated trends, the equations that can model the time-based market value of cellphones were formulated. For the given data in this study, curve fitting provided a higher R^2 value for a 4th degree polynomial curve as compared to the exponential curve. However, to align with expert opinion and the consensus that value depreciation is exponential across all types of products, the 4th degree polynomial has not been used in this study. The equation used for the remaining value curve is in the form [1- S_0×e^(-at)], where S_0 is the initial product sale price, a is the depreciation constant, and t is time in years after the release of the product. Based on the data collected from [29], the value for "a" was found to be a= 0.46. So, Remaining Value= 1- S_0 ×e^(-0.46t).

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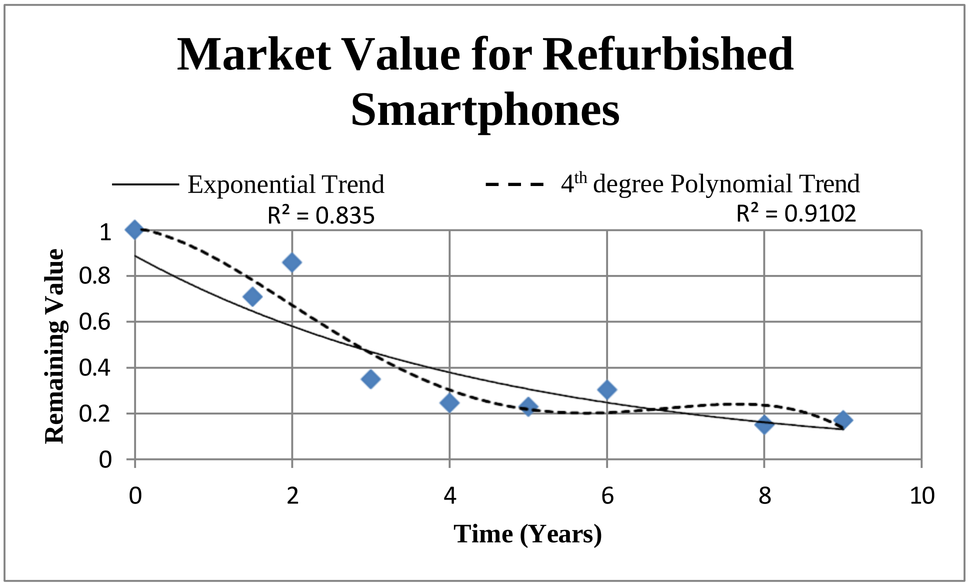

Fig. 3: market value of refurbished phones from online data [29]

Additionally, data was collected from websites to model refurbishing costs and calculate refurbish profits analytically. The equations comprehensively include the factors that affect profit revenues from recovery options that are: 1) total usage hours of phone, denoted by the letter u, and 2) length of ownership of phone in years, denoted by letter T.

It is good to note that refurbishing costs and refurbishing profits are sensitive to both u and T. While the equation for refurbishing revenue was derived from real time e-commerce data as mentioned above, the equation for refurbishing cost was adapted from [30] as it is as follows:

$$\text{Remanf Cost}\,(u, T) = \sum_{i} P_i(u) \times \text{Component Price}_i\,(T)$$

Where the Remanufacturing Cost of each unit depends on:

$P_i(u)$= probability of failure of a component i after being used for u hours, and

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Component Price_i (T)= cost of buying a new component i to replace the failed component at time T.

The revenue from direct reuse was similarly modeled by collection of pricing data of used phones with respect to length of usage, from e-commerce websites. In addition, revenue from direct sales depends on T. For this study, it is assumed that the costs of directly reusing a product are negligible since such products do not require any repairs. Therefore, revenue from direct reuse from sales is equivalent to profit obtained from that sale. The equation for revenue from direct reuse is:

$$Reuse\ Price(T) = S_0 \times e^{(-0.202T)}$$

Where S_0 is the initial sale price at T= 0 for a new product unit.

Since the cellphones consumer market is volatile, the pricing trends and their equations are dynamic. The model exhibits flexibility for such situations by allowing alterations to profit equations in an easy manner.

Artificial Neural Network Model

This section considers steps 5 to 8 that were identified earlier in Figure 1. The final step of this methodology, before inputting the data into the ANN model, is to analyze the profit generated from the three recovery options and apply that toward the prediction of the return quality group. From a business model perspective, each returned product should enter the recovery stream that yields that maximum amount of profit. The sample layout of the input and output variables in the training dataset is presented in figure 4 below. With the training dataset created and the profit-based criteria for predicting return quality established, the next step would be to create an ANN model, and train the model using the training dataset, so that it can predict the recovery profits for each type of the returns.

The input for the ANN model will be the age of each individual consumer and the population density, which has been taken in this model as a numerical characteristic of each region. The outputs of the ANN model will be:

1) Total Usage Hours, 2) Purchase Frequency, 3) Profits from reuse at time of return, and 4) Profit from refurbishment at time of return.

The outputs from the ANN model will be saved in a spreadsheet, where the profit maximization function will be applied to individual data points to assign the final return quality. A histogram will then be plotted to visualize how many returns are assigned to each recovery option for predicted returns.

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It must be noted that the Return Quality (RQ) number cannot be predicted as an output in the ANN model and must be calculated based on the profit data. This is because it introduces complexity in training the network due to multiple datasets having the same return quality values of either 1, 2, or 3. This makes it necessary to train the ANN model for predicting the recovery profits first, and then separately analyzing the profit values to predict the return quality grades. It is good to note that, since recycling profits are independent of the return conditions of the phone, they have been set at a constant value of $100 for this study.

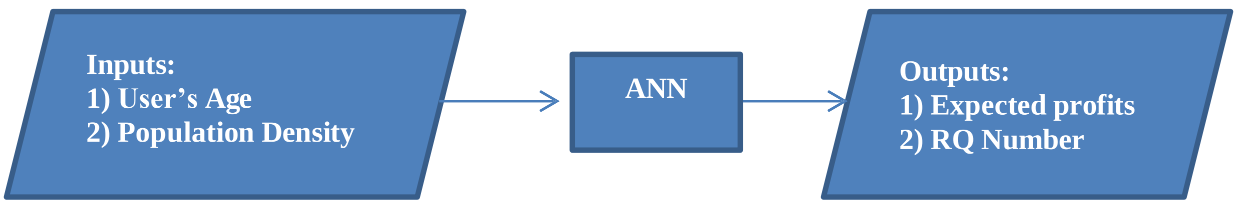

Fig. 4: inputs and outputs of the ANN model

A sample of the dataset (with the input and output variables shown above in figure 4) consisting of 1000 data points was used as a training set for the ANN. Two additional datasets, each with 1000 and 100 data points were generated for validation and testing dataset, respectively. The partition of the sets for training, validation, and testing was done manually in the software. The ANN model was built and trained in MATLAB 19.0 using the ANN interface available in the deep learning toolbox. The training was done using the forward feedback propagation method for 1,000,000 epochs with a learning rate of 0.001. The target error was set to 0.0001 as an optimum value. It was found that having smaller errors increases the simulation time without significantly improving the accuracy of the results. Since the ANN predicts profit values, which are classified into RQ numbers, an error of 0.0001 is undoubtedly acceptable. The optimum configuration of the neural network was two layers with 10 neurons in the first layer. Through trial and error with the set of training algorithms available in MATLAB19.0, LearningLM and LearningR provided the best results for the given dataset. However, LearningLM completed the simulation in a shorter amount of time, less than 190 seconds with lesser iterations as compared to LearningR. The latter required over 100 iterations and took longer than 30 minutes without producing significant improvement in the results. For this reason, LearningLM was considered for the given dataset.

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Through the results produced, the ANN model was successfully trained to predict total usage, return timing, and recovery profit for a returned cellphone, if provided with the age of user and region (population density) as input. According to the error analysis feature provided in MATALB's ANN tool, the R-value was 0.99 for testing the dataset, see figure 5, below.

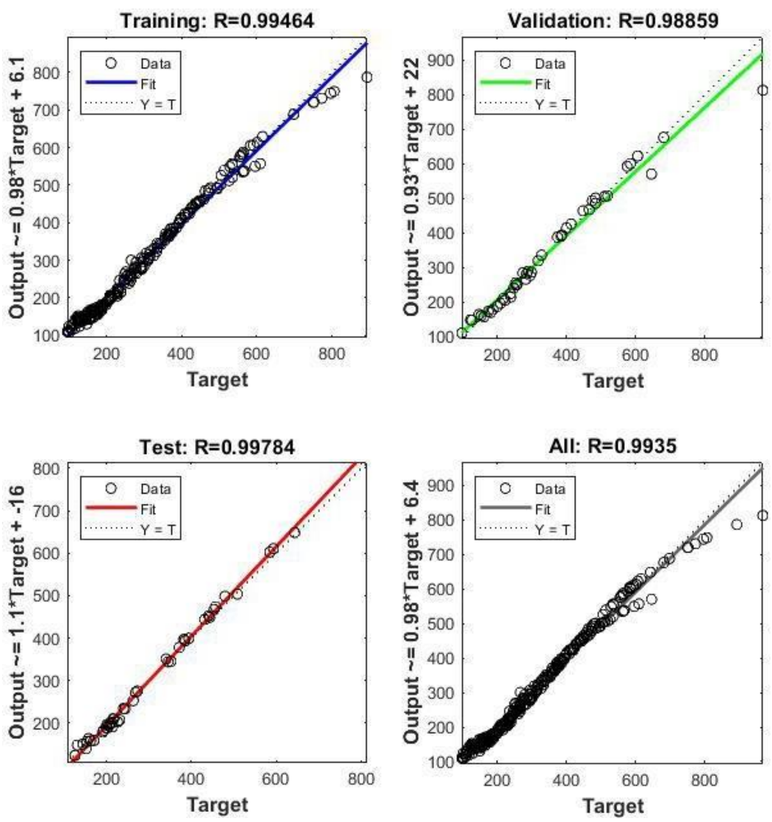

Fig. 5: analysis of ANN model results

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ANN Model Results Analysis and Discussion

This section has four subsections. The first one discusses the performance of the ANN model and related error analysis. The second is about the positive findings enforcing the dependence of return quality on region and age distribution, along with comparison to published literature. The third subsection tackles profitability calculations. Finally, discussions on the applicability and implementation of the model in practical scenarios are presented.

ANN Performance and Error Analysis

The output of the ANN results, consisting of the predicted recovery profits from each of the 3 recovery streams for each return were saved into a spreadsheet. The profit maximization function was applied to assign each return in the dataset to a return quality group as shown below in the last column of table 2. The plot in figure 6 shows the comparison of the actual return quality number/group of each data point in the testing dataset, compared with the predicted return quality number for corresponding data point obtained from the results of the ANN model.

The R value of 0.99 obtained for the ANN model in figure 5 and the results shown below in figure 6, validate that the ANN model has been successful in achieving the following objectives: 1) Predicting usage and failure probability of any device based on a user's age, 2) Predicting the time-dependent profits from given recovery options, and 3) Providing reliable results that can be processed to predict return quality of cellphones with only one input variable, which is the user's age.

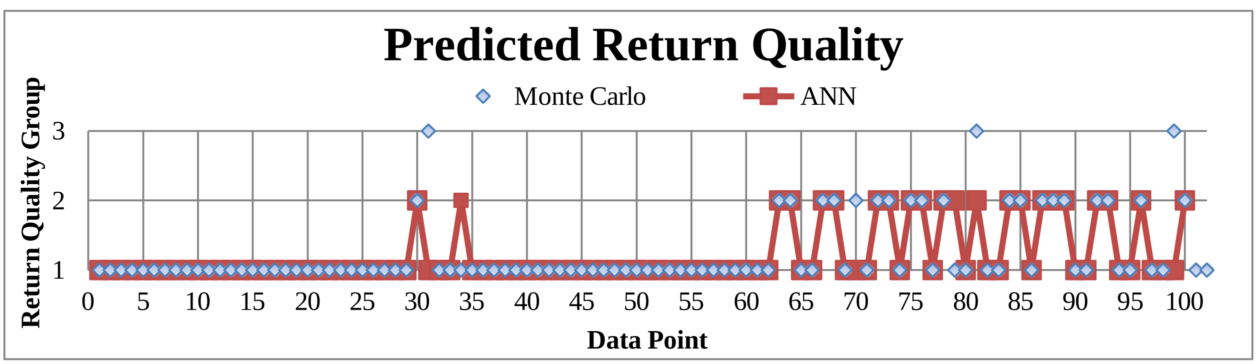

Fig. 6: comparison of the ANN model results with Monte-Carlo testing dataset

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The two numerical examples shown in table 2 below are for two randomly generated users of age 22 years and age 31 years for whom the end of use cellphone device would have incurred a total usage (according to the ANN prediction) of 1094.0 hours and 2736.7 hours, respectively. Based on the usage value, the ANN model predicted the expected profits from the three recovery options available, which are direct reuse, refurbish, and recycle. By applying the maximum profit function on these values, the cellphone returned by the 22-year-old user would be eligible for direct reuse, while the best recovery option for the device returned by the 31-year-old user would be refurbishment. These results produced by the ANN model are logical since the second device has a longer lifetime, its failure probability and repair costs may be higher. This makes the device unsuitable for direct reuse. Comparing this result to the first device that has a shorter lifetime of only 1094 hours, makes it possible to assign the first to RQ 1. This is due to a possibly better return quality.

Table-2: ANN results showing predicted return quality

ANN Inputs		ANN Outputs			
Age (Yrs.)	Population Density (/km2)	Usage (Hrs.)	Reuse Profit ($)	Refurbish Profit ($)	RQ
22	1444.3	1094.0	615.17	442.97	1
31	238.7	2736.7	150.65	207.83	2

Through the above discussion, the ANN model seems trained appropriately and can be used to predict the quality of future returns.

RESULTS AND DISCUSSIONS

This subsection presents the results of the ANN model, which are the predicted return quality for cellphone returns from different cities in Canada. The graphs in Figures 7 to 9 below, present “return quality ratios.” By considering batches (each of 1000 units) from different Canadian cities, these return quality ratios provide the number of returns expected to enter the reuse, refurbish, or recycle stream. The equation below shows the return quality ratio for the direct reuse option. Additionally, the graphs in figures 7 to 9 present the length of ownership, denoted by T in years. This is with the assumption that at time T= 0, all devices were new. Results have been generated for different cities

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across Canada to illustrate the differences between return qualities based on age and regional distributions. From the results, cities like Toronto, Vancouver and Winnipeg represent large urban population centers across the three provinces of Ontario, British Columbia, and Manitoba, respectively. In addition, cities like St. John's in Newfoundland and Labrador (NFL) and Kingston (Ontario) have been included to represent smaller population centers.

$$Return\ Quality\ Ratio\ for\ Reuse = \frac{\#of\ Returns\ Expected\ for\ Reuse}{Total\ Number\ of\ Returns}$$

The following discussions highlight the findings of this study:

Result 1: Different regions produce different return quality ratios because of varying age distribution and regional consumer trends. This confirms the hypothesis suggesting that age and region can be used to forecast return qualities; see figure 7 below.

Result 2: Identical population centers have similar consumer behavior and thus, similar return quality ratios even though their age distributions might be different. This can be seen in figure 7, which shows that all the large cities, Toronto, Vancouver, and Winnipeg have similar return quality ratios despite the differences in the age distributions of their population. This means that these cities have no difference in return quality, despite different geographical locations. Consequently, the consumers' usage and return behaviors in the above-indicated three cities can be explained as comparable in identical population centers.

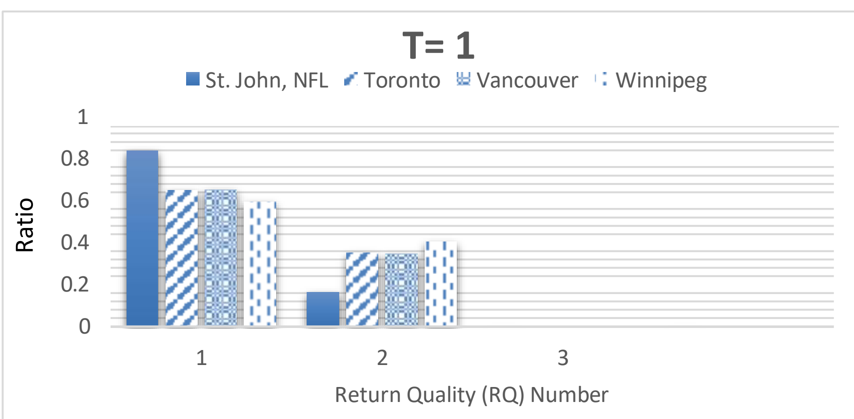

Fig. 7: ratios of return quality for T= 1 by city

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Result 3: The ratios of the return quality are dependent on length of ownership T. This is contrary to the literature that assumes deterministic and constant return quality ratios in a multi-period setting. However, from figure 7 and figure 8 the return quality ratios for period T= 1 year, are very different from the ratios for T= 2 years. The results suggest that the return quality ratio for reuse is higher in T= 1, while the ratio for refurbishing is higher in T= 2. These results have been verified by expert opinion, which suggests that, due to low usage and the high market value of returns in the first year, the condition of returned phones is of high quality. This makes them eligible for direct reuse.

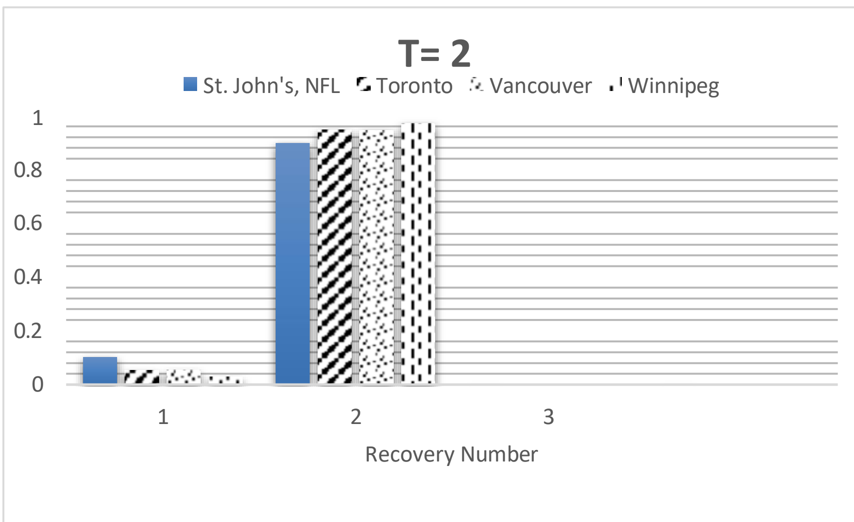

Fig. 8: ratios of return quality for T= 2 by city

Result 4: After the third year, T= 3, most returns are expected to go for either refurbishing or recycling. From figure 9, the refurbishing ratio follows a depreciating trend after T= 3. As T (in years) increases, the ratio of returns that can go for refurbishing decreases, and the ratio attributed to recycling increases. The exact ratios differ based on the city of origination of the returned products. The urban areas such as Toronto and Vancouver have identical ratios for each period. The ratios of return quality for these cities are greater than those in smaller population centers such as St.

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John's. This is because consumers in the larger city tend to replace their phones more frequently; therefore, the T value is smaller, and the quality grade of the returns is better.

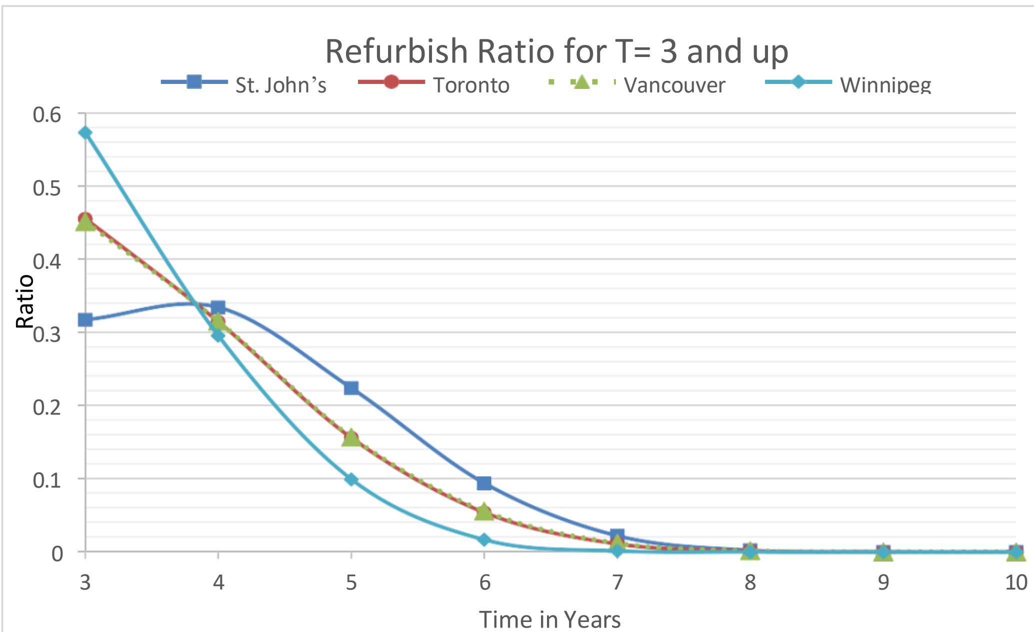

Fig. 9: refurbishing ratios by city

Profitability Calculations and Comparison of Results

In this section, an attempt is made to measure the usefulness of the proposed model in maximizing economic profitability of recovery operations. For this purpose, a comparison is made between the expected profits from the ANN model and the expected profits from the literature. The study by Blackburn et al. (2004), [31] is chosen as a reference point.

The profits are calculated for a randomly generated sample of 1000 expected returns from three cities in Canada: Toronto, Kingston, and St. John's. The sample was inputted into the ANN model to predict the quality grade of each return and to assign it to one of the three recovery options (reuse, refurbish, or recycle). The profits were then summed up for each of the three options.

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According to the results of the ANN model, see Table 3, the following conclusions are made:

1. Different cities generate different profits from the three recovery streams based on whether they are a large, medium, or small population center. This can be perceived by comparing the individual profits generated from Toronto with the profits generated from Kingston or St. John's. This result emphasizes that, contrary to existing literature, it must not be assumed that the return quality ratios from all regions can be expected to be uniform. It also emphasizes that it is important to factor in regional consumer trends of usage and return behaviors when designing network for profitability because some regions, such as Toronto, will generate more profit than other regions.

Table-3: reverse logistics profit generation by applying the forecast model

	Toronto, Ontario	Kingston, Ontario	St. John's, NFL	Literature
Profit Reuse	$64,200	$57,400	$54,800	$38,000
Profit Refurbish	$280,000	$270,400	$277,000	$200,000
Profit Recycle	$1385	$5660	$5660	
Profit Total	$345,585	$333,460	$337,460	$238,000

2. Large urban center, represented by Toronto, generates the largest profit, $64,200, from direct reuse. The other two cities (Kingston or St. John's) generate similar profits of $55,000 on average, from direct reuse. This can be attributed to the difference in the length of usage distributions of consumers in large urban areas who purchase new devices more frequently as opposed to consumers in smaller urban cities.

3. The model maximizes profit generation by optimizing the return ratios allocated to reuse, refurbish, or recycle. Hence, profit generated from recycling is negligible. On closer observation of the model results, only the returns after the third year have been attributed to recycling. This can be seen in figures 7 and 8, in which the graphs show the return quality ratios for recycling stream in T= 1 and T= 2 as zero.

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To provide a numerical illustration of the difference between the proposed results and the results in the literature, calculation of profits from the literature is based on Blackburn et al. (2004). The authors report that on average, 20% of returned products are good for reuse and can generate a profit of about $190 per unit in the reuse stream. The remaining 80% of returns can be sent for different repair options such as refurbishment, remanufacturing, salvaging, or recycling with a maximum profit of $250 from each unit. Based on this study, every 1000 returns would contain a fixed number of 200 returns that were eligible for reuse, which would then generate a fixed total profit of (200 × $190) $38,000. Similarly, if the maximum profit is assumed for each of the repaired units, then the remaining 800 returned units would generate a profit of (800×$250) $200,000. Blackburn et al. (2004), [31] assume that the return quality ratios of 20% and 80% are constant for every region and in every period. Therefore, the profits are expected to be the same regardless of where the returns originate. Additionally, they suggest that the profits will be the same regardless of the period, which means that the time-value of the product has not been factored in the calculation of the ratios.

However, the results from the proposed ANN model are clearly different because they consider both regional usage and length of ownership trends, and Market value and depreciation trends of product. The results of the ANN model provide an opportunity to maximize profitability and effectively plan network design by offering a means of forecasting profits and expected returns for different recovery streams in a multi-period setting.

Pertinence of the Model and Suggested Implementation

The model leverages the effectiveness of ANNs to provide a cost effective and efficient method for predicting return timing and quality of cellphones, which is a major concern for sustainable recovery of natural resources. The advantages of the model are that: 1) It requires straightforward inputs,

2) The results of the model can be adjusted in real time to reflect dynamic consumer behavior in volatile markets, and

3) Multiple stakeholders of the RLN can use the results of the model.

Initially, the ANN model relies on meaningful and simple input data to formulate empirical cellphone usage and purchasing trends, which can easily be obtained through survey or at point-of-sale systems when consumers buy new phones. Simple questions at retail points such as:

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"How many hours a day do you intend to use your new cellphone?"

"What are you planning to do with your old phone?"

"When do you expect to make your next purchase?"

Answers to these questions can provide sufficient data to create predictive analytics and probability distributions of total usage hours of phones, and timing of returns. The ANN model can then be updated by minimal changes in parametric values of distributions, to reflect the subsequent changes in the quality of future returns. Such methods of obtaining real-time data directly from consumers allow the quality and reliability of the results of the ANN model to be iteratively improved, by enhancing the reliability of the empirical data used in the formulation of the probability distributions. This makes the ANN model highly adaptable and versatile in multi-period reverse logistics.

Additional questions (if answered) about age and income groups at retail points can enable the creation of a database that can correlate socio-economic factors with the above-mentioned usage behaviors that can further be utilized in forecasting reliable return quality ratios and improve the profitability of strategic RLN planning. The implementation of the above-mentioned method of data collection at retail points is highly feasible from a business model perspective as well. Currently, most major retail points are already collecting data such as email addresses, postal addresses, and other relevant information at checkout points. Therefore, the idea of extracting other relevant information at acquisitions of premium goods, especially electronics, is a plausible idea.

Applicability and benefits to multiple stakeholders

OEMs: OEMs can use the results of this model for planning purposes associated with RL network design, for procurement decisions for each period, and enhancing the profitability of the overall recovery processes.

Retailers: The findings of the forecast model do not apply directly to the retailers since their activities do not carry out any reprocessing operations. Their concerns are very much with gatekeeping and collection.

Third-Party Collectors: From the findings of the forecast model, it is possible to determine the ratios of high quality of returns by location/ regions and periods. Thus, the efforts of third-party collectors can be better invested in pricing of cellphone returned batches even prior to any sampling and physical collection.

Governmental Reprocesses: Since government agencies are mandated to protect and prioritize the environment, the forecast model can support these agencies estimating the ratios of returned quality of the cellphones in all regions,

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urban and rural areas. This finding may support the recommendation of locating and subsidizing recycling centers as to favor the sustainable reprocessing of these returned cellphones in a location that do not necessitate the transportation of the collected cellphones over a long distance for reprocessing and proper disposal.

Applicability to Variety of Products

Given the purchase behavior of cellphones compared to other products such as large appliances that have a stable / predictable demand that does not change based on socio-economic attributes, the proposed forecast model is not suitable for such products. However, the model is more appropriate for products with a short lifecycle with substantial demand for reused and refurbished products that can be sold in a well-established secondary market.

Conclusion and Recommendations for Future Research

A socio-economical modeling approach based on Monte-Carlo simulation and ANN has been developed and implemented to forecast the return quality of future cellphone returns at their end-of-use stage. The proposed model comprehensively included three major factors, which influence return quality. These are consumer daily usage and purchase behavior, product length of ownership at time of return, and secondary market value of product with respect to time.

The results of this study find that the most relevant socio-economic factors to predict the return quality of cellphones are the consumer's age group, income group, and region of location. This key finding is a significant advantage for cellphones recycling and refurbishing companies as they can now predict incoming quality ratios with better accuracy and plan their production capacities and workforce accordingly. The model has been applied to the case of returns from different provinces in Canada for prediction of return quality in batches of returned cellphones. An error analysis of predicted and actual output values has been presented and the results discussed.

The results show that the model can be a useful tool in forecasting return quality ratios for cellphones based on the city of collection. The model can flexibly be used for other regions by simple alteration of consumer behavior distributions that govern daily usage and length of ownership of cellphones. Moreover, the applicability of the model extends in the same way for other products through updating of the market value equations and consumer behavior probability distributions.

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The findings of this forecast model can leverage the strategic planning of reverse supply chains by providing, in advance, information of the optimum recovery capacities required and future trends in pricing of returned batches, which both are impacted by return quality ratios. OEMs, third-party recovery companies, or even governmental organizations that are ambitious to meet sustainable development goals, can use these results.

Future research could address the challenge of how to best model the behavior of consumer trends in the case of active and incentivized returns.

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