CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Dynamic Pricing and Wages Model for Crowd Shipping

by

Emmad Adil

A thesis submitted in partial fulfillment for the degree of Master of Science in Engineering Management

in the

Faculty of Engineering

Department of Mechanical Engineering

2021

This research work is dedicated to my family and teachers without their support this journey wouldnt have been possible.

CERTIFICATE OF APPROVAL

Dynamic Pricing and Wages Model for Crowd Shipping

by

Emmad Adil

(MEM173001)

THESIS EXAMINING COMMITTEE

S. No.	Examiner	Name	Organization
(a)	External Examiner	Dr. Uzair Khaleeq uz Zaman	NUST, Islamabad
(b)	Internal Examiner	Dr. Salman Sagheer Warsi	CUST, Islamabad
(c)	Supervisor	Dr. Taiba Zahid	CUST, Islamabad

Dr. Taiba Zahid
Thesis Supervisor
June, 2021

Dr. M. Mahabat Khan
Head
Dept. of Mechanical Engineering
June, 2021

Dr. Imtiaz Ahmad Taj
Dean
Faculty of Engineering
June, 2021

Author's Declaration

I, **Emmad Adil** hereby state that my MS thesis titled "**Dynamic Pricing and Wages Model for Crowd Shipping**" is my own work and has not been submitted previously by me for taking any degree from Capital University of Science and Technology, Islamabad or anywhere else in the country/abroad.

At any time if my statement is found to be incorrect even after my graduation, the University has the right to withdraw my MS Degree.

(Emmad Adil)

Registration No: MEM173001

Plagiarism Undertaking

I solemnly declare that research work presented in this thesis titled "**Dynamic Pricing and Wages Model for Crowd Shipping**" is solely my research work with no significant contribution from any other person. Small contribution/help wherever taken has been duly acknowledged and that complete thesis has been written by me.

I understand the zero tolerance policy of the HEC and Capital University of Science and Technology towards plagiarism. Therefore, I as an author of the above titled thesis declare that no portion of my thesis has been plagiarized and any material used as reference is properly referred/cited.

I undertake that if I am found guilty of any formal plagiarism in the above titled thesis even after award of MS Degree, the University reserves the right to withdraw/revoke my MS degree and that HEC and the University have the right to publish my name on the HEC/University website on which names of students are placed who submitted plagiarized work.

(Emmad Adil)

Registration No: MEM173001

Acknowledgement

First and foremost, I thank Allah Almighty, the most merciful and the most gracious, for granting me the immense patience and courage to complete this dissertation.

I would like to express my deep and sincere gratitude to my supervisor **Dr. Taiba Zahid** for her guidance and help throughout my work. Her wisdom and grace has been of an immense value for my academic as well as non-academic concerns throughout the time spent here at CUST.

I also want to acknowledge the efforts of my parents and family, who supported me through thick and thin and did everything beyond their capabilities to help me complete my higher studies.

(Emmad Adil)

Abstract

The main objective of this research work is to exploit the potential benefits of crowd shipping which has added a new dimension in e-commerce and huge contribution in economic growth. This research focus on the different compensation schemes/pricing strategies for instore customer/ad-hoc driver and online customer. The instore customer/ad-hoc driver while on way back to his destination delivers the orders to online customers location with minimum detouring and reasonable compensation. Online customer may place order according to the urgency or need in different time slots to minimize the cost of delivery and time. Experiments and results suggest the reasonable reduction in cost for delivering the order through crowd shipping comparing to dedicated fleet of vehicles. Moreover both prices and wages dynamically change with distance and time.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

Presently, the outbreak of pandemic COVID-19 has changed the attitude of whole world. People are confined to their places and cannot walk away to crowded places to keep themselves safe. In order to fulfill the needs of people while being confined to their places, e-commerce is the fastest emerging marketing place for the customers to buy variety of goods and services online. Online purchasing of goods contributed approximately 200 billion euros in 2014 in the west and doubledover the next five years [44]. In the present scenario of COVID-19, people are more inclined towards online shopping compared to the visiting stores. After COVID-19 people are spending more in online shopping up to 30% particularly for grocery items [45]. Due to the huge increase in home deliveries, stores put up the requirement of reliable logistics for the delivery of orders to destinations. Online delivery platforms lead to quick growth in crowd shipping and targeting a huge market, in 2015approximately 210 billion dollars have been spent online for the delivery of foodin USA alone annually [1]and now in 2020 total spending increased upto 862 billion dollars for e-commerce only [46].The two main stream online delivery platforms i.e Grub hub and Eat24 contributed 3 billion dollars in sales of food and catching small segment of thehuge market in 2019. To earn more customer satisfaction and cost effectiveness, concept of “Shared Economy” has been coined by the companies. The sharing economy is peer-to-peer (P2P) IT based an economic model, sharing access to goods and services that is often facilitated by a community-based on-line platform.

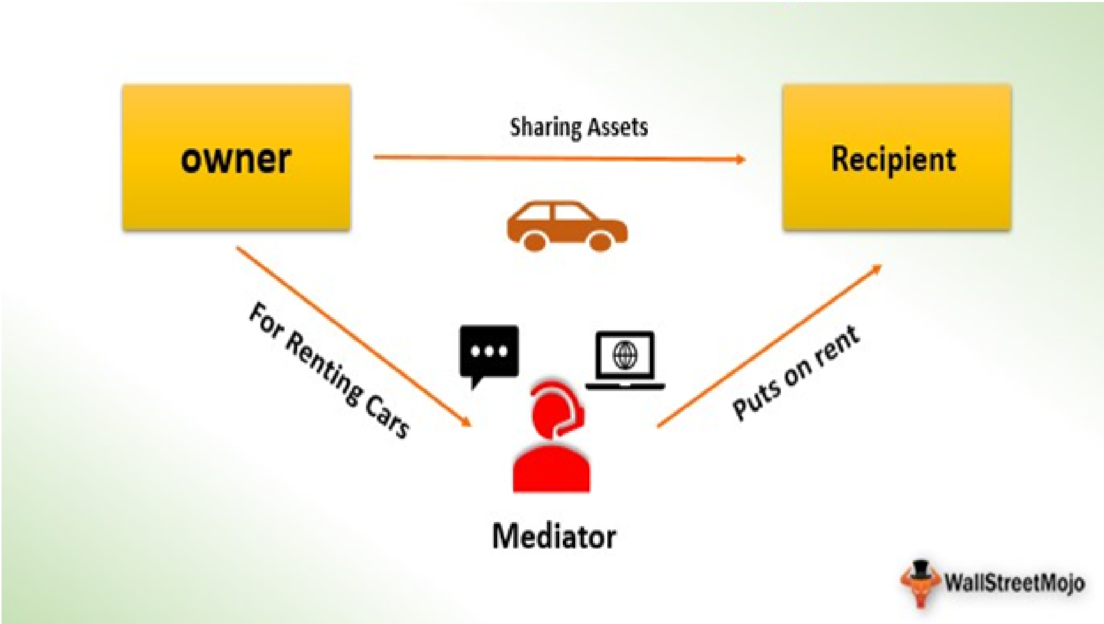


FIGURE 1.1: Shared Economy Model.

If we focus on the concept of shared economy, novel ideas to share the underutilized resources or assets are being implemented. According to the estimates, it is expected that shared economy will contribute to 335 billion dollars worldwide by 2025 [2]. The rapid increase of online orders will made the deliveries of medium and small size packages uneven that need to be delivered to the destination in time. Though a last-mile delivery service being an important aspect of shared economy for the customers, it creates substantial transportation challenges for the organizations or firms one of which is the delivery of large size packages [3]. Last mile delivery is either carried out through crowd sourcing (which we will study in detail in next section) or fleet of dedicated vehicles. A bigger dedicated fleet of vehicles owned by the organizations increase economical, traffic and environmental complications in urban areas. In USA alone 6.9 billion hours of time consumed by the drivers and 3.1 billion gallons of fuel is used in traffic congestion to make the deliveries which cost 160 billion dollars [4]. The road transportation sector adds alot in emissions of greenhouse gases. 30-40% of carbon dioxide emissions come from road sector [5]. Moreover, the transportation sector alone contributed 14%

of the carbon dioxide emissions in 2010 worldwide according to [6]. One important factor that needs to be highlighted is the reduction in the carbon dioxide by the occasional drivers compared to the dedicated drivers. The average emissions produced by the average private car were 107 g/km of carbon dioxide in 2014 [7]. Moreover, average emissions produced by the delivery vans are 165 g/km of carbon dioxide. Therefore, dedicated vehicles produce on average 54% more carbon dioxide emission. To address the environmental problems innovative solutions are required to be implemented. In 2015, 195 countries have signed the agreement on greenhouse emissions mitigation in Paris. Cardinals of the agreement were to reduce the carbon dioxide emissions and keep global warming to 2 degrees Celsius. So improvement in different planning methods could help in easing the pressure on the environment produced by transportation sector.

1.2 Crowd Shipping

The growth of "sharing economy" has added new dimension for companies who can deliver services to consumers. The difference between the amazon and crowd sourcing is that amazon is one of the leading e-commerce company and acts as warehouse which receives order online and delivers to the destination of online customer through third party logistics. On the other hand, in crowd sourcing, orders are being delivered by using the already available customers while enroute to their destination. The company may not centrally plan its working hours by assigning workers to shifts. As a substitute, workers render their services to govern their plans and the organizations provide platform that connects customers and service providers [8]. In crowd sourcing there are three main stake holders, online customer who orders the product, instore customer/ad-hoc driver who is available in store and delivers the product to online customers destination and lastly the platform which connects the other two stake holders, that is, online and instore customer/ad-hoc drivers.

Although the platform has little control on providers work at a time, providers may schedule the working hours as per their intent to work, giving them flexibility

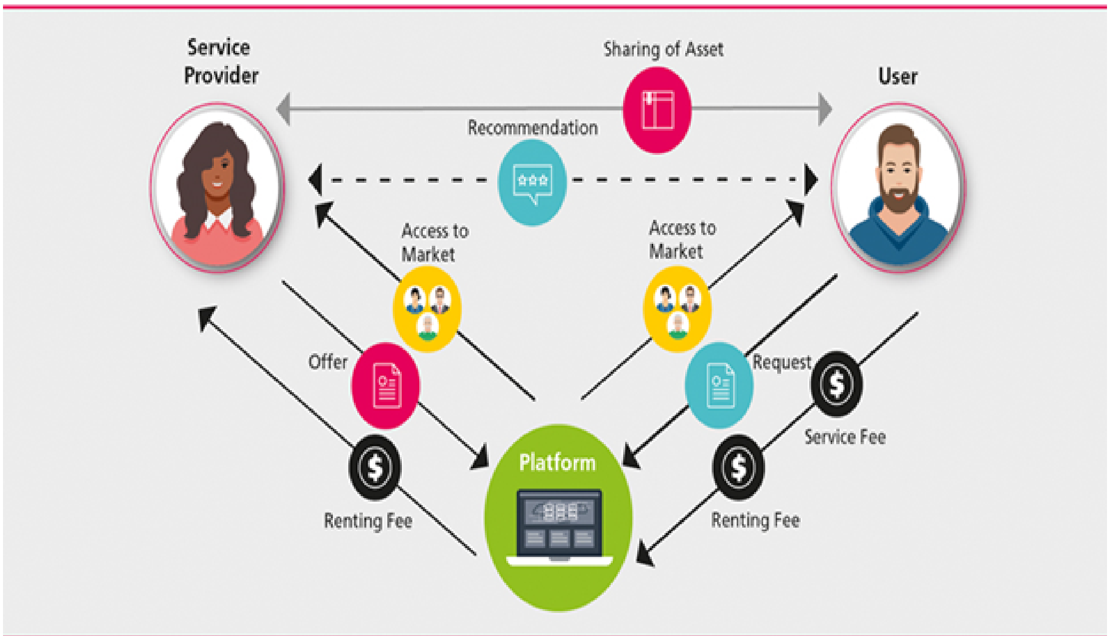


FIGURE 1.2: Stake Holders in Crowd Sourcing.

to align them with personnel commitments [9]. To make it practical, consumers may be charged reasonably and must be effectively served. Instances of delivering such platforms for self-scheduling includes Post mates and Insta cart for delivery at the destination.

The procedure for crowd sourcing is started when a online customer request for pickup and delivery of orders through the app by giving the attributes including the, pick-up, drop-off locations, delivery time slots and order size. The order is strike as published by the app. After the submission of order app then calculates the delivery price on the basis of size, total delivery distance and shows the delivery charges to all eligible adhoc drivers. Any adhoc driver can forward his offer or proposal in reply to the published delivery order. The online customer may accept or reject the offer or proposal, keeping in mind the reviews and ratings of that particular adhoc driver. The status of the order changes to accepted, when the online customer accepts the offer or proposal forwarded by the adhoc driver. When the order has been delivered to the customer then the status of order changes to delivered. There are such situations where adhoc drivers do not respond to the submission request before expiry of the time window, then status changes to expired. At any point in time if online customer or adhoc driver refuses the request before the delivery of order, the status changes to cancelled. Maximum three requests can be refused or rejected by the online customers and adhoc drivers. After which their profiles are deactivated by the system. Delivery integrity is measured to be the most significant attribute [10].

Potential providers rendering their services must initially make the decision to join the platform if they want to be compensated more. After joining a platform they must make another decision of how frequent to work. All such decisions may be taken on hourly basis, so that maximum providers are available for matching and maintain the required service level. The decision of participation is completely based on the wages received by the providers per service and how likely they are to get work, which depicts the number of drivers/providers available and demand on the platform. For instance, Uber or Careem drivers know that demand may be increased on rainy seasons, thus more drivers are available as a consequence. Important thing which is significant to the driver is capacity available with respect to the demand at that particular moment.

In this thesis, we focused on the following parameters: (i) There are a large number of potential occasional drivers willing to participate. (ii) Drivers join the platform with the expectation of earnings. (iii) The platform fix percentages of prices for consumer and a wages paid to driver for delivery. (iv) The platform cannot set the schedule for work. (v) Demand is stochastic. (vi) If the providers are not enough to serve consumers, then to maintain service level dedicated vehicles are used as back up option. (vii) The delivery price depends on detouring distance and level of urgency i.e. same day delivery or next day delivery. Three key features that make this model more dynamic are driver self-scheduling during working hours and the platform which offer dynamic wages and prices. Lyft and uber in cooperated dynamic wages and prices alslo known as surge pricing. Large literature is available on dynamic models; however the literature on dynamic prices/wages is negligible. Lastly, decisions are made at two different times: Drivers make a "long run" judgement of joining the platform and then "short term" judgement when to participate. The platforms primary goal is to maximize its profit and for that, design a contract that ensures drivers to expect reasonable profit. Profit maximization is main objective for the platform or organizations, however, number of problems emerged with this model. For example drivers are not sufficiently compensated being employees and few believes that in dynamic pricing customers are discriminated as a result. Subsequently, a platform should balance the both driver and consumer incentives.

The five different possible models are: Commission contract, which is similar to surge pricing in which platform dynamically regulate both wages and prices in reaction to demand, but having restriction of a certain commission, that is, a fixed ratio between wages and prices for instance, Uber offers fixed 80% commission to the drivers in marketplaces. It is been argued that this limitation may significantly lower the platforms profit (The Economist 2014). Optimal contract, which dynamically regulates both wages and prices without imposes the limitation of a fixed commission. Fixed contract, in which providers and consumers are offered fixed wages and prices. Dynamic price contract, in which, the platform chooses dynamic prices with a fixed wage. And lastly Dynamic wages contract, in which dynamic wages with a fixed price chooses by the platform.

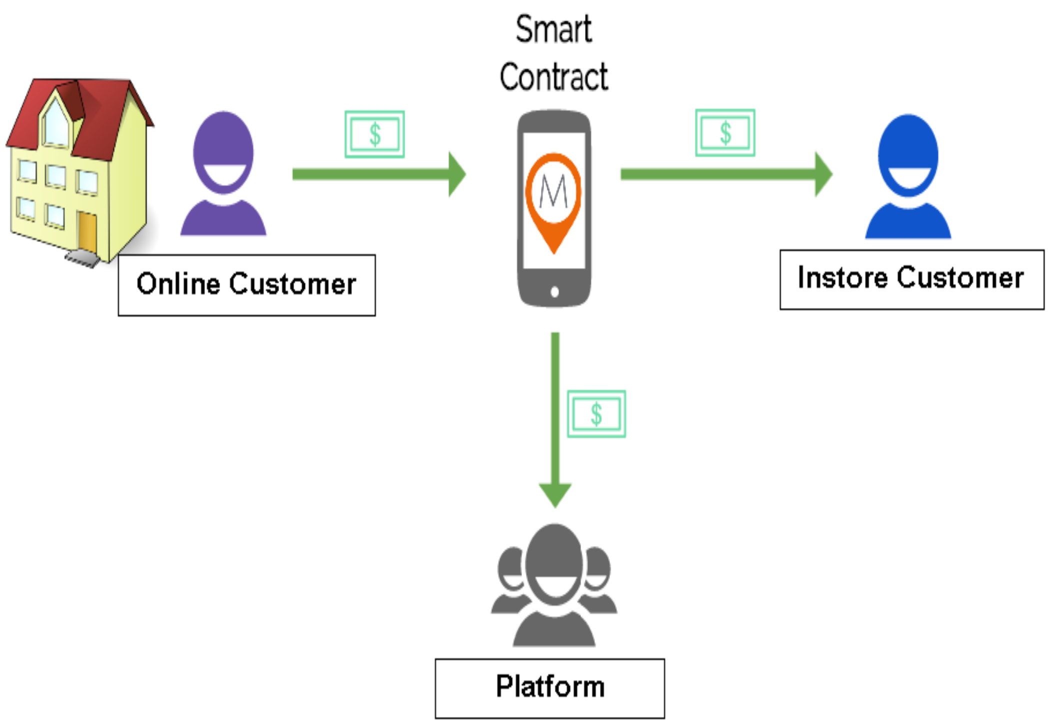


FIGURE 1.3: Flow of Money in Contract.

1.3 Objectives of Research

The objectives of this research are to examine:-

a. The cost effectiveness and response of instore customer/adhoc driver in different time slots while delivering the orders to destination.

b. The cost effectiveness of dynamic model (dynamic pricing and wages) for crowd source delivery over professional / dedicated fleet of vehicles.

c. The impact of crowd sourcing on environment and traffic congestion in Pakistan.

We cannot carry out the analysis of existing dynamic pricing and wages model as no literature is available on the subject for local delivery. However extensive literature is available for dynamic pricing model of ride sharing services.

1.4 Organization of Thesis

The rest of the thesis is arranged in the following order. Chapter 2 consists of review of theoretical and empirical literature. Chapter 3 comprises of theoretical frame work and methodology. Chapter 4 consists of experiments and results. Chapter 5 comprises of conclusion and recommendations.

Chapter 2

Literature Review

This chapter attempts to provide the intuitive assessment of the existing theoretical and empirical literature on frame work and dynamic pricing strategies of crowd source delivery system, Moreover, its impact on growth of e-commerce and traffic congestion. As discussed in previous section, one of the dimensions of e-commerce is Shared economy, which is defined as peer-to-peer (P2P) IT based an economic model, sharing access to goods and services that is often facilitated by a community-based on-line platform. The shared economy encompasses either dedicated vehicle for delivery of goods and services or crowd shipping. This section primarily covers the literature review of crowd shipping which is also area of our research.

Crowd shipping involves exploiting the everyday people with the capacity and free time by using online platforms or mobile apps to manage the delivery demand. Crowd shipping, while cost effective in transportation and improved the related negative environmental effects, may results to the last-mile deliveries. Hence, bring advancement in the outdated logistics. Many other possible gains associated with the crowd shipping may include providing stretchy work breaks, delivery time slots flexibility and removal of topographical restrictions in few situations. Furthermore, crowd shipping proposes an occasion to increases the connection socially for users. Crowd shipping also helps to reduce the carbon emissions from environment and traffic congestion in urban areas. As greater the number of crowd shippers will decrease the number of dedicated vehicles.

2.1 Theoretical Literature

This research is primarily related to three dimensions in the current literature: research on dynamic pricing and wages, dynamic frame work of crowd source delivery using R language and recent papers on different existing platforms. For the consistency and simplicity, we refer to different documents using terms related to our model. For instance, the "platform" is responsible to design market, "Service providers" are responsible for generating capacity, "dynamic prices" are the payments made from customers to platform for services, and "dynamic wages" are payments made through platform to service providers. Several articles shows competition between service providers which may lead to excessive entry [11], and platform discourages competition which help to reduce losses in the system [12]. However, these papers do not take into account dynamic approach in prices. A number of articles discuss the application of high prices during the peak demand [13]. The main motivation is to improve the revenues by adjusting demands from normal to that peak time periods. We are not including this capability in our model. For instance, customer cannot delay their needs for transportation and wait for better weather.

Self-scheduling and self-selecting behavior of adhoc drivers has a significant impact on service and profit. Results of study suggested that hybrid delivery capacity (i.e., adhoc drivers and dedicated drivers) can both improve service level as well as profit. However, the use model is not limited to investigating delivery capacity composition questions. It can be also used to evaluate and compare various strategies to improve courier's compliance. For example, offering extra compensation for orders that are more likely to be rejected by couriers and how large the extra compensation should be to achieve certain goals [14]. There is need for a new methodology to calculate adequate compensation values for OCs (occasional couriers), taking into account the dynamics involved in the delivery process. Both OCs willingness and fees should be based on probability functions obtained from historical data on each OC, so that stochastic aspects associated to the problem could be represented properly in the model, and a dynamic compensation mechanism could be defined appropriately [15]. Transport costs are linearly related to vehicle miles throughout the system and cost reductions correspond to distance reductions. Reducing the total vehicle mileage of the entire system from the use of ad-hoc drivers can provide environmental benefits, such as reducing emissions and congestion. However, this only applies if the ad hoc drivers produce less than or equal miles compared to dedicated drivers. The study found that the profitability of the system increases with the willingness to stop drivers. This refers to an increase in the number of tasks that are served by ad hoc drivers. The number of tasks or orders matched increases if the no of stops for driver increases from two to four and also suggested that by combining the delivery of multiple tasks, we need fewer drivers to do the same amount of work along with required number of dedicated vehicles.Dedicated vehicle decreases as the stop willingness of the in store customer / ad-hoc driver increases. This is intuitive because when the ad hoc drivers can serve more tasks, we need fewer dedicated vehicles. Moreover, study also investigated the viability of the crowd sourced delivery concept under the setting of a peer-to-peer platform and the time flexibility and the stop willingness of ad hoc drivers have a strong impact on the performance of the system. Also, results indicated that benefits of using instore customer / ad-hoc drivers in addition to dedicated vehicles are very pronounced. Study also suggested that a setting in which store customers serve delivery tasks that originate from that store may be most suitable for crowd delivery [16].

Uber enable extremely flexible work schedules, and the degree to which Uber driver-partners take advantage of that flexibility. In 4-hour break definition, the median driver-partner averages less than three and a half hours per session, and varies that session length considerably to take advantage of surge pricing using the surge multiplier (SM). To the degree that the sharing economy promises greater work flexibility, Uber driver-partners appear to take advantage of that flexibility in ways that increase their hourly earnings [17].

There are two different rolling horizon delivery approaches,one incorporates only available information of both online and instore customer / ad-hoc drivers while making decisions and other incorporates probabilistic information about the future online and in-store customers.One of the key problems faced by the different organizations is the size of dedicated vehicles in parallel with the use of instore customers / ad-hoc drivers to deliver orders. To maintain the high level of serviceability for the customers the importance of dedicated vehicles cannot be ruled out. A bigger back up of dedicated vehicles can absorb fluctuations for the delivery of orders to maintain the required service level. However, results shows that a bigger fleet increases the service quality but at higher cost. Frequent checking of system improves the match rate between available in-store customers and online orders. Service quality improves while making decisions on facts rather than estimations.Study also developed the idea that the impact of smaller radius and coverage area results in lower probability of matching an in-store customers. Hence, the average cost and lateness deteriorated.

The service quality has the direct relation with the problems faced. If more time is available between order placement and time of delivery, chances of matches increases which ultimately lower the total cost of delivery [18]. MILP formulation is proposed for matching,utilization of private drivers fully and compensation on each order. Result depicts that cost of transportation lowers with the variable compensation scheme per minute.A fixed price of parcels may lead to more orders per vehicle and no of instore customers / ad-hoc drivers who want to make deliveries.Moreover, fixed price on each parcel is easy to understand than dynamic pricing which keep on changes with time and distances. However, Trunkr totally rely on the dedicated vehicles and dont ignore its importance while making same day deliveries and maintaining the high service level.All the stages involves in the distribution channel which ultimately leads to last mile delivery are required to be executed by the dedicated vehicles ie first mile delivery and line haul. The dedicated vehicles are better suited for all these operations which lowers the cost. In last mile delivery orders not being matched with the instore customer / ad-hoc driver may be delivered through dedicated vehicle [19].

The study suggests to use rolling horizon approach for all the known orders of present and future times irrespective of the timings ie day or night. A primary judgement that involves while running the rolling horizon approach is how frequent and when to execute it. One option is to the rolling horizon approach each time when the new order becomes visible. However, initiates new optimization while the previous optimization is in progress might lead to synchronization issues. For the ease of working, he suggested to run the optimization after the fixed regular intervals [20]. The dynamic pricing performs ideally in comparison with the static pricing strategies in the market. According to his study, optimum output of both the policies are same, however utility of dynamic prices lies to discover the correct static price through stochastically mixing both lower and higher prices [21].The future requests incorporates with the routing decision may lead to make better informed decisions. The result shows that maximum requests of deliveries can be fulfilled if orders are being spread evenly throughout the day compared to those orders which come late in the day. However, the predictions of future orders are important when orders time windows follow late in the day. If the flexibility increases ie the number of vehicles increases the value of anticipation of future orders decreases [22].

A linear correlation with notable difference between scattered and clustered scenarios and the impact on match rate of the request/trip ratio i.e. the percentage of matched transportation requests. The matching rate will remains constant to 100% until a request/trip ratio of 40% has been reached and then falls quickly.The match rate of 87.6% will be achieved unless it reaches to the interval of 40 mins. In his study to get the optimum results the interval between 20 to 80 mins are recommended. Moreover, match rate value of 47.2%, which is considerably less than the optimum in the rolling horizon case, thus use of a rolling horizon approach is recommended over the use of instant match calculation [23]. Study suggested that output of the ride sharing system in partially available information problems get worse quickly ultimately as more people come to know each other and break the system matches and prefer to create matches out of blocking pairs. The system seems to attain steady state where system vehicle miles savings are around 93% of the proposed unstable maximum. Moreover results suggested that the participants with feasible matches always creates more savings and are in blocking pairs when constraints of stability are overlooked [24].

The research revealed that the maximization of system-wide drivers profit and cost savings to passengers generated 10.34 dollars per passenger savings compared to a direct taxi service between passengers origin and destination. To gain maximum profit, drivers needs to share rides with the maximum number of passengers (not exceeding vehicle capacity), and passengers can save travel cost as more passengers share total trip costs, which make per person travel cost lower. System-wide passengers waiting time minimization provided the least savings ($8.73 per passenger). Optimization of the ride sharing service prevented drivers from providing rides to those passengers who required significant amount of pick-up time due to long detours, which led to less number of passengers in each vehicle to share total trip cost [25]. There are strong economic paybacks of using of new mobility systems [26]. The primary motivation for the organizations in employing the crowd shipping is the clear economic advantages [27]. For same day delivery crowd sourcing may lead to lower cost which further allows the consumer to pay the low price [28]. One key point of crowd shipping or logistics is the environmental sustainability. The core result of crowd shipping is reducing the number of vehicles on road by utilizing the free space in cars. Eventually reducing the traffic congestion ultimately lowers carbon emissions. Crowd source delivery also encourages cycling, scooters and delivery by foot etc which are environment friendly compared to delivery vans. Such means reduce the carbon emission in urban areas up to 94% and 82% in a suburban area [29]. While investigating the major causes of motivation of people to participates in the sharing economy activities.People are mostly motivated by the economic benefits. Though factors such as exercise in outcome of the activity, enjoyment and social awareness are also important which cannot be ruled out [30]. Same result was reported in the case study of a crowd shipping where financial benefits although important were not the main cause for participation [31].

Normally, dynamic wage contracts, dynamic price contracts and fixed contracts perform unreasonably compare to the optimal contract, earn 75.5%, 76.2% and 79.1% of the profit individually. Though, the average performance of all three contracts are better ie 96.6%, 97.1% and 98.1%. Moreover, although dynamic price and wage contracts perform better than fixed contracts, their increased performance is not significant. It indicates that in the pretext, it is not sufficient to go with one dimension dynamically ie (wage or price). In comparison, the commission contract is not ideal though, its output is almost optimal, the profit received in commission contract is around 99.3% of the optimal profit and in 95% of cases, itmakes at least 96.6% of the optimum profit. Nevertheless, there are a few situations in which the output of commission contract is poor, in the worst case, the commission contract earn only 63.7% of the optimum profit. The addition of dynamic wages in fixed contract offers minimal improvement, while the addition of dynamic prices considerably increases the platform's profit. However, there are considerable losses at dynamic prices. Instead, the commission contract improves its performance especially in the worst scenario, is improved (obtaining 82.4% of the optimal profit). It is worthy noting that the optimal contract (or commission contract) performs good in comparison to the fixed contract as it charged too little during high demand and charged too much in case of low demand [32].

The average initial total delivery cost is 7.298, when all the customers are served by the professional fleet. In 24 of the 25 instances reduction of total delivery cost is due to proposing crowd shipping of parcels. Since each delivery task may be accepted by an occasional couriers or not the final cost is an expected value. The compensation fee is paid to the occasional driver for serving this customer and the customer's location is omitted from professional fleet routing. On the other hand the customer is served by the dedicated vehicle. Each order may be accepted or rejected to the corresponding probability. The cost of delivery must be computed which includes the compensation fees paid to occasional drivers for delivery and to dedicated vehicles for serving remaining customers. Cost of delivery is reduced by 9% averagely due to crowd shipped parcels [15]. The delivery time bracket is generated randomly from 9 in morning to 7 in evening, keeping in view the practical situation. Moreover, an origin and destination location for each is specified with an same possibility, the error ratio of time cost and fuel consumption are minimal when the time is 15 minutes relative to other situations. Moreover he also studied that adjustment of driving skill and fuel efficiency index affect the prediction errors of both travel time and fuel cost with around 20 percent error ratio reduction. The study implements two baseline methods, one Closest Deadline First (CDF) and second Shortest Distance First (SDF). In first method task close to deadline assign to the first with the earliest departure time. In second method task matched with the shortest detouring distance. The task delivery rate improves consequently for every method as the delivery bracket relaxed. In the delivery bracket of 2 hours, Car4Pac extraordinarily and leave behind SDF and CDF by 21 and 75 percent.These results indicate that Car4Pac is more proficientin accomplishing timely delivery [33].

Research examined the effects of two different compensation schemes. One scheme based on the high charges while making delivery from depot to customer location. Second based on the cost of extra detouring charge from the customer.Results of both the compensation schemes were acceptable. However he suggested study suggest that compensation schemes based on the "cost-to-serve" of a customer may be most appropriate. Moreover, significant cost reduction results when there is reasonable adhoc drivers are available ie increased flexibility for the deliveries. That might depend on the compensation offered on large extent. Formulation of adequate and cost effective compensation scheme is one of the primary challenges associated with crowd shipping while implementation [34].

The study shows a model in which service provider offers discounts to online customer in exchange of the increase delivery flexibility. Using an exact dynamic programming approach algorithm in the experiment shows that, cost saving of around 30 percent can be achieved in different settings. Moreover, study gives well insight of pricing as a device to improve delivery flexibility. This approach may be a staticapproach, where customers have specified their choices before applying pricing to gain delivery flexibility [35].

Incentive mechanism is necessary for handling of delivery time slots which is essential in time sensitive deliveries. The suggested incentive optimization mechanism makes use of the variability in the minimal fulfillment price and customers choice of delivery slots. By using the approximate dynamic programming approach, minimal fulfillment price can be well estimated employing historical order data and customer choices. In this research, the savings in terms of the total fulfillment price the proposed ADP Incentive mechanism afforded are greater than the Free Choice mechanism. Proposed incentive mechanism was successful in reducing the routing price considerably from order clustering and improved capacity utilization on minimum price. Moreover, proposed mechanism has combined effect with marketing strategies that rises customer arrivals. Suggested ADP mechanism is significant more when vehicles are available in more quantity ie additional flexibility. Order density is effective up to the point where the delivery capacity is saturated. And then third-party deliveries are required to be exploited [36].

The study shows that the benefit of dynamic approach decreases compared to the a priori approach as the number of order increases. The study shows that the dynamic approach has maximum benefits where potential orders are 20 to 50. However for smaller number of orders, that is, less than 20, the exact optimal solution is optimal and for larger number of orders, that is greater than 50, a priori approach is near to optimality. Same day delivery requests, for instance, home delivery of grocery, may expect orders daily around these numbers. Correspondingly,benefits of dynamic approach decrease as orders become available in the start of the planning horizon. In other words, if orders are not placed on the same day and carried over from the previous day, in such case, an a priori approach performs well. It is exactly in the most ambiguous environments, where orders may appear at any instant [37].

There are two different time windows to illustrate the model, that is, one time window with peak hours, high demand and traffic congestion characteristics and other time window with non-peak hours and low demand characteristics. Result shows that the optimal wages and the optimal prices are higher for the duration of the peak hour window compared to the non-peak hour window, as peak hour window has higher customer requests which is intuitive.Moreover, results show that the optimal payout ratio is always higher during the peak hour window compared to the non-peak hour. Numerical results suggested that fixed payout ratio would not perform reasonable through different time windows and using the time-based optimal payout ratio can significantly increase the income than using a fixed payout ratio. This suggested that platform must use a time-based scheme to achieve higher profits across all time windows / slots [38]. Crowd shipping also reflects a possibility to alleviate the adverse effects of metropolitan logistics. The study revealed that 75% of the revenue is generated by the 90% deliveries which are within a distance of 50 miles. The large size packages contributed to 54% of deliveries and accounted for 45% of the total income. Super-large and extra-large packages over longer distances are the upcoming areas for advancement in deliveries.

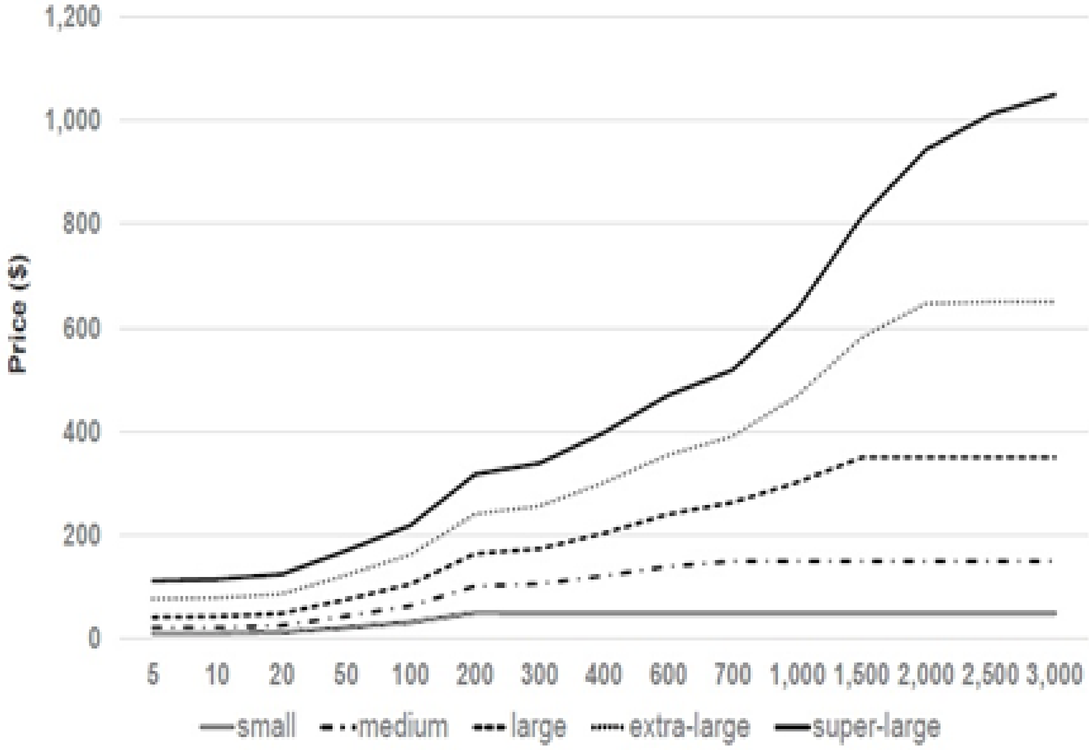


Figure 2.1: Price Vs Size of Packages (Taniguchi and Thompson,2018).

In between 2015 and 2016 huge numbers of deliveries have been successfully carried out (73.18%). However, 6.68% of requests have been rejected by the drivers before expiry of deadline and 19.11% delivery orders were cancelled. Generally, the completed orders make up 47.10% to the revenue collected and expired/cancelled delivery orders make up 48.98% of the total revenue. The completed orders make up a total 31.77% of total covered distance and comprises of 71.04 miles for each delivery, however the expired/cancelled orders make up 63.33% of the covered distance and comprises of 401.09 miles for each delivery. Findings specifies that orders at longer distance face difficulty in finding the driver willingness to carry out the successful delivery. Figure 2.2 indicates that average distance traveled with per order price of the successful delivery is lesser compared to the expired or cancelled ones.

Orders, which did not get response from the drivers are termed as published orders. Such orders need extraordinary delivery price and distances per delivery. This also symbolizes that requests for delivery is higher, that is 72.54% for super-large and extra-large orders normally have longer distance for delivery as compared to the large, average and small orders. The large distance for the delivery in published orders during the specific time might be because of arrival of additional customers for the use of service for longer distances. Due to non-availability of data of customers, reason is difficult to guess for that high delivery distances for the published orders.

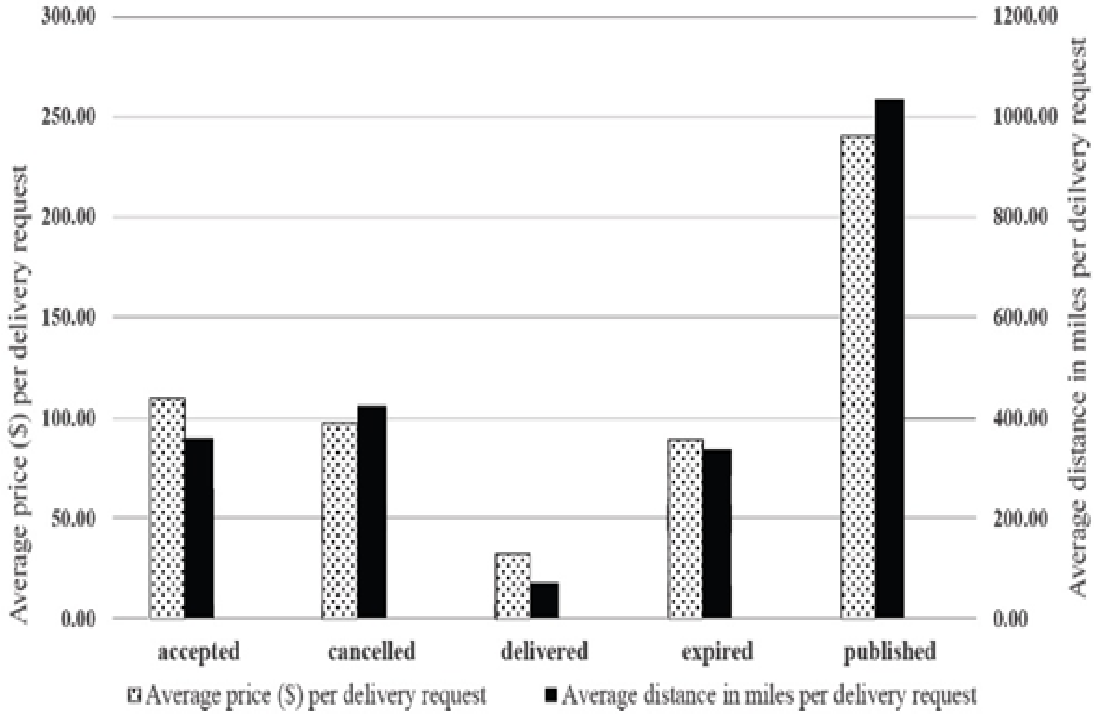


Figure 2.2: Cost to Distance Relationship for all types of Deliveries (Taniguchi and Thompson,2018).

The company recorded a total of 20,234 shipments between 2015 and 2016. Figure 2.3 offers growth for supplies, total distance traveled and the cost incurred. This reflects reasonable progress in the shipments provided to firm and indicates that this delivery mechanism is suitable to consumers. More money needs to be invested on what delivery distances and package sizes are acceptable by consumers and the nature of consumers results in successful delivery systems. Study shows steady growth in delivery of all order/package sizes. Though, major growth during the study period was seen in large package sizes.

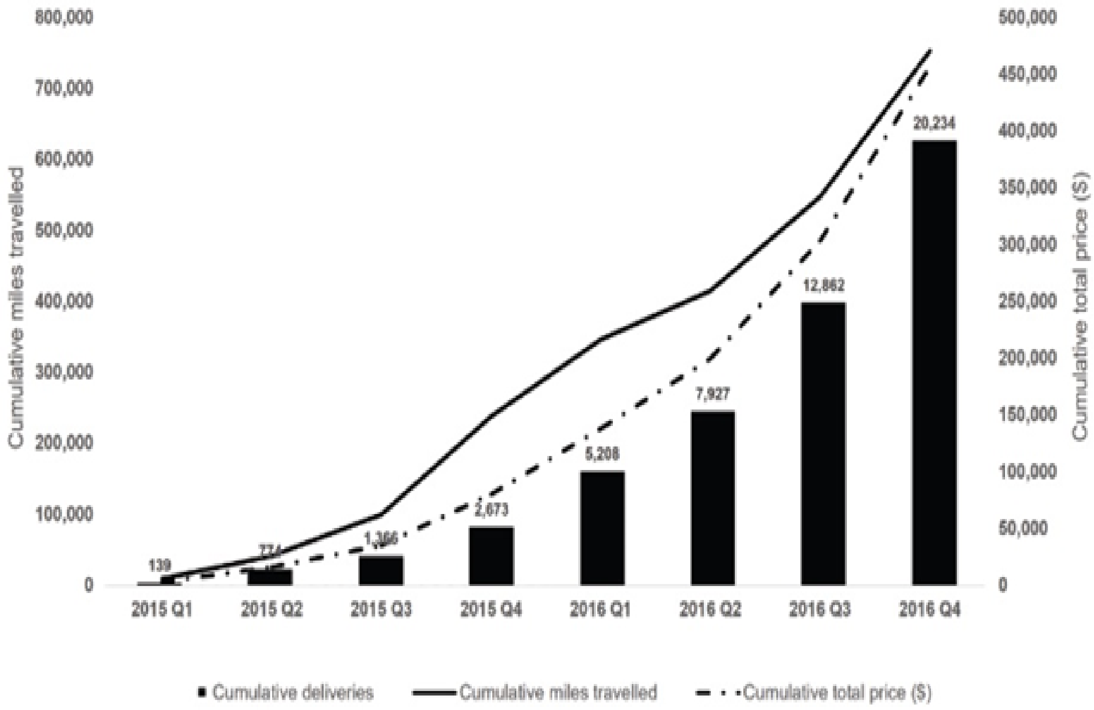


Figure 2.3: Growth of supplies, distance traveled and total cost incurred (Taniguchi and Thompson,2018).

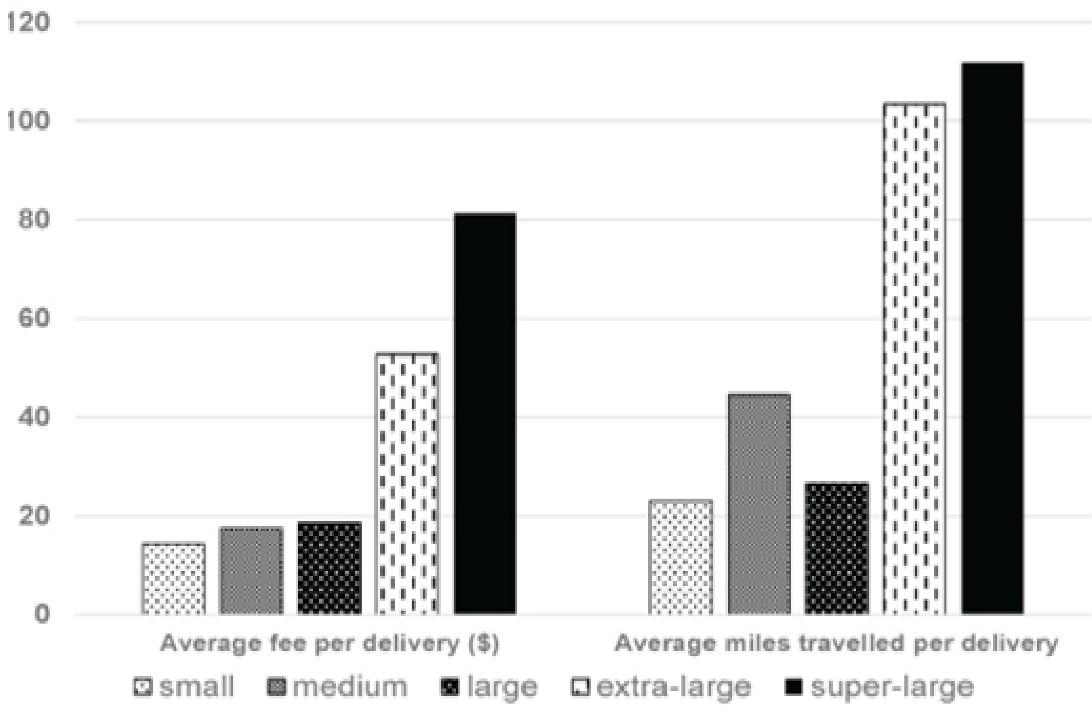


Figure 2.4: Performance measurements for different sizes of package (Taniguchi and Thompson,2018).

Figure 2.4 offers performance measurements for different sizes of package for all shipments. Figure 2.5 displays that the maximum revenue collected, that is, 77%

and maximum deliveries, that is, 93% are limited to 50 miles, which shows intercity travel.

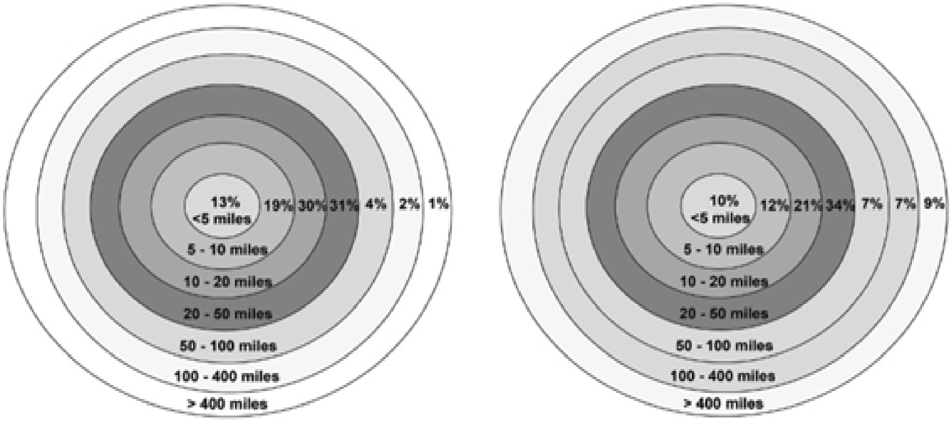


FIGURE 2.5: Revenue collected in comparison with the distances.

Table 2.1 shows that large proportion of small and medium-sized packages are less than 100 miles, while deliveries of super-large and extra-large packages result into distance greater than 100 miles. Regardless of the delivery distance, large pack sizes remain popular.

TABLE 2.1: Share of different sizes of packages (Taniguchi and Thompson,2018).

	Percentage of total deliveries completed				
Distance in miles	Small	Medium	Large	Extra-large	Super-large
0 to 5	37.12%	27.05%	24.67%	3.12%	8.03%
5 to 10	21.34%	19.42%	52.77%	2.43%	4.03%
10 to 20	15.48%	18.24%	60.05%	2.10%	4.12%
20 to 50	10.88%	14.52%	67.16%	3.20%	4.24%
50 to 100	8.34%	20.92%	47.75%	10.53%	12.45%
100 to 400	9.07%	22.33%	14.65%	20.93%	33.02%
400 +	7.80%	26.78%	20.34%	14.92%	30.17%

The registered users with age groups and delivery drivers showed that the 35 to 44 age group is popular with both consumers and drivers. Big number of users did not provide any information about the age as it is not a compulsory condition via firms app, despite the fact it is a necessity for drivers. Maximum users who gave ages are in the 35 to 44 age group, while more than 80% of the drivers are in the 24 to 54 age group. Most workers between the ages of 35 and 44 are familiar with the Internet and willing to participate in systems such as drivers and offer opportunities to increase their income. This is used in conjunction with other collaborations where small population is a large share of the users. Identify the status (8.41%) of the users providing this statement to the firm. Though, no driver traveling on the delivery has registered himself as a company, while a huge percentage (96.95%) has not registered as company or an individual. This also shows that crowd shipping is suitable for business to consumer platform, which emphases on transactions between businesses and consumers through the online platforms. Therefore, for the company's interests it is important to provide a distinct pricing model for all those companies interested in using crowd source delivery services.

The larger package is 54% in total delivery and 45% in total revenue collected. Moreover, it is important to high light that delivery is restricted to distances less than 90 miles. This equates to more than 75% of the total fee for the completed delivery. Therefore, opportunities in new markets are less (and larger package sizes are desired). Figure 2.2 reflects that delivery distances for canceled and expired ordrs are greater than 300 miles. Moreover, study shows that super-large and extra-large packages are the most expensive (per mile) among the other package sizes. Figure 2.3 reflects that the extra-large and super-large deliveries have longer distance deliveries, that is, greater than 50 miles. Therefore, the future growing areas are in deliveries to longer distances, for instance, extra-large and super-large package sizes. It can also be seen from figure 2.2 that the large and extra large packages have the highest revenue in each size. Figure 2.2 shows that super and extra-large deliveries include long distance transfers, that is greater than 50 miles. In this way, future market areas may be for extra and super-large packages [10].

2.2 Research Gap

The thorough review of literature suggests that different pricing strategies of crowd souring is an important step for the growth of e-commerce, however to keep the incentives of platform, instore and online customer alive that is to maximize their profitability, there is need to further investigate and construct the model of dynamic pricing and wages in real time environment to maximize the interest of all stake holders. The impact of dynamic pricing and wages will ultimately contribute towards economic growth and reduction in traffic congestion in case of Pakistan. This study aims to construct theoretical and empirical model of dynamic pricing and wages in real time environment over dedicated vehicles for the profitability of all the stake holders (instore customer/ad-hoc drivers, online customer and platform).

This study is concerned with different pricing strategies for application in attended home delivery, especially e-grocery delivery. The objective is to dynamically calculate pricing for each delivery slot, for each arriving online customer, considering the ultimate delivery, such that the total profit is maximized. In this study we do not consider order rejection and non-purchase, the objective of profit maximization is equivalent to delivery cost minimization. For every new online customer arrival, the customer provides the order data and the delivery location. The instore customer/ad-hoc driver then uses this information, along with previously accepted order, to generate delivery routes on the basis of minimum distance detouring from his destination. The online customer then selects one of the delivery slots/time windows and awaits delivery.

The aim of our research is to enhance our understanding of cost effectiveness, which affects the online customer behavior, to decrease delivery cost. Moreover we scrutinize the benefits of offering discounts on delivery time periods in return for delivery flexibility. The contributions of this study are summarized as follows:

a. This study shows the dynamic pricing with delivery flexibility to reduce delivery costs by offering discounts to customers on their selected delivery time periods ie Urgent package, Premium package and Economy package.

b. We develop a dynamic programming algorithm to compute optimal time slot to maximize cost effectiveness.

c. Real time data is being used through google maps using API key i.e. distances of occasional drivers and online customers with time taken to fulfill the deliveries.

d. All matched occasional drivers and online customers are plotted on OSM (Open Street Map) using R studio for better data visualization.

e. We conduct several experiments to determine the effectiveness of our proposed approach and to get insights about the potential benefits of the suggested demand management. For the considered problem our results indicated following:

   i. In specific instance, the percentage of total cost in urgent package can exceed up to 44% and percentage of occasional drivers (ODs) used up to 100% (in 72hour slot and 33% in overall instance) in economy package.

   ii. Higher the flexibility, more cost savings are achieved in each time windows.

Chapter 3

Frame Work and Methodology

3.1 Frame Work

We are considering a platform that receives orders continuously and instore customers / ad-hoc drivers with arrival rate over time. Each online customer shares his location and selects the appropriate time slot according to the requirement. To optimize the cost of delivery three different time slots are introduced. Online customer opt for the time slot best suited for him, for instance same day deliver, next day deliver and next to next day delivery. The cost of delivery varies as the time slot changes. The lesser the time, higher the cost and vice versa. The reason of high cost is that in short intervals, less instore customers/ad-hoc drivers are available and chances for matching of instore and online customers are less. However, in case of longer period more instore customers/ad-hoc drivers are available over the time and therefore chances for matching are very high. In this study time of delivery is restricted to maximum three days period for the sake of simplicity.

Instore customers/ad-hoc drivers are assumed to be generated randomly in store or depot with the arrival rate. For the convenience, location of instore customers/ad-hoc drivers is restricted to one of the store or depot as shown in figure 3.2 (A) which may be any other place. Different scenarios are reflected in figure 3.2. After arrival of instore customer/ad-hoc driver in store or depot, he will take the decision of joining the platform to earn the profit.

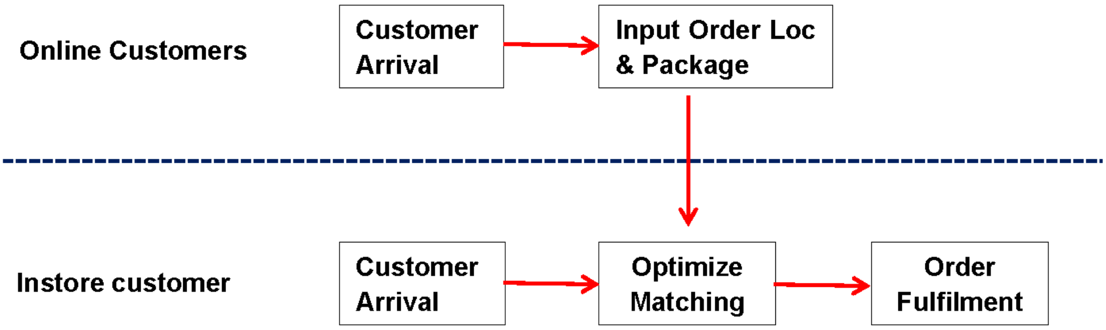


FIGURE 3.1: Illustration of E-Commerce Ordering Process.

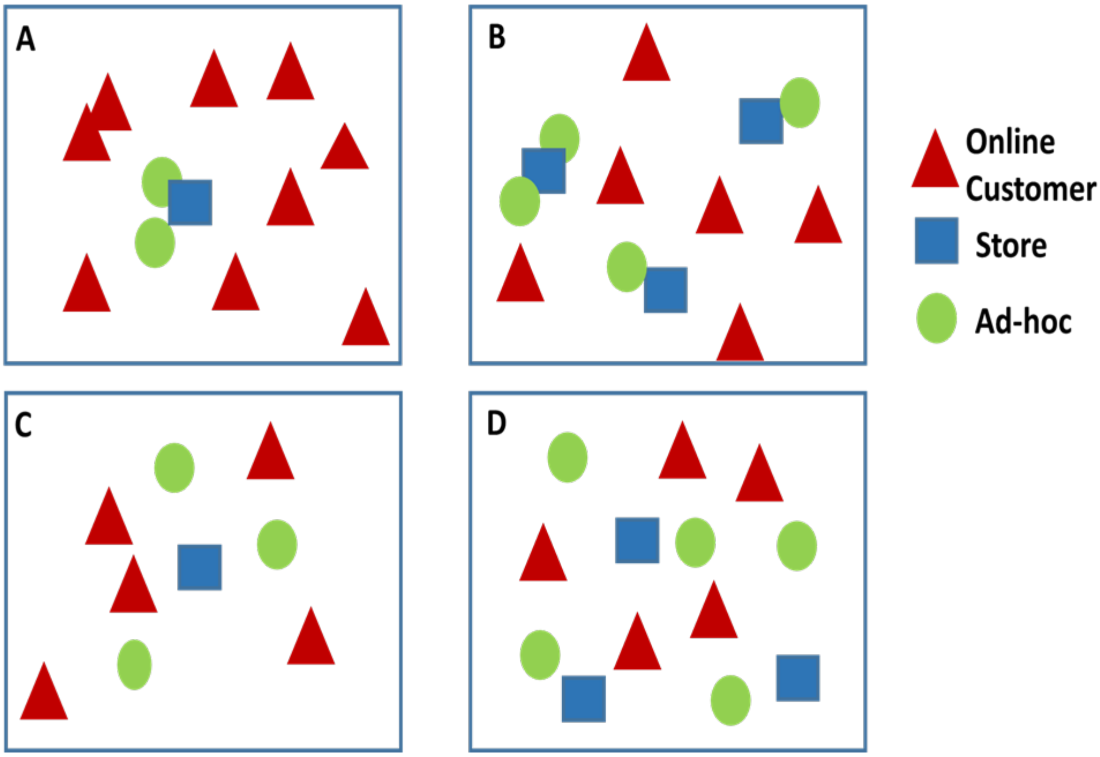


FIGURE 3.2: Different scenarios of Instore customer/ad-hoc drivers.

In this study we assumed that all the generated instore customers/ad-hoc drivers have to join the platform without any exceptions. After joining the platform all instore and online customers are matched with each other. The important parameters for matching are detouring distances from destination and the delivery time. The instore customer/ad-hoc driver may delivers as many parcels as possible, if the match is within specified distance from the destination. In this study, online customers are assumed to place orders in available time slots and specified service period. At every time t, the probability that online and instore customer/ad-hoc driver arrives is uniformly distributed. When two or more persons are connected via internet and share information with each other, without being connected to main server, it is referred as Peer to peer platform (P2P). All stake holders part of P2P platform is reflected in figure 3.3.

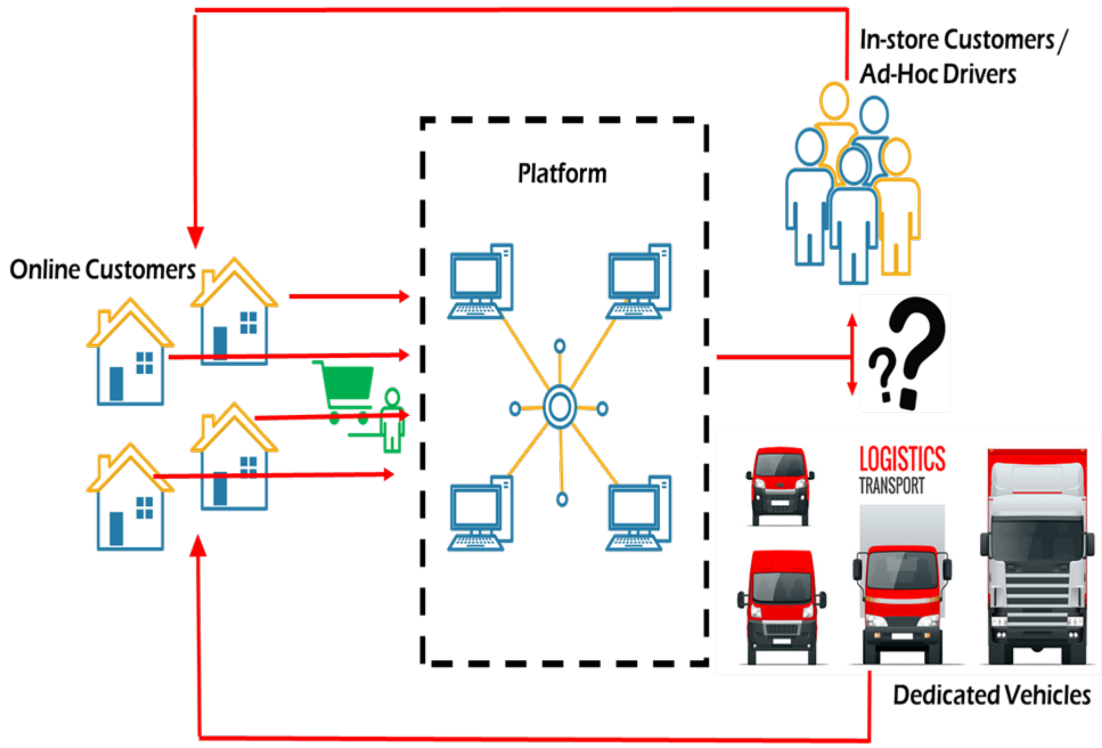


FIGURE 3.3: Depiction of Peer to Peer platform (P2P).

However, a situation may occur where no online order is generated within the specified distance from the destination of instore customer/ad-hoc driver. Every day optimization run is carried out for matching of both instore and online customers. After which matched orders are delivered and unmatched are considered in next day optimization run. If orders are not matched as per defined parameters, the orders are delivered through dedicated fleet of vehicles. To maintain certain service level we assumed that fleet of dedicated vehicles is available round the clock.

The instinct behind the suggested procedure is to influence online customers to select delivery slots which is cheaper for the delivery to be carried out. In other words, the compensation mechanism aims to influence the online customers preference such that it is aligned with the instore customers/ad-hoc drivers objective of cost minimization. It is expected that the eventual delivery routing will be clustered (if there is more than one match) into regions for each slot, knowing that it is cheaper to deliver orders within the same region instead of dispatching dedicated vehicles or even separate ad-hoc driver. In this study prices and distances of clustered deliveries are taken average of all the matched customers for better optimization and cost effectiveness.

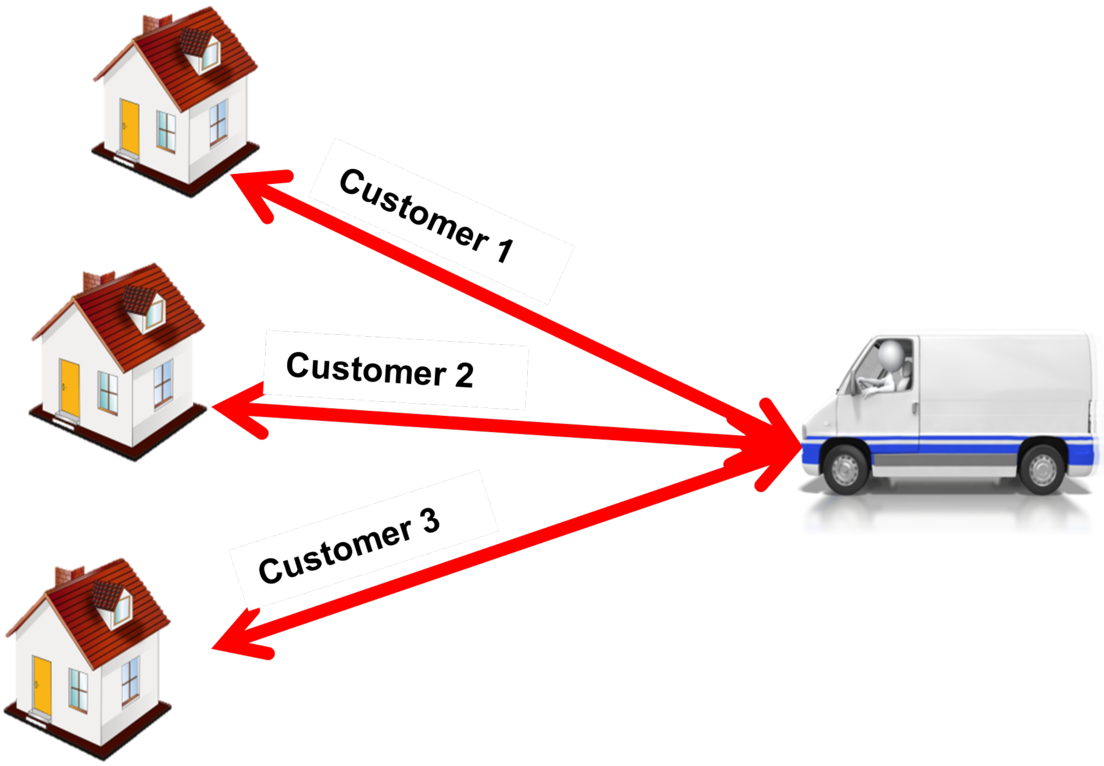


FIGURE 3.4: Clustered Delivery to destination by Instore customer/ad-hoc drivers.

Online customers/orders arrive with the different probabilities (will be discussed in next section) shares the delivery location. The option will be shown to each online customer for selection of appropriate time slot, after which the delivery slot is committed and the instore customer/ad-hoc driver has to deliver the order in that selected delivery slot. The corresponding delivery cost will be known and realized at the end of the selected time slot, that is, after all online customers have arrived and selected their delivery slots. Because of this dynamic nature, the objective of the problem is then to dynamically match with the instore customer/ad-hoc driver to maximize the total profit or minimize the eventual delivery cost. This is different to static pricing problems where the price for each delivery slot is fixed irrespective of the changes occurred in time and distance. In the problem considered different pricing strategies are calculated for each online customer. In general, all the matched tasks are being dispatched before latest departure time

(LDt). The latest departure time is the latest time that instore customer/ad-hoc driver can start its trip to serve all tasks on time. Detail timelines are reflected in figure 3.5.

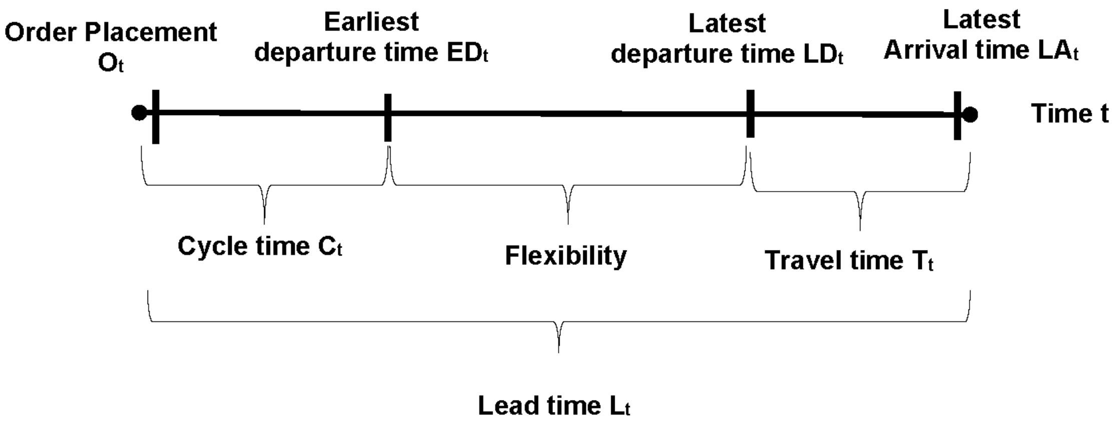


FIGURE 3.5: Orders/tasks and Instore customer/ad-hoc drivers timelines.

This is same for the dedicated vehicles and all dedicated vehicles start and end their route at the store. If the latest departure time (LDt) is less than interval t (where t is running/real time) and match is not found, same order will be consider in next optimization run. However, if the latest departure time (LDt) is greater or equal to interval t, the order will be delivered through dedicated vehicle as reflected in figure 3.6. Detailed flow charts for crowd shipping and estimation of cost is reflected in figures 3.6 and 3.7.

3.2 Methodology

3.2.1 Instance Generation

We generate three random instances (each instance include different numbers of online and instore customer/ad-hoc driver ie 2000, 4000 & 6000 with arrival rate of 2, 4 & 6 customers per min) with different flexibility. Flexibility is ratio of number of instore customers/ad-hoc drivers to online customers (F= I/O). If number of Instore customers/ad-hoc drivers and online customers are same, flexibility equals to one. However, if instore customers/ad-hoc drivers are more than online customers, the flexibility will be greater than one. If instore customers/ad-hoc drivers

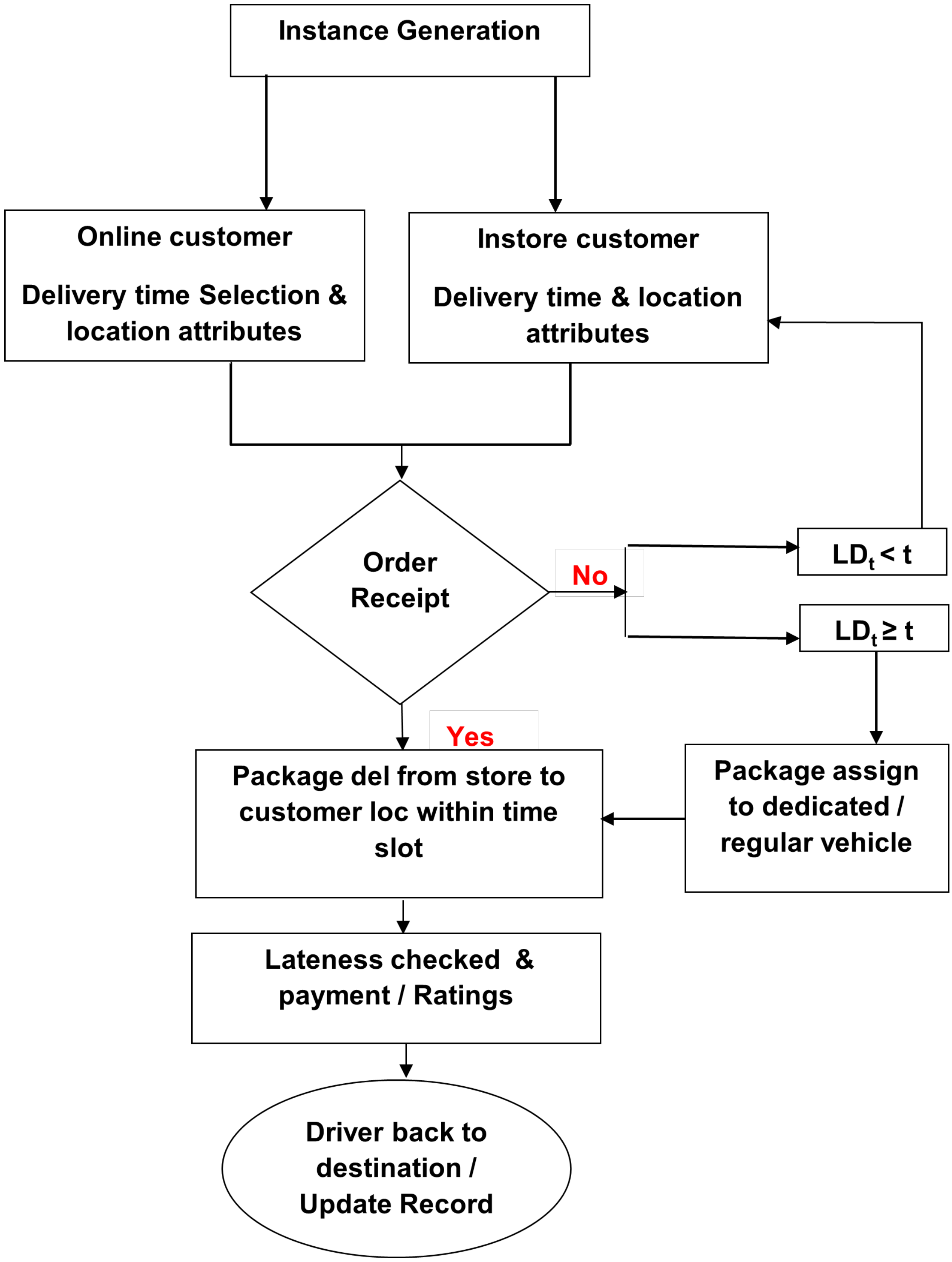


FIGURE 3.6: Flow Chart Of Crowd Shipping.

are less than online customers, the flexibility will be less than one. Here we are considering the three different values of flexibility ie one, less than one and greater than one. To study the viability of crowd source delivery system and validate the performance, tasks and instore customers/ad-hoc drivers generated within a square area with a store at center. In particular, we are using setting inspired

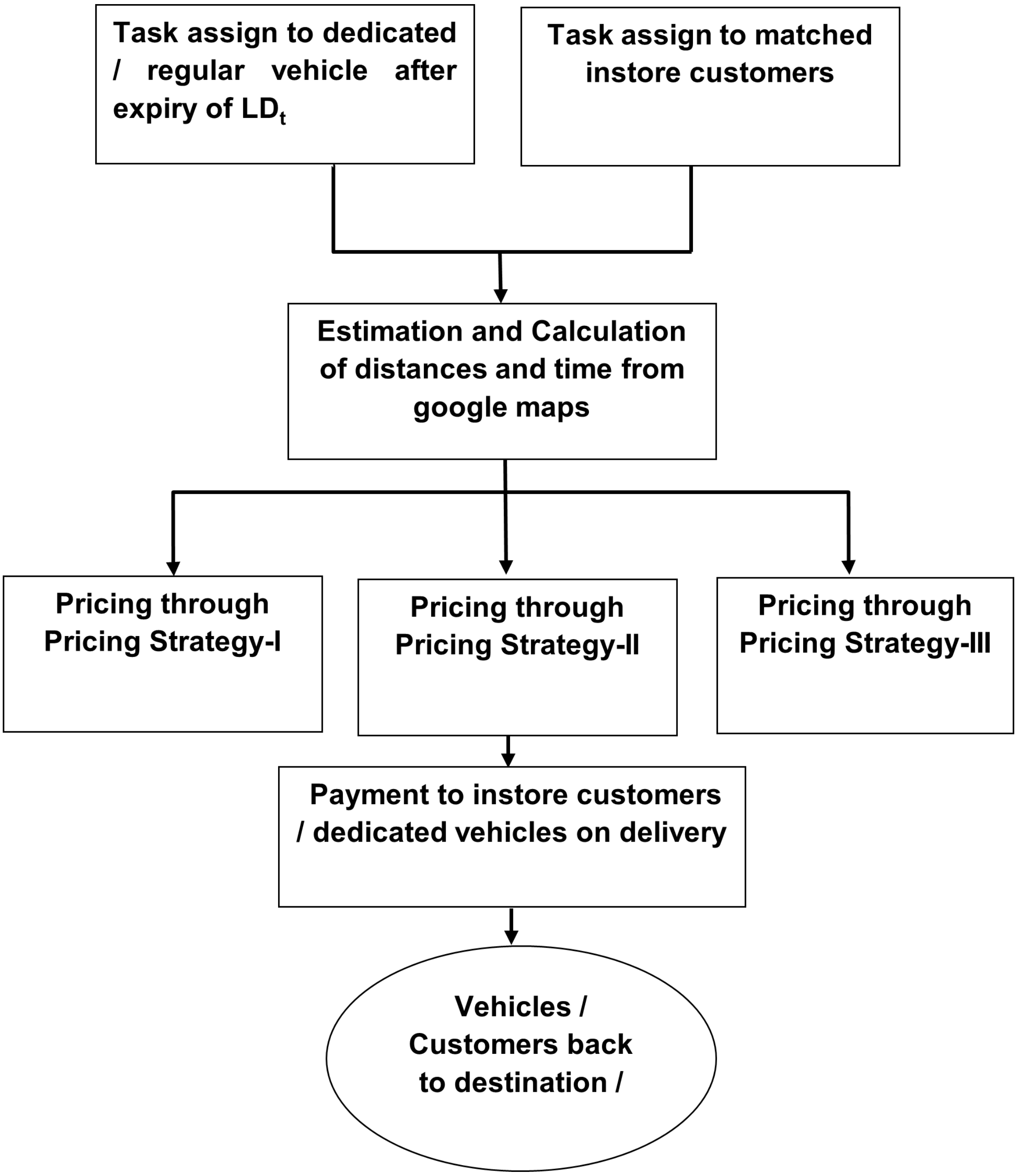


FIGURE 3.7: Flow Chart Of Cost Estimation.

by Walmart where all parcels or tasks and instore customers/ad-hoc drivers are originated from same place located in center of region i.e. store, whereas delivery locations are distributed randomly in the region. The other possible settings which are not taking into account for the simplicity are instances with different locations of instore customers/ad-hoc drivers and stores as already reflected in the figure 3.2. While considering the setting each instore customer/ad-hoc driver may carry multiple tasks or parcels if matched lies within the specific distance. The sizes of package are restricted to small, medium and larger which can be accommodated in the trunk of private cars [39].

We assume that task or order and instore customer/ad-hoc driver originates at any time randomly during the day and each instore customers/ad-hoc drivers have the same matching and departure period. We use euclidian distances for matching and assumed speed of 60km per hour. Service time at the picking and drop-off locations are considered negligible.

In computational study, the cost of using a instore customer/ad-hoc driver and regular/dedicated vehicle varies according to the different time slots or package i.e. urgent, premium or economy package. Moreover, we assume that the cost per unit distance and parcel fixed fee is same for the dedicated vehicles and the ad-hoc drivers. However, driver pay and maintenance cost will only be considered in dedicated/regular vehicles and will be discussed in detail in section 3.2.3.

All online orders and instore customers/ad-hoc drivers arrive round the clock and matching will be carried out in specific service period. We assume that the stores or pickup locations are open 24 hours and 7 days a week. To attain maximum service level the platform have unlimited back up vehicles (Uber and Creem) and available 24 hours throughout the week. All orders or tasks have the same time delivery windows available i.e. urgent package, premium package and economy package. The distances and time between the locations are taken from google maps in R Studio using API key.

3.2.2 Event Based Rolling Horizon Approach

While online and instore customers / ad-hoc drivers trip announcements constantly arrived which necessitates dynamic service provider to explore the potential matches each and every moment throughout the day. Everytime the service provider executes the procedure for planning matches, there are possibilities of unknown future requests. To address the issue of uncertainty the common approach is using deterministic rolling horizon approach while planning. In deterministic rolling horizon approach,plans and matching are made on the basis of known information and decisions are finalized until necessitated by a deadline. After each iteration the planning horizon is "rolled" to incorporate all available and known information about the tasks or orders [20].The study established two different rolling horizon delivery approaches, one incorporates only available information of both online and instore customers / ad-hoc drivers while making decisions and other incorporates probabilistic information about the future online and in-store customers [18].

While online order and instore customer/ad-hoc driver comes all over the time, we considered rolling horizon approach which initiates the optimization run and solves matching problem each time new order or instore customer/ad-hoc driver arrives. We finalize the matches based on all information that is available to the system at that particular time in each iteration of rolling horizon. At any instant t, order or task arrives if it is not matched previously and expired yet. The instore customers/ad-hoc drivers and tasks that are matched at any instant t are not part of any optimization runs after t. we assume that regular drivers are available in the vicinity of the depot throughout the day. Each optimization run results in match between orders and instore customers/ad-hoc drivers or dedicated vehicle (if latest departure time expires).

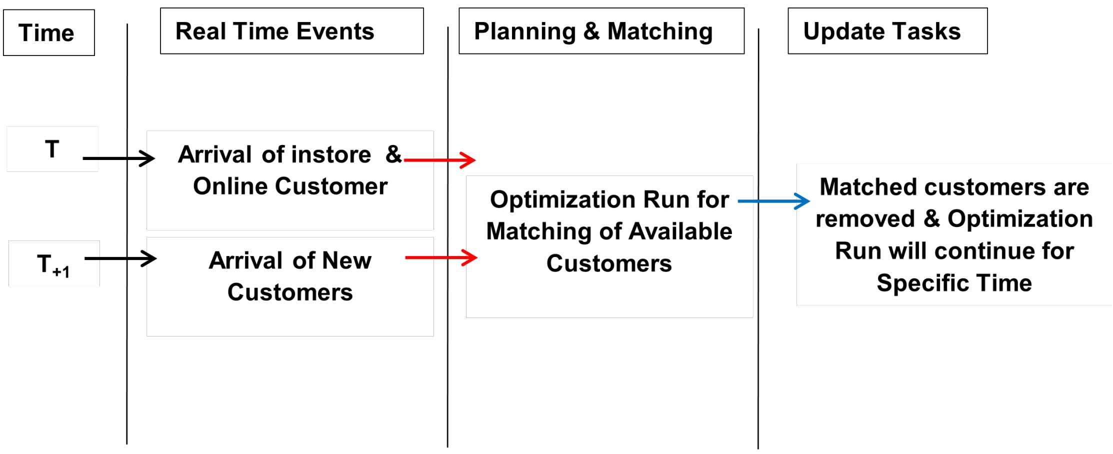


FIGURE 3.8: Illustration of Rolling Horizon Approach.

3.2.3 Pricing Strategies

For the model where online customers are given different delivery options or time slots, for example, same day, next day or next to next day delivery options on surplus premium. We are considering here three pricing strategies. Dynamic pricing strategy-I in which pricing is combination of different factors. For example, dynamic pricing performs ideally in comparison with the static pricing strategies in the market[21].The study examined the effects of two different compensation schemes. One scheme based on fixed delivery charges while making delivery from depot to customer location. Second scheme based on the cost of extra detouring charged from the customers. Results of both the compensation schemes were acceptable. However he suggested that compensation schemes based on the "cost-to-serve" of a customer may be most appropriate. Moreover, significant cost reduction results when there are reasonable ad-hoc drivers available for the deliveries. That might depend on the compensation offered on large extent. Formulation of adequate and cost effective compensation scheme is one of the primary challenges associated with crowd shipping while implementation [34].Service provider offers discounts to online customer in exchange of the increase delivery flexibility. Using an exact dynamic programming approach algorithm in the experiments show that, cost saving of around 30 percent can be achieve in different settings. Moreover, study gives well insight of pricing as a device to improve delivery flexibility. This approach may be a staticapproach, where customers have specified their choices before applying pricing to gain delivery flexibility [35].

The platform of uber regulates prices using a dynamic algorithm in real time. Surge price is outcome of dynamic algorithm which rises automatically when demand exceeds the supplies in particular area.Delivery cost is regulated by multiplying the output of the surge algorithm with the primary components which make up the total cost. Primary components include sparcel cost, the per mile cost and and cost of time. Both riders and partners are communicated with the multiplier before each journey begins. Customers are shown with surge multiplier when they are offered a pickup and also through heat-maps displayed on the application [17]. Keeping in view the basic parameters reflected in the study, we will propose the model of dynamic pricing for online customer and ad-hoc drivers as follows:

$$\begin{aligned} \text{Dynamic price } (D_p) = [&\text{Detouring distance cost } (d) + \text{Fixed parcel Price } (p) \\ &+ \text{Cost of Time } (t)] \times \text{Urgency factor } (\beta) \end{aligned} \tag{3.1}$$

Where urgency factor (β) is multiplier and varies with the selected time slot and cost of time will be considered negligible (will be considered in third pricing strategy for comparison). The reason for this factor is intuitive as flexibility is less in short time span and increase as the time increases. Secondly to shift the load of demands to other time slots, so that only needy customer opts for the speedy delivery on extra premium. Value of urgency factor is considered 2 for urgent package, 1.5 for premium package and 1 for the economy package. Here we may define the dynamic price, an amount charged from online customer for delivering parcel to his location from the store. One vendor who is currently employing pricing strategy -I is Amazon. The platform makes full use of its logistics to attend its customer in time as well as getting profit.

On the other hand, to identify the parameters involved in pricing of dedicated vehicles or regular drivers, there are two important parameters, total distance driven from depot to destination and the unit transportation cost [40]. The primary component in computing the pricing for dedicated vehicle is the per mile cost. However, maintenance cost and pay of the driver must not be ignored [41]. Therefore, we may propose the model for dedicated or regular drivers as follows:

$$\begin{aligned}\text{Dynamic price } (D_p) &= \text{Total distance driven (per mile cost)} + \text{Fixed parcel fee } (f)\\ &+ \text{Maintainance Cost} + \text{Driver Pay}\end{aligned} \tag{3.2}$$

Consequently, dynamic Pricing strategy-I in which price is calculated by incorporating the detouring distance, fixed parcel fee and the urgency factor as discussed earlier. Second strategy considered here is dynamic Pricing strategy-II, which incorporates all the factors in pricing strategy-I with additional discount on total delivery price. [41] in his study suggested that, a discount strategy involves in selling a goods or services on a reduced cost for a limited time. This reduce price must generate enough additional transactions to reimburse the reduction in revenue. When an order discount is offered for a specific time period it relates to all orders, which sometimes leads to unsuccessful results also. Let us consider a set of orders sold at cost c each. During a time period T, the company receives m orders with benefit b. The company chooses to put on $x\%$ discount, assumed $xc/100 \leq b$, which shows that the discount is less than the benefit offered. Now after giving a discount, how many additional orders required to be received to reimburse the cost of discount? Let z the number of additional orders that must be received. It can be validate through:

$$Z \geq \frac{m \times x \times c}{100 \times b} - x \times c \tag{3.3}$$

Now suppose, for example m =10,000, c = 50 and b = 15. Figure 3.9 gives the minimum number of extra orders that must be received to balance the discount in revenue [42]. We may propose the pricing strategy-II as follows:

$$\text{Dynamic price } (D_p) = \{[\text{Detouring distance cost } (d) + \text{Fixed parcel Price } (p) + \text{Cost of Time } (t)] \times \text{Urgency factor } (\beta)\} \times \text{Discount\%} \tag{3.4}$$

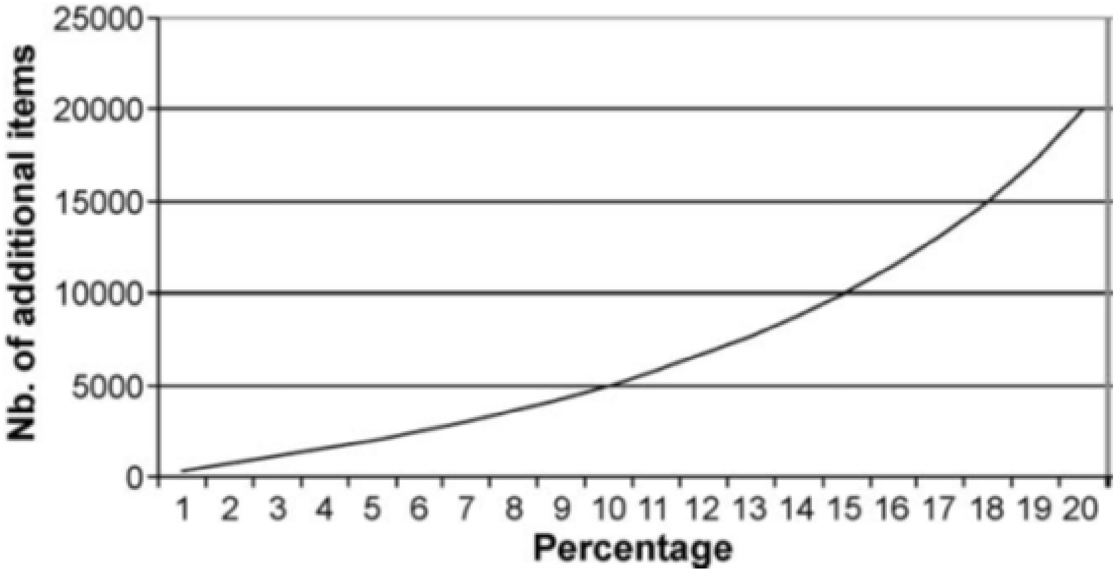


FIGURE 3.9: Comparison of numbers of orders with discount percentages.

Thirdly, pricing strategy-III where crowd shippers are being paid on the basis of hourly rate.Business to consumer platforms, for instance wolt and amazon pay either scheduled hours and earn a certain hourly rate or just earn per delivery depending on distance covered [26]. Study shows that compensation schemes for

OCs used in crowd shipping companies are either on hourly rate (Deliv, Kanga, AmazonFlex) or on the number of parcels delivered (Renren,Kuaidi, Trunkrs). No company used a mixed compensation policy combining working hours and the number of parcels. The information required by the companies include travel time, origin and destination. Unfortunately, there is no such information how such data is used in computing the OCs fee [43]. However in our study, locations and time travelled is being calculated through google maps using API. We may propose our third pricing strategy as follows:

$$\begin{aligned}\text{Dynamic price } (D_p) = [&\text{Fixed parcel Price } (p) + \text{Cost of Time } (t)] \\ &\times \text{Urgency factor } (\beta)\end{aligned} \tag{3.5}$$

Moreover,the commission contract is similar to Ubers pricing policy which regulates wage and price according to requirement. However it imposes the restriction that both have constant ratio. For instance, the platform gets a demand-based price and gives providers wage ie w = β, where β is the (fixed) commission factor. The commission rate is appropriate that enables the platform to earn profit. On the other hand, in optimal contract both prices and wages might change relative to the demand without the fixed ratio [32]. Both the two components enable the platform to maximize its profit. In this pretext, we may propose the model of dynamic wage as follows:

$$\text{Dynamic Wages } (D_w) = (\beta D_p) \times \lambda \tag{3.6}$$

Where λ is total tasks that have arrived. We may define dynamic wages as payment made to the ad-hoc drivers for delivery of parcel from store to the location of online customer. Dynamic wage will vary as the dynamic price changes but we assume that commission rate is fixed to 80%. Therefore, profit of platform may be proposed as follows:

$$\text{Platform Profit } (P_p) = D_p - D_w \tag{3.7}$$

In dynamic pricing detour distances and time taken to deliver the task is calculated by the google maps through distance matrix using API key to get the real time data. Moreover, generation of instances, matching of task and optimization/simulation is run in R studio.

3.2.4 An Integer Programming Formulation

To authenticate the performance of the heuristic presented in next chapter of different instances, we formulated the viable integer programming model which is appended below.

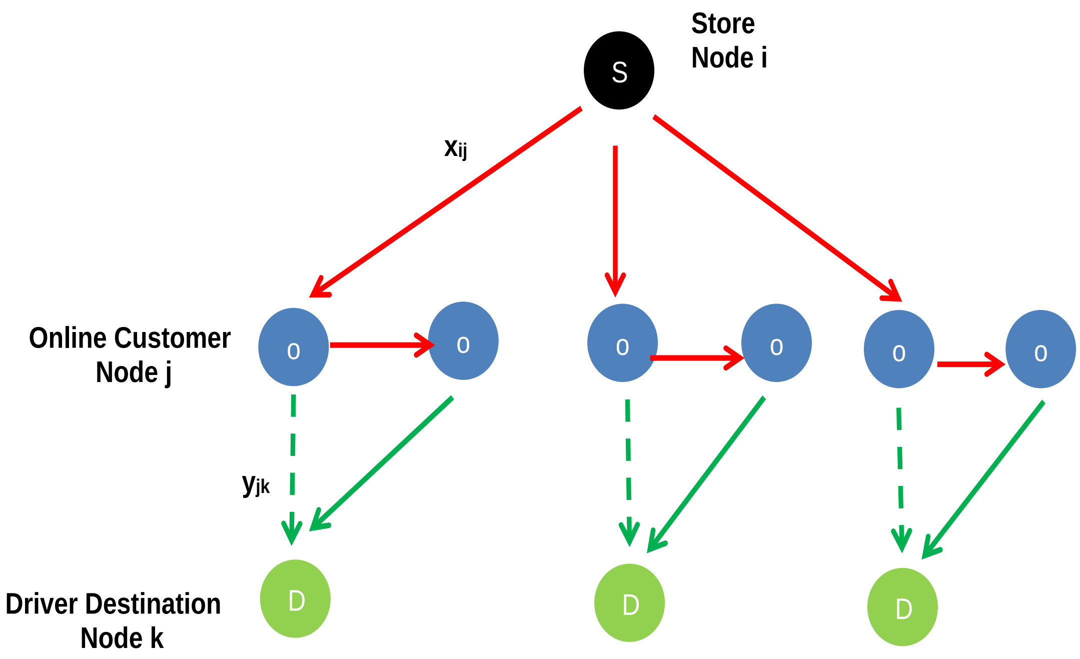


FIGURE 3.10: Integer Programming Formulation.

Let a binary variable x_{ij} indicating movement of vehicle traverses from node i to node j. Let y_{jk} be a binary variable representing movement of vehicle traverses from node j to node k. Let K_{ij} be a variable representing the occasional drivers carrying parcels from node i to node j. Let P_{ij} be a variable representing the number of parcels that must be assign to the instore customers/ad-hoc drivers for delivery. Finally, let O_{ij} indicate customer that must be served. For the ease of presentation, let C indicate the total cost incurred on delivery to customer j. The dotted arrows represent the single parcel delivery and solid arrows represents the multiple parcel delivery. The cost model can be expressed as follows:

$$\sum_{i}\sum_{j} C_{ij}X_{ij} + \sum_{j}\sum_{k} C_{jk}Y_{jk} \tag{3.8}$$

$$\sum_{j} X_{ij} = \sum_{j}\sum_{k} Y_{jk} \quad \forall i \tag{3.9}$$

$$\sum_{j} x_{ij}K_{ij} > 0 \quad \forall i \tag{3.10}$$

$$\sum_{j} x_{ij}P_{ij} = 1 \quad \forall i \tag{3.11}$$

$$\sum_{j} x_{ij}O_{ij} = 1 \quad \forall i \tag{3.12}$$

$$x_{ij} \epsilon \{0,1\}$$

$$y_{ij} \epsilon \{0,1\}$$

The model aims to represent the total cost incurred during the delivery. Constraint (3.9) is flow conservation constraint. Constraint (3.10) ensures that each occasional driver can take any number of parcels. Constraint (3.11) ensures that each parcel is assigned to one occasional driver. Constraint (3.12) establishes that each customer is served once.

Chapter 4

Experiments and Results

4.1 Benefits of Employing Instore Customer / Ad-hoc Drivers

The merits of engaging instore customers/ad-hoc drivers to deliver the orders depend on three factors:

a) Flexibility, that is, number of instore customers/ad-hoc drivers available relative to online orders that need to be served, i.e $|I|/|O|$.

b) Limitation an instore customer/ad-hoc driver has i.e no of orders instore customer/ad-hoc drivers can carry.

c) Effects of different time slots/windows and their cost effectiveness.

To get quantitative insights of above mentioned factors, we solve each instance with different combination of pricing strategy, flexibility, that is, $F = |I|/|O|$ against the different time slots/windows available, for instance in urgent package, premium package and economy package.

We analyze the advantages of employing instore customers/ad-hoc drivers by examining and comparing the percentage of total cost incurred by dedicated drivers and the number of instore customers/ad-hoc drivers matched to make deliveries. In this study, we also include the solution when less instore customers/ad-hoc drivers are accessible (upper bound for cost) and when instore customers/ad-hoc drivers are available freely or flexible (lower bound for cost).

4.2 Analysis of an Instance

We are considering three delivery time windows/slots, that is, S, within specific service time for making delivery. The numbers of available online orders in instance are 2000, 4000 and 6000. The numbers of adhoc drivers (K) arrive with different arrival rate of 2, 4 and 6 customers per minute. The order density (ρ) considered, which is number of tasks/orders delivered per vehicle in each delivery slot is random, that is, greater than one or equal to one. Therefore, number of orders or the length of the time horizon becomes $T = \rho \times K \times S$. In arrival process, the total probable number of orders per vehicle in each delivery slot is given by $\lambda \times \rho$. Vehicle moves at a speed of one kilometer per minute and total delivery cost is proportionate to the distance traveled and allowing various deliveries by a single vehicle within the delivery window. Moreover, the probability of selection of each delivery slot is equal, that is p_1, p_2, $p_3 = 0.33$ with $\sum p = 1$.

We start by studying the results for one instance in detail. The instance with 2000 online customers are placing orders with the arrival rate of 2, 4 and 6 customers per minute and instore customer with same arrival rate. The locations of online customers, instore customers/ad-hoc drivers and the store are shown in Figure 4.1. The square represents the depot, the red circles represents online customers and the black triangles the destinations of instore customer/ad-hoc drivers.

In figure 4.1 store, online and instore customers/ad-hoc drivers are randomly generated throughout the region. Generally, each side of region is representing the availability of instore customers/ad-hoc drivers which can carry parcel or order of as many online customers as possible within the defined distance. Complete area represents a prospect for cost-savings. By taking advantage of instore customers/ad-hoc drivers in any area, it is not necessary for dedicated drivers to visit that area.

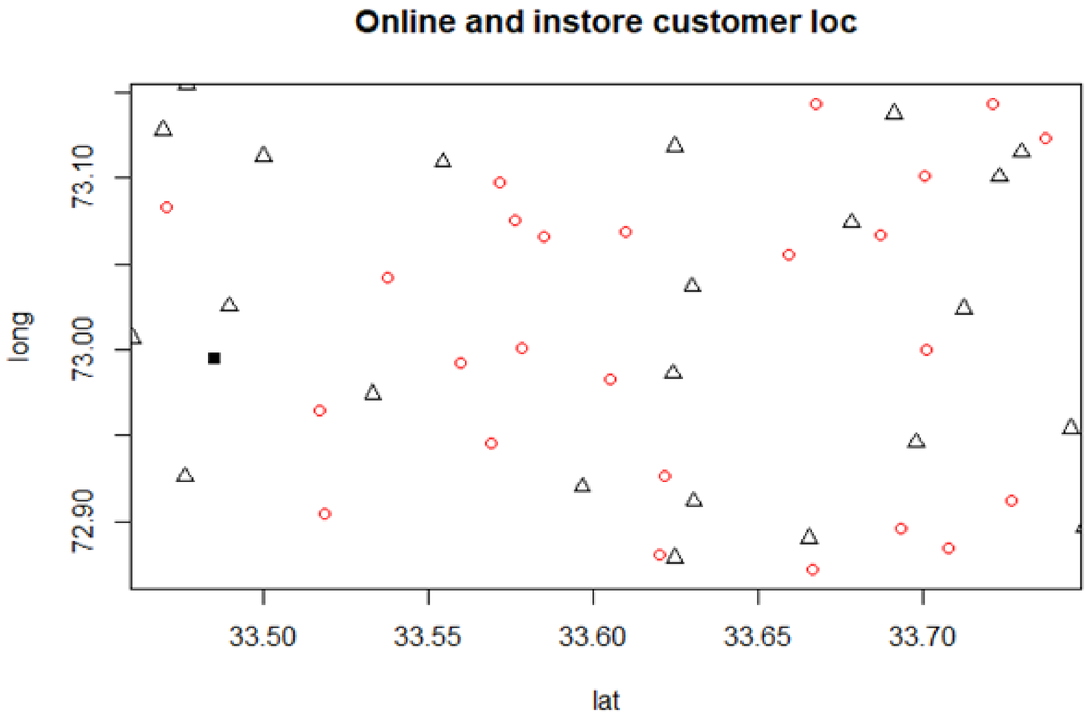


FIGURE 4.1: Locations of Store, Instore and Online customers.

Subsequently, we look on the solution obtained when instore customers/ad-hoc drivers are fairly flexible or less in different time slots. Results of matched instore and online customers are obtained up to the distance of 10 kilometers.

4.2.1 Impact of Pricing Strategy I

Table 4.1 reflects the percentages of available instore customers/ad-hoc drivers used and percentages of the total cost during the experiments. Table is organized as follows. The columns show the three different packages with the percentages of instore customers/ad-hoc drivers used and total cost incurred by them. Each row corresponds to number of online orders available for the delivery with different values of flexibility. Values reported in the last columns are taken averages of orders delivered in all three time slots/available packages. Percentages of ODs used and ODs cost mentioned are the sum of all the packages matched during each instance.

We first comment on the results obtained when first time slot of Urgent package is selected in Tables 4.1 with flexibility greater than 1. It is pertinent to highlight

Table 4.1: Percentages of ODs used and of ODs cost for pricing strategy-I.

No of Orders Available	**Flexibility**	**Urgent Package**		**Premium Package**		**Economy Package**	
		% of ODs Used	**% of ODs Cost**	**% of ODs Used**	**% of ODs Cost**	**% of ODs Used**	**% of ODs Cost**
2000	>1	30.5	43.1	33	32.5	33	23.4
	1	27.7	44.3	31.6	32	32.7	23.6
	<1	22.8	42.1	23.3	33.9	23.6	24
4000	>1	7	43.6	15.3	32.9	32.9	23.4
	1	6.3	42.8	14.8	36	29.1	21.2
	<1	5.9	44.4	11.2	35.6	20.3	19.9
6000	>1	4.9	41.4	13.5	33.3	24.6	25.3
	1	3.9	42.4	7.1	32.3	20.1	25.2
	<1	3.5	40.5	6.5	36	15.4	23.5

that percentages of occasional drivers used decreases as the number of online orders required to be delivered are increasing. This is due to the reason that in limited time it is not possible to match all the orders with instore customer/ad-hoc drivers. Secondly, only those orders are matched which lies in specific radius of instore customer/adhoc driver and lastly, it also depends upon the order density, that is, we incorporated the order density which is number of orders carried by the each vehicle to one or greater to one. As the number of orders required to be delivered increases, chances of generating the order in the vicinity of instore customer/ad-hoc driver destination also increases. Therefore, instore customer/ad-hoc driver is bound to deliver the order if it occurs within the specified distance of instore customer/ad-hoc driver. However as the flexibility of time increases, that is, in third time window (economy package) the match rate increased up to the 100% in economy package and 33% over all in the instance. This shows that, as more time is available for making delivery, chances for instore customer/ad-hoc driver arrival is more. However, in urgent package the percentage of occasional driver increased to 30.5% when the orders required to be delivered are 2000 and drops to 4.9% when orders are 6000. Moreover, in premium package the percentage of occasional driver used is 33% which decreases to 13.5% as the number of orders increased to 6000. Also as expected, when the flexibility of time is maximum in economy package, the percentage of occasional drivers used is 33% for 2000 orders and drops to 24.6%. The percentage drop in economy package is not as much as in other two packages. Even With 6000 orders, the percentage of occasional drivers matches are still 24.6% which shows that minimum no of dedicated vehicles are required in economy packages and ultimately cost of delivery is reduced for the online customers. However in other two packages more no of dedicated vehicles are required to maintain the certain service level and ultimately increases the cost of delivery. All reported values are taken on the averages of five random instances.

If we set the flexibility to one, that is, number of orders required to be delivered and number of instore customers/ad-hoc drivers available are same. In such case percentages decreased in comparison with the flexibility greater than one, that is, 27.7% from 30.5% in urgent package, 31.6% from 33% in premium package and 32.7% from 33% in economy package for 2000 orders. The matched percentage decreased to 3.9%, 7.1% and 20.1% from 4.9%, 13.5% and 24.6% for 6000 orders. The reason is, limited number of instore customers were available, therefore probability of matching also decreased. If we set the flexibility to less than one, in such case percentages further decreased in comparison with the flexibility greater than one, that is, 22.8% from 30.5% in urgent package, 23.3% from 33% in premium package and 23.6% from 33% in economy package for 2000 orders. The matched percentage decreased to 3.5%, 6.5% and 15.4% from 4.9%, 13.5% and 24.6% for 6000 orders. The reason is, due to less number of instore customers were available, therefore, probability of matching further decreased. In the end, we may conclude that maximum customers matched after taking the averages in all packages are 32.1% for 2000 customers and 8.4% for 6000 customers. The prices of all the packages are calculated as per the pricing strategy-I explained in previous chapter. The percentage share for ODs cost is maximum in urgent packages being less cost effective. Increases in number of orders has no effect on cost percentages of instore customers/ad-hoc drivers and are maximum in urgent packages.

Price for clustered orders matched with instore customers/ad-hoc drivers within the specified distances are taken average for all the such instances.

4.2.2 Impact of Pricing Strategy II

TABLE 4.2: Percentages of ODs used and of ODs cost for pricing strategy-II.

No of Orders Available	**Flexibility**	**Urgent Package**		**Premium Package**		**Economy Package**	
		% of ODs Used	**% of ODs Cost**	**% of ODs Used**	**% of ODs Cost**	**% of ODs Used**	**% of ODs Cost**
2000	>1	33	45.1	33	32.5	33	21.4
	1	31.8	44.3	33	32	33	23.6
	<1	26.2	43.1	26.7	33.9	27.1	23
4000	>1	10.1	44.6	17.5	32.9	33	22.4
	1	9.1	43.8	17	36	33	20.2
	<1	8.5	45.4	12.8	35.6	23.3	18.9
6000	>1	7.1	42.4	15.5	33.3	28.2	24.3
	1	5.7	43.4	8.1	32.3	23.1	24.2
	<1	5	41.5	7.4	36	17.7	22.5

Table 4.2 reflects the percentages of matched instore customers and percentages share of cost in pricing strategy II. Pricing Strategy II has been discussed in the previous chapter, in experiment the percentage of discount rate and the customers inclination towards the discount is same, that is, we assumed that discount is 15% and the number of additional customers inclined toward the discount are also 15%. The matched rate obtained in pricing strategy II are improved due to the discount rate, as 15% additional customers assumed to be arrived, hence the matching rate increased. The percentage share of urgent package is still the maximum among all the packages as obtained in pricing strategy I and no significant change has been observed. Moreover, the decreasing trend pattern of match rate from 2000

customers to 6000 customers is also observed as discussed in pricing strategy I. Over all the results of pricing strategy II are similar to pricing strategy I with improved matched rate.

4.2.3 Impact of Pricing Strategy III

TABLE 4.3: Percentages of ODs used and of ODs cost for pricing strategy-III.

No of Orders Available	**Flexibility**	**Urgent Package**		**Premium Package**		**Economy Package**	
		% of ODs Used	**% of ODs Cost**	**% of ODs Used**	**% of ODs Cost**	**% of ODs Used**	**% of ODs Cost**
2000	>1	30.3	41.3	33	32.5	33	25.4
	1	27.8	42.5	31.4	32	32.5	25.6
	<1	22.6	40.3	23.6	33.9	23.9	26
4000	>1	7	41.8	15.3	32.9	32.9	25.4
	1	6.3	41	14.8	36	29.3	23.2
	<1	5.9	42.6	11.2	35.6	20.5	21.9
6000	>1	4.9	39.6	13.5	33.3	24.8	27.3
	1	3.9	40.7	7.1	32.3	20.3	27.2
	<1	3.3	39.9	6.7	36	15.6	25.5

Table 4.3 reflects the percentages of matched instore customers and percentages share of cost in pricing strategy III. Pricing Strategy III has been discussed in the previous chapter. In experiment, we assumed the cost of time is 10 rupees per minute. The matched rate obtained in pricing strategy III is similar to pricing strategy I. The percentage share of urgent package is still the maximum among all the packages as obtained in pricing strategy I & II and no significant change has been observed. Moreover, the decreasing trend pattern of match rate from 2000

customers to 6000 customers is also observed as discussed in pricing strategy I. Over all the results of pricing strategy III are similar to pricing strategy I.

4.2.4 Effect of Order Density

First, we fix the arrival probability and run a set of experiments, but the value of order density, ρ is flexible, that is, each vehicle carries multiple orders. If we recall the order density, is the number of tasks/orders per vehicle per time slot. The total number of orders delivered increases proportionately as more adhoc drivers are available. As the order density increases, the savings generated by the pricing strategies also increases. When arrival probability increases, this implies to more revenue and higher benefit, when more orders are to be fulfilled. When delivery capacity is fully used and orders are not being rejected as assumed earlier, dedicated/regular vehicles are engaged and cost of delivery increases quickly. The platform is able to relieve this by uniform distribution of orders to all time slots as assumed earlier. This result in high level of savings when order density is high and the proposed pricing strategies successfully reduce the need for outsourcing. Increasing order density allows to packs more orders into each vehicle when there are more vehicles available with less dependence on dedicated vehicles and lower cost of delivery. After the delivery capacity is filled, it requires dedicated vehicles to fulfill the orders delivery. However, if the order density is fixed, that is, each vehicle carries only one order, the cost saving decreases, match rate decreases, more number of adhoc drivers/dedicated vehicles are required and cost of delivery also increases. In our experiment, result shows that match rate decreases to 4.3% for 2000 customers instance, 2.7% for 4000 customers instance and 1.2% for 6000 customers instance.

Figure 4.11 represents the cost and distance relationship of both adhoc drivers and regular/dedicated vehicles. The cost of delivery for regular/dedicated vehicles is more as compared to the adhoc drivers on the same instant due to the additional parameters as shown in equation 3.1 and 3.2. Moreover, adhoc driver carries multiple parcels and cost for each parcel is taken average of all parcels delivered.

On the other hand, dedicated vehicle carries single parcel for ensuring timely delivery to destination after expiry of latest departure time.

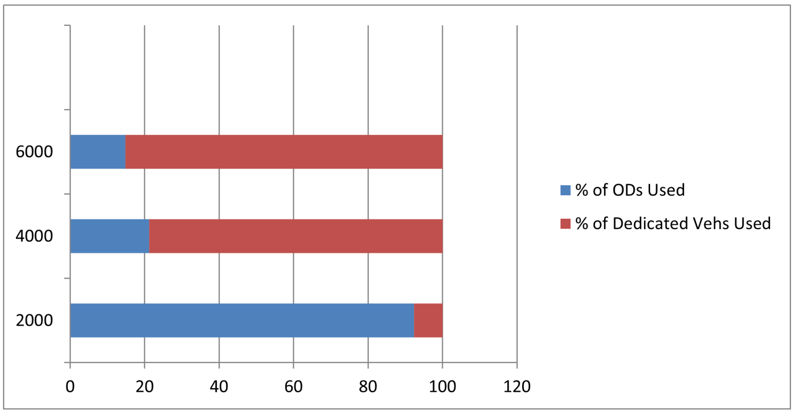


FIGURE 4.2: Percentages of ODs Used and Cost For flexibility >1 (Urgent Package).

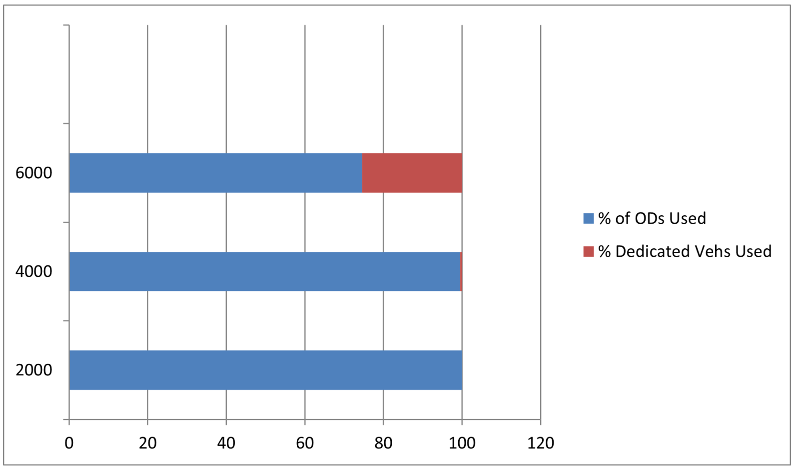


FIGURE 4.3: Percentages of ODs Used and Cost For flexibility >1 (Economy Package).

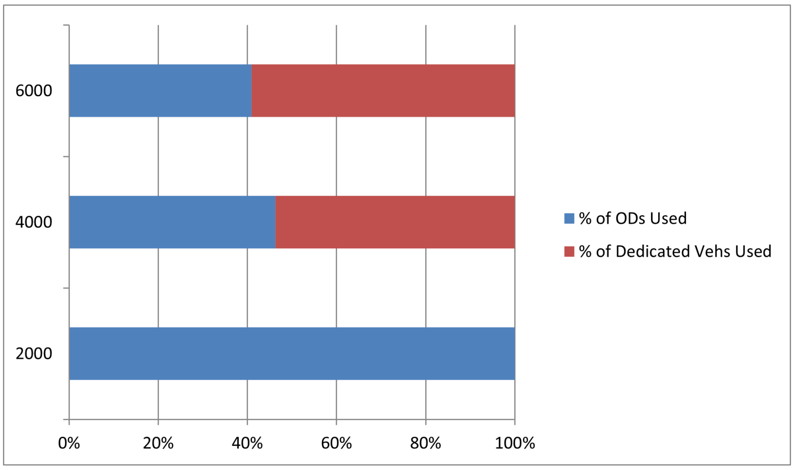


FIGURE 4.4: Percentages of ODs Used and Cost For flexibility >1 (Premium Package).

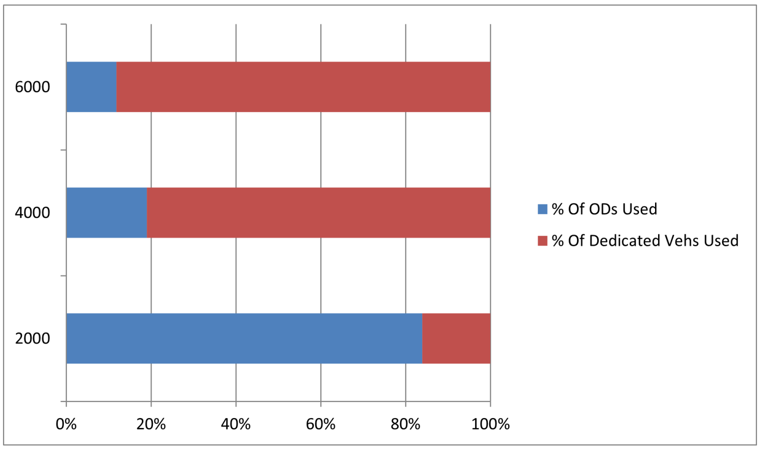


FIGURE 4.5: Percentages of ODs Used and Cost For flexibility = 1 (Urgent Package).

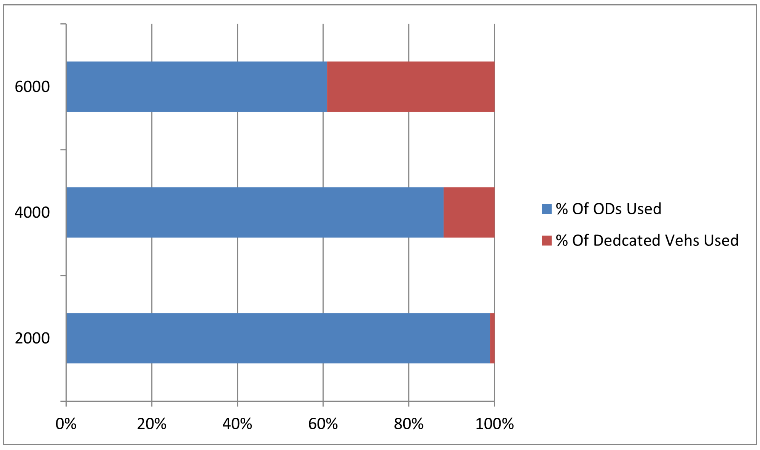


FIGURE 4.6: Percentages of ODs Used and Cost when flexibility = 1 (Economy Package).

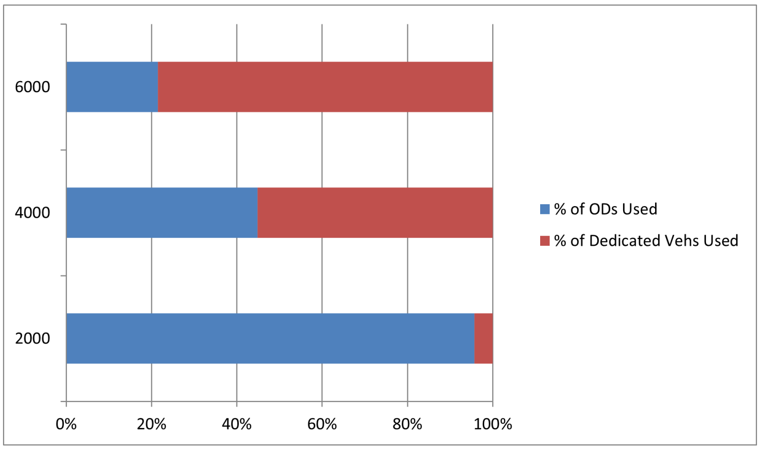


FIGURE 4.7: Percentages of ODs Used and Cost when flexibility = 1 (Premium Package).

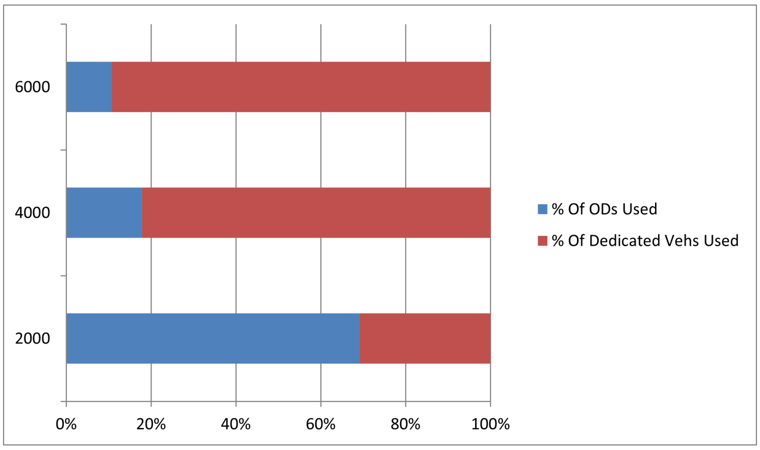


FIGURE 4.8: Percentages of ODs Used and Cost when flexibility is < 1 (Urgent Package).

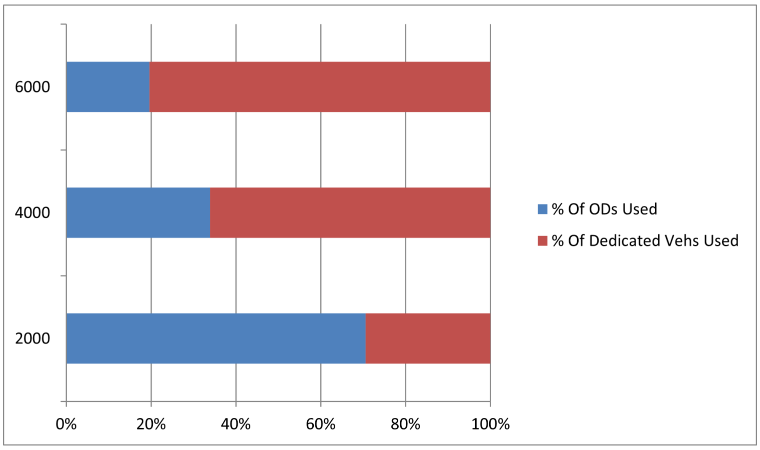


FIGURE 4.9: Percentages of ODs Used and Cost when flexibility is < 1 (Premium Package).

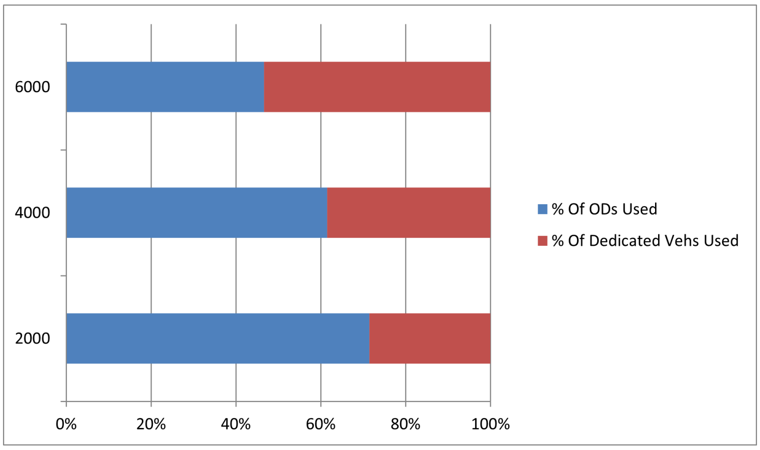


FIGURE 4.10: Percentages of ODs Used and Cost when flexibility is < 1 (Economy Package).

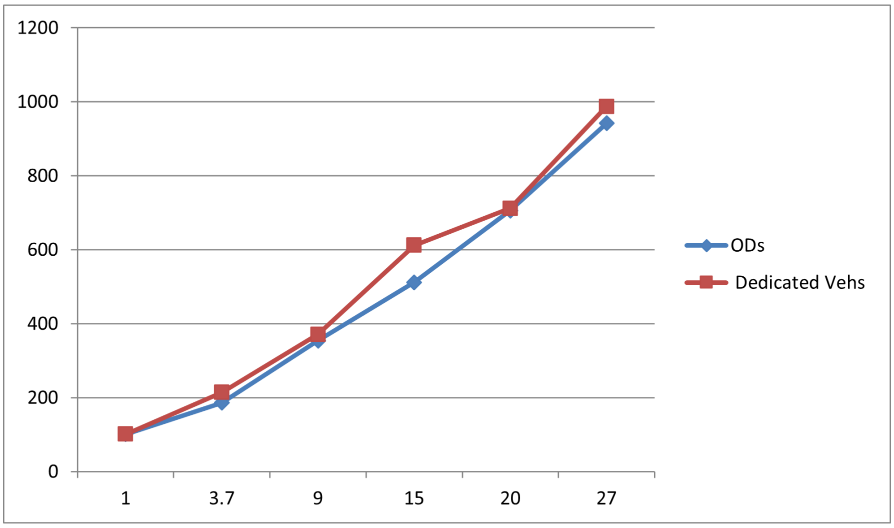


FIGURE 4.11: Cost and Distance Relationship of ODs and Dedicated Vehicles.

4.3 Matched Customers Visualization on OSM

For the better visualization, all the matched online and instore customers/ad-hoc drivers in specific instance are plotted on OSM (open street map) in figure 4.12. Red circle represents the instore customer/ad-hoc drivers, blue represents online customers locations and black square represents the store. All the matched orders with customers are taken within the region of 50 kilometers in general area of Rawalpindi. Moreover, distances are calculated through google maps and reflected in figures 4.13 & 4.14 and matching of nearest instore and online customers are shown in figures 4.15 & 4.16.

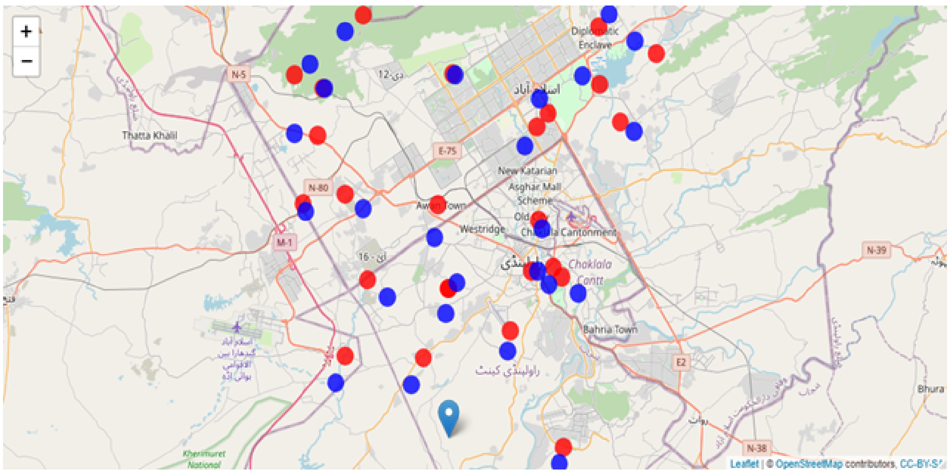
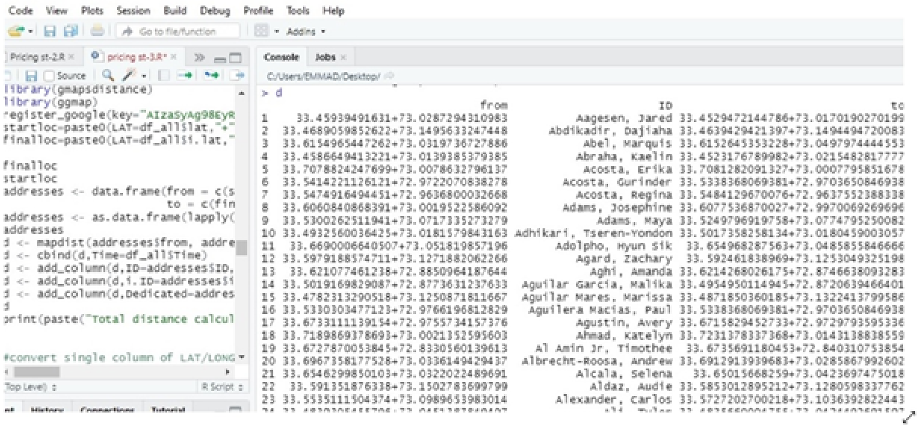
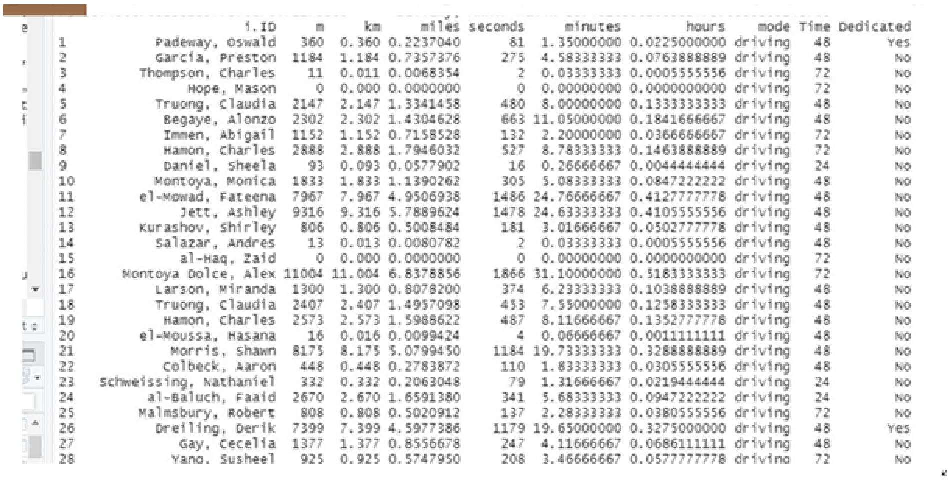


FIGURE 4.12: Visualization of Instore and Online Customers on OSM.



	from	ID	to
1	33.45939491631+73.0287294310983	Aagesen, Jared	33.4529472144786+73.0170190270199
2	33.4689059852622+73.1495633247448	Abdikadir, Dajiaha	33.4639429421397+73.1494494720083
3	33.6154965447262+73.0319736727886	Abel, Marquis	33.6152645353228+73.0497974444553
4	33.4586649413221+73.0139385379385	Abraha, Kaelin	33.4523176789982+73.0215482817777
5	33.7078824247699+73.0078632796137	Acosta, Erika	33.7081282091327+73.0007795851678
6	33.5414221126121+72.9722070838278	Acosta, Gurinder	33.5338368069381+72.9703650846938
7	33.5474916494451+72.9636800032668	Acosta, Regina	33.5484129670076+72.9637552388338
8	33.6060840868391+73.0019522586092	Adams, Josephine	33.6077536870027+72.9970069269696
9	33.5300262511941+73.0717335273279	Adams, Maya	33.5249796919758+73.0774795250082
10	33.4932560036425+73.0181579843163	Adhikari, Tseren-Yondon	33.5017358258134+73.0180459003057
11	33.669000640507+73.051819857196	Adolpho, Hyun Sik	33.654968287563+73.0485855846666
12	33.5979188574711+73.1271882062266	Agard, Zachary	33.592461838969+73.1253049325198
13	33.621077461238+72.8850964187644	Aghi, Amanda	33.6214268026175+72.8746638093283
14	33.5019169829087+72.8773631237633	Aguilar Garcia, Malika	33.4954950114945+72.8720639466401
15	33.4782313290518+73.1250871811667	Aguilar Mares, Marissa	33.4871850360185+73.1322413799586
16	33.5330303477123+72.9766196812829	Aguilera Macias, Paul	33.5338368069381+72.9703650846938
17	33.6733111139154+72.9755734157376	Agustin, Avery	33.6715829452733+72.9729793595336
18	33.7189869378693+73.0021352595603	Ahmad, Katelyn	33.7231378337368+73.0143138838559
19	33.6727870053845+72.8330560139613	Al Amin Jr, Timothee	33.673569118045 3+72.840310753854
20	33.6967358177528+73.0336149429437	Albrecht-Roosa, Andrew	33.6912913939683+73.0285867992602
21	33.6546299850103+73.0322022489691	Alcala, Selena	33.65015668259+73.0423697475018
22	33.591351876338+73.1502783699799	Aldaz, Audie	33.5853012895212+73.1280598337762
23	33.5535111504374+73.0989653983014	Alexander, Carlos	33.5727202700218+73.1036392822443

Figure 4.13: Location estimation through Google Maps Using Lat & Long.



	i.ID	m	km	miles	seconds	minutes	hours	mode	Time	Dedicated
1	Padeway, Oswald	360	0.360	0.2237040	81	1.35000000	0.0225000000	driving	48	Yes
2	Garcia, Preston	1184	1.184	0.7357376	275	4.58333333	0.0763888889	driving	48	No
3	Thompson, Charles	11	0.011	0.0068354	2	0.03333333	0.0005555556	driving	72	No
4	Hope, Mason	0	0.000	0.0000000	0	0.00000000	0.0000000000	driving	72	No
5	Truong, Claudia	2147	2.147	1.3341458	480	8.00000000	0.1333333333	driving	48	No
6	Begaye, Alonzo	2302	2.302	1.4304628	663	11.05000000	0.1841666667	driving	48	No
7	Immen, Abigail	1152	1.152	0.7158528	132	2.20000000	0.0366666667	driving	72	No
8	Hamon, Charles	2888	2.888	1.7946032	527	8.78333333	0.1463888889	driving	72	No
9	Daniel, Sheela	93	0.093	0.0577902	16	0.26666667	0.0044444444	driving	24	No
10	Montoya, Monica	1833	1.833	1.1390262	305	5.08333333	0.0847222222	driving	48	No
11	el-Mowad, Fateena	7967	7.967	4.9506938	1486	24.76666667	0.4127777778	driving	48	No
12	Jett, Ashley	9316	9.316	5.7889624	1478	24.63333333	0.4105555556	driving	48	No
13	Kurashov, Shirley	806	0.806	0.5008484	181	3.01666667	0.0502777778	driving	48	No
14	Salazar, Andres	13	0.013	0.0080782	2	0.03333333	0.0005555556	driving	48	No
15	al-Haq, Zaid	0	0.000	0.0000000	0	0.00000000	0.0000000000	driving	72	No
16	Montoya Dolce, Alex	11004	11.004	6.8378856	1866	31.10000000	0.5183333333	driving	72	No
17	Larson, Miranda	1300	1.300	0.8078200	374	6.23333333	0.1038888889	driving	48	No
18	Truong, Claudia	2407	2.407	1.4957098	453	7.55000000	0.1258333333	driving	48	No
19	Hamon, Charles	2573	2.573	1.5988622	487	8.11666667	0.1352777778	driving	48	No
20	el-Moussa, Hasana	16	0.016	0.0099424	4	0.06666667	0.0011111111	driving	48	No
21	Morris, Shawn	8175	8.175	5.0799450	1184	19.73333333	0.3288888889	driving	48	No
22	Colbeck, Aaron	448	0.448	0.2783872	110	1.83333333	0.0305555556	driving	48	No
23	Schweissing, Nathaniel	332	0.332	0.2063048	79	1.31666667	0.0219444444	driving	24	No
24	al-Baluch, Faaid	2670	2.670	1.6591380	341	5.68333333	0.0947222222	driving	24	No
25	Malmsbury, Robert	808	0.808	0.5020912	137	2.28333333	0.0380555556	driving	72	No
26	Dreiling, Derik	7399	7.399	4.5977386	1179	19.65000000	0.3275000000	driving	48	Yes
27	Gay, Cecelia	1377	1.377	0.8556678	247	4.11666667	0.0686111111	driving	48	No
28	Yang, Susheel	925	0.925	0.5747950	208	3.46666667	0.0577777778	driving	72	No

Figure 4.14: Distances and time calculations of locations.

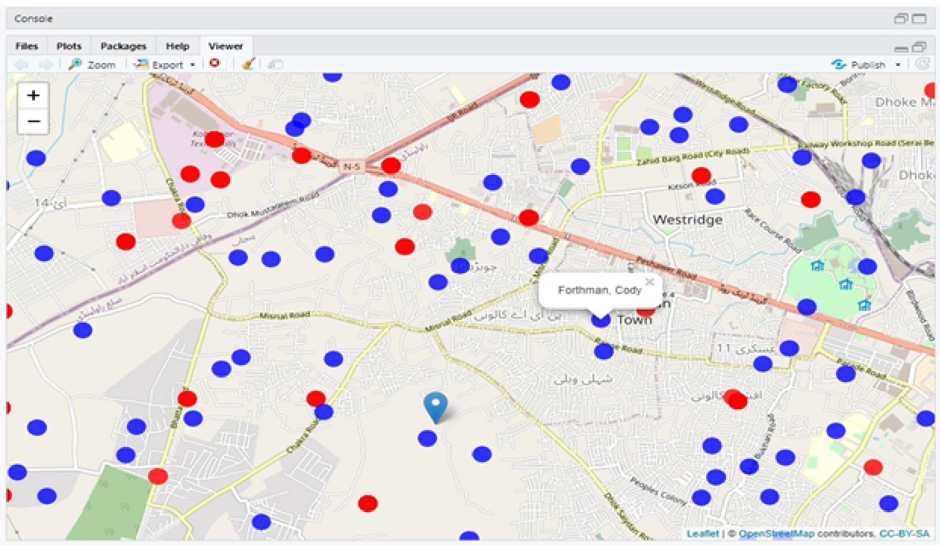


Figure 4.15: Matching of Nearest Instore & Online Customer.

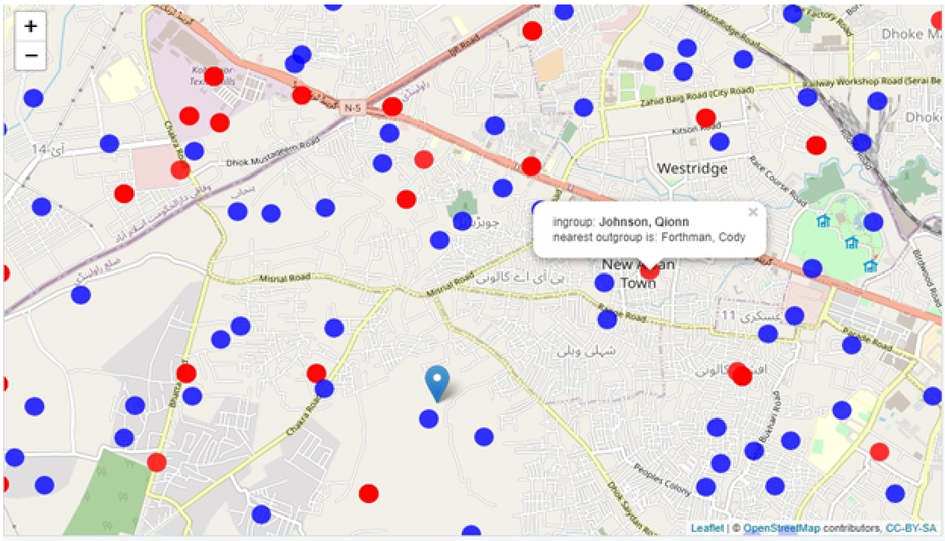


Figure 4.16: Matching of Nearest Instore & Online Customer.

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

Aim of this study was to gain an insight of all possible benefits and the associated challenges while implementing crowd shipping. The research is encouraged by the growing e-commerce industry, especially in Southeast Asian cities. We have presented three different pricing strategies and there comparison for better selection of compensation mechanism for managing delivery time slots/windows, which is important in time sensitive deliveries.

The proposed pricing strategies follow a framework for crucial parameters i.e. number of orders required to be delivered with different numbers of available in-store customers/adhoc drivers. The pricing strategies have been demonstrated to work efficiently in real life problems. We have shown that the proposed pricing strategies exploits the variability in the cost and customers matching in delivery time slots. The cost can be well estimated through any of the pricing strategies keeping in mind the importance of parameter, that is, detouring distance, time and available discount. Through this research, we observe that the pricing or cost afforded by the proposed strategies are optimal for adhoc drivers and dedicated vehicles, reducing the routing cost significantly, through order clustering, better capacity utilization and real time data using google maps.

The results of this study are inspiring that shows significant cost savings can be attained when number of instore customers available to make deliveries are bigger. It depends largely on the compensation offered to both instore and online customers. Designing cost effective system is one of the key challenges connected with crowd delivery. We tried three different pricing strategies and found that the performance of each was acceptable but sensitive to parameter selection.

5.2 Future Research Work

All pricing strategies will be more effective when more instore customers are available, as it is able to exploit the additional flexibility. However, increasing order density is beneficial where the delivery capacity is not saturated and where expensive third-party deliveries are required and there is limited flexibility to be exploited. Although the insights are valuable, we acknowledge some limitations of the current study, which form the direction for future studies and extensions.Researching more complex compensation schemes or pricing strategies are both interesting and necessary. We assumed that the adhoc driver or instore customer only declares that they want to make a delivery after arriving at the store (warehouse). This is reasonable in the context of supermarkets with reasonable footfall. An interesting extension is the study of the setup in which adhoc drivers offer to make a delivery at different origins or locations while combining the dynamic nature of settings with the Vehicle routing Problem (VRP). The rejection of online orders and their sizes may also be catered.

5.3 Recommendations

In view of this research study following is recommended in case of Pakistan:-

a. In last few years, especially due to outbreak of COVID-19 huge growth of e-Commerce has been observed to avoid continuous increasing traffic on roads, timely delivery of orders, ease in ordering of goods and cost effectiveness. Calibration of the existing compensation schemes with different time slots or proposed compensation schemes with the already suggested parameters may lead to huge economic growth.

b. To manage the demand and supply round the clock for different segment of people, compensation scheme may be design as per the time slots that is, same day delivery, next day delivery and next to next day delivery.

c. At very first instant the crowd sourcing or alternately crowd shipping may be integrated with daily life needs that is grocery stores or marts as a test case.

d. Integration of crowd shipping with the existing platforms in general and Uber and Careem in particular seems feasible without any tedious change.

e. All platforms globally are incorporated with improved data visualization and real time data, therefore existing platforms are recommended to integrate data analysis platforms/tools where possible for better data visualization, real time data and future research and development.

Bibliography

[1] A. Choi, "Morgan stanley perspectives on sustainable investing: Acceleration and integration", *Journal of Applied Corporate Finance*, vol. 28, no. 2, pp. 62-65, 2016.

[2] T. Adame, A. Bel, B. Bellalta, J. Barcelo, and M. Oliver, "IEEE 802.11ah: The Wi-Fi Approach for M2M Communications", pp. 1-10, 2014.

[3] B. Montreuil, "Toward a Physical Internet: meeting the global logistics sustainability grand challenge", *Logist. Res.*, vol. 3, pp. 71 - 87, 2011.

[4] D. Schrank, B. Eisele, T. Lomax, and J. Bak, "Urban mobility scorecard", pp. 1-8, 2015.

[5] S. Grischkat, M. Hunecke, S. Bhler, and S. Haustein, "Potential for the reduction of greenhouse gas emissions through the use of mobility services", *Elsevier*, vol. 35(C), pp. 295-303, 2014.

[6] *Anon Climate Change: Mitigation of Climate Change - Intergovernmental Panel on Climate Change*. Intergovernmental Panel on Climate Change, Working Group III - Google Books, vol 3, pp. 100-201, 2014.

[7] van C Cas Cooten, *Crowdsourced delivery the traditional delivery method*. Master's Thesis, Eindhoven University of Technology, pp. 1-9, 2016.

[8] J. Cramer and A. B. Krueger, "Disruptive change in the taxi business: The case of uber", *American Economic Review*, vol. 106, pp. 177-182, 2016.

[9] J. V. Halland A. B. Krueger, "An Analysis of the Labor Market for Ubers Driver-Partners in the United States," *ILR Rev.*, vol. 71, pp. 705 - 32, 2018.

[10] S. Ballare and J. Lin, "Preliminary Investigation of a Crowdsourced Package Delivery System: A Case Study", *City Logistics 3: Towards Sustainable and Liveable Cities (Chapter 6)*, pp. 1-6, 2018.

[11] N. G. Mankiw and M. D. Whinston, "Free Entry and Social Inefficiency", *The RAND Journal of Economics*, vol. 17, no. 1, pp. 48-58, 1986.

[12] F. Bernstein and A. Federgruen, "Decentralized Supply Chains with Competing Retailers Under Demand Uncertainty", *Manage. Sci.*, vol. 51, pp. 1829, 2005.

[13] I. L. Gale and T. J. Holmes, "Advance-Purchase Discounts and Monopoly Allocation of Capacity", *The American Economic Review*, vol. 83, no. 1, pp. 135-146, 1993.

[14] B. Yildiz and M. Savelsbergh, "Service and capacity planning in crowd-sourced delivery", *Transp. Res. Part C*, vol. 100, pp. 177 - 99, 2019.

[15] K. Gdowska, A. Viana, and J. P. Pedroso, "Stochastic last-mile delivery with crowdshipping," *Transportation Research Procedia*, vol. 30, pp. 90-100, 2018.

[16] A. M. Arslan, N. Agatz, L. Kroon, and R. Zuidwijk, "Crowdsourced DeliveryA Dynamic Pickup and Delivery Problem with Ad Hoc Drivers", *Transportation Science*, vol. 53, no. 1, pp. 1-10, 2018.

[17] M. K. Chen and M. Sheldon, "Dynamic Pricing in a Labor Market: Surge Pricing and Flexible Work on the Uber Platform", pp. 119, 2015.

[18] I. Dayarian and M. Savelsbergh, "Crowdshipping and Same-day Delivery: Employing In-store Customers to Deliver Online Orders," *Prod. Oper. Manag.*, vol. 29, pp. 21532174, 2020.

[19] van C Cas Cooten, *Crowdsourced delivery the traditional delivery method*, pp. 4-7, 2016.

[20] N. A. H. Agatz, A. L. Erera, M. W. P. Savelsbergh, and X. Wang, "Dynamic ride-sharing: A simulation study in metro Atlanta", *Transp. Res. Part B*, vol. 45, pp. 1450-1464, 2011.

[21] S. Banerjee, R. Johari, and C. Riquelme, "Dynamic Pricing in Ridesharing Platforms," vol. 15, pp. 65 - 70, 2016.

[22] S. A. Voccia, A. M. Campbell, and B. W. Thomas, "The Same-Day Delivery Problem for Online Purchases", pp. 1118, 2015.

[23] D. S. Setzke, M. Schreieck, M. Wiesche, C. Pflgler, and S. Frhlich, "Matching Drivers and Transportation Requests in Crowdsourced Delivery Systems", *Full Paper*, pp. 110, 2017.

[24] X. Wang and A. Erera, "Stable Matching for Dynamic Ride-sharing Systems", pp. 5-6, 2014.

[25] P. Reports and R. Citation, "Modeling and Evaluation of a Ridesharing Matching System from Multi-Stakeholders: Perspective Modeling and Evaluation of a Ridesharing Matching", pp. 8-9, 2018.

[26] B. Odongo, "How crowdsourcing is transforming the face of last mile delivery", *Crowd Logistics*, pp. 4-5, 2017.

[27] A. Mladenow, C. Bauer, and C. Strauss, "Crowdsourcing in Logistics: Concepts and Applications Using the Social Crowd Location-based Services View project Artist in the loop View project", pp. 20-21, 2015.

[28] C.-I. Hsu and W.-T. Chen, "Optimizing fleet size and delivery scheduling for multi-temperature food distribution", *Applied Mathematical Modelling*, vol. 38, no. 3, pp. 1077-1091, 2014.

[29] K. Suh, T. Smith, and M. Linhoff, "Leveraging socially networked mobile ICT platforms for the last-mile delivery problem", *Environ. Sci. Technol.*, vol. 46, pp. 9481 - 90, 2012.

[30] J. Hamari, M. Sjklint, and A. Ukkonen, "The Sharing Economy: Why People Participate in Collaborative Consumption", vol. 67, pp. 2047 - 2059, 2015.

[31] H. Paloheimo, M. Lettenmeier, and H. Waris, "Transport reduction by crowdsourced deliveries a library case in Finland", *Journal of Cleaner Production*, vol. 132, pp. 240-251, 2016.

[32] G. P. Cachon, K. M. Daniels, and R. Lobel, “The Role of Surge Pricing on a Service Platform with Self-Scheduling Capacity”, *Manufacturing & Service Operations Management*, vol. 19, no. 3, pp. 6-7, 2017.

[33] F. Wang, F. Wang, X. Ma, and J. Liu, “Demystifying the Crowd Intelligence in Last Mile Parcel Delivery for Smart Cities”, *IEEE Network*, vol. 33, no. 2, pp. 23-29, 2019.

[34] C. Archetti, M. Savelsbergh, and G. Speranza, “The Vehicle Routing Problem with Occasional Drivers”, *European Journal of Operational Research*, vol. 254, no. 2, pp. 472-480, 2016.

[35] B. Yildiz and M. Savelsbergh, “Pricing for delivery time flexibility”, vol. 133, pp. 230-256, 2020.

[36] A. Vinsensius, Y. Wang, E. P. Chew, and L. H. Lee, “Dynamic Incentive Mechanism for Delivery Slot Management in E-Commerce Attended Home Delivery”, *Transportation Science*, vol. 54, no. 3, pp. 8-9, 2020.

[37] M. A. Klapp, A. L. Erera, and A. Toriello, “The One-Dimensional Dynamic Dispatch Waves Problem”, *Transportation Science*, vol. 52, no. 2, pp. 7, 2016.

[38] J. Bai, K. C. So, C. S. Tang, X. (M.) Chen, and Hai Wang, “Coordinating Supply and Demand on an On-Demand Service Platform with Impatient Customers”, *Manufacturing & Service Operations Management*, vol. 21, no. 3, pp. 3-4, 2018.

[39] Punel and Stathopoulos, “Exploratory analysis of crowdsourced delivery service 1 through a stated preference experiment.”, pp. 6-7, 2016.

[40] N. Kafle, B. Zou, and J. Lin, “Design and modeling of a crowdsource-enabled system for urban parcel relay and delivery”, vol. 99, pp. 62, 2017.

[41] A. M. Arslan, N. Agatz, L. Kroon, and R. Zuidwijk, “Crowdsourced DeliveryA Dynamic Pickup and Delivery Problem with Ad Hoc Drivers”, *Transportation Science*, pp. 1-32, 2016.

[42] A. Dolgui and J. M. Proth, “Pricing strategies and models”, *Annu. Rev. Control*, vol. 34, pp. 101, 2010.

[43] A. M. Arslan, N. Agatz, L. Kroon, and R. Zuidwijk, “Crowdsourced DeliveryA Dynamic Pickup and Delivery Problem with Ad Hoc Drivers”, *Transportation Science*, pp. 1-29, 2016.

[44] Prologis. 2015. “European e-commerce, e-fulfilment and job creation”, 15 Feb 2021.

[45] James Melton. 2021. “Corona virus add 105 Billion $ to US ecommerce in 2020”, 10 Feb 2021.

[46] Fareeha Ali. 2021.“ US e-commerce in 2020”, 15 Feb 2021.