APPLICATION OF REVENUE MANAGEMENT IN INDUCTION CAPACITY ALLOCATION OF POSTAL SERVICES

Ahmad Teymouri

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University of Ottawa

Abstract

Online shopping has been growing as an essential part of customer behavior over the past 15 years. The number of companies that offer online shopping opportunities has increased while customers have become enthusiastic online shoppers. The parcel volumes are collected from different online retailers (e.g., Amazon, eBay, Shopify) and delivered through the logistics networks of delivery companies and postal services. The fast-growing parcel volume, specifically e-commerce parcel volume, has turned induction capacity management into a serious challenge for postal organizations. Induction is the first step of the processing where the parcel volume gets inside the processing facility and starts its flow through the postal services supply chain.

Postal services should allocate the existing capacity to the dynamic and increasing parcel arrival patterns of online retailers. The literature suggests overcoming this challenge by increasing the efficiency of the sorting equipment (i.e., optimized sort schematic and machine scheduling) or by increasing the productivity of the transportation network (i.e., higher truck utilization, optimized routing). However, these solutions, which are mainly considered as a part of the traditional supply chain, are cost-sensitive, temporary, and sometimes not feasible for postal services. Hence, most of the developed models focus on improving the operations performance indicators but not the revenue. Revenue Management (RM) has been applied in many industries (e.g., airlines, hotels, air cargo, rail freight) that have fixed and perishable capacity, and it should be utilized over a finite period of time. Successful applications of the RM allow many companies to generate higher revenue and increase their business profitability through overbooking, forecasting, and capacity allocation. The postal industry has not implemented RM approaches to address the capacity allocation problem. This research fills this gap and explores the application of revenue management techniques for allocating limited induction capacity among different classes of customers and develops a model to compute an optimum allocated/protected capacity. The developed induction capacity allocation model allows maximizing the expected revenue of postal services. This thesis contributes by developing an innovative solution for induction capacity allocation in postal services. The model implements the dynamic arrival patterns of demand from multiple classes of customers. The RM Induction Capacity Allocation Model (ICAM) was validated through simulation and optimization analyses considering all possible scenarios and a number of classes of customers.

Acknowledgment

Getting through my dissertation required more than academic support, and I have many people to thank for listening to and, at times, having to tolerate me over the past years. I wish to thank those whose assistance was a milestone in the completion of this thesis.

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Glossary

3PL	Third-Party Logistics
ARIMA	Auto-Regressive Integrated Moving Average
B2B	Business-to-Business
CPC	Canada Post Corporation
CRM	Cargo Revenue Management
DCA	Dynamic Class Allocation
DM	Direct Marketing
DP	Dynamic Programming
EMSR	Expected Marginal Seat Revenue
ETR	Expected Total Revenue
FCFS	First Come First Serve
ICT	Information and Communication Technologies
IP	Integer Programming
LM	Letter Mailer
LP	Linear Programming
LTL	Less Than a Truck Load
LVM	Large Volume Mailers
MNL	Multinomial Logit Model
MQC	Minimum Quantity Commitment
MTO	Make-to-Order
NCA	Nested Class Allocation
NLP	Nonlinear Programming
OD	Origin-Destination

ODF	Origin-Destination Fare
RM	Revenue Management
RM-ICAM	Revenue Management Induction Capacity Allocation Model
SCM	Supply Chain Management
SP	Stochastic Programming

Introduction

1.1. Postal Services Background

The different products offered by postal services fall into three main categories: Letter Mail (LM), Direct Marketing (DM), and Parcels (David et al., 2013). LM used to be a convenient and cost-effective way to send personal messages and other mail, including business correspondence, invoices, and billing statements. DM is a proven and effective advertising medium that offers customers the ability to personalize their mailing and tailor their promotional messages to specific consumers or prospects. It includes newspapers, newsletters, or magazines, which meet specific requirements and are generally produced for the purpose of public dissemination of news and information. This category also covers advertising and marketing products such as publications and addressed and unaddressed advertisement mail. *Parcels/Packets* are postal service products that cannot be considered normal transaction mail because of their size, weight, or shape. For the last 15 years, the move toward electronic communication substitutes has significantly impacted the postal industry. Emerging Information and Communication Technologies (ICTs) have significantly transformed the way people communicate, share information, socialize, and purchase products and services. According to the Internet World Stats, more than half of the world's population has access to the Internet. At the same time, the European online community is 85%, and North America has a population with 95% Internet users (Miniwatts Marketing Group, 2020).

On the one hand, as a result of digital transformation, there has been an acknowledged constant decline in the demand for LM delivery (e.g., invoices, bills, letters), advertising mail (e.g., flyers, coupons), and hard-copy publications (e.g., newspapers, newsletters, magazines, books). Reports from 32 major postal operators in advanced economies indicate a negative trend in transactional mail, advertising mail, and publications, with the volume declining, on average over the 2008 - 2018 period, from 0.2% to 18.9% (Winklbauer, 2018).

On the other hand, e-commerce and online shopping have significantly increased parcel volumes. Online shopping has been growing over the past 15 years (Snoeck et al., 2020). More than 10% of the global retail landscape is related to e-commerce, and it is expected to double by 2023, generating US$ 6.5 trillion (Winkler, 2020). The increasing popularity of online shopping significantly stimulates the growth of the Business-to-Consumer (B2C) and Business-to-Business (B2B) parcel delivery markets with double-digit annual growth nationally and internationally in most countries. While the parcel delivery market is growing, the growth is mostly associated with Large Volume Mailers (LVMs) known as major online retailers (e.g., Amazon, Alibaba) that generate the vast majority of the parcel volume. Moreover, small- and medium-sized businesses use LVMs' platforms and online marketplaces (e.g., Amazon) to boost their sales and contribute to LVMs' shipping parcel volumes (Levy, 2019).

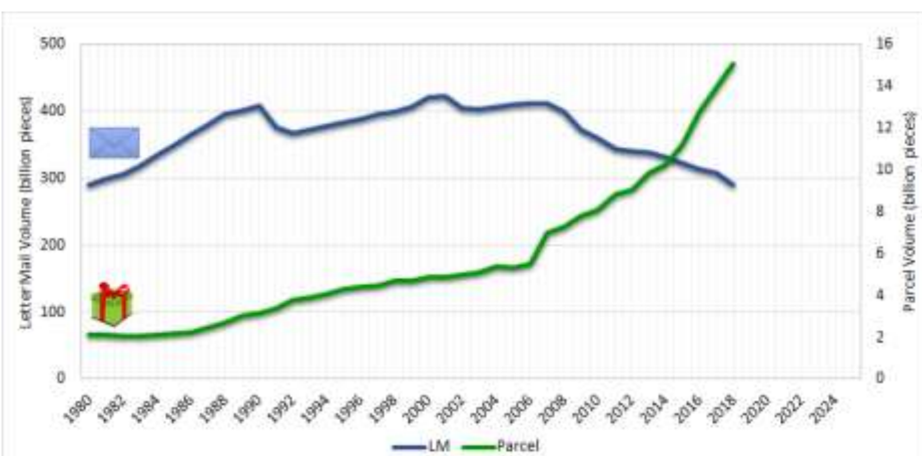


Figure 1: LM and Parcel volume of postal services

Postal services have been trying to expand and optimize their extensive sorting and delivery facilities and infrastructure to satisfy the parcel delivery sector's growing demand and stay competitive in the parcel delivery market. Figure 1 demonstrates negative LM and positive Parcel volume trends of postal services since 1980.

E-Commerce consumers decide what, when, and where to buy online, expecting fast, cheap or free delivery regardless of location and time constraints. As a result, LVMs (e.g., Amazon) have to customize and adapt their business processes to meet customers' expectations by providing mobile shopping options, all kinds of delivery options, and free or low-cost shipping. Amazon, for example, responded to these customer demands with free shipping and a Prime membership strategy. However, to allow a low-cost shipping strategy, many LVMs used their size and market presence to apply significant downward pressure on postal services to process more volumes with lower prices. It turned the delivery and shipping market into a low-margin business for many postal services. Also, some LVMs (e.g., Amazon) in order to address the growing demand, started to run their own delivery and logistics service in the most profitable areas (e.g., downtown). They employ postal and delivery services companies for the rest areas with the high delivery cost. Hence, the processing capacity expansion investment cannot be seen as the optimum and sometimes valid solution for postal services. Postal services need to consider the feasibility of the processing capacity expansions to guarantee the return of investments.

Notwithstanding the constant and positive trend in parcel volumes, postal services indicate a decline in parcel profits. It is mainly due to the growing operational costs, such as upgrading transportation networks, modernization of sorting hubs, installing parcel lockers, and further investing in new information technologies. Postal services also have had to make significant financial investments in capacity management to keep up with e-commerce impact and meet its demand, causing an over 40% increase in the capital expenditure from 2008 to 2017.

The short-term initiatives were; (1) low-cost LM business solutions such as community mailboxes, expanding convenience through postal franchises, or changes to delivery service standards, (2) evolving into digital business solutions such as the development of digital products, taking full advantage of the mobile opportunity, and development of digital mail products, (3) liberalization and privatization solutions that provide a higher level of authority, easier decision making, and clear accountability to address the cost of labor, and (4) parcel performance solutions such as streamlining operations, parcel networks' improvement, and transportation.

1.2. Problem Statement

The generic value chain of postal services can be defined by three main stages associated with the whole process: (1) *induction*, (2) *processing*, and (3) *dispatch*. *Induction* is the first stage of the postal service process when the whole volume delivered to a processing plant should be accepted (e.g., scanned) for further processing. The volume that should be inducted consists of all postal services products, including LM, DM, and parcels collected from post offices and street mailboxes. However, the parcel volume sent directly by LVMs to the processing plant represents the vast majority of the whole volume. Postal services have a limited *induction capacity* - the number of items that can be inducted by a processing plant per specific period (e.g., hour). These limitations are related to the induction throughput (e.g., limited number of docks/gates and space during the induction, induction scanning machines, etc.) but mostly associated with the further limitations related to the postal services' processing capability. The processing plant cannot induct more than it can process. Hence, induction is the first stage of the process, representing a bottleneck when it cannot satisfy the arrival demand and delays downstream.

After the induction, the volume is processed (i.e., prepared, sorted, and sequenced). Each processing plant can have several regional and local centers. If an item's final destination is local (within a specific zone (e.g., city), it is sorted and sent to one of the regional or local centers for the final sort and delivery. However, if the item's final destination is outside the processing plant's zone, it should be sent to a downstream primary processing plant. Depending on the delivery priority (e.g., regular, express, etc.) and to meet the delivery service standard (time), postal services may use road, air, and/or rail to send volume from one processing plant to another one. Generally, delivery standards for items deposited at facilities are subject to cut-off times. Cut-off times are required by a postal organization to allow time for local processing (sorting and dispatching to downstream locations) to meet delivery standards. It means that if the volume arrives before the cut-off time (e.g., 4:00 pm), it is considered local volume and should be processed on the same day. If the volume arrives after the cut-off time, it will be processed the next day.

The dynamic demand for online shopping parcel delivery has turned induction capacity management into a severe challenge for postal organizations. Specifically, the arrival pattern of LVMs' e-commerce volume has created a problem with the existing capacity allocation for postal services and impacting the generated revenue. Figure 2 demonstrates a typical volume arrival pattern to a postal service’s operator facilities for 24 hours. As can be seen, most LVMs send their volume between 4 pm and 10 pm, and that leads to the induction overcapacity or bottleneck problem for postal services.

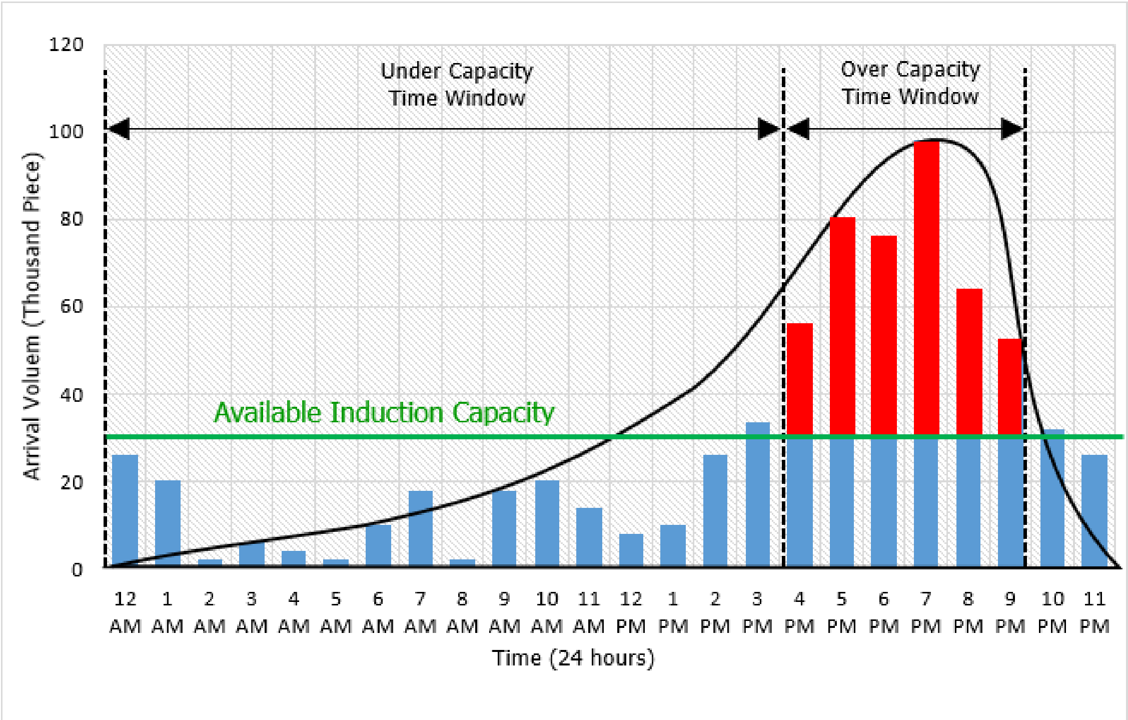


Figure 2: Example of daily postal services' volume induction arrival pattern

As a result, the bottleneck is created because there is no evenly distributed and concentrated arrival of large volumes for the induction. Moreover, this problem escalates, especially during peak seasons (i.e., Christmas time) or any other sale or promotion events offered by online LVMs. Furthermore, the overcapacity issue from the originating plant then cascades downstream in the postal value chain, generating new bottlenecks on the way in downstream plants and local hub sorting facilities. A generic view of the postal service value chain is shown in Figure 3.

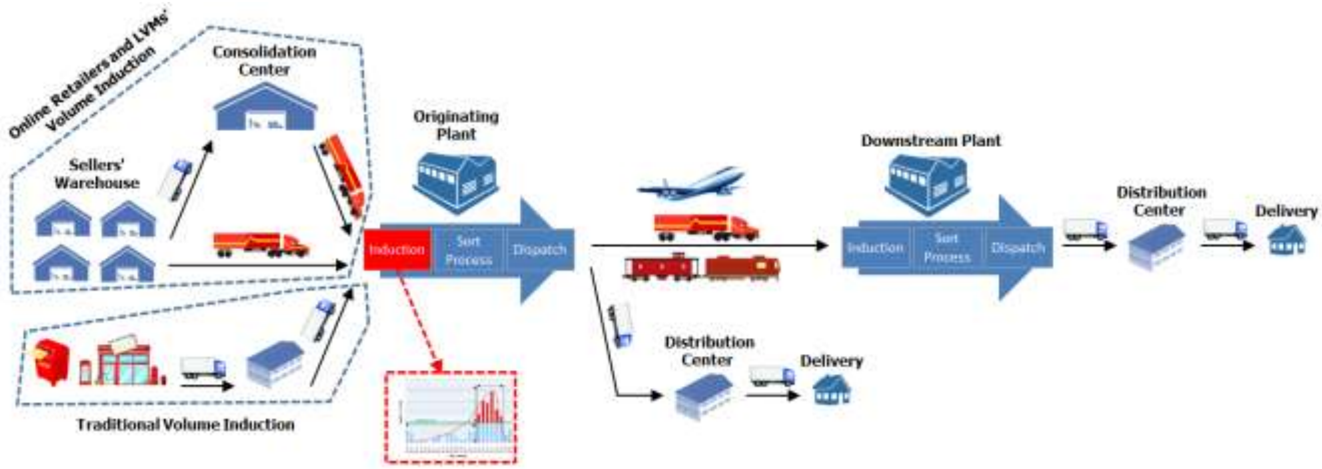


Figure 3: Postal services' high-level value chain

The stochastic arrival pattern of the constantly increasing volumes of LVMs leads to capacity challenges for postal services, especially during the peak season (e.g., Christmas holidays, COVID19 lockdowns). The induction capacity is currently utilized according to the first-come-first-serve approach that creates a bottleneck in the originating plants and low service performance in downstream plants. In some cases, postal services have to refuse to process some LVMs' shipments, resulting in losing revenue opportunities and imposing the associated penalties. During peak seasons, parcels LVMs trucks sometimes can wait few days in the queue for induction, which means missing service standards and imposing cost pressure and penalties for postal services.

1.3. Research Question and Objectives

Most of the existing solutions for the capacity management problem emphasize improving operations' performance indicators but not revenue. However, these solutions are cost-sensitive, temporary, and sometimes not feasible for postal services. This study aims at reconsidering traditional approaches of capacity management through the application of revenue management for induction capacity management of postal services. Revenue management was successfully implemented for resolving capacity allocation problems in different service industries such as airlines (e.g., Zhao et al., 2017), hotels (e.g., Aydin & Birbil, 2018), air cargo (e.g., Li & Xianyong, 2006), sea cargo (e.g., Hui & Jingzhi, 2008), railway (e.g.,Yuan & Nie, 2020), and cruise (e.g., Lu & Joseph, 2007).

Postal services should properly allocate their induction capacity to LVMs to optimize their capacity utilization (e.g., avoid bottlenecks or idle capacity) and maximize the revenue. In other words, the induction capacity should not be assigned just based on the scheduling problem, which mostly originates in operations management solutions. It should be allocated to increase the expected revenue contribution of LVM customers.

Therefore, the research question of this study is “how to model and improve the allocation of the existing induction capacity among Large Volume Mailers (LVMs) while maximizing the expected revenue for postal services?”

The research aims to resolve the induction capacity allocation for major LVMs since (1) they generate the vast majority of the parcel volume for postal services (Winklbauer, 2019), and (2) the arrival pattern of LVMs’ volumes represents the main threat for the induction overcapacity or bottleneck of postal services’ processing plants.

To answer the research question, the following objectives have been developed:

1) To review postal services’ current strategies, priorities, and solutions regarding the capacity management problem.
2) To review capacity management solutions in other industries with a similar problem.
3) To develop a mathematical induction capacity allocation model that operationalizes large volume retailers’ revenue contribution by computing a protected/allocated

capacity for each class of LVMs customers to maximize the expected revenue of postal services.

4) To validate the developed model with simulation.

1.4. Publications Based on Thesis

Various aspects of this thesis have led to the following publications (please see Appendices C – J).

Peer-Reviewed Journal

Submitted:

1. Teymouri, A., Andreev, P., Kuziemsky, C, Khataie, A. (2020) Revenue Management for Induction Capacity Allocation of Postal Services: Model Conceptualization and Empirical Validation", *International Journal of Production Economics (IJPE)*, Submitted

Under revision before the submission:

2. Teymouri, A., Andreev, P., Kuziemsky, C, Khataie, A. (2020) The State of Revenue Management Modeling Research in First Mile Delivery Logistics, *International Journal of Revenue Management (IJRM)*

Conferences

3. Teymouri, A., Andreev, P., Khataie, A, Kuziemsky, C. (2018) *Application of revenue management in capacity planning of postal services, Case Study: an empirical modeling of e-commerce parcel business*" European Operations Management Association (EurOMA) Conference, Budapest, Hungary, June 2018.

4. Teymouri, A., Andreev, P., Khataie, A, Kuziemsky, C. (2017) *Application of Revenue Management in Supply Chain of Postal Services*, IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, December, 2017

Awards, Workshops and Presentations

5. Teymouri, A., Andreev, P., Khataie, A, Kuziemsky, C. (2018) *E-commerce Parcel Volume Challenge for Postal Services - Application of Revenue Management in*

Capacity Planning, Second Place, Graduate Thesis Poster Competition Award, University of Ottawa, March 2018

6. Teymouri, A., Andreev, P., Khataie, A, Kuziemsky, C. (2018) *Application of Revenue Management in Postal Services – Case Study: Canada Post Parcel Transportation Network*, Telfer-Sprott-UQO Thesis Competition, September 2018.

7. Teymouri, A., Andreev, P., Khataie, A, Kuziemsky, C. (2017) *Application of Revenue Management in Postal Services – Case Study: Canada Post Parcel Transportation Network*, First Place, Graduate Thesis Poster Competition Award, University of Ottawa, March 2017

8. Teymouri, A., Andreev, P., Khataie, A, Kuziemsky, C. (2017) *Application of Revenue Management in Capacity Planning of Postal Services*, Telfer-Sprott-UQO Thesis Competition, September 2017

9. Teymouri, A., Khataie, A, (2017), *Postal Services Competitive Business and Global Trends,* White Paper, Presented to Canada Post Senior Executives, July 2017

10. Teymouri, A., Andreev, P., Khataie, A, Kuziemsky, C (2017) *Application of Revenue Management in Postal Services – Case Study: Canada Post E-Commerce Parcel Supply Chain*, Telfer School of Management Graduate Research Programs Cocktail Reception, November 2017.

11. Teymouri, A., Andreev, P., Khataie, A, Kuziemsky, C (2016) *Dynamic Parcel Input by Controlling Trucks Arrival for Postal Industry – Case Study: Canada Post Toronto Processing Plant*, First Place, Graduate Thesis Poster Competition Award, University of Ottawa, March 2016.

1.5. Thesis Outline

The next chapter represents the review of the current capacity management solutions in postal services and the systematic literature review on capacity management and revenue management modeling. This chapter identifies, evaluates, and interprets relevant studies of capacity management solutions in other industries with a similar problem. Chapter 3 develops the framework of a revenue management capacity allocation model for postal services. In this chapter, the main elements for theorizing a postal service capacity management model are identified, and the conceptual revenue management model is developed. It also describes and solves three possible demand scenarios for two, three, four, and n classes of LVMs customers. Chapter 4 presents an empirical validation of the revenue management capacity allocation model. It shows simulation-based heuristic results that decision-makers can use when there are different customer classes with probabilistic demand. The last chapter provides the discussion and conclusion and future research potential. It also discusses the limitations of model developments and simulation.

Research Background

This chapter reviews the literature on models of revenue management for the capacity allocation problem. First, an overview of postal services' current approaches and strategies, priorities, and solutions regarding the capacity management problem of e-commerce parcel is presented. The systematic literature review is then conducted to extract and synthesize the existing knowledge regarding revenue management modeling for capacity management in different industries.

1.6. Capacity Management Solutions for Postal Services

The most common solutions related to parcel capacity management of the postal industry fall into one of three categories (Table 1): 1) Operations Management and Processes Improvement; 2) Induction and Delivery solutions; and 3) Customer Behavior and Marketing solutions. Most of the current solutions related to the Operations Management and Processes Improvement category are associated with:

1. Efficiency - optimizing input and output of goods and services,
2. Lead time - minimizing throughput-time and reducing delays, waiting time, and idle time,
3. Cost - minimizing the cost of production,
4. Customer Experience - Meeting customers' expectations concerning types and standards of services,
5. Quality - ensuring that the solutions meet pre-set quality specifications.

However, the identified operations management solutions have three major flaws for the postal industry (Boyd & Gupta, 2004). First, due to a considerable variation and growth of e-commerce parcel volume, the optimization solutions are not permanent, and usually, they are short-term or temporary. Second, they require a significant investment in equipment and facilities. For example, improving the processing line's productivity and efficiency with technology needs an investment in advanced machines (e.g., sorters), equipment, and systems. Finally, in some cases, it is not feasible to implement these solutions due to limitations or the lack of availability of various resources.

The second solution category (Table 1) corresponds mostly to Supply Chain Management (SCM) solutions through planning and coordination of activities across the supply chain from raw material suppliers to the customers (Burke et al., 2008).

A postal services' supply chain is a cross-functional approach responsible for relocating products such as LM and parcels between different facilities, including processing plants, depots, and post offices. The postal industry has taken advantage of SCM's rapid evolution in the past few years from cost and coordination perspectives. However, uncertain velocity, variety, and volume of e-commerce parcels cause inefficiency in postal services' supply chains. The postal industry has taken advantage of SCM's rapid evolution in the past few years from cost and coordination perspectives. However, uncertain velocity, variety, and volume of e-commerce parcels cause inefficiency in postal services' supply chains (Hofmann, 2017). The impact is more significant, especially for substantial nodes of the supply chain (e.g., Canada Post's Toronto processing center). In general, managing the capacity limitation without sacrificing the service level creates considerable cost pressure in transportation, downstream sort, and delivery processes. For example, removing or readjusting the transportation capacity between two hubs changes the arrival pattern of volume in the destination hub. The constraints on the number of dock doors, the offloading equipment, and staging link space add more complexity to the postal service's capacity management problem.

The third solution category (Table 1) relies on customer behavior mechanisms commonly used to shift demand on supply chain nodes from one period to another (e.g., peak to off-peak). Customers may strategically respond to any fluctuation in the price. For example, they can react to reducing shipping costs if the delivery time increases. Postal services have been paying significant attention to modeling customer behavior.

Table 1: E-commerce capacity management solutions in the postal industry

Solution Category	**Solution Focus**	**Characteristics**		
		Short-term	**Expensive**	**Not Feasibl**
1. Operations Management and Processes Improvement	- Machines' performance (e.g., Julka et al., 2007) - Facility layout (e.g., Pandey et al., 2000) - Man-hour (e.g., Jack & Powers, 2009) - Operation shifts (e.g., Hwang et al., 2010) - Productivity rates (e.g., Bittencourt et al., 2018)	×	×	×
2. Induction and Delivery	- Transportation modes (e.g., Barnhart et al., 2012) - Container types (e.g., Lee et al., 2014) - Facility location (e.g., Correia & Melo, 2017) - Capacity utilization (e.g., Shah et al., 2011)	×	×	
3. Customer Behavior and Marketing	- Marketing and sale promotions (e.g., Lee & Ng, 2001) - Customer behavior (e.g., Hwang & Lambert, 2009)		×	×

In a nutshell, the current solutions for the capacity management challenge focus on increasing the collection and delivery efficiency (e.g., induction and transportation productivity) and processes (i.e., fewer mis-sorts). The existing solutions from all categories have multiple limitations related to their temporal impact (e.g., not considering the growth rate); high direct and indirect costs associated with purchasing of advanced and expensive equipment, technologies, and facilities; and sometimes to the lack of feasibility of implementation due to numerous constraints. Implementation of revenue management can be seen as the potential to overcome the shortcomings of the existing solutions. In the next subsection, we summarize how revenue management was implemented in other industries and how it can be employed for the induction capacity reallocation problem for the postal services.

1.7. Literature Review

We follow Kitchenham's systematic literature review approach (Kitchenham, 2004) to systemize the existing knowledge on revenue management solutions in capacity allocation. The approach consists of three main steps: (1) planning the review, (2) conducting the review, and (3) reporting the results. In the first step, we describe the process of selecting papers and explain how we identify the sources, defining inclusion/exclusion criteria and queries. In the second step, we identify a set of papers that resulted from running queries for all selected database sources. In the last step, we categorize, summarize, and systematize the existing knowledge of the RM solutions of revenue management elicited from the selected papers. Below we provide details with each step of the review process. Figure 4 shows a literature review flowchart.

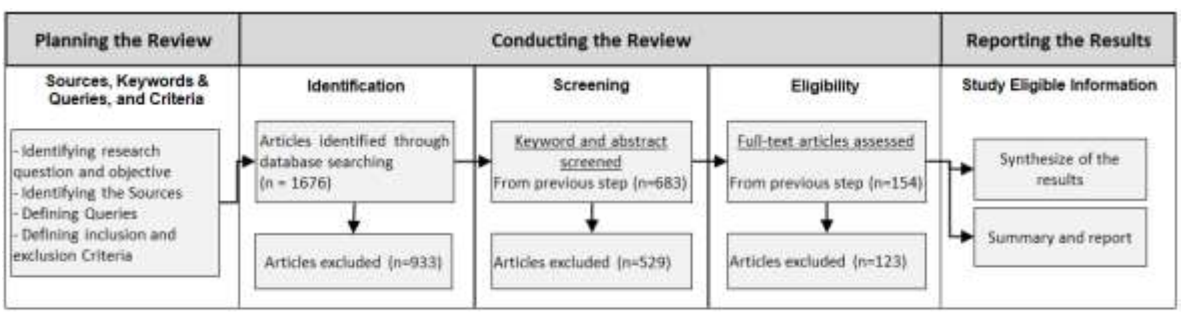


Figure 4: Systematic literature review flowchart

1.7.1. Planning the Review

Identifying objective: This literature review aims to find a comprehensive corpus of journal and conference publications and systematize the knowledge concerning the empirical modeling of revenue management for capacity allocation. Specifically, this review aims at understanding how key problem areas of RM have been modeled and what the main decision variables were considered for other industries with a similar capacity allocation problem.

Identifying the Sources**:** We used four core databases of journal and conference papers: IEEE Xplore, SpringerLink, ABI/INFORM, and Web of Science. The study of revenue management extends back to the early 1970s. The search was conducted for 30 years from 1990 till 2020. Later, using a snowball approach to review references, the key studies were published before 1990.

Defining Queries**:** The queries included a combination of the following four themes: "Revenue Management," "Capacity Allocation", "Modeling ", and "Postal Service". A set of keywords was generated with the OR operator for each concept. For instance, the first concept also included "yield management", "overbooking", "inventory control", "capacity control", and "cancellation", etc. The capacity allocation concept presented with "capacity management", "capacity allocation", "capacity problem", "capacity assignment", and "capacity control". The modeling concept included "method", "programming", and "approach." And finally, the postal service concept presented with "postal service", "postal industry" , "parcel carriers", and "parcels."

Queries that combined all four concepts did not return any results, indicating the lack of such studies for postal services. Therefore, we excluded the "postal services" concept from the queries and considered other industries with similar problems. The queries were adjusted for each search engine due to the different input requirements of search engines. For example, databases have limitations for the query length (e.g., Springer Link does not accept a query longer than 64 characters). Some databases have specific conditions to keywords and their variations (e.g., modeling and modeling). Using parenthesis was not possible for some search engines. Therefore, queries were customized based on the requirements of each search engine.

Inclusion/Exclusion Criteria: After gathering a corpus of potentially relevant research papers, all papers were screened and assessed for eligibility to be included. In the screening stage, the duplicate papers and journal/conference articles published in other than the English language were excluded. Then, the remaining papers' abstracts were reviewed, and just relevant papers remained in the corpus. In the eligibility step, we assessed the full text of the selected pool of papers and excluded irrelevant papers to model capacity allocation with revenue management.

1.7.2. Conducting the Review

Identification: The running of the search queries resulted in the identification of 997 potential sources: IEEE Xplore (58 papers), SpringerLink (429 papers), Web of Science (533 papers), and ABI/INFORM (633 papers). In the second round, after the snowball reference review of selected papers, 23 additional papers were added to the corpus of the identified sources. After combing the results and removing duplications, the number of total identified articles was 683.

Screening: First, we removed any irrelevant "Type" of papers such as books, book chapters and reviews, and non-English language materials. We filtered articles by screening their titles, keywords, and abstracts. All articles were assigned to three categories at the initial stage: "included", "excluded", or "not-sure" (conflict category where two raters had no agreement). It was decided to include all not-sure (conflict) papers for the next stage. There were 154 articles after the screening stage.

Eligibility: The full-text assessment resulted in 31 papers eligible for the study. Table 2 summarizes the results of the conduct of the review stage.

Table 2: Literature Review Results

	IEEE	Springer Link	ABI/IN FORM	Web of Science	RM other	Total
Number of papers found	58	429	633	533	23	1676
Identification	41	191	275	168	8	683
Screening	21	36	52	43	2	154
Eligibility	6	8	9	6	2	31

1.7.3. Reporting the Results

To report the results, we developed a reporting framework to identify, analyze, and summarize the existing knowledge for RM modeling for capacity allocation. The framework systematizes findings for two main parameters: (1) industry type (2) approach/method used to develop the quantitative models. All modeling approaches were grouped into five main groups; LP and IP (Linear Programming and Integer Programming), NLP (Nonlinear Programming), DP (Dynamic Programming), SP (Stochastic Programming), and other modeling approaches such as Discrete-Time Markov Decision, Mathematical Modeling , and Multinomial Logit Model (MNL). Also, for each study, we highlighted (1) if the study computed the optimal allocated/protected capacity; (2) if they accepted/rejected booking requests; (3) if a capacity management policy was developed; (4) number classes of customers; (5) if the developed model was joint with overbooking; and (6) if the developed model was empirically validated.

1.7.3.1. Revenue Management Background

Successful applications of the Revenue Management (RM) approach allow companies to be more efficient, generate higher revenue, and increase their business profitability by better utilizing the existing capacity. Revenue management is an approach of "selling the right product to the right customer at the right time for the right price." (Van Ryzin & Talluri, 2005). RM is applicable for industries that sell perishable goods or services with limited capacity over a finite time. In some service industries, customers are willing to pay different prices for a product or service depending on specific conditions (e.g., hotel rooms, airline seats), which creates an opportunity for customer segmentation with varying prices for each segment. For instance, in the airline industry, customers from the business class have different preferences than economy class passengers (e.g., the flexibility of reservation and cancellation policy) that customers are ready to pay higher rates (Gosavi et al., 2007). The main focus of RM has been on determining the optimal allocation of unused capacity to different classes of demand. Specifically, it determines the amount of allocated/protected capacity for the customers willing to pay a full price compared to those paying a discounted price (Stanciu et al., 2010).

The airline industry became a mainstream application of RM studies in the 1970s, and since then, they have made a significant investment in developing complex and sophisticated RM solutions. Airlines have made a significant investment in developing RM complex and sophisticated solutions. Implementation of these solutions allowed them to improve the airline industry's overall financial performance and it has become one of the essential business strategies (Bart & Luuk, 2004). In the 1990s, the application of RM significantly increased in other service industries (e.g., car rentals). The RM model became more complex, considering various decision variables (e.g., price policy) that made them more industry-specific (Stanciu, 2009). In addition to airlines and hotels that were pioneers of the revenue management application, RM has contributed significantly to other service industries (e.g., car rentals, cargos, restaurants, etc.). These industries are also facing similar problems in determining the optimum allocated capacity for different classes of customers willing to pay different prices.

McGill and Van Ryzin (1999) proposed three main problem areas of application for revenue management for airlines, but which are relevant for any service industry: (1) forecasting, (2) overbooking, and (3) inventory/capacity control.

Forecasting: Accuracy in forecasting is essential for revenue management. In high demand flights, the airline industry increased revenue by 0.5–3.0% through improving forecast accuracy by 10% (Weatherford & Kimes, 2003). Gamma and Normal demand distributions have shown a good continuous approximation for customer arrival patterns. Homogeneous, nonhomogeneous, and compound Poisson distribution has been used in many models (Stanciu, 2009). Also, Weatherford and Kimes (2003) discussed three types of forecasting RM methods:

1. Historical (same day or last year, moving average, exponential smoothing, and other time series such as ARIMA);
2. Advanced booking (additive, multiplicative, and other time series);

3. Combined (weighted average of historical and advanced booking forecasts, regression, full information model).

Overbooking: Studies that developed models for airline forecasting are also related to overbooking since the calculation of overbooking highly depends on the accuracy of demand forecasting (McGill & Van Ryzin, 1999). Compared to other RM problems, overbooking received most of the research attention (McGill & Van Ryzin, 1999). The reason for the popularity of *overbooking* was because of the competitive advantages involved in overbooking modeling , including the possibility of cancellations, no-shows, and changing flights, in airlines when a customer is denied boarding or moved to another flight. Overbooking models should monitor and balance the cost/benefit of extra reservations according to the probability of cancellation or no-show and to avoid having empty seats in flights or empty rooms in hotels. Overbooking models cover both static and dynamic models in one or multiple periods with two or multiple classes of customers (Subramanian et al., 1999; Van Ryzin & Talluri, 2005; Gosavi et al., 2007; Talluri et al., 2009; Tse & Poon, 2017)

Inventory/Capacity Control: In RM, the complexity of seat (capacity) allocation is controlled by mechanisms that are responsible for allocating a limited amount of capacity to each customer segment while protecting the revenue. The purpose of control mechanisms is to determine whether or not a demand should be accepted, rejected, or postponed. Van Ryzin and Talluri (2005) discussed four main control mechanisms; (1) Booking Limits: the maximum amount of capacity that can be allocated to a specific class, (2) Protection Levels: a protection level indicates the required capacity that should be reserved (protected) for the specific class or set of classes, (3) Bid Prices: bid price control defines a threshold price in order to accept or reject a demand request, (4) Nesting: updating the booking limit and estimate for the future demand according to the number of arrived and accepted demand requests. Models considering the inventory control (seat inventory) problem have evolved since the first proposed acceptance/rejection rule for two fare classes by Littlewood (1972). There are various studies exploring the Expected Marginal Seat Revenue (EMSR) control for multiple classes, optimal booking limits for single-leg flights, segment control, and Origin-Destination Fare (ODF) control for multiple flights (McGill & Van Ryzin, 1999).

Successful implementation of revenue management techniques can be modelled, tackling one or more problem areas - forecasting, overbooking, and inventory/capacity control (McGill & Van Ryzin, 1999). Such RM models should also consider industry-related decision variables and parameters. The critical aspect of successful RM modeling is the right selection of the appropriate decision variables and knowing how to integrate them in the models for specific key problem areas (McGill & Van Ryzin, 1999). Since revenue management has its origin in the airline and hotel industry, the vast majority of models were developed and specialized for these two industries. There are many comprehensive reviews in the literature, helping to identify the best models for different areas of problems and to select appropriate decision variables for the two pioneered service industries: airline and hotel. However, although RM became highly popular in other sectors, there is a lack of such studies related to other service industries.

Generally, demand fluctuation shows the variations (peaks and valleys) of market interest for a service or product over time, which causes a level of uncertainty in the demand forecast. To increase their revenue, balance the demand, and manage the capacity utilization, many businesses (e.g., hotels) reduce the price in low-demand periods and increase the price in high-demand periods. The firms always need to ensure that the available capacity meets the required capacity. Also, changing the capacity level in the short run is impossible or very expensive. They can shift their capacity for the demand according to some other factors (e.g., time). Therefore, short delivery time orders are charged higher than longer delivery time orders that can be completed in the free capacity. Many companies use customer segmentation to offer different prices at various points in time and for the same product. This is opposite to mass marketing, where the opportunity of the entire market is considered the same (Heo & Lee, 2011).

1.7.3.2. Capacity Allocation Problem

Capacity allocation is considered to be a critical component of revenue management in many operations (Kunnumkal & Topaloglu, 2008). Talluri and Ryzin (2004) defined capacity allocation as the task of selling an optimal amount of fixed, perishable capacity within a given time period. It reflects uncertainty about future requests and helps decide if a customer's request (e.g., itinerary in airline) should be accepted. Capacity allocation interacts with overbooking decisions to determine how many additional booking requests (in addition to available capacity) should be sold to minimize unused capacity. Capacity allocation originates in the seat inventory control problem in American airlines by looking at the single-leg inventory control or origin/destination (OD) control (Talluri & Ryzin, 2004). Two typical examples of inventory control are controlling the booking requests on a single flight leg of an airline and rooms in hotels for different fare classes (Talluri et al., 2009). Since 1972 when Littlewood developed a rule/policy to accept/reject the booking requests for two fare classes, the capacity control problem has been expanded in *many* industries and for multiple classes of customers (Stanciu, 2009).

Table 3: Summary of studies related to capacity allocation models

Paper (sorted by year)	Industry	Modeling Approach Category	Capacity Allocate/Protect	Accept/Reject Booking Requests	Capacity Policy Configuration Policy	Number of Classes of Customers	Joint with Overbooking	Empirical Validation
Pak et al. (2003)	Airline	Nonlinear Integer Programming				2	✓	✓
Barut and Sridharan (2005)	Manufacturing	Dynamic Programming		✓		n		✓
Li and Xianyong (2006)	Aircargo	Stochastic Programming	✓			3		
Michael et al. (2006)	Airline	Stochastic Programming			✓			
Barz and Waldmann (2007)	Airline	Dynamic Programming			✓	n		
Defregger and Kuhn (2007)	Manufacturing	Discrete Time Markov Decision		✓		2		✓
Lu and Joseph (2007)	Cruise	Mathematical Modeling	✓			3		✓
Sharifyazdi and Modarres (2007)	Airline	Dynamic Programming	✓			n	✓	
Alexander and Huseyin (2008)	Airline	Dynamic Programming			✓		✓	✓
Hui and Jingzhi (2008)	Sea Cargo	Linear Integer Programming		✓				
Kunnumkal and Topaloglu (2008)	Airline	Dynamic Programming		✓	✓	n	✓	✓
Li (2008)	Logistic	Stochastic Programming		✓	✓		✓	✓
Lifan and Xu (2008)	Manufacturing	Stochastic Programming		✓	✓	n		
Lin (2009)	Logistic	Stochastic Programming		✓		n		
Modarres and Sharifyazdi (2009)	Manufacturing	Dynamic Programming	✓	✓		2		✓

Paper (sorted by year)	Industry	Modeling Approach Category	Capacity Allocate/Protect	Accept/Reject Booking Requests	Capacity Policy Configuration Policy	Number of Classes of Customers	Joint with Overbooking	Empirical Validation
Ma and Zhang (2010)	Hotel	Stochastic Programming		✓		2		✓
Zurheide (2011)	Sea Cargo	Linear Integer Programming		✓		2		
Stanciu et al. (2010)	Healthcare	Mathematical Modeling	✓			n	✓	
Modarres et al. (2012)	Manufacturing	Dynamic Programming	✓	✓		2		✓
Ratcliffe et al. (2012)	Healthcare	Mathematical Modeling	✓			2	✓	✓
Schonberger and Kopfer (2012)	Logistic	Mathematical Modeling		✓				
Zurheide and Fischer (2012)	Sea Cargo	Stochastic Programming		✓				✓
Hoffmann (2013)	Air Cargo	Stochastic Programming			✓			✓
Fu et al. (2016)	Sea Cargo	Linear Programming		✓				✓
Marcotte et al. (2016)	Logistic	Mathematical Modeling		✓	✓	2		✓
Aydin and Birbil (2018)	Hotel	Dynamic Programming		✓	✓			✓
Oki Anita Candra (2018)	Airline	Dynamic Programming		✓		2	✓	
Ayvaz et al. (2019)	Cruise	Multinomial Logit Model (MNL)			✓			✓
Mou et al. (2019)	Airline	Linear Integer Programming		✓		n	✓	✓
Pimentel et al. (2019)	Hotel	Nonlinear Programming		✓		2	✓	✓
Yuan and Nie (2020)	Railway	Discrete Time Markov Decision		✓				✓

Table 3 shows a summary of studies related to capacity allocation models. The literature review revealed different modeling approaches such as linear programming, integer programming, nonlinear programming, dynamic programming, stochastic programming, etc. Developed models had one or two of the following three objectives: (1) to develop and configure the *capacity* management policy, (2) to accept/reject booking requests, or (3) to compute the optimal allocated/protected capacity. The focus of this thesis is on the last objective, which applies to postal services.

Develop and configure a capacity management policy: Studies that had an objective to develop and configure a capacity management policy mainly applied the developed RM models to booking and reservation systems. These studies assessed the impacts of resource assignment policies *between* booking classes on revenue. Pak et al. (2003) developed a capacity configuration model that offers an airline company the possibility to adjust the plane's capacity to the demand pattern at hand from one class to another class. They incorporated the shifting capacity opportunity into a dynamic, network-based revenue management model. Michael et al. (2006) established an event-driven stochastic simulation model to evaluate the revenue impacts of a continuously adjusted fleet assignment during the booking period. They developed dependencies between booking classes for realistic consumer behavior and simulation. Lifan and Xu (2008) proposed the optimal order acceptance and capacity allocation policies in order to maximize the revenue. Policies can also connect capacity control and overbooking decisions through an iterative and simulation-based method to approximate the penalty cost. Alexander and Huseyin (2008) and Kunnumkal and Topaloglu (2008) considered a penalty cost policy for denying boarding to the reservations at the departure time. The policies also make assumptions and simplify the complex RM capacity problems by breaking them into some simple problems and addressing them separately. Li (2008) decoupled a two-dimensional problem into two one-dimensional individual problems for four container types. In this study, a heuristic is used by decomposing the problem and reducing the dimensionality to make computation more feasible. Aydin and Birbil (2018) presented day- and pair-based decomposition approaches in order to model for the dynamic room allocation problem in hotel revenue management. Policies are also presented as technical and practical constraints in most reservation systems. Marcotte et al. (2016) proposed a customer choice-based mathematical model in order to estimate time-dependent bid prices. The model is flexible to embed the technical and practical constraints of most central reservation systems. They used a column generation algorithm to compute the optimal allocation of resources. (Ayvaz et al., 2019) considered the dependency between different elements of booking requests and developed the policy to assign booking requests to cabins and maximize revenue. Hoffmann (2013) proposed a heuristic for solving the air cargo capacity control problem efficiently. The policy decomposed the decision model into a weight and volume subproblem and offered monotone opportunity cost with computations.

Accept/Reject booking requests: Another group of studies developed models that tried to maximize revenue by selectively accepting or rejecting booking requests for multiple classes of customers when demand exceeds capacity constantly over the short term. Barut and Sridharan (2005) investigated a tactical capacity management policy's effectiveness to guide accept/reject decisions in order-driven production systems. Defregger and Kuhn (2007) and Yuan and Nie (2020) considered customer arrival and purchase preferences in the capacity reservation model. Hui and Jingzhi (2008) introduced a model for accepting or rejecting the demands of sea cargo containers and maximizing the total revenue. Ma and

Zhang (2010) followed the basic idea of the mathematical model by Raeside and Windle (2000) and established a stochastic model on hotels in order to maximize the revenue in a time horizon. The model accepts/rejects the customer booking requests through an optimal room allocation module, which increases the hotel revenue. Zurheide (2011) developed an optimization model to create booking limits for standard segmentations of liner shipping. The model optimizes the number of accepted demand requests. Zurheide and Fischer (2012) added a slot allocation module to Zurheide's model, which creates booking limits for a liner shipping network with different ship cycles and booking cycles. Schonberger and Kopfer (2012) analyzed a dynamic transportation logistics problem representing the acceptance or rejection of a freight carrier. In order to reduce the negative impacts of inadequate capacity requirement forecasts, they continuously observed the booking acceptance process and adjusted the bid-price calculation. Fu et al. (2016) continued this research and addressed the container slot allocation problem with Minimum Quantity Commitment (MQC) and the dynamic demand. Oki Anita Candra (2018) developed a dynamic programming model as the policy of accepting and rejecting booking requests between passengers with air cargo in order to maximize the expected revenue. The study integrated the process of capacity decision for luggage passengers with air cargo based on air cargo space control. Mou et al. (2019) added no-show, late cancellation, and denied boarding for a set of flight legs over an airline network. The model helps to make a decision whether to accept or reject a booking request and defines those accepted requests that can become reservations. Pimentel et al. (2019), instead of the traditional sequential approach, computed overbooking levels and allocation levels simultaneously. Their model assists in making a decision to accept or reject a hotel booking request according to the computed overbooking levels for two classes of rooms.

Capacity Allocated/Protected: Another group of studies modeled an optimal booking policy that can be characterized by protected/allocated capacity levels depending on the actual booking class. Since the *objectives* of these studies are similar to the main objective of this thesis, we summarized the contributions and the improvement areas.

Li and Xianyong (2006) considered an air cargo capacity allocation problem with a multi-leg network and developed a stochastic model. They developed an allocation policy near-optimal that could improve the revenue of an airline company. The model answers a similar question to this thesis - “how to allocate the capacity according to the demand in order to maximize the revenue?” However, cargo has its unique characteristics making Cargo Revenue Management (CRM) models not directly applicable for postal services. First, the available space for the Cargo depends on the number of passengers and the amount of space required for their bags. Therefore, the capacity has to be considered unknown and probabilistic (Kasilingam, 1997). Second, weight, volume, and the number of available space/slot are three key factors of cargo that all must be integrated together. Therefore, the load factor optimization of cargo capacity requires that we look at these three dimensions instead of one. Cargo may have to be transferred through multi-routings according to the availability of cargo space in airplanes. Finally, the reservation period for cargo has to be closed for the departure date (up to two weeks) due to the dynamic behavior of passenger demand (Bart & Luuk, 2004).

Lu and Joseph (2007) applied Nested Class Allocation (NCA), which is a modified version of EMSR (Belobaba, 1989), and Dynamic Class Allocation (DCA), which is adapted from the method of Tak and Marvin (1993) to cruise inventory control. The model helps a decision-maker to decide to accept/reject a booking request and maximize generated revenue in the cruise industry. Although they verified the benefits that can be derived under a simulated reservation process of the model, there are some assumptions that may not be practical in postal services. First, they assumed the demands are normally distributed for three customer classes. Second, customers' arrival order is from lowest to highest fare class, and the model does not consider random order of arrival. Finally, at most, one request arrives in a single decision period, and the model does not consider simultaneous booking request arrival.

Sharifyazdi and Modarres (2007) and Modarres and Sharifyazdi (2009) formulated stochastic capacity allocation problems in Make-to-Order (MTO) random-capacity production using a revenue management technique. They applied Littlewood's rules (1972) and computed total revenue gained from the income of ticket sales minus the penalty of booking cancellation for two classes of customers, frequent and occasional. They computed the revenue based on the price of the fare class and the cancellation fee. The model considered the demand distribution function, the capacity distribution function, the product price, and the order cancellation penalty rate for each class. Modarres et al. (2012) proposed an improved approach for a greater number of scenarios with discrete and mixed random variables. The model has some assumptions that are not applicable to postal services. First, the capacity is stochastic, and the exact size cannot be forecasted in advance. Second, there are two classes of customers where first-class customers have priority at a lower price rate. Finally, orders are processed one by one and cannot arrive at the same time.

Stanciu et al. (2010) studied the application of revenue management in operating rooms with several surgical procedures. They assumed random resource utilization, which means each booking request uses a random amount of surgery time. This assumption does not apply in postal services since the resource utilization (processing time) for parcels is fixed. Also, patients arrive in random order. The model is a modified version of the EMSRb algorithm (Belobaba, 1989) to decide on near-optimal protection levels for various patients' classes. The model computes how much time to reserve to satisfy the demand coming from each class of patients while maximizing the revenue. Patients were segmented based on two criteria: the need for a specific surgery and financial reimbursement level. The model is useful for surgical units for scheduling elective surgeries over a certain period.

Ratcliffe et al. (2012) presented a joint capacity control and overbooking model for medical clinics to maximize profits by controlling bookings from two patients' classes with different no-show rates. They developed bounds and approximations and compared these via a numerical case study with the optimal policy. Appointment requests from each class arrive individually, not simultaneously; class two of patients arrive before class one. These assumptions do not apply to postal services. Also, the model does not consider service time variation between the two patients' classes.

1.8. Summary

Businesses with fixed, limited capacity are facing complex decisions regarding their capacity allocation with different pricing strategies. Founded in the 1970s, RM helped to generate incremental revenues from an existing fixed capacity, originally in the airline and then in the hotel industries. Over time it has been expanded to many other industries, such as car rentals, air cargo, restaurants, media and advertising, and railway. RM is defined as an approach maximizing revenue by managing a limited capacity while selling a product to the right customer, at the right time, for the right price. The literature review found that capacity allocation is one of the key components of RM models with three subgroups of studies. The first group developed a revenue management capacity policy configuration that the model assesses how different resource assignment policies can improve the revenue. The second group helps decide to accept/reject a booking request. Finally, the last group computes a capacity protection/allocation level for different customer classes with a revenue maximization objective.

The focus of this thesis is on the last group. A variety of models have been developed based on the Littlewood (1972) rule in airlines in which there are two classes of customers with prices p_1 *and* p_2 $(p_1 > p_2)$. The fixed capacity C should be assigned to each class with the demand D_i $(i = 1,2)$ in order to maximize the revenue. It is assumed demands arrive in specific order that the class two (D_2) arrives before the class one (D_1).

We discussed studies with a similar problem in Air cargo, Cruise, Airline, Manufacturing, and Healthcare (Li & Xianyong, 2006; Lu & Joseph, 2007; Sharifyazdi & Modarres, 2007; Modarres & Sharifyazdi, 2009; Stanciu et al., 2010; Modarres et al., 2012; Ratcliffe et al., 2012). They considered different capacity utilization for different classes. In healthcare, for example, required time and resources for surgeries are different in a hospital surgical department. Each patient request needs a variable resource usage as appropriate for the situations encountered. In postal services the processing time is considered equal for all parcels.

In order to use RM in the postal services revenue management model, it is necessary to have a concrete framework with guidelines on how to assign/allocate an optimum level of capacity to each class of customers according to their revenue contribution and demand behavior while maximizing the total expected revenue. In the next chapter, we implement the Stanciu et al. (2010) approach to construct the model and the Modarres et al. (2012)

approach to compute the expected revenue for different protection levels. Both studies were constructed based on Littlewood's rule for two classes of customers.

Development of Revenue Management Induction Capacity Allocation Model for Postal Services

Application of Revenue Management (RM) in the postal industry is relatively new compared to other service industries that apply RM and made significant contributions to their profitability. Moreover, certain aspects of the RM problem in the postal industry need to be taken into account to develop an RM capacity allocation model that is different from other industries and should be customized. In other industries:

- Demand arrives in an increasing fare pattern, from the lowest to highest fare. It generally applies to airlines when leisure travel customers make reservations as early as possible to take advantage of lower price policies. However, there is a random order of arrival in postal services.
- There is different capacity utilization for different classes. For instance, in healthcare, not only is the capacity allocated to each class of patients different, but also the amount of capacity for each patient in that class is different. The required time and resources for surgeries vary for different patients in a hospital surgical department. Each patient request needs various resources depending on multiple criteria and the surgery process and outcomes. In postal services, the processing time is considered equal for all parcels for all mailers.
- In manufacturing, the solution for capacity allocation, capacity, and demand are both stochastic, and there are booking limits for classes. Therefore, the concept of nesting and protection level is not meaningful in this case, which needs a fixed amount of capacity. For example, in a more general case of make-to-order manufacturing

systems, the exact size of capacity cannot be estimated at the time of arriving orders. However, in postal services, the available capacity is fixed.

- There is a possibility to overbook the capacity level to consider cancellations/no-shows. For example, in airlines, the overbooking capacity is higher than the available capacity depending on the probability of cancellation and show. Postal services need to protect a specific level of capacity for different classes of customers.
- The developed models can be applied just for two classes of customers. For instance, the air cargo capacity is determined at the last minute when all passengers' luggage is put in the cargo area, and the remaining space is measured. The model is not dynamic in order to employ new data and compute the updated protection level. But, in postal services, there might be a need for more classes of customers (e.g., three classes) during the peak seasons (e.g., Christmas).
- In many service industries (e.g., airlines), if the customer demand cannot be met, then the customer is considered "lost" from a revenue perspective. However, for postal services, it is different. Customer demand is not lost, but it may be postponed and must still be satisfied. Such postponing can reduce performance and leads to penalties. Satisfying the postponed demand makes the RM's implementation in postal services different from other industries where RM has been successfully implemented.
- A customer can dictate the time of service (e.g., in the hospitality industry) when s/he buys a ticket/room for a specific date and time, and the duration of the process (e.g., flight from one city to other cities/length stay in a hotel) does not change. But, in postal services, customers have little or no decision on arrival time.

To develop the capacity allocation model, we consider Stanciu et al. (2010) and Modarres et al. (2012) that used Littlewood's rule (seat inventory problem for a single-leg flight with two fare classes). They assume two classes with fares p_1 and p_2 while $p_1 > p_2$. The total available capacity is C, the demand for customer class one is D_1, and customer class two is D_2. The demand for class two comes before demand for class one. Like in Littlewood model, their model stops accepting customer class two when its revenue is exceeded by the revenue of customer class one times the probability of having demand from customer class one at least that many numbers of seats. The number of seats is represented with x. Therefore, the demand for class 2 is accepted if $p_2 \geq p_1 \times P(D_1 \geq x)$.

Model development general assumptions:

- Customers' demand arrives with stochastic pattern
- Overbooking and cancellation are not allowed
- Discounts, promotions, and other price-related agreements and commitments are not allowed
- The additional volume of over-allocated capacity should be rejected
- Customers are grouped base on their revenue contributions, which volume multiply by the price
- Delivery standards are considered regular, which means priority courier and express post products are not allowed
- There is no penalty factor when customers don't utilize the protected capacity

The rest of this section is organized as follows. The induction capacity allocation model for postal services is developed for two classes of customers, considering two possible scenarios. The model computes the level of capacity allocated to each class of customers to maximize the revenue while considering the price (p) and the customer class arrival pattern defined as an arrival (demand) distribution. A step-by-step algorithm for calculating the optimum protected capacity for two classes of customers is presented. Next, the model is expanded for multiple classes of customers according to two scenarios one and two. The mathematical models are developed for three and four classes of customers. Finally, the mathematical model is developed for n classes of customers. The models will help postal services compute an optimum allocated/protected induction capacity for different classes of customers to maximize the expected revenue.

1.9. Model Development for Two Classes of Customer

In this research, customers are online retailers (e.g., Amazon), named Large Volume Mailers (LVMs), that send their volumes (demand) to a postal service facility to be processed and then delivered. An effective conceptual induction capacity allocation model should optimize the throughput at the originating sort and maximize LVMs revenue contribution. The conceptual induction capacity allocation model considers the existing processing capacity C of postal services and two classes of customers (the number of classes will be increased for further model development stages). Price ranges were used to group customers into two classes in such a way that the first group has p_1 price (where p_1 has a uniform distribution) and it is greater than p_2 for the price of the second class (where p_2 also has a uniform distribution). f_I represents the probability density function for customer class i's demand (D_i). The typical arrival pattern of the volume to postal services is divided into two time-windows during a day; period one from 00:00 am to 4:00 pm and period two from 4:00 pm to 00:00 am. In the first-time window, most of the volume has already been processed in other nodes (plants) of the postal service, called Incoming volume. In the second time window, most of the volume belongs to LVM customers, and the local volume around the processing center is called Originating volume. Let D_{ij} be the volume of the LVM j ($j = 1,2, \dots m$) in-class i ($i = 1,2$) delivered to the operating sort for induction. Hence, the total demand of each class of customers is computed by $D_i = \sum_{j=1}^{\mathrm{m}} D_{ij}$ $(i = 1,2)$. Therefore, $\mathcal{W}_{ij} = p_i D_{ij}$ is the revenue contribution of each class of customers. For simplicity, $\mathcal{W}_i = p_i D_i$ is a realization of $\mathcal{W}_{ij}$ for LVM i. Let $E[\mathcal{W}_i] = \mu_i$ be the expected value of revenue contribution of a customer i. Hence, there are two possibilities:

(1) $\mu_{i|w_1>w_2} = E[\mathcal{W}_i|\mathcal{W}_1 > \mathcal{W}_2]$, and

(2) $\mu_{i|w_1<w_2} = E[\mathcal{W}_i|\mathcal{W}_1 < \mathcal{W}_2]$, ($i = 1,2$).

Hence, the revenue contribution of customers' class i is computed by Equation 1, where the probability that $\mathcal{W}_1$ is greater than $\mathcal{W}_2$ is presented by θ and $\mathcal{W}_2$ is greater than $\mathcal{W}_1$ by $1 - \theta$.

Equation 1: $$\boldsymbol{E}[\boldsymbol{\mathcal{W}_i}] \equiv \boldsymbol{\mu_i} = \boldsymbol{\theta\mu_{i|w_1>w_2}} + (\mathbf{1} - \boldsymbol{\theta})\boldsymbol{\mu_{i|w_1<w_2}}$$

In Equation 1, when

$\theta \to 0$ then $\mu_i \to \mu_{i|w_1<w_2}$ and $\mu_{2|w_1<w_2} > \mu_{1|w_1<w_2}$ and when $\theta \to one$ then $\mu_i \to \mu_{i|w_1>w_2}$ and $\mu_{2|w_1>w_2} < \mu_{1|w_1>w_2}$.

Let x be an amount of the processing capacity that should be reserved (protected) for the LVM class 1. It means that the postal service does not use this capacity for class customers 2. Hence, the main problem is to define the protected capacity x that the postal service should reserve for the customers' class 1 that pays a higher price (p_1) and another customers' class $C - x$ that pays a lower price (p_2) to maximize revenue. This problem becomes more complex when customer demand is stochastic. In order to address the problem, we develop three possible scenarios:

- Scenario 1: The demand for each of two classes (D_i) is lower than the available capacity C, but the total demand of both classes of customers is greater than the available capacity C. Therefore, $P[D_1 < C] = 1$ and $P[D_2 < C] = 1,$ but $P[D_1 + D_2 > C] = 1$.
- Scenario 2: The demand of the customer class one (which pays a higher price) is lower than the available capacity C, but the demand of customer class two (that pays a lower price) is greater than the available capacity C. Therefore, $P[D_1 < C] = 1$ and $P[D_2 > C] = 1$.
- Scenario 3: The demand of the customer class one (which pays a higher price) is greater than the available capacity C, but the customer class two (which pays a lower price) has lower demand than the available capacity C. Therefore, $P[D_1 > C] = 1$ and $P[D_2 < C] = 1$.

Obviously, scenario 3 is the ideal situation for postal services and does not require optimization. All the capacity C can be allocated to the customer that has a higher price (p_1) that generates the maximum expected revenue. If the postal services don’t have any commitments to satisfy their demand (e.g., contracts) of customers class 2, all the capacity can be allocated to customer class 1. Hence, scenario 3 is excluded from the scope of the model.

<u>Scenario 1:</u>

Table 4 represents the allocated capacities and revenue contribution of each customer class when an individual customers’ class demand is lower than the available capacity for both classes ($D_1 < C \; and \; D_2 < C$) , but their total demand is greater than the available capacity ($D_1 + D_2 > C$).

Table 4: Capacity allocation and revenue contribution in scenario 1

Revenue Contribution	Induction Capacity Allocation customer 1	customer 2	Expected Revenue Contribution
$\mathcal{W}_1 > \mathcal{W}_2$	$\min\{D_1, x\}$	$min\{D_2, C - x\}$	$R(x) = p_{1\mid\mathcal{W}_1 > \mathcal{W}_2} \min\{D_1, x\} + p_{2\mid\mathcal{W}_1 < \mathcal{W}_2} min\{D_2, C - x\}$
$\mathcal{W}_1 < \mathcal{W}_2$	$\min\{D_1, x\}$	$min\{D_2, C - x\}$	$R(x) = p_{1\mid\mathcal{W}_1 > \mathcal{W}_2} \min\{D_1, x\} + p_{2\mid\mathcal{W}_1 < \mathcal{W}_2} min\{D_2, C - x\}$

The expected value of the generated revenue considering x as a protected capacity for customer class one can be computed by Equation 2:

Equation 2: $E[R(x)] = p_1 \, E[min\{D_1, x\} + p_2 E[min\{D_2, C - x\}]$

An integral equation of the probability density function is used to simplify the expected value of a minimum function. Then, solving $\frac{E[R(x)]}{dx} = 0$, the optimum amount of capacity shown by x^*, that maximizes $E[R(x)]$ should satisfy the condition of Equation 3:

Equation 3: $p_1 P[D_1 > x^*] = p_2 P[D_2 > C - x^*]$

Equation 3 represents the revenue management induction capacity allocation model for two classes of customers under scenario 1. The difference $p_1 P[D_1 > x^*] - p_2 P[D_2 > C - x^*]$ is computed to be zero.

<u>Scenario 2:</u>

The demand for class one, which pays a higher price, is lower than the available capacity ($D_1 < C$), but the demand for class two, which pays a lower price, is greater than the available capacity ($D_2 > C$). Two situations need to be considered within this scenario, as shown in Table 5.

Table 5: Capacity allocation and revenue contribution in scenario 2

Revenue Contribution	Probability	Induction Capacity Allocation		Expected Revenue Contribution
		customer 1	customer 2	
$\mathcal{W}_1 > \mathcal{W}_2$	θ	$\min\{D_1, x\}$	$C - x$	$R(x) = p_{1\mid\mathcal{W}_1>\mathcal{W}_2} \min\{D_1, x\} + p_{2\mid\mathcal{W}_1>\mathcal{W}_2}(C - x)$
$\mathcal{W}_1 < \mathcal{W}_2$	$1 - \theta$	x	$min\{D_2, C - x\}$	$R(x) = p_{1\mid\mathcal{W}_1<\mathcal{W}_2} x + p_{2\mid\mathcal{W}_1<\mathcal{W}_2} min\{D_2, C - x\}$

The expected revenue considering x as a protected capacity for customer class one can be computed by Equation 4. But there is a probability θ that $w_1$is greater than w_2 and $1 - \theta$ that $w_1$is less than w_2. The total expected revenue is computed by Equation 4:

Equation 4: $E[R(x)] = \theta\left[p_{1\mid\mathcal{W}_1>\mathcal{W}_2}\, min\{D_1, x\} + p_{2\mid\mathcal{W}_1>\mathcal{W}_2}(C - x)\right] + (1 - \theta)\left[p_{1\mid\mathcal{W}_1<\mathcal{W}_2} x + p_{2\mid\mathcal{W}_1<\mathcal{W}_2} min\{D_2, C - x\}\right]$

An integral equation of the probability density function is used to simplify the expected value of a minimum function. Then, solving $\frac{E[R(x)]}{dx} = 0$, the optimum x^*, that maximizes $E[R(x)]$ should satisfy the condition of Equation 4:

Equation 5: $\theta p_{1\mid\mathcal{W}_1>\mathcal{W}_2} P\,(D_1 > x^*) + (1 - \theta) p_{1\mid\mathcal{W}_1<\mathcal{W}_2} = (1 - \theta) p_{2\mid\mathcal{W}_1<\mathcal{W}_2} P(D_2 > C - x) + \theta p_{2\mid\mathcal{W}_1>\mathcal{W}_2}$

Equation 5 represents the revenue management induction capacity allocation model for two classes of customers under scenario 2. The difference $\theta p_{1\mid\mathcal{W}_1>\mathcal{W}_2} P\,(D_1 > x^*) + (1 - \theta) p_{1\mid\mathcal{W}_1<\mathcal{W}_2} - (1 - \theta) p_{2\mid\mathcal{W}_1<\mathcal{W}_2} P(D_2 > C - x) - \theta p_{2\mid\mathcal{W}_1>\mathcal{W}_2}$ is computed to be zero.

For two classes of customers and under two possible scenarios, the developed RM induction capacity allocation models (Equation 2 and Equation 4) will balance postal services' capacity according to the generated revenue of each class of customers. Models maximize the expected revenue by protecting defined capacity x^* for customer class one and

$C - x^*$ For customer class two. More details regarding the mathematical model calculations can be found in Appendix A. Figure 5 summarizes a step by step algorithm regarding calculations of x^* for all three possible scenarios.

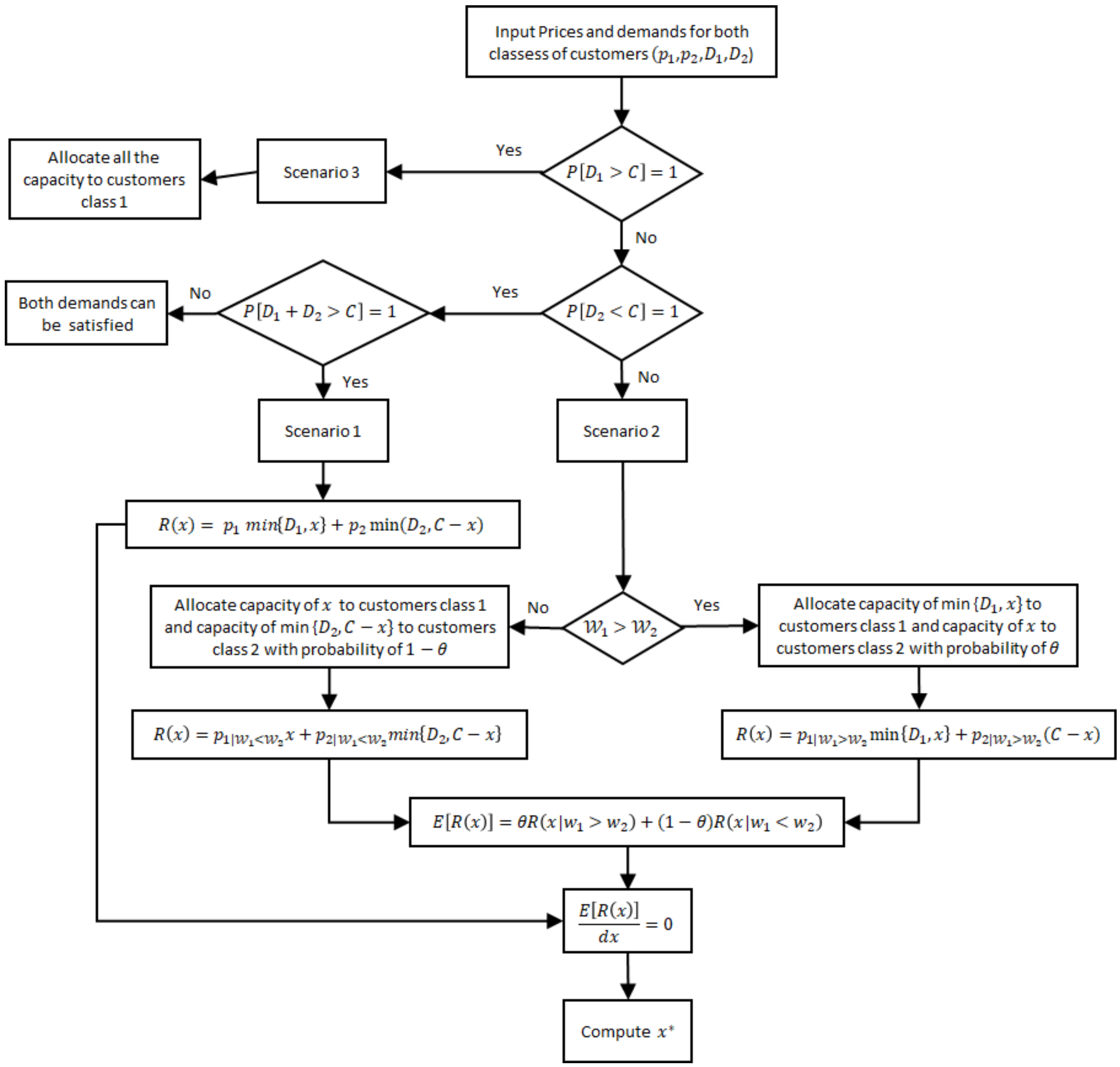


Figure 5: Optimum capacity allocation algorithm for two classes of customers

1.10. Model Development for Three Classes of Customer

Companies can improve their revenue by serving multiple customer segments and different prices for each segment. Let's consider the existing processing capacity C of a postal service with three classes of customers with the prices of p_1, p_2, p_3 while $p_1 > p_2 > p_3$.

Customers' demand arrives in random order, and no cancellation and overbooking is allowed. f_i represents the probability density function for customers' class i and V_i represents the volume of the customer class i $(i = 1,2,3)$ where the total demand customer classes are computed by D_i. Therefore, $\mathcal{W}_i = p_i D_i$ is the revenue contribution of each of the classes of customers. Let $E[\mathcal{W}_i] = \mu_i$ be the expected value of revenue contribution of customer i. Three possible scenarios are considered:

- Scenario 1: Customer class demands are less than the available capacity, but the total demand of all customer classes is greater than the available capacity.
- Scenario 2: The demand of customer class one (which pays a higher price) is lower than the available capacity C, but customer classes who pay lower prices have the demand greater than the available capacity C.
- Scenario 3: The demand of customer class one (which pays a higher price) is greater than the available capacity C, but the other customer classes (which pay a lower price) have lower demand than the available capacity C.

Obviously, scenario 3 is the ideal situation for postal services and does not require optimization. All the capacity C is allocated to the customer that has a higher price (p_1) and generates the maximum expected revenue. The postal service does not have any pre-commitment of the capacity to customer classes two and three. Hence, scenario three is excluded from the scope of the model.

Scenario 1:

Two protection levels (x_1, x_2) should be computed. The protection level x_1 is assigned to customer class one, x_2 is allocated to customer classes one and two. The expected revenue can be computed by Equation 6:

Equation 6: $E[R(x_1, x_2)] = E[p_1 \min(D_1, x_1) + p_2 \min(D_2, x_2 - x_1) + p_3 \min(D_3, C - x_2)]$

An integral equation of the probability density function is used to simplify the expected value of a minimum function. Then, solving $\frac{E[R(x_1,x_2)}{dx_1} = 0 \; and \; \frac{E[R(x_1,x_2)}{dx_2} = 0$, the optimum x_1^*, x_2^* that maximizes $E[R(x_1, x_2)]$ should satisfy the condition of both Equation 7 and Equation 8:

Equation 7: $p_2 P(D_2 > x_2^* - x_1^*) - p_1(D_1 > x_1^*) = 0$

Equation 8: $p_3 P(D_3 > C - x_2^*) - p_2 P(D_2 > x_2^* - x_1^*) = 0$

<u>Scenario 2:</u>

Two protection levels (x_1, x_2) should be computed. The protection level x_1 is assigned to customer class one, x_2 is allocated to customer classes one and two together. The probability of ordering of revenue contribution of n classes of customers is presented by $\theta_{i_1 i_2 \ldots i_n}$ as $\theta_{i_1 i_2 i_3} = p\left(\mathcal{W}_{i_1} > \mathcal{W}_{i_2} > \mathcal{W}_{i_3}\right)$. There are (3! = 6) possible situations of expected revenue from three classes of customers. The expected revenue can be computed by Equation 9:

Equation 9: $\boldsymbol{E[R(x_1, x_2) = \theta_{123} E(p_{1|w_1>w_2>w_3} \, min\{D_1, x_1\} +}$
$\boldsymbol{p_{2|w_1>w_2>w_3} \, min\{D_2, x_2 - x_1\} + p_{3|w_1>w_2>w_3}(C - x_2)) +}$
$\boldsymbol{\theta_{132} E(p_{1|w_1>w_3>w_2} \, min\{D_1, x_1\} + p_{2|w_1>w_3>w_2}(x_2 - x_1) +}$
$\boldsymbol{p_{3|w_1>w_3>w_2} \, min\{D_3, C - x_2\}) + \theta_{213} E(p_{1|w_2>w_1>w_3} \, min\{D_1, x_1\} +}$
$\boldsymbol{p_{2|w_2>w_1>w_3} \, min\{D_2, x_2 - x_1\} + p_{3|w_2>w_1>w_3}(C - x_2)) + \theta_{231} E(p_{1|w_2>w_3>w_1} x_1 +}$
$\boldsymbol{p_{2|w_2>w_3>w_1} \, min\{D_2, x_2 - x_1\} + p_{3|w_2>w_3>w_1} \, min\{D_3, C - x_2\}) +}$
$\boldsymbol{\theta_{312} E(p_{1|w_3>w_1>w_2} \, min\{D_1, x_1\} + p_{2|w_3>w_1>w_2}(x_2 - x_1) +}$

$\boldsymbol{p_{3|w_3>w_1>w_2}\, min\{D_3, C - x_2\}}) + \boldsymbol{\theta_{321} E(p_{1|w_3>w_2>w_1} x_1} +$
$\boldsymbol{p_{2|w_3>w_2>w_1}\, min\{D_2, x_2 - x_1\}} + \boldsymbol{p_{3|w_3>w_2>w_1}\, min\{D_3, C - x_2\}})$

An integral equation of the probability density function is used to simplify the expected value of a minimum function. Then, solving $\frac{E[R(x_1,x_2)}{dx_1} = 0 \; and \; \frac{E[R(x_1,x_2)}{dx_2} = 0$, the optimum x_1^*, x_2^* that maximizes $E[R(x_1, x_2)]$ should satisfy the condition of both Equation 10 and Equation 11:

Equation 10: $p_1 P(D_1 > x_1^*) + \theta_{231}\, p_{1|w_2>w_3>w_1} + \theta_{321}\, p_{1|w_3>w_2>w_1}\, (1 - P(D_1 > x_1^*)) = p_2 P(D_2 > x_2^* - x_1^*) + \theta_{132}\, p_{2|w_1>w_3>w_2} + \theta_{312} p_{2|w_3>w_1>w_2}\, (1 - P(D_2 > x_2^* - x_1^*))$

Equation 11: $p_2 P(D_2 > x_2^* - x_1^*) + \left(\theta_{123}\, p_{2|w_1>w_2>w_3} + \theta_{312}\, p_{2|w_3>w_1>w_2}\right)\left(1 - P(D_2 > x_2^* - x_1^*)\right) = p_3 P(D_3 > \mathrm{C} - x_2^*) + \left(\theta_{123} p_{3|w_1>w_2>w_3} + \theta_{213}\, p_{3|w_2>w_1>w_3}\right)\left(1 - P(D_3 > C - x_2^*)\right)$

For three classes of customers and under two possible scenarios, Equation 7 and Equation 8 in scenario one and Equation 10 and Equation 11 in scenario two will balance postal services' capacity according to the generated revenue of each class of customers. The models maximize the expected revenue by protecting defined capacity x_1^*, $x_2^* - x_1^*$, and $C - x_2^*$ for customer classes 1, 2, and 3, respectively. More details regarding the mathematical model calculations can be found in Appendix B.

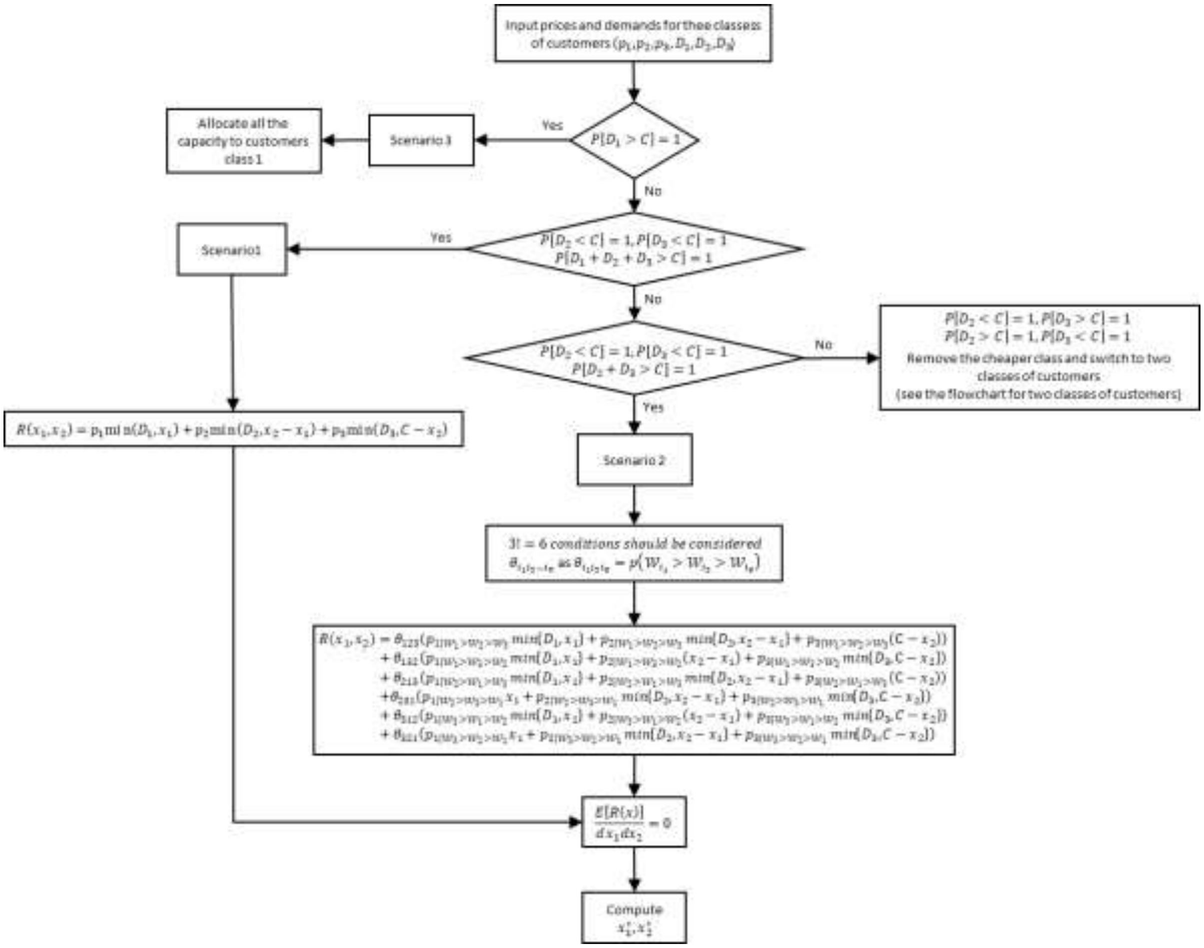


Figure 6: Optimum capacity allocation algorithm for three classes of customers

Figure 6 summarizes a step by step algorithm regarding calculations of x_1^*, x_2^* for all three possible scenarios.

1.11. Model Development for Four Classes of Customer

Let's consider the existing processing capacity C of a postal service having four classes of customers with the prices of p_1, p_2, p_3, p_4 while $p_1 > p_2 > p_3 > p_4$. Customers' demand arrives in random order, and no cancellation and overbooking is allowed. f_i represents the probability density function for customer class i and V_i represents the volume of the customer class i $(i = 1,2,3,4)$ where the total customer demand is computed by D_i.

Therefore, $\mathcal{W}_i = p_i D_i$ is the revenue contribution of each class of customer. Let $E[\mathcal{W}_i] = \mu_i$ be the expected value of revenue contribution of customer i.

Three possible scenarios are considered:

- Scenario 1: Customer class demands are less than the available capacity, but the total demand of all customer classes is greater than the available capacity.
- Scenario 2: The demand of customer class one (which pays a higher price) is lower than the available capacity C, but customer classes who pay lower prices have the demand greater than the available capacity C.
- Scenario 3: The demand of customer class one (which pays a higher price) is greater than the available capacity C, but the other customer classes (which pay a lower price) have lower demand than the available capacity C.

Obviously, scenario 3 is the ideal situation for postal services and does not require optimization. All the capacity C is allocated to the customer that pays a higher price (p_1) and generates the maximum expected revenue. The postal service does not have any pre-commitment of the capacity to customer classes two, three, and four. Hence, scenario 3 is excluded from the scope of the model.

<u>Scenario 1:</u>

Three protection levels (x_1, x_2, x_3) should be computed. The protection level x_1 is assigned to customer class one, x_2 is allocated to customer classes one and two, x_3 is allocated to customer classes one, two, and three. An integral equation of the probability density function is used to simplify the expected value of a minimum function. Then, solving $\frac{E[R(x_1,x_2,x_3)}{dx_1} = 0$, $\frac{E[R(x_1,x_2,x_3)}{dx_2} = 0$, and $\frac{E[R(x_1,x_2,x_3)}{dx_3} = 0$ the optimum x_1^*, x_2^*, x_3^* should satisfy the condition of Equation 12, Equation 13, Equation 14:

Equation 12: $p_2 P(D_2 > x_2^* - x_1^*) - p_1 P(D_1 > x_1^*) = 0$

Equation 13: $p_3 P(D_3 > x_3^* - x_2^*) - p_2 P(D_2 > x_2^*) = 0$

Equation 14: $p_4 P(D_4 > C - x_3^*) - p_3 P(D_3 > x_3^* - x_2^*) = 0$

Equation 12, Equation 13, Equation 14 represent the revenue management induction capacity allocation model for four classes of customers under scenario 1.

Scenario 2:

Two protection levels (x_1, x_2) should be computed. The protection level x_1 is assigned to customer class one, x_2 is allocated to both customer classes one and two. The probability of ordering of revenue contribution of different classes of customers is presented by $\theta_{i_1 i_2 \dots i_n}$ as $\theta_{i_1 i_2 i_3} = p\left(\mathcal{W}_{i_1} > \mathcal{W}_{i_2} > \mathcal{W}_{i_3}\right)$. There are $(3! = 6)$ possible expected revenue situations from three classes of customers. An integral equation of the probability density function is used to simplify the expected value of a minimum function. Then, solving $\frac{E[R(x_1,x_2,x_3)}{dx_1} = 0$, $\frac{E[R(x_1,x_2,x_3)}{dx_2} = 0$, and $\frac{E[R(x_1,x_2,x_3)}{dx_3} = 0$ the optimum x_1^*, x_2^*, x_3^* should satisfy the condition of Equation 15, Equation 16, Equation 17:

Equation 15: $p_1 P(D_1 > x_1^*) + (\sum_{i_1 i_2 i_3 \neq 1} \theta_{i_1 i_2 i_3}\, 1 p_{1|w_{i_1} > w_{i_2} > w_{i_3} > w_1})(1 - P(D_1 > x_1^*)) \;=$

$p_2 P(D_2 > x_2^* - x_1^*) + (\sum_{i_1 i_2 i_3 \neq 2} \theta_{i_1 i_2 i_3}\, 2 p_{1|w_{i_1} > w_{i_2} > w_{i_3} > w_2})(1 - P(D_2 > x_2^* - x_1^*))$

Equation 16: $p_1 P(D_2 > x_2^* - x_1^*) + (\sum_{i_1 i_2 i_3 \neq 2} \theta_{i_1 i_2 i_3}\, 2 p_{1|w_{i_1} > w_{i_2} > w_{i_3} > w_2})\,(1 -$

$P(D_2 > x_2^* - x_1^*)) \; = p_2 P(D_3 > x_3^* - x_2^*) + (\sum_{i_1 i_2 i_3 \neq 3} \theta_{i_1 i_2 i_3}\, 3 p_{1|w_{i_1} > w_{i_2} > w_{i_3} > w_3})(1 -$

$P(D_3 > x_3^* - x_2^*))$

Equation 17: $p_1 P(D_3 > x_3^* - x_2^*) + (\sum_{i_1 i_2 i_3 \neq 3} \theta_{i_1 i_2 i_3} 3p_{1|w_{i_1} > w_{i_2} > w_{i_3} > w_2})\ (1 - P(D_3 > x_3^* - x_2^*)) = p_2 P(D_4 > \mathrm{C} - x_3^*) + (\sum_{i_1 i_2 i_3 \neq 4} \theta_{i_1 i_2 i_3} 4p_{1|w_{i_1} > w_{i_2} > w_{i_3} > w_3})(1 - P(D_4 > C - x_3^*))$

For four classes of customers and under two possible scenarios, Equation 12, Equation 13, Equation 14 in scenario one and Equation 15, Equation 16, Equation 17 in scenario two will balance postal services' capacity according to the generated revenue of each class of customers. Models maximize the expected revenue by protecting defined capacity x_1^*, $x_2^* - x_1^*$, $x_3^* - x_2^*$, and $C -\ x_3^*$ for customer classes 1, 2, 3, and 4, respectively.

1.12. Model Development for Multiple Classes of Customers

Let's consider the existing processing capacity C of a postal service in which there are multiple (n) classes of customers with the prices of $p_1, p_2, \dots, p_n$ while $p_1 >\ p_2 > \cdots > p_n$. Customers' demand arrives in a random order, and no cancellation and overbooking is allowed. f_i represents the probability density function for the customer class i ($i = 1,2, \dots$, n) where the total demand is computed by D_i. Therefore, $\mathcal{W}_i = p_i D_i$ is the revenue contribution of each class of customer. Let $E[\mathcal{W}_i] = \mu_i$ be the expected value of revenue contribution of customer i.

Scenario 1:

Equation 18 presents the conditions for n classes of customers where k=1, 2, …, n with $x_n^* = C$ and $x_0^* = 0$ with the optimum protection capacity of $x_1^*, x_2^*, \dots, x_\mathrm{n}^*$.

Equation 18: $p_{k+1} P(D_{k+1} > x_{k+1}^* - x_k^*) - p_k P(D_k > x_k^* - x_{k-1}^*) = 0$

Scenario 2:

Equation 19 presents the conditions for n classes of customers where k=1, 2, …, n with $x_n^* = C$ and $x_0^* = 0$ with the optimum protection capacity of $x_1^*, x_2^*, \dots, x_\mathrm{n}^*$.

Equation 19: $\boldsymbol{p_{k-1}P(D_{k-1} > x_{k-1}^{*} - x_{k-2}^{*}) + \left(\sum_{i_1 i_2 \ldots i_{n-1} \neq k-1} \theta_{i_1 i_2 \ldots i_{n-1}} (k - 1) p_{k-1|w_{i_1} > w_{i_2} > \cdots > w_{i_n} > w_{k-1}}\right)\left(1 - P(D_{k-1} > x_{k-1}^{*} - x_{k-2}^{*})\right) = p_k P(D_k > x_k^{*} - x_{k-1}^{*}) + \left(\sum_{i_1 i_2 \ldots i_{n-1} \neq k} \theta_{i_1 i_2 \ldots i_{n-1}} (k) p_{k|w_{i_1} > w_{i_2} > \cdots > w_{i_n} > w_k}\right)\left(1 - P(D_k > x_k^{*} - x_{k-1}^{*})\right)}$

Equation 18 and Equation 19 present the revenue management induction capacity allocation models for n classes of customers under scenarios 1 and 2, respectively.

1.13. Summary

In practice, selecting an optimum protection level might be based on management experience, customer expectations, or other practical factors when customers' demand level and price are uncertain. The developed induction capacity allocation model computes this protection level for each class of customer while maximizing the expected revenue. It considers distributions of classes of customers' demand and price in order to allocate the optimum capacity allocation of postal services' capacity between different customer classes to maximize the expected revenue. The next chapter provides an empirical validation of the developed model.

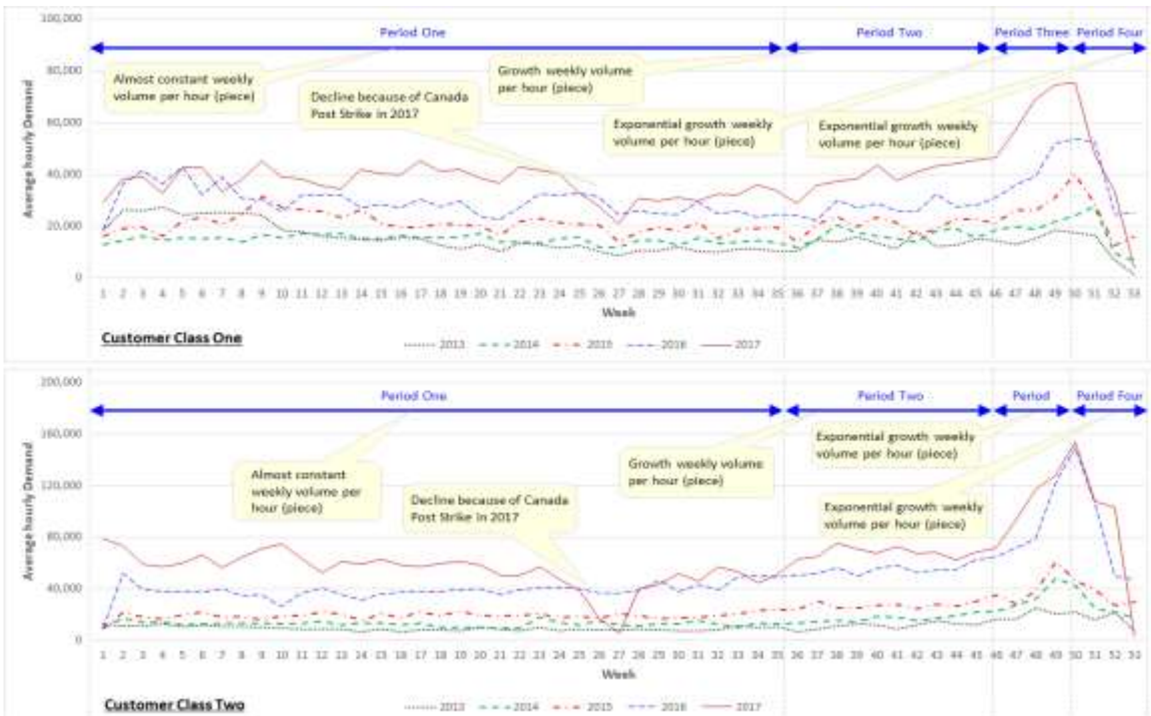
Empirical Validation of Revenue Management Induction Capacity Allocation Model (RM-ICAM)

In this chapter, the Revenue Management Induction Capacity Allocation Model (RM-ICAM) for postal service is assessed using the Canada Post Corporation (CPC) transaction and validated through simulations. An optimization study is conducted using simulation output. Results show the recommended protection levels for each class of customers while computing the maximum generated revenue. The complexity of implementing the model for four and more classes of customers is discussed. The simulation-based optimization outputs help decision-makers to determine an optimal protected level of induction capacity, which is very close to the theoretical one, according to customer class revenue contribution.

1.14. Two Classes of Customers

To empirically validate the developed conceptual revenue RM-ICAM model for postal services, a sixty-month demand dataset, from January 2013 to December 2017 has been used. Eighty-two LVMs are selected, which is around 20% of LVM customers, and they generate about 75% of the total parcel volume (Pareto rule). To assign customers to two classes; first, we categorized all LVMs based on the price distributions, then we calculated their revenue contributions and grouped them accordingly. The average revenue per hour (average demand per hour × price) is computed for each customer. All LVMs' demand, in the current settings, arrives in random order, and it is processed based on a first-come-first-served basis. The historical data provides us with an estimation of the distribution of LVMs demand for the 2013 - 2017 period. The average hourly demand for week 1 to week 52 for all LVMs was computed. The data analysis revealed that there are four periods during a year with similar demand trends that were consistent during all five years of observations.

Figure 7: Typical Average weekly demand per hour for two classes of customers



Period one (Stable Demand) covers week 1 to week 35 with some weekly fluctuations but almost constant average demand for these 35 weeks. Period two (Growing Demand) covers an 11-week period from week 36 till week 46 with constant growth. Period three (Exponential Demand) covers a four week period from week 47 till week 50 with exponential growth in demand mainly because of Christmas and holiday online shopping. Period four (Falling Demand) covers the last three weeks of the year (week 51 till week 53), which is associated with after holidays period and demonstrates an exponential decay. Figure 7 illustrates the demand behavior for two classes of customers where customers' class one pays a higher price compared to the customers' class two. As can be seen, the demand periods are similar for both classes. However, although the trends in demand behavior repeat every year, there is a significant growth in demand for both classes each year. The five-year data (2013 to 2017) helped to make a more accurate estimation of the future demand and to consider potential growth in demand. The simulation models were run and computed the protected capacity for two classes of customers for each period based on the volume of 2017. The simulation models were developed in order to follow the mathematical model assumptions and steps described in the flowchart in Figure 6. Oracle Crystal Ball 11th edition simulation package and IBM SPSS software were employed for the simulation and analysis. The raw data were extracted for the selected LVM customers. The dataset included the ticket number, time of order, date of order, and volume/demand (pieces). The data were checked for consistency and cleaned. Since the raw data have been extracted from the shipping label system, there were almost no missing values. The simulations have been run for 10,000 times for each period, 40,000 in total. For both scenarios, we used simulation to validate the mathematical models (Equations 3 and 7). Customers were manually selected and assigned to each class for the simulations to satisfy the conditions of scenario 1 and 2 regarding prices (p_1, p_2) and demands (D_1, D_2).

<u>Scenario 1:</u>

The available daily capacity is $C = 15{,}000$ parcels per hour, $p_1 and\ p_2$ have discrete uniform distributions with a minimum and maximum of \$10-\$12 for p_1 and \$6-\$8 for p_2 accordingly. The empirical demands of customers' classes one and two (D_1 and D_2) have different distributions in four periods of the year (Table 6):

Table 6: The hourly demand distribution of two classes of customers (scenario 1)

Customer Class	Period 1 Week 1 – 35	Period 2 Week 36 - 46	Period 3 Week 47 – 50	Period 4 Week 51 - 53

Customer Class One	Normal Mean = 5,925 SD = 2,147	Logistic Mean = 7,070 Scale = 1,360	Logistic Mean = 11,655 Scale = 4,276	Logistic Mean = 8,068 Scale = 3,479
Customer Class Two	Normal Mean = 6,004 SD = 2,633	Logistic Mean = 8,708 Scale = 1,745	Logistic Mean = 15,432 Scale = 2,632	Logistic Mean = 7,968 Scale = 2,497

Customers' demand distribution parameters are computed through the "Fit Distribution" function in the Oracle Crystal Ball 11th edition simulation package. The best fit of distribution has been chosen according to the volume data for each class of customers. Figure 8 shows the distribution results for each class of customers in each of the four periods of the year.

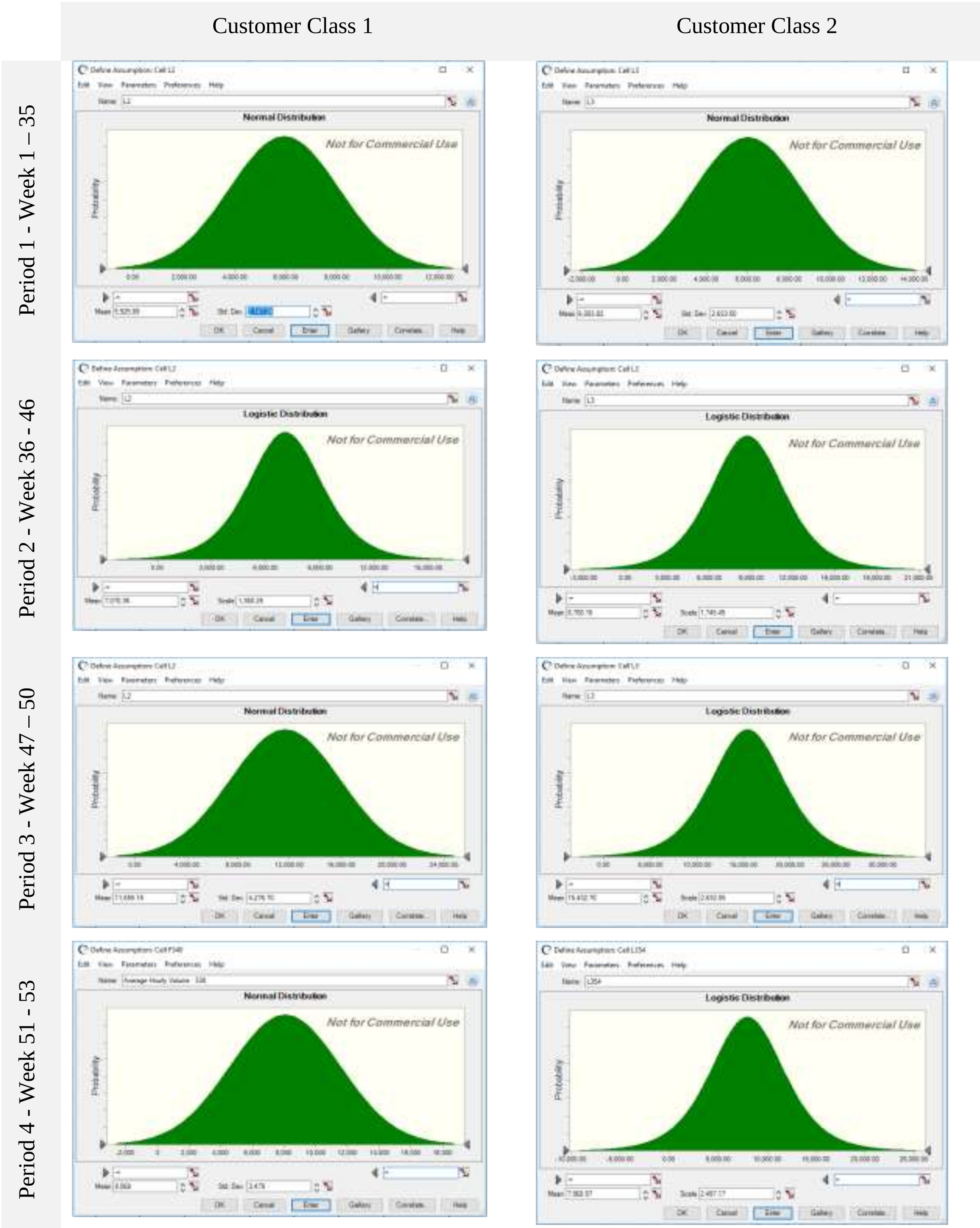


Figure 8: The hourly demand distribution of two classes of customers (scenario 1)

Figure 9 illustrates the results of the simulations for Scenario 1, showing the expected total revenue (ETR) in a million dollars, the percentage of the total capacity associated with the "protected" for customer class one (x^*) and the percentage related to the remaining capacity "protected" for customers' class two ($C - x^*$) along with the "difference" as explained before in equations 3 and 4. It shows that in period one, with stable demand for both classes, protecting 42% of the available induction capacity for customers' class one will maximize ETR=319 while minimizing the computed difference at this point is 0.06. In period two, with constant demand growth, the protected induction capacity for customer class one should be increased to 50% to obtain maximum ETR=116 for period two and a minimum difference of -0.04. For period three, with the exponential growth demand, maximum ETR=44, and minimum difference of 0.01 require protecting 40% capacity for the customers' class one. Finally, in the last period, when the demand has exponential decay, protecting 66% of the induction capacity for the customers' class one maximizes ETR=21 and minimizes the difference of 0.02.

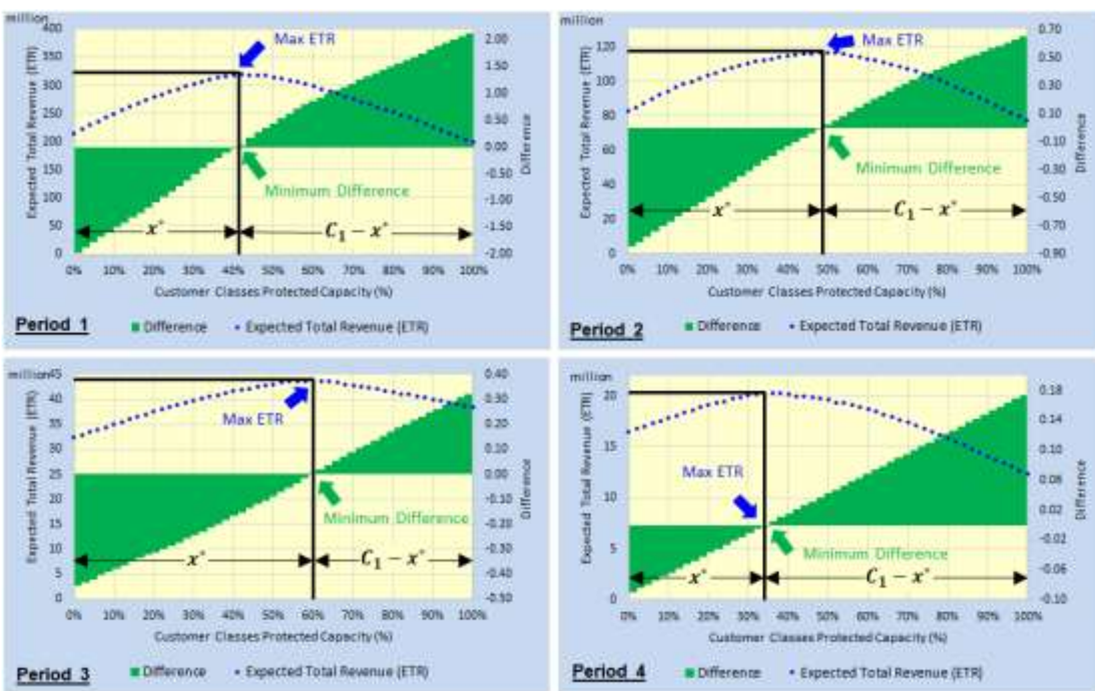


Figure 9: Optimum allocated capacity for two classes of customers (scenario 1)

Scenario 2:

The available daily capacity is $C = 15{,}000$ parcels per hour, $p_1 and\ p_2$ have discrete uniform distributions with a minimum and maximum of \$10-\$12 and \$6-\$8, respectively. The empirical demands of customer class one and two (D_1 and D_2) have different distributions in four periods of the year (Table 7).

Table 7: The hourly demand distribution of two classes of customers (scenario 2)

Customer Class	Period 1 Week 1 – 35	Period 2 Week 36 - 46	Period 3 Week 47 - 50	Period 4 Week 51 - 53
Customer Class One	Normal Mean = 3,635 SD = 1,210	Logistic Mean = 3,334 Scale = 669	Normal Mean = 4,879 Scale = 1,696	Logistic Mean = 3,225 Scale = 682
Customer Class Two	Normal Mean = 12,448 SD = 4,384	Logistic Mean = 15,944 Scale = 3,428	Logistic Mean = 33,680 Scale = 5,812	Logistic Mean = 22,593 Scale = 4,510

Customers' demand distribution parameters are computed through the "Fit Distribution" function in Oracle Crystal Ball 11th edition simulation package. The best fit of distribution has been chosen according to the volume data for each class of customers. Figure 10 shows the distribution results for each class of customers in each of the four periods of the year.

Customer Class 1 | Customer Class 2

Period 1 - Week 1 – 35

Period 2 - Week 36 - 46

Period 3 - Week 47 – 50

Period 4 - Week 51 - 53

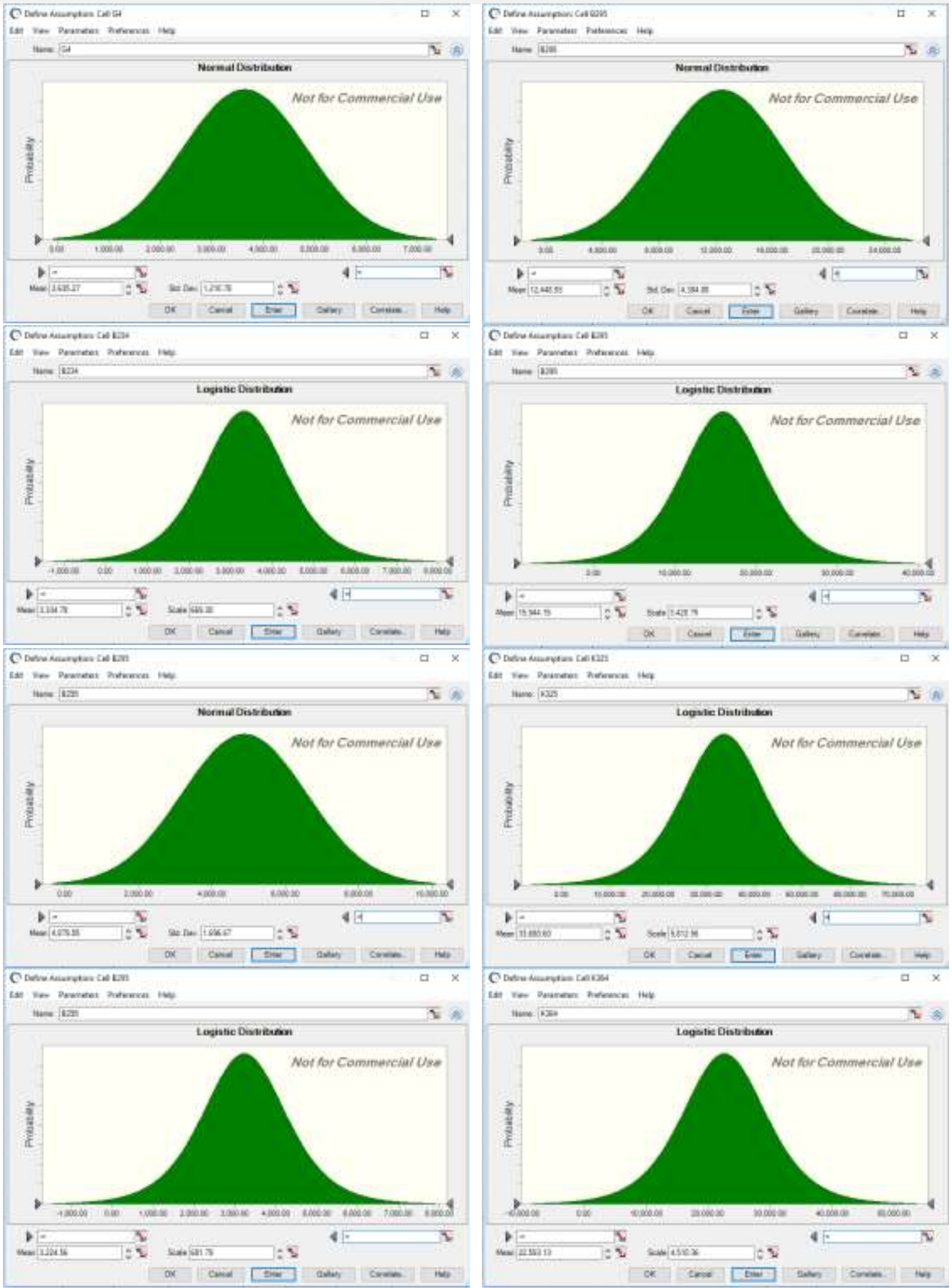


Figure 10: The hourly demand distribution of two classes of customers (scenario 2)

Figure 11 shows Expected Total Revenue (ETR) on the Y-axis (left), the difference mentioned in equations 3 and 7 on the Y-axis (right), and the percentage of capacity protected for customer class one (x^*) and percentage of remaining capacity protected for customer class two ($C_1 - x^*$) on the X-axis. Graphs show that in period one, protecting just 26% of the capacity for customer class one maximizes ETR=457 while minimizing the computed difference at this point is 0.08, which is very close to zero. In period two, the protected capacity of customer class one should be increased to 32% to obtain maximum ETR=149 and a minimum difference of 0.06. In period three, maximum ETR=59 and minimum difference of -0.08 require protecting 40% capacity for the customer class one. In the last period, protecting 18% of the induction capacity for customer class one maximizes ETR=31 and minimizes the difference of 0.02.

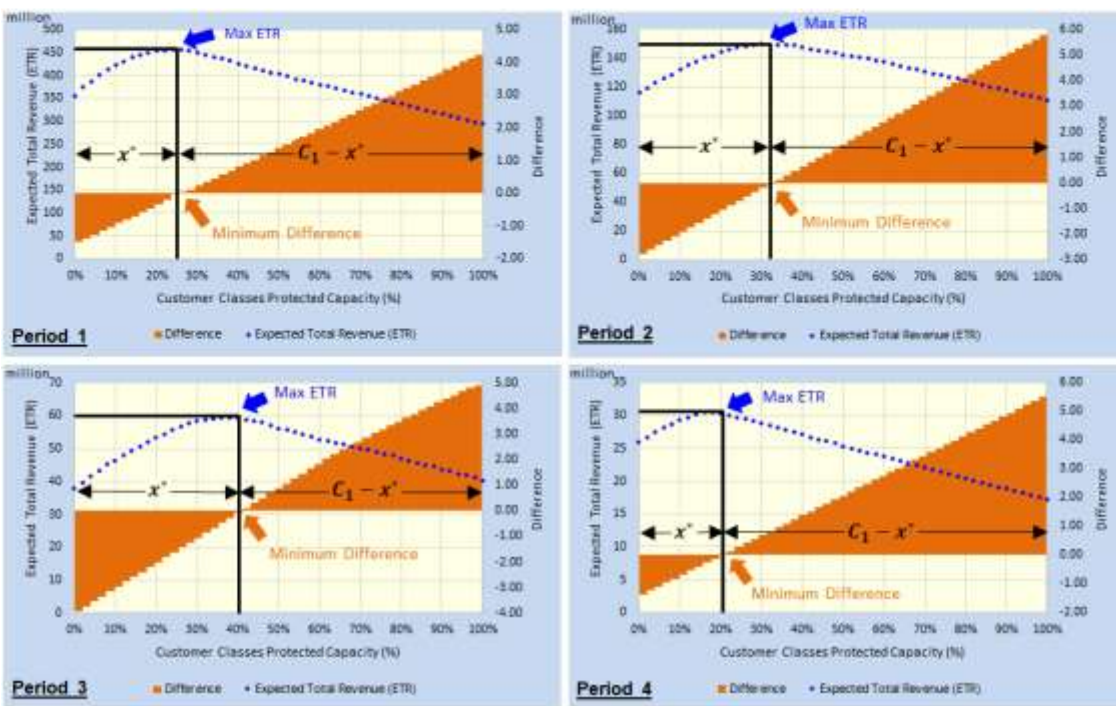


Figure 11: Optimum protected capacity for two classes of customers (scenario 2)

The results of both scenarios show minimum difference (as required by the Littlewood rule) of $p_1 P[D_1 > x^*] - p_2 P[D_2 > C_1 - x^*]$ and $p_{1|w_1>w_2} P\ (D_1 > x^*) - \theta p_{2|w_1>w_2} - (1-\theta) p_{2|w_1<w_2} P\ (D_2 > C_1 - x^*) - (1-\theta) p_{2|w_1<w_2} (D_2 > C_1 - x)$. These differences were explained where we developed Equations 3 and 4.

For all simulations, the minimum differences are very close to zero, which shows the computed protected capacity's accuracy when two sides of the equation are equal by using the protected capacity. Also, coefficients of determination (R^2) were computed for the trend of ETR lines. All coefficients are from 0.87 to 0.99 and show that the proportion of the variance in ETR is highly predictable from the protected capacity for customer classes. Table 8 summarizes computed ETR, differences, and protected capacity for both scenarios in four periods. The last column in the table shows the coefficient of determinations of ETR lines.

Table 8: Allocated capacity and ETR summary - two classes of customers

Scenarios	Period of the Year	Capacity Allocated		Expected Revenue (million $)	ETR (million $)	Difference (Equation 3 & 4)	$\boldsymbol{R^2}$ of ETR Line
		Class one x^*	Class Two $C_1 - x^*$				
Scenario 1	Period 1	42%	58%	319.812	500.68	0.06	96.75%
	Period 2	49%	51%	116.782		-0.04	99.50%
	Period 3	60%	40%	43.852		0.01	99.47%
	Period 4	34%	66%	20.242		0.02	98.80%
Scenario 2	Period 1	26%	74%	457.101	665.06	0.08	88.57%
	Period 2	32%	68%	148.573		0.06	88.64%
	Period 3	40%	60%	59.392		-0.08	86.54%
	Period 4	18%	82%	30.420		0.02	94.71%

1.15. Three Classes of Customers

From January 2013 to December 2017, a sixty-month demand data set is used to test and validate empirically the developed RM-ICAM model for three classes of customers in four time periods of the weekly demand per hour. Periods one, two, three, and four cover week 1 - 35, week 36 - 46, week 47 - 50, and week 51 – 52. Simulation and optimization have been used to follow the required mathematical model assumptions and steps. Customers have been randomly assigned to three classes while conditions regarding prices (p_1, p_2, p_3) and demands (D_1, D_2, D_3) for each scenario are satisfied.

<u>Scenario 1:</u>

The demand for all three classes of customers is less than the available capacity ($\mathrm{P}[\mathrm{D}_1 < \mathrm{C}_1] = 1$, $\mathrm{P}[\mathrm{D}_2 < \mathrm{C}_1] = 1$, and $\mathrm{P}[\mathrm{D}_3 < \mathrm{C}_1] = 1$) but the total demand for them is greater than the available capacity ($\mathrm{P}[\mathrm{D}_1 + \mathrm{D}_2 + \mathrm{D}_3 > \mathrm{C}_1] = 1$). The available capacity is $C_1 = 15{,}000$ parcels per $hour/day$, p_1, p_2, and p_3 have a discrete uniform distribution with minimum and maximum of \$14-\$16, \$11-\$13, and \$7-\$10, respectively. The empirical demands of three classes of customers (D_1, D_2, and D_3) have different distributions in four periods of the year (Table 9):

Table 9: The hourly demand distribution of three classes of customers (scenario 1)

Customer Class	Period 1 Week 1 – 35	Period 2 Week 36 - 46	Period 3 Week 47 – 50	Period 4 Week 51 - 53
Customer Class One	Normal Mean = 4,260 SD = 1,813	Normal Mean = 3,303 SD = 1,283	Normal Mean = 4,732 SD = 1,948	Logistic Mean = 2,898 Scale = 1,174
Customer Class Two	Normal Mean = 4,915 SD = 1,939	Logistic Mean = 6,234 Scale = 1,047	Normal Mean = 11,885 SD = 4,283	Logistic Mean = 8,506 Scale = 2,439
Customer Class Three	Normal Mean = 7,130 SD = 2,637	Logistic Mean = 9,289 Scale = 1,596	Logistic Mean = 21,053 Scale = 3,550	Logistic Mean = 16,710 Scale = 5,282

Customers' demand distribution parameters are computed through the "Fit Distribution" function in Oracle Crystal Ball 11th edition simulation package. The best fit of distribution has been chosen according to the volume data for each class of customers.

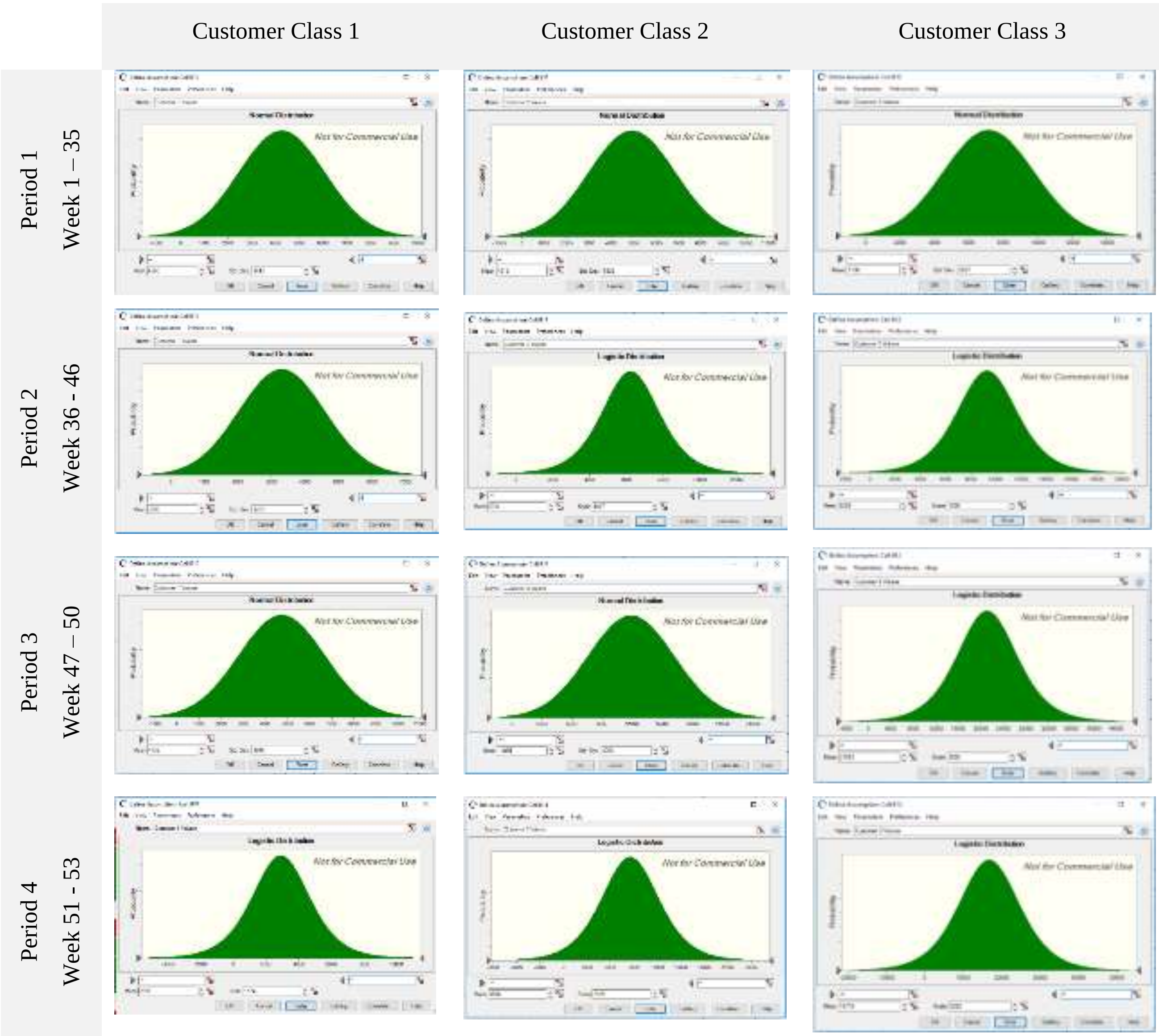


Figure 12: The hourly demand distribution of three classes of customers (scenario 1)

Figure 12 shows the distribution results for each class of customers in each of the four periods of the year. Due to the limitations of the Oracle Crystal Ball 11th edition simulation package regarding the number of decision variables (maximum two decision variables) in simulation, the capacity allocated to three classes of customers (x_1^*, x_2^*, x_3^*) are computed differently. One decision variable is the capacity allocated to customer classes 1 & 2 ($x_1^* + x_2^*$) together, therefore, $x_3^* = C_1 - x_1^* - x_2^*$. Another decision variable is the ratio (r) allocated to customer class 1 out of ($x_1^* + x_2^*$). In other words, $x_1^* = r(x_1^* + x_2^*)$ and $x_2^* = (1 - r)(x_1^* + x_2^*)$.

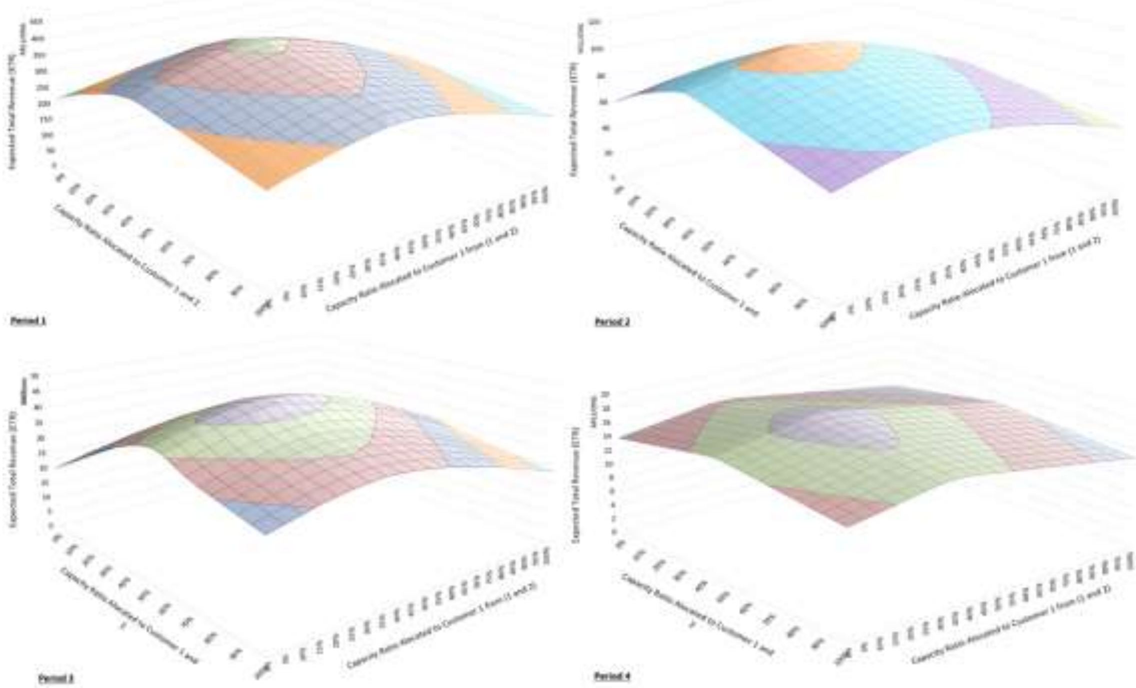


Figure 13: Optimum allocated capacity for three classes of customers (scenario 1)

In Figure 13, the Y-axis shows expected total revenue (ETR) in a million dollars, the X-axis shows the percentage of capacity allocated to customer classes 1 and 2, and the Z-axis shows the ratio allocated to customer class 1 out of the percentage shown in the X-axis. The graphs show that in period one (35 weeks), by protecting 45% of the capacity for customer classes one and two, 55% of the capacity remains for customer class three, which maximizes ETR=412 million. In period two (11 weeks), by protecting 40% of the capacity for customer classes one and two, 60% of the capacity remains for customer class three, which maximizes ETR=107 million. In period three (4 weeks), by protecting 55% of the capacity for customer classes, one and two, 45% of the capacity remains for customer class three, which maximizes ETR=48 million. Finally, in period two (2 weeks), the maximum ETR=19 million is obtained through protecting 45% of the capacity for customer classes one and two and 55% for customer class three.

Scenario 2:

The demand of the customer classes one and two (which pays a higher price) is less than the available capacity ($\mathrm{P}[\mathrm{D}_1 < C] = 1$ and $\mathrm{P}[\mathrm{D}_2 < \mathrm{C}] = 1$) but the customer class three (which pays a lower price) is greater than the available capacity $P[D_3 > \mathrm{C}] = 1$. Obviously, all three classes of customers together ($\mathrm{P}[\mathrm{D}_1 + \mathrm{D}_2 + \mathrm{D}_3 > \mathrm{C}] = 1$) have a demand greater than the available capacity.

The available capacity is $\mathrm{C} = 15{,}000$ parcels per hour per day p_1, p_2, p_3 have a discrete uniform distribution with minimum and maximum of \$10-\$12, \$8-\$10, and \$6-\$8, respectively. The empirical demands of customer classes one and two (D_1, D_2, and D_3) have different distributions in four periods of the year (Table 10):

Table 10: The hourly demand distribution of three classes of customers (scenario 2)

Customer Class	Period 1 Week 1 – 35	Period 2 Week 36 - 46	Period 3 Week 47 – 50	Period 4 Week 51 - 53
Customer Class One	Normal Mean = 4,260 SD = 2,013	Normal Mean = 3,303 SD = 1,283	Normal Mean = 4,732 SD = 1,948	Logistic Mean = 2,897 Scale = 1,174
Customer Class Two	Normal Mean = 4,915 SD = 2,139	Logistic Mean = 5,624 Scale = 1,581	Logistic Mean = 11,159 SD = 3,268	Logistic Mean = 7,600 Scale = 2,098
Customer Class Three	Normal Mean = 10,550 SD = 4,388	Logistic Mean = 14,087 Scale = 2,5952	Logistic Mean = 28,229 Scale = 4,769	Logistic Mean = 19,877 Scale = 6,021

Customers' demand distribution parameters are computed through the "Fit Distribution" function in Oracle Crystal Ball 11th edition simulation package. The best fit of distribution has been chosen according to the volume data for each class of customers. Figure 14 shows the distribution results for each class of customers in each of the four periods of the year.

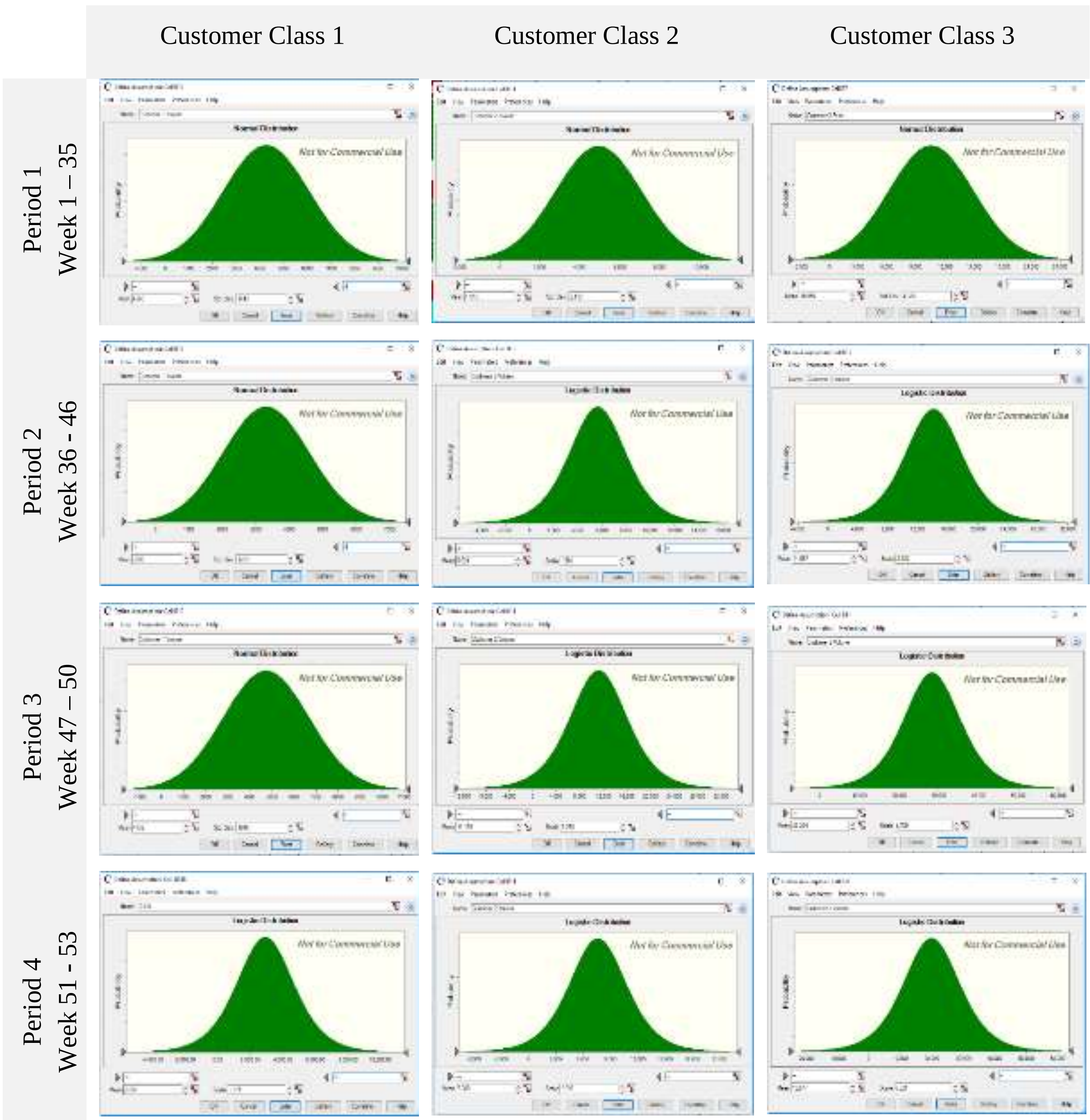


Figure 14: The hourly demand distribution of three classes of customers (scenario 2)

Due to the limitations of Oracle Crystal Ball 11th edition simulation package regarding the number of decision variables (maximum two decision variables) in simulation, the capacity allocated to three classes of customers (x_1^*, x_2^*, x_3^*) are computed differently. One decision variable is the capacity allocated to customer classes 1 & 2 $(x_1^* + x_2^*)$. Therefore, $x_3^* = C - x_1^* - x_2^*$. Another decision variable is the ratio (r) allocated to customer class 1 out of $(x_1^* + x_2^*)$. In other words, $x_1^* = r(x_1^* + x_2^*)$ and $x_2^* = (1 - r)(x_1^* + x_2^*)$.

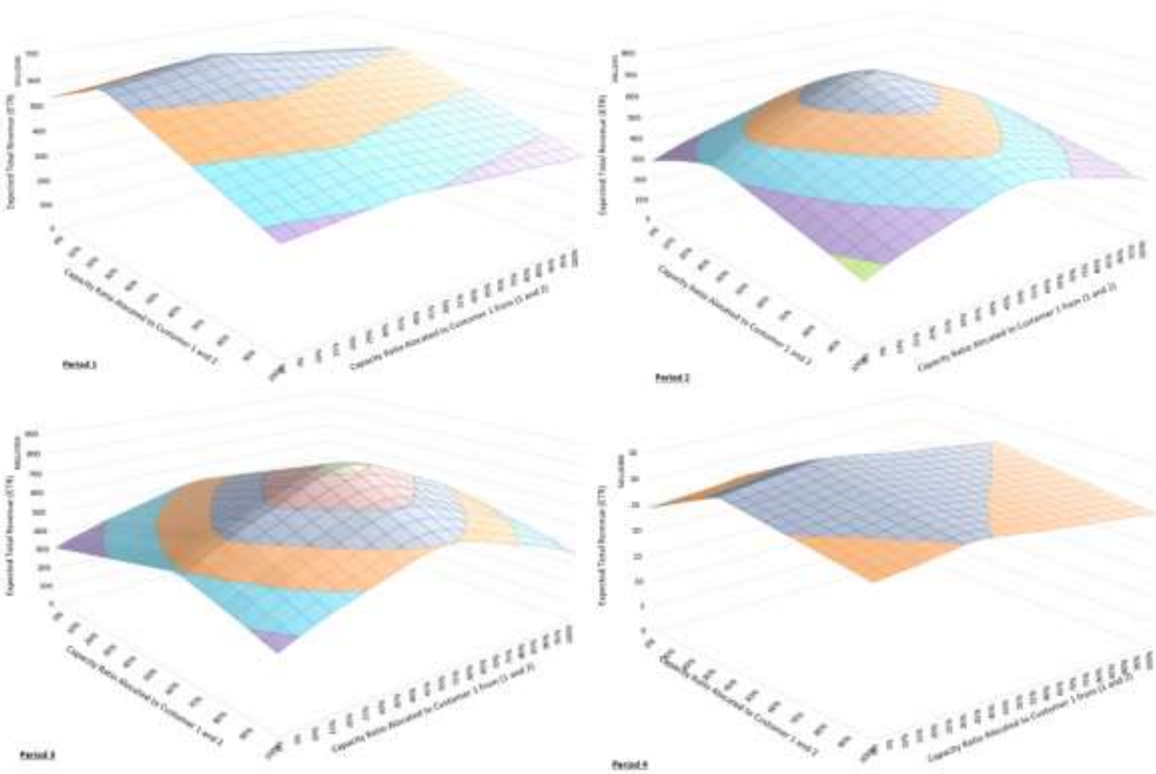


Figure 15: Optimum allocated capacity for three classes of customers (scenario 2)

In Figure 15, the Y-axis shows expected total revenue (ETR) in millions of dollars, the X-axis shows the percentage of capacity allocated to customer classes 1 and 2, and the Z-axis shows the ratio allocated to customer class 1 out of the percentage shown in the X-axis. Graphs show that in period one (35 weeks), by protecting 30% of the capacity for customer classes one and two, 70% of the capacity remains for customer class three, which maximizes ETR=693 million. In period two (11 weeks), by protecting 40% of the capacity for customer classes one and two, 60% of the capacity remains for customer class three, which maximizes ETR=221 million. In period three (4 weeks), by protecting 30% of the capacity for customer classes one and two, 70% of the capacity remains for customer class three, which maximizes ETR=70 million. Finally, in period four (2 weeks), the maximum ETR=34 million is obtained through protecting 35% of the capacity for customer classes one and two and 65% for customer class three. Table 11 provides a summary of computed protected capacity and ETR for each class of customers in both scenarios.

Table 11: Allocated capacity and ETR summary - three classes of customers

Scenarios	Period of the Year	Protected Capacity			ETR (million $)
		Class one x_1^*	Class Two x_2^*	Class Three x_3^*	
Scenario 1	Period 1	18%	27%	55%	412.849
	Period 2	14%	26%	60%	107.949
	Period 3	19.25%	35.75%	45%	48.498
	Period 4	15.75%	29.25%	55%	19.087
Scenario 2	Period 1	10.5%	19.5	70%	693.834
	Period 2	14%	26%	60%	221.493
	Period 3	12%	18%	30%	70.035
	Period 4	12.25%	22.75%	35%	34.634

1.16. Multiple Classes of Customers

For multiple classes of customers, simulation and optimization have been used to validate the results of the developed RM-ICAM model. Due to the complexity of the simulation for four classes of customers, we used Oracle Crystal Ball 11th edition optimization package (OptQuest), which shows the results in a performance chart format.

In scenario one, the demand for all four classes of customers is less than the available capacity ($\mathrm{P}[\mathrm{D}_1 < \mathrm{C}] = 1$, $\mathrm{P}[\mathrm{D}_2 < C] = 1$, $\mathrm{P}[\mathrm{D}_3 < C] = 1$, and $\mathrm{P}[\mathrm{D}_4 < C] = 1$) but the total demand for them is greater than the available capacity ($\mathrm{P}[\mathrm{D}_1 + \mathrm{D}_2 + \mathrm{D}_3 + \mathrm{D}_3 > C] = 1$). In scenario two, the demand of the customer classes one, two, and three (which pays a higher price) are less than the available capacity ($\mathrm{P}[\mathrm{D}_1 < C] = 1$, $\mathrm{P}[\mathrm{D}_2 < C] = 1$, $\mathrm{P}[\mathrm{D}_3 < C] = 1$) but the customer class four (which pays the lowest price) is greater than the available capacity $P[D_4 > C] = 1$. Obviously, all four classes of customers together ($\mathrm{P}[\mathrm{D}_1 + \mathrm{D}_2 + \mathrm{D}_3 + \mathrm{D}_4 > C] = 1$) have a demand greater than the available capacity.

Table 12: Allocated capacity and ETR summary - four classes of customers

Scenarios	Period of the Year	Protected Capacity				ETR (million $)
		Class one x_1^*	Class Two x_2^*	Class Three x_3^*	Class Four x_4^*	
Scenario 1	Period 1	27.5%	27.5%	13.9%	31.1%	588.331
	Period 2	26.2%	38.5%	14.6%	20.7%	189.106
	Period 3	32.0%	53.2%	14.8%	0%	79.257
	Period 4	18.7%	52.8%	19.4%	9.1%	32.662
Scenario 2	Period 1	4.2%	32.8%	31.9%	31.1%	619.636
	Period 2	23.2%	29.2%	29.5%	18.1%	190.725
	Period 3	38.6%	54.2%	7.2%	0%	85.229
	Period 4	28.5%	38.5%	16.2%	16.8%	38.783

Table 12 shows the optimization results that maximize the generated revenues in each period. The protected capacities are the results of 500 trials of optimization, which simulated 1,000 times (500,000) in each period. The available capacity is $\mathrm{C} = 15{,}000$ parcels per hour/day $p_1 > p_2 > p_3 > p_4$ have a discrete uniform distribution with minimum and maximum of \$14-\$16, \$11-\$13, \$9-\$10, and \$6-\$8, respectively. The same assumption applies regarding the empirical demands of four classes of customers (D_1, D_2, D_3 and D_4) which have different distributions in four periods of the year.

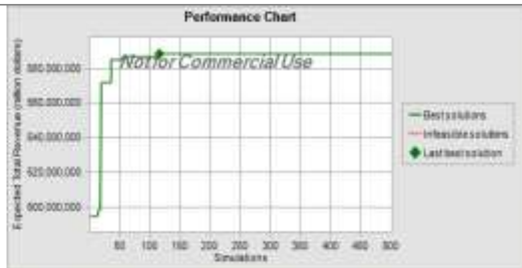
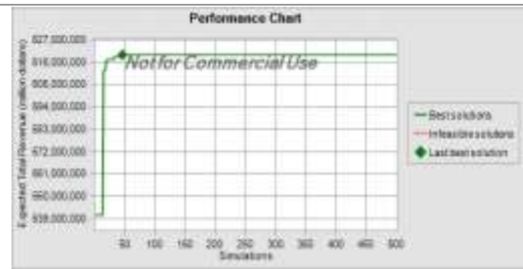
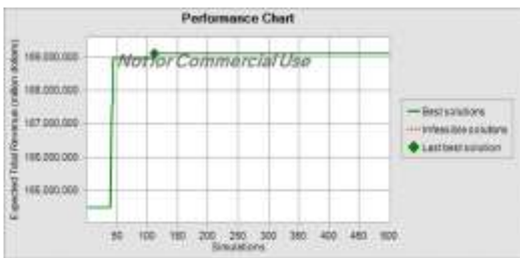
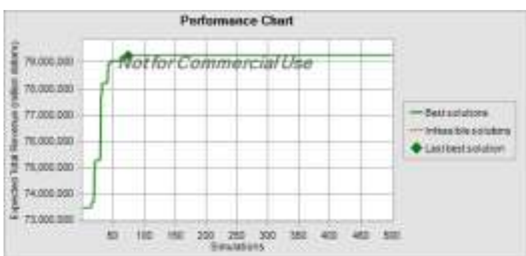
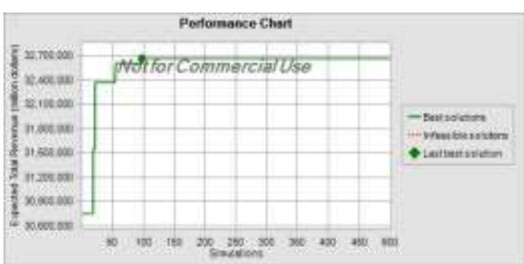
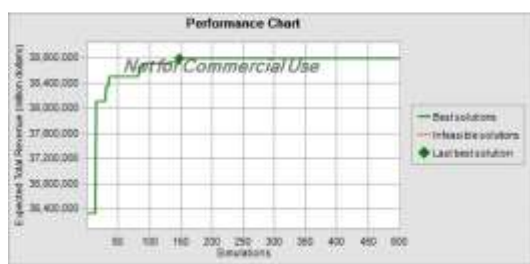
Period	Scenario 1	Scenario 2
Period 1		
Period 2		
Period 3		
Period 4		

Figure 16: Optimum allocated capacity for four classes of customers (scenarios 1&2)

Optimization graphs are presented in Figure 16, which show the maximum revenue through 500 trials.

1.17. Assessment of the Models' Performance

This section computed the expected total revenue in the current situation without applying the RM-ICAM model. Currently, the first-come-first-served (FCFS) policy is being used to process customers' demands. The available capacity is $C = 15{,}000$. We used the average volume per/hour multiplied by the price distribution for each customer to compute the expected revenue for each customer. Then, we compared this revenue with the results using the RM-ICAM model when we had two, three, or four classes of customers under two discussed capacity scenarios. Table 13 shows the improvement of expected revenue by applying RM-ICAM to allocate capacity. For two, three, and four classes of customers, the expected revenue increased by 19.5%, 31.6%, and 54.8% in scenario 1 and 42.3%, 60.6%, and 57.0% in scenario 2.

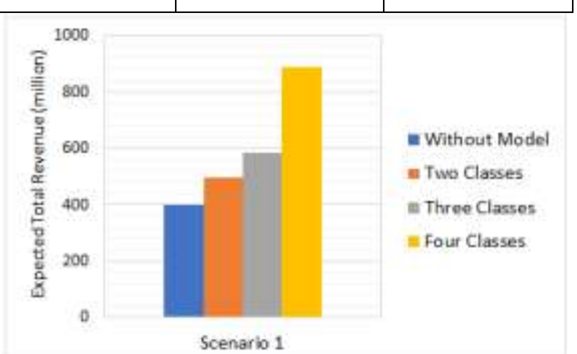
Table 13: Revenue comparison with and without using the capacity allocation model

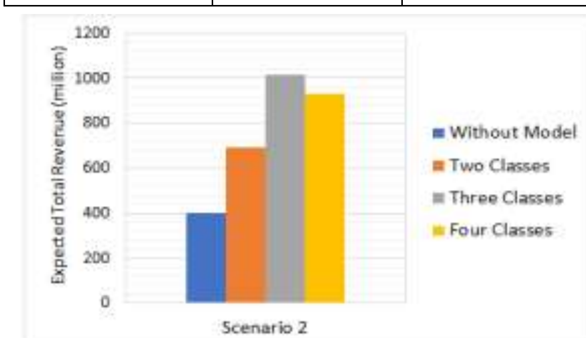
Scenario 1

Two Classes	(+/-)	Three Classes	(+/-)	Four Classes	(+/-)
498	19.5%	586	31.6%	888	54.8%

Scenario 2

Two Classes	(+/-)	Three Classes	(+/-)	Four Classes	(+/-)
695	42.3%	1,018	60.6%	932	57.0%





In this chapter, we summarized the validation results of the developed capacity allocation model for postal services. A real sixty-month period demand data set (542,933,927 online shopping transactions), from January 2013 to December 2017, has been used. Using the Oracle Crystal Ball 11th edition optimization package (OptQuest) enabled us to validate the model for multiple customers' classes. The validation results have been provided for two, three, and four classes of customers in this section. However, there is no limitation to the number of classes of customers by using optimization software. To make a revenue comparison between the current ones versus the ones obtained in simulation and optimization, the revenue gap has been computed for each scenario for two, three, and four classes of customers. The result shows 19.5%, 31.6%, and 54.8% revenue improvement for two, three, and four classes of customers, respectively, in scenario one. The results show more improvement in scenario two, with 42.3%, 60.6%, and 57% for two, three, and four classes of customers, respectively. The results confirm, considering all assumptions, the revenue management main concept that differential pricing increases total profits for a firm.

Discussion and Conclusions

1.18. Implications for Research and Key Contributions

Postal services have recently been challenged by processing increased parcel volumes generated mostly by large volume mailers who want to deliver purchases generated by growing online shopping to their customers. As a result, postal services face the processing capacity problem where induction (i.e., number of items that can be inducted by a processing plant per specific period of time) overcapacity or bottleneck represents the primary bottleneck. The literature suggests overcoming this challenge either by increasing the efficiency of the sorting equipment (e.g., optimized sort schematic and machine scheduling) or by increasing the productivity of the transportation network (e.g., truck utilization, optimized routing). However, these solutions are cost-sensitive, not long-term, and sometimes not feasible for postal services. Moreover, most of the developed models focus on improving the operations performance indicators but not the revenue of postal services.

This study reconsiders the traditional approaches and offers an innovative and novel revenue management approach for parcel induction capacity management of postal services by maximizing generated revenue with the existing capacity. The application of revenue management to manage capacity allocation has been successful in many industries, including airlines, hotels, cargo delivery, etc. The discipline of RM is a process that helps companies to generate more revenue and increase the profitability of their business from the existing capacity. RM contains strategies, methods, and tools to maximize the revenue through capacity allocation for multiple customers with different prices. Although most successful examples of the application of RM are from the travel and hospitality industry, specifically airlines, car rentals, and hotels, many other services, and manufacturing industries (e.g., manufacturing, healthcare, freight transportation, etc.) with similar capacity problems have successfully implemented RM.

This research integrates revenue management concepts with the e-commerce supply chain by developing a conceptual induction capacity allocation model for postal services. The developed model computes an optimum protected capacity under different scenarios for each class of customers and generates maximum revenue. This study also addresses issues regarding the capacity allocation decisions during peak sessions (e.g., Christmas) by regulating the allocation of capacity through determining a protected capacity for each class of customers. The developed model provides a long-term solution for postal services that increase delivery performance by removing the bottleneck and improves customers' expectations from e-commerce parcel delivery performance.

This research analyzes the dynamic hourly demand and allocates the capacity based on the arrival (demand) patterns across multiple customer classes. The model uses hourly volume data to develop a distribution/pattern for different customer classes' demand. The model then uses this demand distribution to formulate and compute the optimum required induction capacity while maximizing each customer class's expected revenue. The model computes the portion of hourly induction capacity named "*protected capacity*" that should be protected for different customer classes. By allocating and protecting the induction capacity, postal services can refuse to accept any extra volume that may create a bottleneck and impact their service performance. Obviously, in the capacity expansion requirement, postal service can compute the net required capacity that should be added through investment on new facilities or advanced equipment.

A real dataset from one of processing plants has been employed to validate the developed model. The results show a realistic situation of the protected capacity levels, which considers customer classes' random arrival patterns. The optimal protection levels determine the amount of demand that should be accepted to maximize the expected revenue.

1.18.1. Research Contributions

From a theoretical and methodological perspective, this Ph.D. thesis offers an innovative and novel approach for induction capacity allocation in postal services for large volume retailers (e.g., Amazon). The research combines revenue management concepts with the e-commerce supply chain by developing a conceptual capacity allocation model for postal companies. The mathematical model considers the dynamic arrival pattern of customers' demand rather than the static pattern, as one of Littlewood's basic model assumptions. The proposed developed model represents more practical situations for postal services when there is a random order of volume arrival of different customer classes.

This research also introduces and implements the concept of protection levels for customer classes in postal services. The protected capacity is a portion of postal services' current induction capacity allocated and reserved for each class of customers. The model computes the protected capacity under different scenarios and is based on critical variables, including parcel volume distribution, the arrival pattern, and price distribution to maximize expected revenue generation.

The model can improve and facilitate capacity allocation decisions specifically in peak times (e.g., Christmas) by optimizing the volume induction across postal services' e-commerce supply chain.

In this thesis, we simulated different demand distribution scenarios than the available induction capacity for multiple classes of customers. Moreover, optimizations for each scenario are also conducted to find an optimum percentage of protected capacity for each class of customers while maximizing expected revenue.

The developed model is flexible and considers multiple cases with a different number of classes of customers (2,3,4, and n) that can be implemented based on the postal service's needs. For example, more classes of customers can be considered during the peak seasons (e.g., Christmas, back to school) and fewer classes of customers during the rest of the year. Rather than making assumptions, the model can also use both the most recent historical or predicted parcel volume data to assign the best fit of hourly, daily, weekly, and monthly demand distributions. The developed model improves the accuracy of computation of the protected capacity and expected revenue.

The developed mathematical model contributes to Littlewood's revenue management model by considering a random order of arrival rather than the order that the demand for low-fare class customers arrives before high-fare class. In other words, the model presents an actual situation of e-commerce parcel volume distribution where the arrival patterns of LVMs' demands are random.

The developed model can be used as a decision-making and planning tool to improve operational decision-making and avoid overbooking. In particular, the optimization results (the expected revenue according to the allocated capacity) in different scenarios and a different number of classes of customers (2,3,…) can be compared to make better and more accurate decisions. Although the model was developed based on postal services' settings and environment, it can be used in other service sectors with similar capacity allocation problems such as third-party logistics (3PL), less than a truckload (LTL), small and medium delivery firms, truckload freight shipping, and warehousing and logistics companies.

1.19. Limitations and Suggestions for Future Research

The developed model holds some limitations as discussed below with proposed possible future research opportunities to address these limitations:

The model does not incorporate any discounts, promotions, and other price-related agreements and commitments that could be stated in the annual contracts between postal services and online retailers. A price discount ratio is considered according to a specific committed level of demand growth expectations in some situations. Future research can consider the promotions and discounts factor in the mathematical calculation. In other words, to allocate capacity, a dynamic pricing policy can be applied according to the volume distribution. It can be dynamically set through price/quantity discount relations for parcels' volume and the corresponding prices to maximize the total revenue over the time horizon.

The developed model does not accept the additional volume of over-allocated capacity. In other words, the surplus of demand is rejected. But, in the real case, postal services may accept additional demand due to other factors. A future extension of the model can consider a higher price to accept surplus volume, generating more revenue for surplus demand. Also, the model can be expanded by considering more processing centers. In this case, one center's surplus demand can be transported to another processing center that can have an available capacity. The transportation cost from one center to another center should be considered in the model. Further research could consider incorporating penalties and could probably consider game theory principles and approaches for modeling.

This research followed revenue management principles for customer allocation to specific classes and calculated each LVM's revenue contribution. First, customers were sorted based on their price distributions. Then, we calculated the revenue contributions and grouped them accordingly. Further research should develop a more reliable and fundamental approach for assigning customers to classes. There are other practical customer segmentation models and tools based on-demand distribution, price sensitivity, group size, etc., that can be considered for future expansion of the model.

The developed model does not allow cancellations and overbookings from both postal services and customers. This is a general assumption in revenue management capacity allocation models that reduces the complexity of mathematical modeling, specifically when the demand arrival pattern is dynamic. However, a penalty factor can be considered for cancelation to compensate for the unused protected capacity. According to the customer classes' demand distribution, a ratio factor can be computed as the overbooking factor.

There were also some limitations regarding the dataset. This study validated the developed model by employing one postal service data set. Although the postal services' processes are very similar, using data from other countries could be useful and could provide us with more external validity of this research. The available data is related to one of the processing hub in the transportation network. We did not have access to data from other hubs such as Montreal or Vancouver for model validation. We grouped customers into different classes based on the available fields in the data volume and price distribution. Availability of more parameters such as origin, destination, postal code, and end-user could allow us to create more sophisticated approaches for LVMs' assignment to customer classes. Finally, for predictions of the LVMs' demand growth, we used five years (2013 – 2017) of historical data of parcel transactions. Obviously, to develop a more accurate demand forecast, more linked data about LVMs' activities are needed.

1.20. Implications for practice

The work carried out in this thesis has clear implications for practitioners that could lead to more revenue and cost savings for postal services.

Supply Chain and Operation Decisions: In the processing plant, the operation team can use the model's results to design a more efficient layout and flow of the volume based on the allocated capacity to each class of customers. After induction, the proper amount of the staging areas should be assigned to store parcels for further processes for each class of customers. Specifically, this is true since most of LVM's parcel volume is inducted loose-loaded, and the volume is off-loaded through flexible conveyors. Loose-loaded means that parcels are loaded individually, one on top of the other, in a truck rather than being placed in a pallet during transportation. The model can also be applied for two processing centers to refer the customers' surplus parcel volume to each other rather than reject the surplus parcels.

Negotiating and Contract Decisions: The model helps estimate and compare the expected revenues under different volume and capacity scenarios and the prices that different customers may offer in the contract negotiation. Since the model involves the distribution of price rather than one number as a price, it helps compute the range of expected revenue according to the volume and price distributions.

Capital Investment and Capacity Expansion Decisions: The model's optimization results can be used during the feasibility study and investment decision for capacity expansion. The model helps compute the current capacity utilization before any capacity expansion decisions. Capacity expansion is one of the most common operations management decisions that generally requires high capital investment since it involves using new technology and construction of a new facility or expanding the current facility. However, the key question is whether the optimum level of current capacity is being used or not? Is the capacity expansion required, or can the postal service allocate an optimum level of capacity to each customer class? The model can also estimate the expected revenue of any future capacity expansion.

1.21. Conclusion

This study focuses on analyzing the allocation of fixed induction capacity across multiple LVM classes. Of customers Capacity allocation problems that have arisen in postal services include under-allocation, over-allocation, and misallocation of capacity. This problem originates from the induction, where the volume arrives at the postal service's processing facility. We analyzed a realistic situation in which postal services induct parcel volumes of different classes of customers. It is known that customers arrive in a random order, which is different than the classical revenue management problem where customers arrive in a specific order. Since postal services' processes are time-sensitive, any problem at the induction creates a bottleneck at the origin processing facility, and then it will be extended to all downstream facilities in the supply chain. This literature discussed capacity allocation solutions through different operation management strategies and modeling. We discussed the disadvantages of these solutions. The rise of global demand for parcel delivery due to online shopping and e-commerce drives postal services to find innovative strategies to stay competitive. Limitation of induction capacity as a function of postal services' supply chain to receive parcel volume from online sellers is one of the main challenges that postal services face. The traditional solutions for this problem are generally borrowed from operation management knowledge areas, including process improvement, supply chain, and transportation management. However, these solutions may not be feasible for postal services or require adding the capacity that needs capital investments due to the technical requirements.

Moreover, traditional solutions may temporarily address the capacity shortage due to the dramatic and ongoing increase in parcel volume generated by e-commerce and online shopping. Revenue management is a technique that helps service and manufacturing industries (e.g., hotel, car rental, restaurant, healthcare, etc.) improve their profitability through their current capacity. However, a postal service is one of the industries in which revenue management has not been intensively implemented. This thesis fills the gap. The developed mathematical model provides the optimal capacity allocations to different classes of customers in the form of protection capacity levels, which dictate the optimum amount of induction capacity assigned and protected for a particular class of LVM customers. This research focuses on a new innovative approach by using revenue management to allocate an optimum induction capacity to multiple customers' classes while maximizing the expected revenue. This study offers a solid starting point for analyzing induction capacity allocation in a complex e-commerce parcel environment characterized by uncertain and random customers’ demand arrivals. Further research can benefit from the research findings and its model that can be extended and modified to account for other various practice situations.

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Appendix A: Capacity Allocation Model Development for Two Classes of Customers

An integral equation of the probability density function is used to simplify the expected value of a minimum function. Then, solving $\frac{E[R(x)]}{dx} = 0$, the optimum x^*, that maximizes $E[R(x)]$ should satisfy the condition of Equation 3 for scenario 1 and Equation 5 in scenario 2.

Scenario 1:

$$E[R(x)] = p\_1 \ E[\min\{D_1, x\} + p_2 E[\min\{D_2, C - x\}]$$

$$= p_1 \int_0^x y f_1(y)dy + p_1 \int_x^\infty x y f_1(y)dy + p_2 \int_0^{C-x} y f_2(y)dy$$

$$+ p_2 \int_{C-x}^\infty (C - x) y f_2(y)dy$$

$$= p_1 \int_0^x y f_1(y)dy + p_1 x P[D_1 > x] + p_2 \int_0^{C-x} y f_2(y)dy$$

$$+ p_2 (C - x) P[D_2 > C - x]$$

Equation 3: $p_1 P[D_1 > x^*] = p_2 P[D_2 > C - x^*]$

Scenario 2:

$E[R(x)] = \theta\left[p_{1|w_1>w_2} min\{D_1, x\} + p_{2|w_1>w_2}(C - x)\right] + (1 - \theta)\left[p_{1|w_1<w_2} x + p_{2|w_1<w_2} min\{D_2, C - x\}\right]$

$E[R(x)] = \theta[p_{1|w_1>w_2} \int_0^x y f_1(y)dy + p_{1|w_1>w_2}\, x \int_x^\infty f_1(y)dy] + p_{2|w_1>w_2}(C - x)] + (1 - \theta)[p_{1|w_1<w_2} x + p_{2|w_1<w_2} \int_0^{C-x} y f_1(y)dy + p_{2|w_1<w_2}(C - x) \int_{C-x}^\infty f_1(y)dy]$

$E[R(x)] = \theta p_{1|w_1>w_2} \int_0^x y f_1(y) dy + \theta p_{1|w_1>w_2} x P\ (D_1 > x^*) + \theta p_{2|w_1>w_2}(C - x) + (1 - \theta) p_{1|w_1<w_2} x + (1 - \theta) p_{2|w_1<w_2} \int_0^{C-x} y f_2(y) dy + (1 - \theta) p_{2|w_1<w_2}(C - x) P\ (D_2 > C - x)$

Equation 5: $\theta p_{1|w_1>w_2} P\ (D_1 > x^*) + (1 - \theta) p_{1|w_1<w_2} = (1 - \theta) p_{2|w_1<w_2} P(D_2 > C - x) + \theta p_{2|w_1>w_2}$

Appendix B: Capacity Allocation Model Development for Three Classes of Customers

An integral equation of the probability density function is used to simplify the expected value of a minimum function. Then, solving $\frac{E[R(x_1,x_2)}{dx_1} = 0 \; and \; \frac{E[R(x_1,x_2)}{dx_2} = 0$, the optimum x_1^*, x_2^* that maximizes $E[R(x_1, x_2)]$ should satisfy the condition of both Equation 7 and Equation 8 for scenario 1 and both Equation 10 and Equation 11 for scenario 2.

Scenario 1:

$$E[R(x_1, x_2) = p_1 \int_0^{x_1} y f_1(y) dy + p_1 x_1 P(D_1 > x_1)$$

$$+ p_2 \int_0^{x_1 - x_2} y f_2(y) dy + p_2(x_2 - x_1) P(D_2 > x_2 - x_1)$$

$$+ p_3 \int_0^{C - x_2} y f_3(y) dy + p_3(C - x_2) P(D_3 > C - x_2)$$

Equation 7: $p_2 P(D_2 > x_2^* - x_1^*) - p_1(D_1 > x_1^*) = 0$

Equation 8: $p_3 P(D_3 > C - x_2^*) - p_2 P(D_2 > x_2^* - x_1^*) = 0$

Scenario 2:

$$
\begin{aligned}
E[R(x_1,x_2)] = {} & \theta_{123} E\left(p_{1|w_1>w_2>w_3}\, min\{D_1, x_1\} + p_{2|w_1>w_2>w_3}\, min\{D_2, x_2 - x_1\}\right. \\
& \left. + p_{3|w_1>w_2>w_3}(C - x_2)\right) \\
& + \theta_{132} E\big(p_{1|w_1>w_3>w_2}\, min\{D_1, x_1\} + p_{2|w_1>w_3>w_2}(x_2 - x_1) \\
& + p_{3|w_1>w_3>w_2}\, min\{D_3, C - x_2\}\big) \\
& + \theta_{213} E\left(p_{1|w_2>w_1>w_3}\, min\{D_1, x_1\} + p_{2|w_2>w_1>w_3}\, min\{D_2, x_2 - x_1\}\right. \\
& \left. + p_{3|w_2>w_1>w_3}(C - x_2)\right) + \theta_{231} E\big(p_{1|w_2>w_3>w_1} x_1 \\
& + p_{2|w_2>w_3>w_1}\, min\{D_2, x_2 - x_1\} + p_{3|w_2>w_3>w_1}\, min\{D_3, C - x_2\}\big) \\
& + \theta_{312} E\big(p_{1|w_3>w_1>w_2}\, min\{D_1, x_1\} + p_{2|w_3>w_1>w_2}(x_2 - x_1) \\
& + p_{3|w_3>w_1>w_2}\, min\{D_3, C - x_2\}\big) \\
& + \theta_{321} E\big(p_{1|w_3>w_2>w_1} x_1 + p_{2|w_3>w_2>w_1}\, min\{D_2, x_2 - x_1\} \\
& + p_{3|w_3>w_2>w_1}\, min\{D_3, C - x_2\}\big)
\end{aligned}
$$

$$[R(x_1,x_2)] = \theta_{123}\left(p_{1|w_1>w_2>w_3}\left(\int_0^{x_1} yf_1(y)dy + x_1P(D_1 > x_1)\right)\right.$$

$$+ p_{2|w_1>w_2>w_3}\left(\int_0^{x_2-x_1} yf_2(y)dy + (x_2 - x_1)P(D_2 > x_2 - x_1)\right)$$

$$\left.+ p_{3|w_1>w_2>w_3}(\mathrm{C} - x_2)\right)$$

$$+\ \theta_{132}\left(p_{1|w_1>w_3>w_2}\left(\int_0^{x_1} yf_1(y)dy + x_1P(D_1 > x_1)\right)\right.$$

$$+ p_{2|w_1>w_3>w_2}(x_2 - x_1)$$

$$\left.+ p_{3|w_1>w_3>w_2}\left(\int_0^{\mathrm{C}-x_2} yf_3(y)dy + (\mathrm{C} - x_2)P(D_3 > (\mathrm{C} - x_2)\right)\right)$$

$$+\ \theta_{213}\left(p_{1|w_2>w_1>w_3}\left(\int_0^{x_1} yf_1(y)dy + x_1P(D_1 > x_1)\right)\right.$$

$$+ p_{2|w_2>w_1>w_3}\left(\int_0^{x_2-x_1} yf_2(y)dy + (x_2 - x_1)P(D_2 > x_2 - x_1)\right)$$

$$\left.+ p_{3|w_2>w_1>w_3}(\mathrm{C} - x_2)\right)$$

$$+\ \theta_{231}\left(p_{1|w_{2>}w_{3>}w_1}x_1\right.$$

$$+ p_{2|w_2>w_3>w_1}\left(\int_0^{x_2-x_1} yf_2(y)dy + (x_2 - x_1)P(D_2 > x_2 - x_1)\right)$$

$$\left.+ p_{3|w_2>w_3>w_1}\left(\int_0^{\mathrm{C}-x_2} yf_3(y)dy + (\mathrm{C} - x_2)P(D_3 > (\mathrm{C} - x_2)\right)\right)$$

$$+\ \theta_{312}\left(p_{1|w_3>w_1>w_2}\left(\int_0^{x_1} yf_1(y)dy + x_1P(D_1 > x_1)\right)\right.$$

$$+ p_{2|w_3>w_1>w_2}(x_2 - x_1)$$

$$\left.+ p_{3|w_3>w_1>w_2}\left(\int_0^{\mathrm{C}-x_2} yf_3(y)dy + (\mathrm{C} - x_2)P(D_3 > (\mathrm{C} - x_2)\right)\right)$$

$$+ \ \theta_{321}\left(p_{1|w_3>w_2>w_1} x_1 \right.$$

$$+ p_{2|w_3>w_2>w_1}\left(\int_0^{x_2-x_1} y f_2(y) dy + (x_2 - x_1) P(D_2 > x_2 - x_1)\right)$$

$$\left. + p_{3|w_3>w_2>w_1}\left(\int_0^{\mathrm{C}-x_2} y f_3(y) dy + (\mathrm{C} - x_2) P(D_3 > (\mathrm{C} - x_2)\right)\right)$$

$$\frac{E[R(x_1, x_2)]}{dx_1} = \theta_{123}\left(p_{1|w_1>w_2>w_3} P(D_1 > x_1) - p_{2|w_1>w_2>w_3} P(D_2 > x_2 - x_1)\right)$$

$$+ \theta_{132}\left(p_{1|w_1>w_3>w_2} P(D_1 > x_1) - p_{1|w_1>w_3>w_2}\right)$$

$$+ \theta_{213}\left(p_{1|w_2>w_1>w_3} P(D_1 > x_1) - p_{2|w_2>w_1>w_3} P(D_2 > x_2 - x_1)\right)$$

$$- \theta_{231}\left(p_{1|w_2>w_3>w_1} - p_{2|w_2>w_3>w_1} P(D_2 > x_2 - x_1)\right)$$

$$+ \theta_{312}\left(p_{1|w_3>w_1>w_2} P(D_1 > x_1) - \ p_{1|w_3>w_1>w_2}\right)$$

$$+ \theta_{321}\left(p_{1|w_3>w_2>w_1} - p_{2|w_3>w_2>w_1} P(D_2 > x_2 - x_1)\right) \ = \ 0$$

$$P(D_1 > x_1)\left(\theta_{123}\, p_{1|w_1>w_2>w_3} + \theta_{132}\, p_{1|w_1>w_3>w_2} + \theta_{213}\, p_{1|w_2>w_1>w_3} + \theta_{312} p_{1|w_3>w_1>w_2}\right)$$

$$- P(D_2$$

$$> x_2 - x_1)\left(\theta_{123}\, p_{2|w_1>w_2>w_3} + \theta_{132}\, p_{2|w_1>w_3>w_2} + \theta_{213}\, p_{2|w_2>w_1>w_3}\right.$$

$$\left. + \theta_{312} p_{2|w_3>w_1>w_2}\right)$$

$$+ \left(- \theta_{132}\, p_{2|w_1>w_3>w_2} + \theta_{231}\, p_{1|w_2>w_3>w_1} - \theta_{312} p_{2|w_3>w_1>w_2}\right.$$

$$\left. + \theta_{321} p_{1|w_3>w_2>w_1}\right) = 0$$

$\frac{E[R(x_1,x_2)]}{dx_2} = \theta_{123}\left(P(D_2 > x_2 - x_1) - p_{3|w_1>w_2>w_3}\right) + \theta_{132}\left(p_{2|w_1>w_3>w_2} -\right.$

$\left. p_{3|w_1>w_3>w_2} P(D_3 > C - x_2)\right) + \theta_{213}\left(p_{2|w_2>w_1>w_3} P(D_2 > x_2 - x_1) - p_{3|w_2>w_1>w_3}\right) +$

$\theta_{231}\left(p_{2|w_2>w_3>w_1}P(D_2 > x_2 - x_1) - p_{3|w_2>w_3>w_1}P(D_3 > C - x_2)\right) + \theta_{312}\ \left(p_{2|w_3>w_1>w_2} - p_{3|w_3>w_1>w_2}P(D_3 > C - x_2)\right) + \theta_{321}\left(p_{2|w_3>w_2>w_1}P(D_2 > x_2 - x_1) - p_{3|w_3>w_2>w_1}\mathrm{P}(D_3 > C - x_2)\right) = 0$

$$
\begin{aligned}
P(D_2 > x_2 - x_1)&\big(\theta_{123}\, p_{2|w_1>w_2>w_3} + \theta_{213}\, p_{2|w_2>w_1>w_3} + \theta_{231}\, p_{2|w_2>w_3>w_1} \\
&+ \theta_{321}\ \ p_{2|w_3>w_2>w_1}\big) \\
&- P(D_3 \\
&> C - x_2)\big(\theta_{132}\, p_{3|w_1>w_3>w_2} +\ \theta_{231}\, p_{3|w_2>w_3>w_1} + \theta_{312}\, p_{3|w_3>w_1>w_2} \\
&+ \theta_{321}\, p_{3|w_3>w_2>w_1}\big) \\
&+ \big(-p_{3|w_1>w_2>w_3} + \theta_{132}\, p_{2|w_1>w_3>w_2} - \theta_{213}\, p_{3|w_2>w_1>w_3} \\
&+ \theta_{312} p_{2|w_3>w_1>w_2}\big) = 0
\end{aligned}
$$

Equation 10: $p_1 P(D_1 > x_1^*) +\ \theta_{231}\, p_{1|w_2>w_3>w_1} + \theta_{321}\, p_{1|w_3>w_2>w_1}\ (1 - P(D_1 > x_1^*))\ = p_2 P(D_2 > x_2^* - x_1^*) +\ \theta_{132}\, p_{2|w_1>w_3>w_2} + \theta_{312} p_{2|w_3>w_1>w_2}\ (1 - P(D_2 > x_2^* - x_1^*))$

Equation 11: $p_2 P(D_2 > x_2^* - x_1^*) + \big(\theta_{123}\, p_{2|w_1>w_2>w_3} + \theta_{312}\, p_{2|w_3>w_1>w_2}\big)\big(1 - P(D_2 > x_2^* - x_1^*)\big) = p_3 P(D_3 > \mathrm{C} - x_2^*) + \big(\ \theta_{123} p_{3|w_1>w_2>w_3} + \theta_{213}\, p_{3|w_2>w_1>w_3}\big)\big(1 - P(D_3 > C - x_2^*)\big)$

Appendix C: International Journal of Production Economics (IJPE) - Submitted

Elsevier Editorial System(tm) for
International Journal of Production Economics
Manuscript Draft

Manuscript Number: IJPE-D-20-01838

Title: Revenue Management for Induction Capacity Allocation of Postal Services: Model Conceptualization and Empirical Validation

Article Type: Research paper

Keywords: Revenue Management
Capacity Allocation
Simulation
E-Commerce
Postal Service

Corresponding Author: Mr. Ahmad Teymouri, Ph.D. Candidate

Corresponding Author's Institution: University of Ottawa

First Author: Ahmad Teymouri, Ph.D. Candidate

Order of Authors: Ahmad Teymouri, Ph.D. Candidate; Pavel Andreev; Craig Kuziemsky; Amir Khataei

Abstract: Constantly growing online shopping parcel volume that needs to be processed and delivered through the postal services network represents a capacity management challenge for postal organizations. There are various approaches to overcome this challenge, including increasing the efficiency of the sorting equipment (i.e., optimized sort schematic and machine scheduling) or increasing the productivity of the transportation network (i.e. higher truck utilization, optimized routing). However, these solutions were found to be either cost-sensitive or not long-term or sometimes not feasible for postal services. Moreover, most of the developed models focus on the improving of the operations performance indicators but not considering the revenue of postal services. This study reconsiders the traditional approaches and offers an innovative and novel revenue management approach for parcel capacity management of postal services by maximizing generated revenue with the existing capacity. We developed a mathematical revenue management capacity reallocation model. The model addresses the capacity issues, specifically in peak times, by regulating and reallocating capacity between two classes of major online retailers. The model computes a "protected" capacity for two classes of customers according to their contribution to the revenue following all possible scenarios. The model is validated with simulation. Furthermore, the developed model provides a long-term solution for postal services, which increases delivery performance by removing the capacity bottleneck and improves customers' experience with online shopping.

Revenue Management for Induction Capacity Allocation of Postal Services: Model Conceptualization and Empirical Validation

Ahmad Teymouri[a], Pavel Andreev[a], Craig Kuziemsky[b], Amir Khataei[a]

[a] Telfer School of Management, University of Ottawa, 55 Laurier Ave E, K1N 6N5

[b] MacEwan University, 10700 104 Ave NW, Edmonton, AB T5J 4S2

Abstract

Constantly growing online shopping parcel volume that needs to be processed and delivered through the postal services network represents a capacity management challenge for postal organizations. There are various approaches to overcome this challenge, including increasing the efficiency of the sorting equipment (i.e., optimized sort schematic and machine scheduling) or increasing the productivity of the transportation network (i.e. higher truck utilization, optimized routing). However, these solutions were found to be either cost-sensitive or not long-term or sometimes not feasible for postal services. Moreover, most of the developed models focus on the improving of the operations performance indicators but not considering the revenue of postal services. This study reconsiders the traditional approaches and offers an innovative and novel revenue management approach for parcel capacity management of postal services by maximizing generated revenue with the existing capacity. We developed a mathematical revenue management capacity reallocation model. The model addresses the capacity issues, specifically in peak times, by regulating and reallocating capacity between two classes of major online retailers. The model computes a "protected" capacity for two classes of customers according to their contribution to the revenue following all possible scenarios. The model is validated with simulation. Furthermore, the developed model provides a long-term solution for postal services, which increases delivery performance by removing the capacity bottleneck and improves customers' experience with online shopping.

Keywords: Revenue Management, Capacity Allocation, Simulation, E-Commerce, Postal Service

Appendix D: Conference Proceedings EurOMA2018

European Operations Management Association

25th Annual EurOMA Conference

To Serve, To Produce and to Servitize in the Era of Networks, Big Data and Analytics

24-26 June 2018 | Budapest, Hungary

Application of revenue management in capacity planning of postal services: conceptualizing and empirical simulation of capacity management

Ph.D. Candidate, Telfer School of Management, University of Ottawa

Pavel Andreev
Associate Professor, Telfer School of Management, University of Ottawa

Amir Khataie
Adjunct Professor, Telfer School of Management, University of Ottawa

Craig Kuziemsky
Full Professor, Telfer School of Management, University of Ottawa

Abstract

The popularity of e-commerce has significantly increased the volume of parcels delivered through the postal services network. The shift toward digital communication (e.g., e-mail) and purchasing (e.g., online shopping) channels have turned capacity management into a serious challenge for postal organizations. Most of the developed solutions focus on process improvements and optimization through improving cost performance indicators but not the revenue. To address the postal service capacity management problem this study reconsiders traditional capacity management approaches and then develops, and empirically validates through simulation a conceptual revenue management model. The proposed model improves capacity allocation while maximizing postal organizations expected revenue.

Keywords: e-commerce parcel, postal services revenue management, capacity planning and control

Appendix E: Conference Proceedings IEEM2017

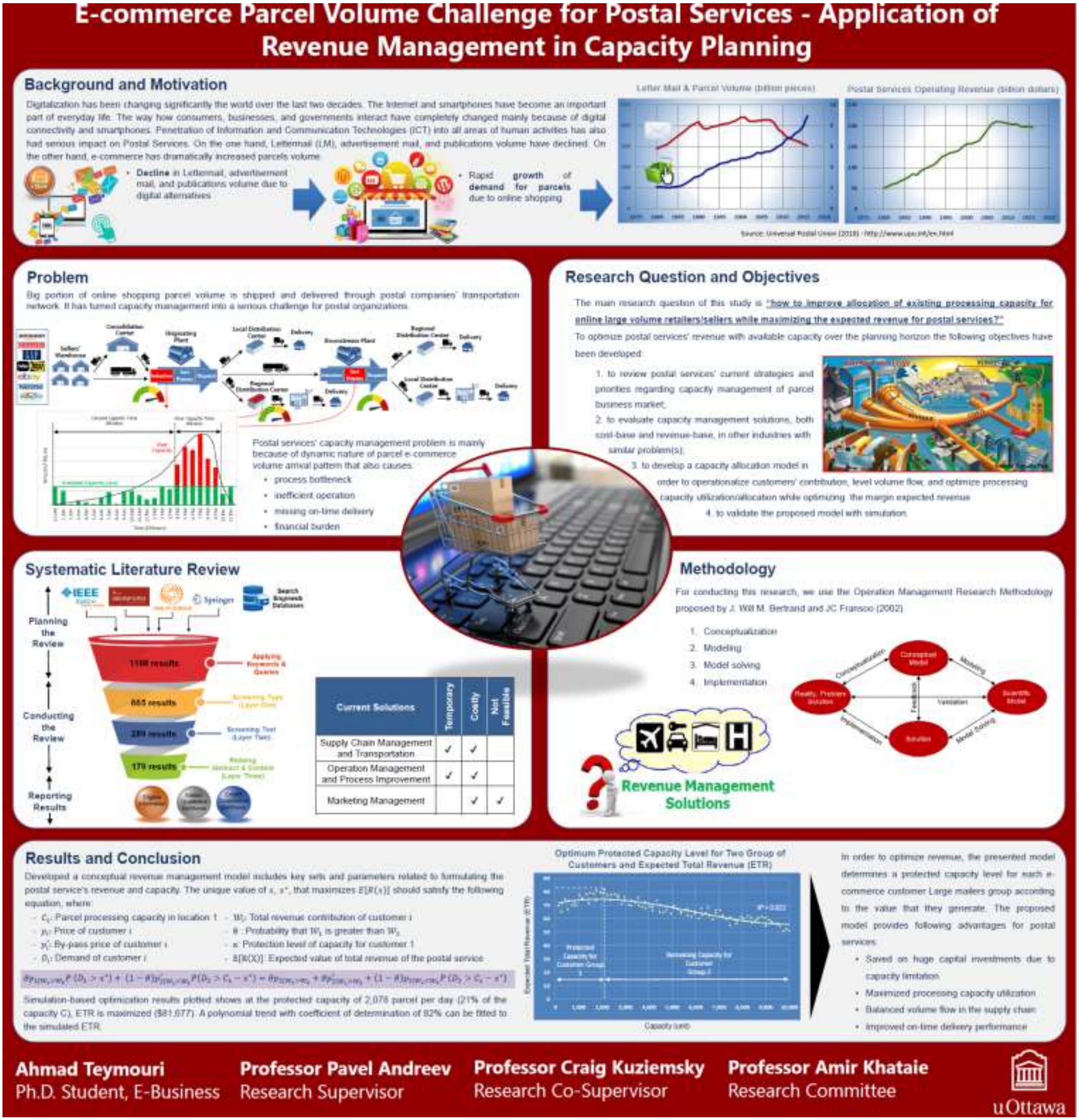
Application of Revenue Management in Supply Chain of Postal Services

A. Teymouri[1], A. Khataie[1], P. Andreev[1], C. Kuziemsky[1]
[1] Telfer School of Management, University of Ottawa, Ottawa, Canada

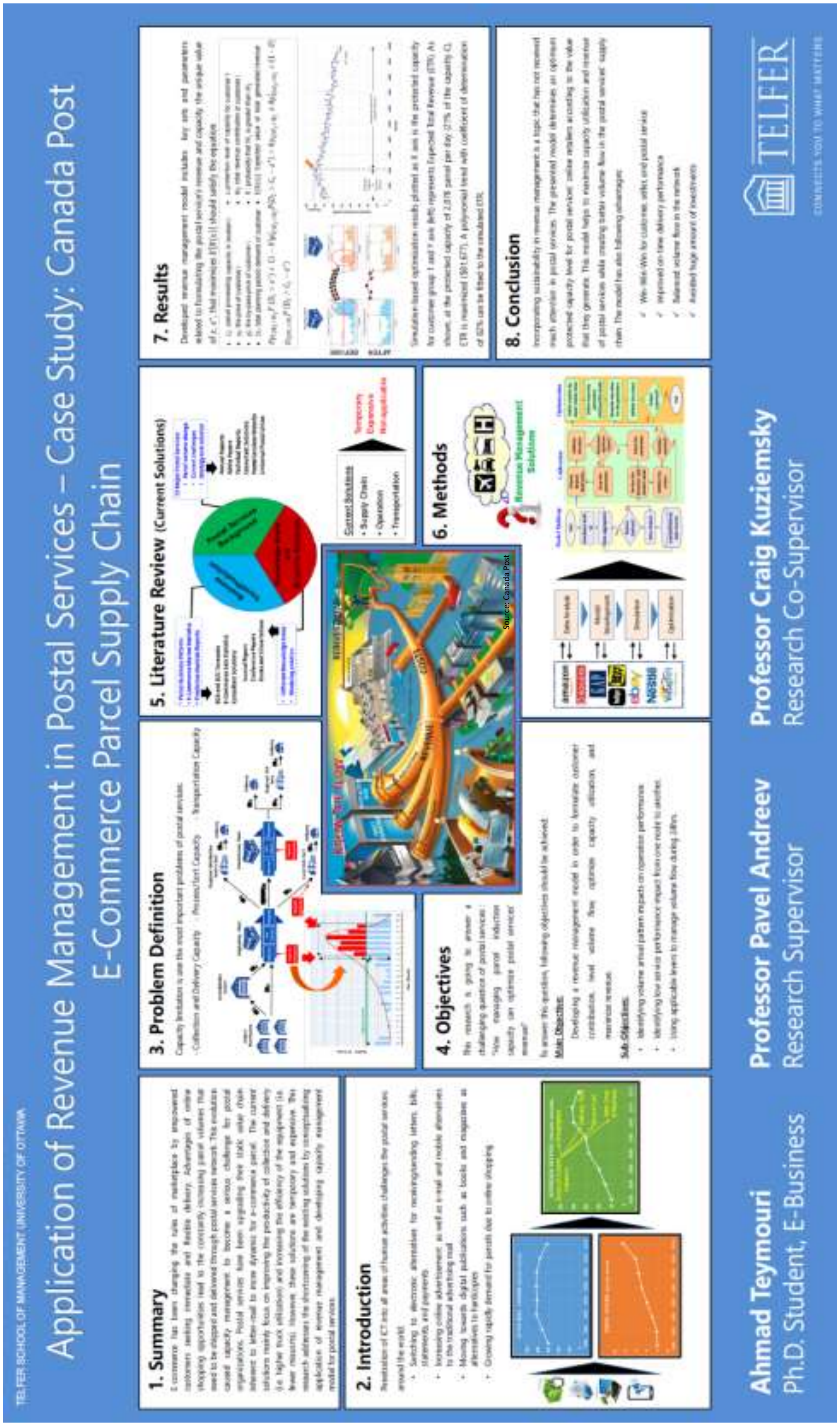
Abstract - E-commerce has been changing the rules of marketplace by empowered customers seeking immediate and flexible delivery. Advantages of online shopping opportunities lead to the constantly increasing parcel volumes that need to be shipped and delivered through postal services network. This evolution caused capacity management to become a serious challenge for postal organizations. Postal services have been upgrading their static value chain inherent to letter-mail to more dynamic for e-commerce parcel. The current solutions mainly focus on improving the productivity of collection and delivery (i.e. higher truck utilization) and increasing the efficiency of the equipment (i.e. fewer missorts). However, these solutions are temporary and expensive. This paper addresses the shortcoming of the existing solutions by conceptualizing application of revenue management and developing capacity management model for postal services.

Keywords - E-commerce, Supply Chain management, Business Analytics, Revenue Management, Capacity Planning

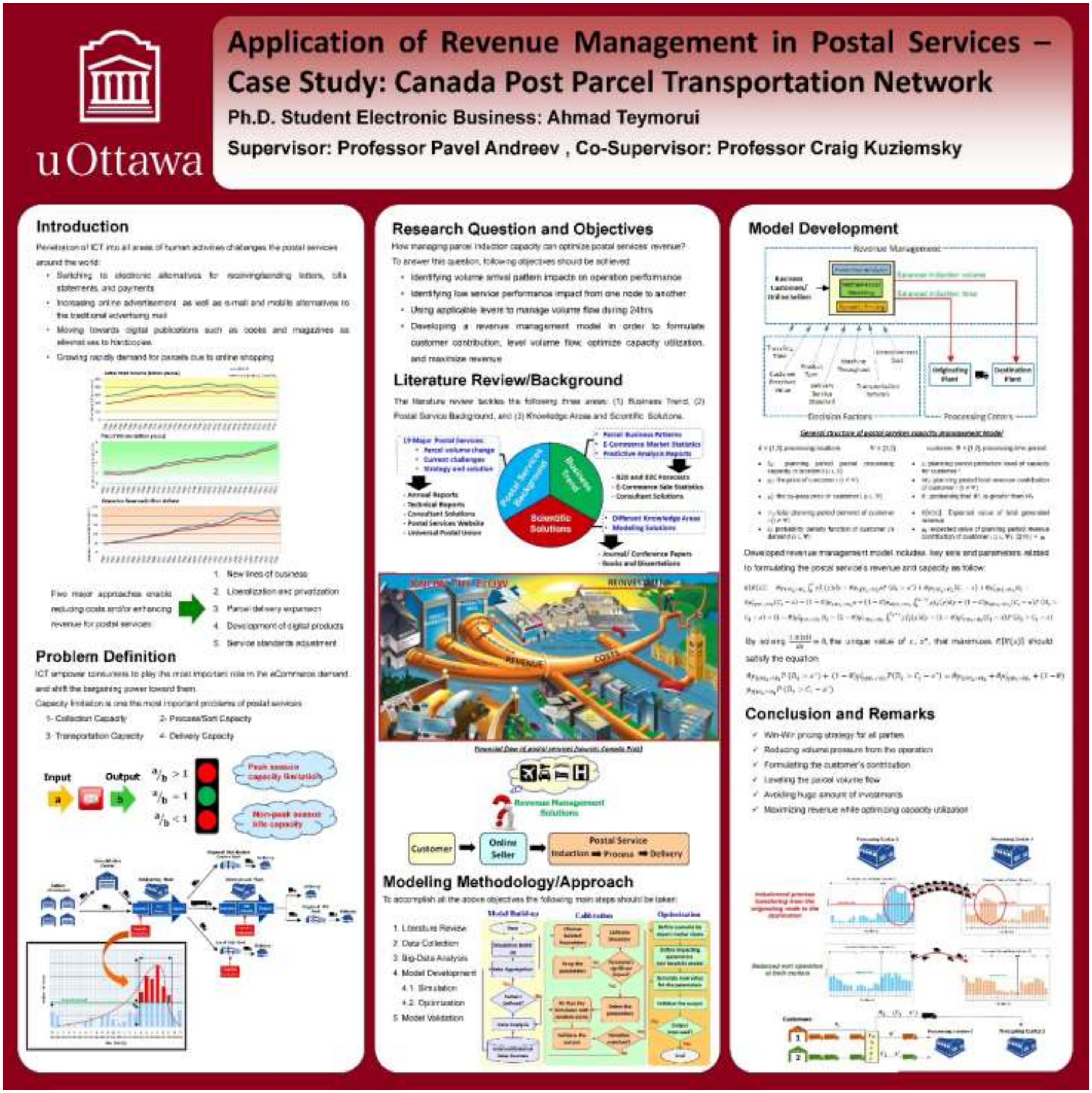
Appendix F: Second Place, Graduate Thesis Poster Competition Award, University of Ottawa (2018)



Appendix G: Telfer-Sprott-UQO Thesis Competition and Poster Session (2018)



Appendix H: First Place, Graduate Thesis Poster Competition Award, University of Ottawa (2017)



Appendix I: Postal Services Competitive Business and Global Trends (White Paper)

Reviewing postal services background had an important contribution to our systematic literature review by providing information not found in the published literature. It also helped to understand the most current situation within the postal industry at the time of this study. The main source for this part of the review was white papers, technical reports, universal postal union (UPU), and postal services annual report. The following provides a short summary regarding challenges and strategies, volume and revenue, and value chain in the postal industry.

Postal services have a broad mandate to transmit messages, information, and. They have a broad mandate to provide the postal service to all individuals and businesses in any urban or rural regions. They not only have the responsibility of delivering mail to a different destination but also should meet the obligations and standards set by the governments or the Universal Postal Union (UPU). Different products that own their unique features and benefits are offered by postal services. However, they fall into three main categories; (1) Transaction Mail, (2) Direct Marketing, and (3) Parcels. Transaction mail used to be a convenient and cost-effective way to send personal messages, business correspondence, invoices, and billing statements. This category includes different sizes of a Letter Mail (LM), such as short, long, and over size. Direct marketing is a proven and effective advertising medium that offers customers the ability to personalize their mailing and tailor their promotional messages to specific consumers or prospects. It also includes a newspaper, newsletter, or magazine, which meets specific requirements and is generally produced for the purpose of public dissemination of news and information. This category mainly covers the advertising and marketing products such as publications, addressed admail, and unaddressed admail. Parcels are those products that are too heavy to be considered as a normal transaction mail. It includes parcels and packets that are taken by customers to a post office or directly collected from the seller's warehouse (e.g., Amazon).

According to annual reports, many postal services face three major global trends; 1) downward trend of LM volume, which seems continues, 2) upward trend of parcel delivery because of rapid advance in E-commerce, and 3) revenue growth in a competitive market and weaker economic conditions (Figure 1).

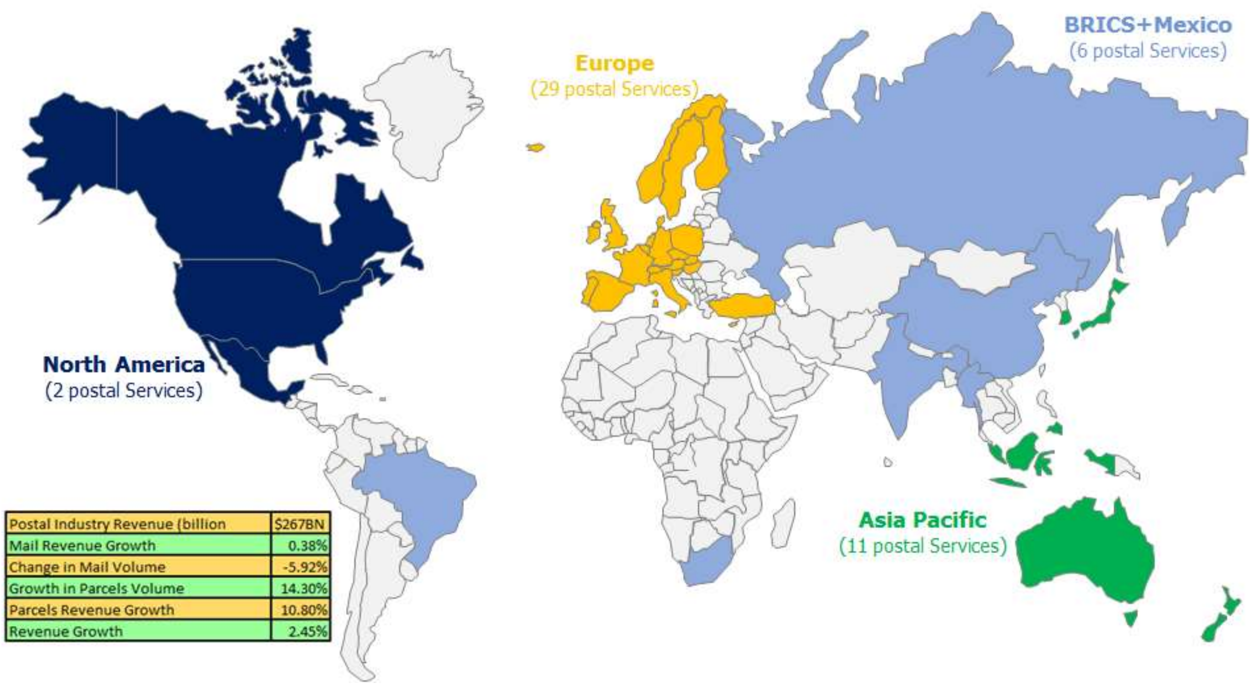


Figure 1: Parcel, Lettermail (LM), and economy trend in postal services
Source: (Winklbauer, 2018)

To cope with these trends, postal services have used different business strategies. They have focused on maximizing sides of their LM business profitability via reducing the operation cost reduction and revenue increase. To have a reasonable operation cost, postal services have been attempting to not only rationalize their strategy for LM network but also use flexible labor contracts and outsourcing activities. To increase their revenue, successful product innovations and the dominance of the domestic market have been used by some postal services. In other words, they try to slow the decline of mail and even grow the LM volume by price incentive strategies. In Germany, a new packing design provides the advertisement opportunity on both inside and outside of the envelope. Besides, they have been able to increase their LM revenue by having control of the domestic market on LM and minimum penetration of the competitors except for the situation that the market is legally shared. Therefore, they have been working on a combination of strategies such as quality of service, careful pricing, and brand management. Postal services recognize that their customers are shifting to mobile technology. To add more value to their existing products, high performers are taking full advantage of the mobile opportunity. For example, they could provide better visibility on the delivery side of the business by sending a text message or email to the sender and recipient. They have also created a direct relationship with the online retail stores (e.g., Amazon) by giving the authority of issuing a ticket for any parcel that is sold. This strategy provides more visibility of the recipient, such as information, preference, delivery options, which are other sources of revenue generation. For example, UPS offers a service that the recipient has flexibility on the home delivery with receiving an alert before the first delivery attempt or the ability to reschedule/redirect the parcel. Recent research shows that the consumers have started this type of expectation and postal organizations provide these services by taking advantage of mobile technology.

Some postal organizations have focused on the shift/change in their ownership. They are considering more level of autonomy and commercial focus, which help them to operate as a private company in many situations. Although they want to maintain their relationship with the government and associated universal service obligations, they prefer to take control of their destiny by having more private shareholders. Generally, privatization shows its effects on three areas that have significant financial impacts; (1) decision making, which is about major decisions less influenced by the governments, (2) international postal rules, which is trying to redefine universal service obligation (USO), and (3) workforce transformation, which focuses on hiring and retaining educated and talented staff.

For many postal services, LM and Ads still generates a significant part of their revenue and provides more cash for future investments. In 2015, some of the European postal services improved their LM performance through smart pricing, reducing fixed and operational costs, increasing automation, exploiting assets, and investing in LM innovation. Analyzing the data provided by Universal Postal Union (UPU) shows that successful postal services (e.g., Germany) generated an average Earnings Before Interest and Tax (EBIT) of 11.1 percent from LM and Ads innovative strategies. This number for low-performance postal service was almost 2 percent. In some cases, they earned more revenue on LM by significant price increases. For example, Portugal's CTT increased the price of a domestic 20g LM by 40 percent in 2015 compared to 2012. From the cost perspective (fixed and operational), successful postal organizations significantly followed cost reduction scenarios by redefining the workday and workforce, creating much-needed time flexibility, and merging LM processing center. They emphasized improving their processing and delivery efficiency per piece by pursuing automation, for instance, SingPost reducing LM processing times by achieving world-class automation rates. Belgium Post, bPost, in its Vision 2020, has a plan for consolidating 400 local mail offices into 60 mail centers. Also, bPost is investing in the automation of its sorting plants. In the delivery mode, Canada Post is implementing the centralized community mailbox project, which significantly improves the number of items delivered per stop. Postal organizations are aggressively and successfully negotiating with their governments and regulators about the universal service obligation (USO) to mitigate consistent LM volume declines. For Example, in Portugal, CCT could obtain approval from its regulator to increase prices above those that already had been granted an amendment for its service quality and objectives for the period 2015 to 2018. Investing in LM innovation not only has successfully slowed the decline rate but also, in some cases, showed growth in marketing LM. For example, Australia Post provided the MyPost solution for its customer. MyPost is a platform with a mobile app. It creates an electronic mailbox for customers and enables them to manage and customize their deliveries such as hold mail, redirection mail, or archive at discounted prices.

In the second priority, postal services are taking the grow parcel opportunity and offer a reasonable price to increase their share market. According to UPU analysis in 2018, there is a clear correlation between parcel growth and revenue. High performer postal services have enabled the customers to manage their delivery. For example, FedEx offers Delivery Manager, UPS provides MyChoice (UPS, 2016a), and Australia Post has MyPost (AustraliaPost, 2016) App for their customers. These solutions not only motivate customers and the growing number of m-commerce purchases but also capture revenue for postal services. A part of parcel e-commerce orders come from cross-border, which is growing faster than domestic e-commerce in most markets. Successful companies are investing in this market because of the great opportunity of increasing their revenue. For example, FedEx purchased Bongo, a package forwarding service for international consumers who wanted to purchase items from US-based websites that did not offer international shipping (Buhler & Pharand, 2015). Also, to become the portal into the European Union, Belgium Post, bpost, has purchased Landmark Global and established offices in Hong Kong, Beijing, and the United States (Info, 2013). In another strategy, successful postal services focus is on improving the profitability and service quality of Business to Business (B2B) and Business to Customer (B2C) deliveries. On the one hand, they know the value of significant change in B2C e-commerce volumes. On the other hand, B2C packages delivery is much harder than B2B. Therefore, they are creating new solutions to generate a better profit for B2C while continuing their B2B market growth (Buhler & Pharand, 2015). Belgium Post, bpost, offers a Combo solution which not only provides more control on delivery for the customer but also seeks for new value-add such as laundry services with the same standard delivery. In another solution, Canada Post has created consolidation points such as lockers, community mailboxes, and pickup locations. These solutions create a multi-parcel B2C delivery rather than a single-parcel delivery (Postal-Delivery-International, 2015). Other solutions such as low-cost, less specialized, and industry segment services have been used for B2B e-commerce. For example, Austrian Post offers one- or two-day delivery only for its B2B customers as a premium and standard with a reasonable price. UPS and Posten Norge provide special service facilities for healthcare and frozen products with the latest technology (UPS, 2016b).

In the last priority, successful postal services are growing their logistic business upstream and downstream, as a diversification strategy. They are using a more complicated value chain compared with the past. To generate more revenue from each customer and meet their expectation, a variety of solutions is offered by postal services such as providing marketplace, payment, fulfillment, and warehousing. For example, FedEx has bought a distribution and warehouse specialist company, GENCO (Stevens, 2015). This process has been accelerated by tending to privatization. Recent research by Accenture global management consulting research (2015) shows a strong correlation between privatization and high performance, especially in the last two years. From their point of view, privatization is a mindset, not a requirement, to commercially focus on the operation and make a difference. Accenture found four reasons to tend privatization by postal service; (1) higher level of authority, (2) easier decision making, (3) clear accountability, and (4) guaranteed higher performance.

Regardless of the decline in different mailing groups, parcel business has shown an opposite trend mainly because of the rapid growth of online shopping, which is typically growing in double digits annually in most countries. The increasing popularity of online shopping significantly stimulates the growth of the business-to-consumer parcel delivery market (Buhler & Pharand, 2015). Therefore, a parcel as a category has shown itself to be, if not a silver bullet, then certainly a golden opportunity. The main driver of this growth is e-commerce, which is typically growing exponentially in most countries. The parcel volume has increased by 9% per year between 2008 and 2017, over 15 billion parcels in 2017.

Today, e-commerce parcel volume is considered the main growth driver of postal services. Furthermore, the shift toward e-commerce has also completely changed the value chain of these companies. The way that the postal industry interacts with retailers and the way that retailers work with their customers has evolved (USPS-Office of IInspector General, 2015). The postal industry, however, has not been able to fast enough to complete the required transformation against these changes. The situation became more complicated when a huge wave of a new product with smaller size and weight, but a much larger volume named e-commerce-small-packets was introduced to the market. These significant and continuous changes in LM and parcel volumes led the postal services to increasingly look to transform through re-aligning and streamlining operations from LM to parcel target. In the past 10 years, they are expanding their market by entering to e-commerce parcel new world. For example, a new parcel center, the largest in the country, has been opened in Germany; two new parcel depots were opened by Kingdom's Royal Mail in fall 2013; Spain's Correos post has considered a collaboration approach to enter Asian markets, and Poland's InPost decided to install 100 self-service parcel terminals in Brazil.

Recent research by Universal Postal Union (UPU) shows 4% operating revenue growth in 2017 compared to 2016, reaching 256 billion dollars. However, it discusses that since inflation and cost of living across countries are different, the postal industry has been consistently underperforming the real economy. This study transformed the operating revenues in real terms by controlling for the GDP deflator and purchasing power parity which identifies the postal output gap since 2007 (Figure 2).

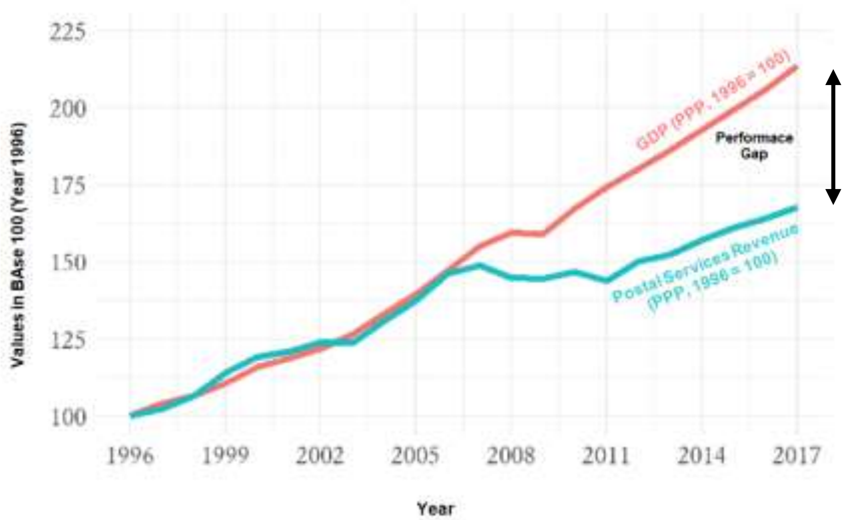


Figure 2: Postal services revenue and GDP comparison
Source: Postal economic outlook 2019 - Latest trends in an evolving sector

As the main reason for this gap started from 2002 and gradually increased (1% in 2006 to 21.5% in 2017), postal services have not taken advantages of growth factors in the real economy, specifically the advent of digitalization, which has pushed many postal organizations to restructure their business process (Berne, 2019).

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