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# TIME SLOT ALLOCATION AND MANAGEMENT OF E-GROCERY

A Thesis submitted for the award of

Master of Philosophy

by

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**Abstract**

The purpose of the study is to present a solution approach to the reduction of exhaust emission by reducing fuel consumption through the time slot allocation to different service areas that minimize the time used in the delivery process. Further, it strives to create a better option solution approach that curtails the existing challenges confronting e-grocery retailers. A mathematical model is designed with appropriate constraints for the decision variables. We present an exact and a heuristic approach for this problem in which an assignment of customers' orders to vehicles is obtained by solving a generalized assignment problem with an objective function which minimizes the time used in the delivery leading to the minimization of the fuel consumption and delivery cost. With Matlab and Cplex MILP (Mixed Integer Linear Programming), our experiment shows that by varying the number of vehicles in the fleet, our exact approach (model) can optimally solve more significant problems that can be used by existing and emerging e-grocers.

## Dedication

This M.phil thesis is dedicated to my lovely husband **Mr. Amoako Agyei**, a selfless man with honour and integrity. He stood firmly with me from the genesis to the end of this study regardless of the undeniable challenges. I am grateful to God for making you an integral part of my life. God bless you so much.

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# 1 Introduction

## 1.1 Online Shopping

Globally, people are hungry for development. Once development is achieved, measures should be put in place to ensure that the development achieved is sustained. Concern over the quick deterioration of the natural environment and resources and their consequences on social and economic development led to the creation of a commission, the United Nations Brundtland Commission [97]. Sustainable development is described by the United Nations Brundtland Commission as ”development that satisfies the requirements of the present without compromising the ability that future generations to satisfy their own needs.” [75]. All definitions of sustainable development (SD) place emphasis on the necessity of fusing environmental protection, economic advancement, and social equality [5] which are termed the three bases of sustainable development (the three pillars of long-term growth). In recent times, lots of publications have documented the deteriorating health of the natural environment across the world [106], and this has made environmental issues gain more and more attention globally.

The notion of sustainable development, or environmental sustainability, has environmental issues as one of its fundamental sources. One of the primary sources of the definition of sustainable development, or environmental sustainability, has been environmental challenges. An emphasis on environmental integrity ensures that human activities do not adversely affect the environment’s finite natural resources. It is well-known that human activities can have significant detrimental effects on the environment, including ozone depletion, greenhouse gas emissions, waste generation, biodiversity loss, and pollution. By putting a focus on environmental integrity, one may be confident that human activities won’t have a negative impact on the environment’s limited natural resources. [103], [17]. A growing amount of focus has been placed on concerns related to environmental impact reduction and the development of eco-friendly methods [135], and many of these concerns are connected to logistics operations [67] , [48], [137], especially last-mile deliveries for electronic commerce (e-commerce) [124].

Transportation is essentially an integral part of human activities, socially and economically. The daily activities of humans are dependent on goods and services such as telephone use, shopping, reading, flying for business or pleasure, etc., are made accessible through some system that has routed messages, goods, or people from one place to another. Freight transportation is one of today's most important activities. According to Crainic and Laporte 1997, and Larsen 1999, transportation represents 15% of national expenditure in the United Kingdom, 9% for France, and Denmark is also 15%. "The annual cost of excess travel in the United States is estimated as $45 billion" (King and Mast 1997). "The turnover of goods transportation in Europe is some $168 billion per year" [34]. The study by De Backer et al. 1997, and Golden and Wasil 1987 [58] postulate that distribution costs account for almost half of the total logistics expenditures.

According to the International Energy Agency (IEA), half of the world's oil consumption comes from transportation, and three-quarters of that energy is used on the roadways (IEA 2012). The International Energy Agency (IEA) predicts that the amount of gasoline used for road transportation will double between 2010 and 2050 if nothing is done. United Nations estimates that by 2050, 68% of the world's population would reside in urban areas, up from 55% today. At 74.5%, Europe has a higher percentage of its inhabitants living in metropolitan regions [99]. As the population of a city grows, so does the need for housing, goods, and services. Traditional brick-and-mortar shops have given way to a more modern kind of e-commerce in recent years because of this desire. Digital items can be ordered from anywhere in the world and delivered to the end buyer, who is typically located in a city. The final step, delivery, appears to be the most difficult to coordinate [57].

The National Science Foundation's 1992 decision to lift its ban on the commercial use of the internet ushered the world into the era of e-commerce. Since the first browser was released in 1993, e-commerce had a huge increase [97]. Worldwide internet usage has increased since that time. Its global patronage in 2020 was 63.2%, while in Europe, it was 87.2% [67]. Due to the advancements in infrastructure and connection speed brought about by smartphones and broadband internet access, e-commerce has become more popular [30].

Commodity distribution in urban regions has changed because of the growth of e-commerce. In the context of e-commerce, "electronic commerce comprises any type of economic activity done by electronic means, which spans from product or service information through selling and/or acquiring things," according to Kalakota and Whinston [72]. Advertising, and obtaining products, and services over the internet are at the heart of e-commerce [131]. The nature of retail distribution has altered because of rising economic digitization. In nations where they do not have a physical presence, many internet enterprises sell remotely. As of 2018, the estimated global value of e-commerce sales, which includes 'Business to Business'(B2B) and 'Business to Customer'(B2C) transactions, was $25.6 trillion, which is equal to 30% of global Gross Domestic Product (GDP). $4.4 trillion in global B2C e-commerce was worth 17% of all e-commerce in 2018. An increase of 7% over 2017 was recorded in cross-border B2C e-commerce sales in 2018, totaling $404 billion. More than one-quarter of the world's population, or 1.45 billion people, aged 15 and older, made online purchases in 2018, according to the United Nations Conference on Trade and Development (UNCTAD).

Over the past decade, the internet growth has changed today's society more than any other media. Recently, the internet in the supply channel, where customers can surf through shops, and merchants can offer their merchandise and services virtually. Digital marketplace has become very crucial for retailers, including the food vending industry. The word "retailing" encompasses all those activities and steps required to serve the last consumer with a product made, or to deliver a service to the customer (Dunne et al. 2011). Retailing is a set of events that proliferates the value of the goods and services sold to the final consumers for use. With online shops, retailers aim to retain current customers and gain new customers in the progressively economical retail setting (Kabadayi et al. 2007, Neslin; Shankar 2009, and Simova, Cinkanova, 2016).

The desire to source goods from other countries has also grown. From 2016 to 2018, the percentage of internet shoppers from outside the United States increased from 17% (200 million) to 23% (330 million). Increasingly, companies can make electronic transactions with other organizations, governments, and customers. For a B2C delivery to be successful, a trade-off must be made between logistics costs and the quality of service provided [24].

The 2018 Consumer Survey of United States of America Healthcare by Oliver Wyman, customers are eager to share their health data (for the right value proposition, that is). According to the research, 41% of consumers believe they would be willing to divulge their shopping habits to guarantee high-quality medical care. Companies have the potential to start combining consumer data points to manage health costs more effectively, empower customers, and engage them. Information of this nature can also assist businesses in the introduction of novel value creation and value capture business models.

In some industries, for instance, the food and drink industries, distribution costs can account for up to 70% of the value-added costs of goods. A study done by Halse (1992) posits that in 1989, 76.5% of all the transportation of goods was done by vehicles, leading to the essence of more study into routing and scheduling problems [26]. According to the e-Marketer, there was a massive worldwide growth in retail e-commerce sales in the year 2020. The percentage change in the worldwide growth is shown in figure 1 below.

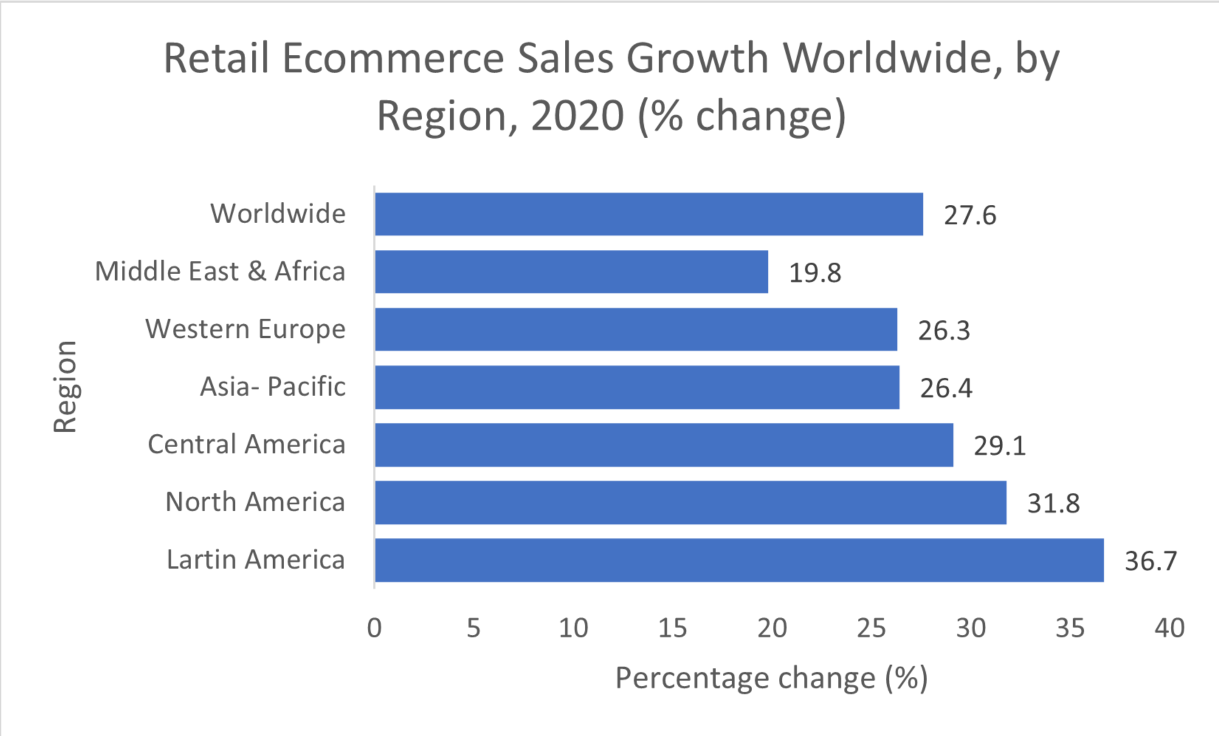



Figure 1: Source: e-Marketer, Dec 2, 2020

A 5.16% annual growth rate is predicted for the UK's e-commerce sector through 2025. By the year 2020, it is expected that 87% of UK households would have done their shopping online.

Customers, over the years, have become more comfortable with e-commerce as it has progressed. As a result, retailers no longer must first earn the trust of their customers. The nicest thing about online grocery shopping is that customers may choose delivery times that work best for them. As a result, customers can expect their orders to arrive on time. E-commerce, particularly B2C, has led to an increase in the demand for home delivery, which has led to an increase in the environmental and social costs of product transportation [100]. There has been tremendous growth in online grocery retailing, or e-commerce associated with grocery (e-grocery), during the past decade and it is likely to continue to grow for many years to come [96].

## 1.2 E-grocery

E-commerce is a challenge when it comes to groceries because of the difficulty in separating material flows from information flows, the huge number of loyal customers, and the average purchase basket's many goods. As a bonus, it helps the community more than selling globally available digital goods like books and clothing. Perishable commodities have a limited shelf life due to their fragile nature, making the task more difficult. While internet purchases of travel, tourism, music, and financial services are on the rise, fundamental products like food have not, according to Rajamma et al [108], accessible statistics. There was an estimated increase in travel sales in 2009 to reach $91 billion, a 33%per cent increase in the total volume of travel services. E-commerce has had a significant impact on financial services [132], and services like online gaming, according to Hughes et al [66], (Greenspan, 2004). No evidence suggests that e-grocery as a business and purchasing channel has been widely used [116], despite the numerous advantages it offers. As a result, the consumer's behaviour patterns regarding the freshness of products like meat, fish, fruit, and vegetables are significantly altered when purchasing food online [60]. Because of the increasing difficulty that people have in managing their time, shopping for goods and services online has become a common practice and method of payment. In e-commerce, there have been many studies, but few in the e-grocery industry. Over 70% of respondents to a survey on online grocery shopping in the United States stated that service convenience and time savings were the most important considerations in their decision to buy food online.

E-grocers have extra challenges because of the lack of suitable and dedicated delivery systems, particularly vehicles with temperature-controlled storage. Most e-grocery stores are built on existing industry infrastructure, which has been optimized for bricks-and-mortar stores, according to an exploratory assessment of e-grocery shops around the world [123]. In the USA, for instance, a section of all

American households have ever bought groceries online at least once. In the UK, e-grocery transactions aggregate to a market share of 3% of over-all British foodstuff retailing (Lebensmittelzeitung 2008). In difference, the market share of e-grocery amounted merely to 0.2% of the aggregate income of the German food retail sector in 2011. Nearly 80% of German patrons have no knowledge of e-grocery. And as low as 1% essentially does weekly grocery shopping in a virtual food shop (Plachetta, Röttig 2012). However, there is still a lot of room for growth in the grocer's business, as groceries remain the largest category in retail, and customers can quickly learn to use a new channel if they use it frequently, not only for groceries but for other purchases as well [107].In comparison to the old-fashioned method of shopping, buyers expected to gain the most from internet shopping's ease and convenience [123]. Even though brick-and-mortar stores are still a convenient way of shopping for groceries, online grocery shopping is rapidly increasing, becoming a trend like social media.

Most transactions in the ecosystem of internet buying happen on handled devices. The use of mobile devices is one of the many touch points for online businesses that are becoming increasingly important. These cases are essentially limitless because of the increased mobility. Mobile apps are a crucial component of the business model and marketing plan for an online grocery store. The mobile application provides more visibility in addition to the simplicity and convenience of internet shopping. For instance, a customer may order groceries via a mobile app. On the other hand, the delivery team can update the status using the delivery app, including picked up, en route, at doorstep, and delivered. Therefore, the smartphone apps for customers and delivery personnel are crucial. This is the reason, in 2018, online grocery shopping crossed $17.5 billion worth of grocery sales in the USA alone not to even talk of the rest of the world where online shopping is a booming and sustainable business 2021, Statistica predicts that online grocery sales will have risen by over $30 billion. An e-grocery shop can also offer new, value-added services to the consumer, notably in the area of planning and organizing. [73].

As technology is advancing, the e-market of groceries has come to stay, and it is growing speedily at an annual growth rate of 42% [21]. More than $100 billion is estimated to be spent by consumers in the e-grocery business in America alone over the next ten years. Globally, this is a positive outlook, and it's predicted to take hold. Market research predicted that by the end of 2018, more than 20 million people will begin to shop for groceries over the internet. 85% of those polled said they would prefer to have their purchases delivered to their door, while the rest would prefer to pick them up in person. People don't have to wait in line for payment at Amazon Go or Walmart, two instances of the latter type of store. An estimated $84460 million in e-grocery sales is predicted to be generated by the sector by 2024. Walmart, Amazon, Kroger, FreshDirect, and Target have all begun to offer e-grocery services to their clients in the worldwide grocery sector. Players have noticed an upsurge in client satisfaction over the last decade.

Consumers have never had it so good, thanks to e-grocery companies' mobile app services and improvements in speed and availability of same-day delivery. The two primary drivers of this development are the expansion of internet accessibility and the widespread use of mobile phones. Online payments and favourable demographics have also had a major impact on the way organizations communicate, connect, and do business with clients. As a result of their hectic work schedules and other responsibilities, many customers now choose to shop online. "When individuals think about this new manner to procure their daily supplies," convenience is "at the forefront of their minds" [109]. For example, conveying a purchase's monetary, time, effort, and mental tension are all examples of conveyed expenses. [12].

The framework of an online grocery store allows the consumer to search, compare, and conveniently access information. Ease of use of e-grocery was shown to be a good factor for consumers who planned to buy groceries online, according to Lynch et al [86]. Customers' attitudes regarding online grocery channel adoption are influenced by the perceived ease of use [53]. Consumers' attitudes toward using online grocery delivery services are influenced by their satisfaction with the quality of the products and services they receive [64], [112], [76]. The consumer's readiness to embrace, and use the e-grocery channel is triggered when they are satisfied with their purchase. As a result, consumers want better service from e-retailers because of the loss of human touch in online purchasing channels [70].

The Covid-19 pandemic has made people afraid to go into stores and shops because of the increased risk of contracting the deadly disease, and this has had a significant impact on how people go about their daily lives. Online portals and websites are increasingly being used to order food like fruits, vegetables, and other perishable and non-perishable items due to the proliferation of online possibilities and the current pandemic that is causing people to stay indoors. E-grocery delivery services from retailers like Walmart, Amazon, and others have become indispensable because of a combination of factors, including customers' desire to avoid going to public places, government restrictions on leaving the house, and the daily need for groceries and other essentials. Online grocery buying has grown by 76% in the year 2021. Since the Covid-19 outbreak, retail firms like Grofers, BigBasket, Amazon, and others have seen their grocery sales rise by roughly 60% as a result of the expanding online grocery buying market (Business Insider Intelligence Report, 2021). Recently, e-grocers have concentrated on improving operations in the supply chain. More especially, the emergence of Covid-19 drastically shifted consumers' behaviour toward online marketing. E-grocery provides consumers with the opportunity to shop online, and the product is delivered at an agreed time and place.

## 1.3 Challenges

According to Forrester Research, online retail sales in the United States are expected to reach $184 billion in 2004 [71], or 7% of all retail expenditure. The logistical challenges of direct delivery have proven to be overwhelming for many organizations, and they are still working to develop direct delivery plans that are both profitable and meet customer expectations. According to Fatbit Chef (2002), "An ideal scenario for value addition is that when an order is placed, it should be delivered to the consumer. Finally, after receiving the item, the consumer should find the item valuable. However, there are times when the consumer orders an item by mistake, finds the received item to be of the wrong shape or size, and more. No matter what the reasons are, it is an operational challenge to make the reverse logistics process profitable. To enable reverse logistics within the grocery ordering and delivery software, features like refund management, order cancellation, and more".

In another example, Peapod's San Francisco-based operations were shut down and Webvan declared bankruptcy due to the difficulty of matching grocery store prices while paying substantial distribution costs. The costs of running an e-grocery firm must be drastically reduced to make it profitable. Flexible options for getting goods at the consumer's end and improved home delivery and picking efficiency can lead to cost savings. The lack of technology to manage and bring visibility in the last mile is one of the main problems with grocery delivery. There is no one-size-fits-all solution for grocery ordering and delivery systems; nevertheless, most of them do provide some basic functionality. Mobile apps for delivery drivers are crucial elements of a successful food delivery system.

In addition, new services and pricing structures also play a significant role in the future of the industry. To have a successful business model, all of these components must work together. There are, nevertheless, some encouraging stories to be found. It's been over twenty years since Peapod, owned by Royal Ahold of the Netherlands, has been delivering goods to customers' homes in select areas of the United States. One of the world's largest online supermarket operators, Tesco has been in profit since 2001, making it one of the first UK grocery retailers to enter the internet industry. In the last several months, Ocado has also made its first operating profit since it was founded in 2011. (Interactive Media in Retail Group (IMRG), 2005). The e-commerce behemoth Amazon appears to be preparing to be a force in home delivery of groceries and it surely has the infrastructure to have an impact more lately. Amazon certainly has the infrastructure.

Several factors should be taken into consideration in checkout and payment processes as well as delivery optimization easier for customers. Nearly 300% growth in e-commerce sales was seen between 2014 and 2019. Online sales currently account for 21% of all retail purchases in the United States, compared to 5% in 2007 [97]. Delivery vans will see a 36% increase in 100 cities throughout the world as the need for last-mile delivery rises by 78% by 2030 [38]. Consumers who previously resisted the shopping technique because they wanted to pick out their groceries themselves and avoid additional expenses have changed their priorities due to the pandemic, according to Business Insider Intelligence (BII). After the pandemic has passed, the sudden emphasis on supermarket delivery will continue to influence customer behaviour. As a result of the epidemic, certain online grocers may be able to retain consumers for the long term: According to a poll by Bain and Google in 2018, 75% of online grocery consumers still used their first-ever online provider. This means that the supermarkets that best serve the demands of their customers during a pandemic are likely to lead the industry when it has subsided. An ever-increasing percentage of supermarket sales were being done online before the COVID-19 epidemic, but it was a small percentage of total sales. E-commerce sales of food and beverages in the United States are predicted to reach over 24 billion dollars in 2020 and 38 billion dollars in 2023, according to an e-marketer prediction from 2019. By 2023, however, this would only account for 3.5% of total US food and beverage revenues. It wasn't

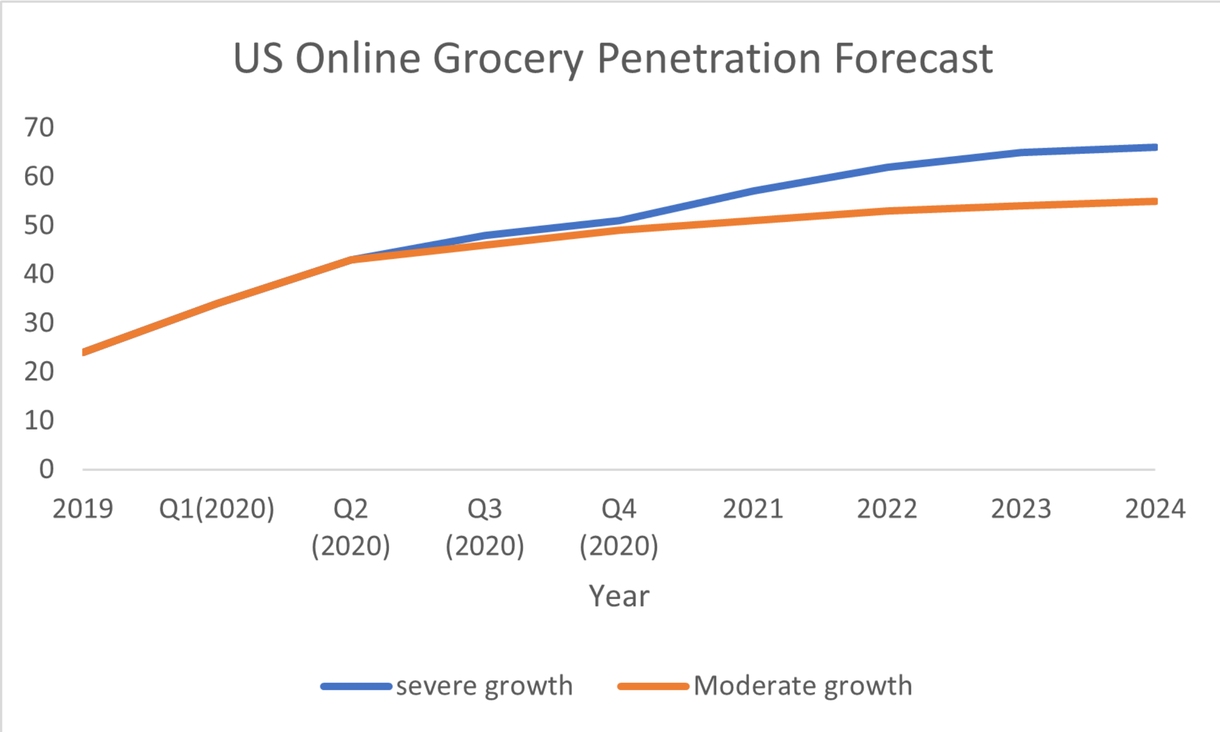



Figure 2: Source: Business Insider Intelligence

expected to take off as it has now, even if online grocery sales had been increasing, because they constituted such a small portion of the overall grocery sector, and because their sales growth was expected to peak in 2020.

E-grocery adoption in the US is expected to reach 55% of consumers by the end of 2024, according to Insider Intelligence, as the pandemic continues. The US online grocery business is forecast to generate 187.7 billion US dollars in sales by 2024, according to a Statista study. The e-grocery sector will nevertheless have a considerably wider penetration than it would have had it not been for the epidemic. Nevertheless, if the pandemic persists in the absence of widespread vaccination or other treatments, the number will soar, reaching 66% in 2024, instead.
The covid-19 pandemic drew many people's attention to the need for engagement in online grocery delivery. A study by Business Insider gives the forecast of US

online grocery penetration. Figure 2 reports the forecast. It has had a significant impact on the rapid growth of e-commerce. In February 2021, the UK's internet sales as a percentage of overall retail sales reached a record high of 36.2%, according to the Office for National Statistics. For the most part, most of the population lives in cities, where online trading has a significant impact on the environment.

There will be a one-third increase in emissions from logistics services, including those associated with online shopping's last-mile delivery, according to current estimates. Last-mile delivery congestion is anticipated to increase by 21% by 2030 [38]. It is therefore anticipated to lead to disastrous consequences which will be severely detrimental to the environment. It seems enough consideration is most often not given to the long-term effects of the consequences of these activities of humans, especially regarding their impact on the environment.

The increasing demand for e-grocery services is linked to the growing number of vehicles on roads with the associated congestion/traffic, noise, and especially the exhaust emissions. The growth in e-commerce contributes to the transportation sector's pollution in urban areas according to T. Karren [77]. Approximately 3% of the UK's total greenhouse gas emissions were attributed to the transportation sector in 2018 [37]. In terms of $CO_2$ emissions, transport accounts for 28.1% of the European Union's total, which is more than any other sector except for the energy industry, which accounts for 34.2%. Road transportation accounts for 72.8% of the total $CO_2$ emissions released by the European transportation industry [87],[11]. Even in non-food purchases, studies show that home delivery reduces $CO_2$ emissions more than store pickups do [43], making online shopping more environmentally beneficial than store pickups [44].

Last-mile logistics is a burgeoning research area [74], [81], however, there has been little attention to reducing the environmental impact of e-commerce last-mile delivery initiatives [91]. As a result, the e-commerce industry must look for environmentally friendly options for last-mile delivery. E-commerce last-mile delivery solutions in cities are now being presented in a fragmented manner, according to a review of relevant literature. So, the most essential research fields and green solutions for urban last-mile e-commerce delivery are limited by the lack of awareness of these areas.

Many of the previous contributions are more concerned with logistics [48], [92] or engineering management perspective [81], whereas environmental protection issues receive too little attention. There is no mention of conserving the environment in any of these papers[74] [81]. In 2014, the environmental effects of e-commerce were discussed. Numerous studies on green last-mile deliveries have been undertaken and new green delivery options have emerged in the years thereafter. It's been suggested by researchers that urban freight flows and vehicle movements may not be adversely affected by the rise of online sales using a variety of delivery options such as home delivery, pickup points, or click-and-collect systems. Even so, it's undeniable that as e-commerce has grown, so too have environmental challenges including increased traffic, $CO_2$ emissions, congestion, and noise. City logistics is responsible for last-mile deliveries [77].

Road freight transport is the most popular means of transportation in urban areas, and it has the worst environmental impact of all modes of transportation. Public officials and the public, on the other hand, have a harder time determining their interests. Studies show that customers prefer home delivery, although it appears that customers have recently discovered the environmental impact of last-mile e-commerce deliveries, despite this [136], [95]. The most popular method of delivery is still the fastest. The reality is that clients may choose an eco-friendly delivery method if made aware of the possibility.

The ecological transition and the reduction of pollution are reasons for the use of green logistics and non-polluting vehicles which led to the introduction of electric vehicles as an alternative and in recent years many technological advances have been developed by the automotive industry to overcome the inherent difficulties of this type of vehicle. Some solutions focused on alternative modes of transportation like electric vehicles and bikes, others on new delivery methods like parcel lockers or crowd-shipping, and still others looked at the issue from an organizational point of view and tried to optimize vehicle routing or implement time windows for deliveries. Last-mile delivery solutions for urban e-commerce are deemed ecologically friendly if they reduce the load on the environment. E-commerce necessitates faster and closer delivery of products to clients. Manufacturers, merchants, and consumers can all help to support and encourage changes to service delivery methods that are less polluting by combining investment and benefit sharing.

Waste is a major issue that must be addressed in enterprises. Businesses are aware of its effects, and through inventory system management, these issues can be fixed. It may be possible to customize an existing online grocery ordering and delivery program to create a new module that addresses the wastage issue. Many software solutions are designed and developed considering regular audiences. During the development phase, many Internet Technology (IT) solution providers tend to skip two areas – web accessibility and design practices to make the website senior friendly. For an online grocery ordering and delivery website, the audience includes older as well as disabled people. As the frequency of ordering groceries might be more than other niche e-commerce segments, hence, it is important to make the website more accessible and senior-friendly. Colours can create differences and bring ease for the older generation to understand the website. Similarly, to make the website accessible for the disabled, one must follow the internal web standards. For example, many disabled people or seniors have poor motor skills and cannot use a mouse. In such a case, keyboard controls are preferred.

The most important long-term trend in the corporate sector is the rapid expansion of information and communication technologies in everyday business activity. There is also a lot of room for expansion when it comes to providing products and services via the internet. Internet retailers' ability to match customers' expectations in a vir-

tual shopping environment is critical to fully utilizing this potential [113].
Most organizations rely on customer pleasure as their principal source of future revenue, according to Fornell (1992) [55]. Increasing client retention by merely 5% increases profitability by (25-95)%, according to Bain and Co. (Customer Interface 2001). The cost per item lowers as the delivery size increases. Increased delivery sizes necessitate longer delivery cycles and longer delays in getting ordered goods, however. As a result, deciding on a delivery window is critical for both the organization and its clients. It is also stated by Hellier and colleagues that consumer happiness is an important component of e-grocery [61], [117]. Customer satisfaction strongly and directly influences the impact of service quality on behavioural intentions, according to Dabholkar et al (2000) [35].
Although there is a wide range of viewpoints, most of the authors agree that customer happiness must be maximized in various ways. Efforts to enhance network and process optimization may have the dual benefit of raising service quality and increasing customer happiness. For instance, as consumer expectations rise, the market is continuously changing. In such a cutthroat climate, a marketing strategy is necessary for success. Important marketing components should be preinstalled in the grocery ordering and delivery software to assist the strategy. "The system should, for instance, contain a newsletter management capability so that newsletters may be sent. Like this, various marketing skills like managing blogs, creating discount coupon codes, managing affiliates, managing paid advertising, and more are necessary for a grocery store to remain profitable." (Fatbit Technologies, 2021). The availability of mobile apps is one of the extra features that significantly enhance the experience.
Small towns are mostly known for their closely knit communities which have different market dynamics. An example is where in certain neighbourhoods a customer is likely to visit the same vendor with a brick-and-mortar store for purchases. For an online grocery business to be successful, the business model must be re-evaluated to

see what works best in the area of operation. A thorough analysis of the area must be made with the discovery of its unique challenges which will inform the right business model to be adopted, whether a single vendor or a multi-vendor. "Based on the selection of business models, one can either start selling your grocery items or on-board vendors. In the latter case, you need to devise vendor on-boarding strategy and make it worthwhile for the vendors to list their products on your website." (Fatbit, 2022)

Fatbit again adds that, as a business owner, you are always short on time. However, the marketing activity is time consuming and yet an important part of the business function that cannot be ignored. While many aspects of marketing can be managed with free digital marketing tools, however, many of the useful ones are paid. For an online business, on-page and off-page search engine optimization (SEO) holds greater importance. On-page (SEO) requires technical knowledge and off-page requires less technical knowledge but consumes more time daily. If time is less, then a digital marketing service provider can be consulted.

A customizable online grocery ordering and delivery solution presents an opportunity to develop important marketing features within the system. For example, if the goal is to reach out to people who are registered members of the online stores, then email marketing features can be used to share relevant information. Similarly, discount coupon code management features can be used to generate coupon codes. Depending on the business model, if you plan to onboard vendors, marketing features can add additional revenue sources.

There are government policies and regulations that govern each business in any jurisdiction. Sometimes government takes the lead to propose changes to its policies or regulations, but businesses are encouraged to take the lead sometimes. "In the case of an online business, the changes have to reflect on the grocery ordering and delivery system as well. While a small business needs few changes, large grocery chains can adopt a more proactive approach to tax management from their existing system.” (Online groceries business ideas, 2022).

## 1.4 Contribution

This awareness brought into view the necessity to construct a vehicle routing plan with a focus on minimizing the harmful greenhouse gas emission. For every vehicle the fuel consumed in the delivery process is directly related to the distance traveled, the time used in the delivery execution, etc. Urban areas have different traffic patterns within a service day which affects the average speed of the vehicle on the delivery day. Companies can estimate the speeds in different service areas in each time slot with technological devices today. Consumer demand in a service area is another factor to consider in optimal routing which could be predicted based on historical data. E-grocers and manufacturers can better understand client wants and maintain timely control of the supply chain if orders from customers are delivered almost entirely online. As a result of the long delivery times per client, inefficient home delivery operations raise operational expenses and impede expansion. We can, however, shorten the time it takes to deliver items by utilizing a variety of delivery methods.

The online food market has grown significantly since the epidemic, thanks to new customers and retailers’ improved capacity. Energy optimization studies can be used to boost e-industrial grocery’s efficiency. Increased $CO_2$ emissions are directly linked to an increase in the number of people using e-grocery services. As a result, cutting delivery time is a logical step toward lowering emissions of $CO_2$ into the atmosphere.

Time slot allocation to different service regions is the topic of this study, which examines the issue of delivering an adequate level of service to clients while also cutting exhaust emissions by reducing delivery time. Customers select the goods and items they wish to buy, select an acceptable delivery time window from the available time slots, and the groceries are delivered as requested by the delivery van in the e-grocery model. The customers' selection of time slot is influenced by:

1. the slot time
2. the price
3. the 'green van' option.

The 'green van' offers a time slot that allows the construction of a route that achieves a low level of exhaust emission. The day's delivery region is divided into several areas. Based on the historical data accessible to the delivery services, it is possible to estimate the overall number of clients in each location. The speed limit set for a particular period of the day helps us to categorize the various types of traffic in each location.

The following is how the rest of the paper is organized: Works of various scholars on the subject of transportation challenges associated with delivery, particularly e-grocery, have been reviewed in Section 2. A formal description of the problem and a definition of an integer linear programme are provided in Section 3. The Exact approach is presented with its numerical values obtained in section 3. Section 4 explains the heuristic solution approach with its numerical findings. And finally, Section 5, presents a comparison of the results obtained from the Exact and Heuristic approaches. Outcomes were analysed, and we draw a conclusion about the work done and give an outlook of further research to extend and improve the present approach.

# 2 Literature Review

In operations research, the term "Vehicle Routing Problem" (VRP) refers to a situation where a set of routes for a fleet of vehicles based at one or more depots must be found for several geographically separated cities or customers. In the Vehicle Routing Problem (VRP), the goal is to find optimal routes for multiple vehicles visiting a set of locations. Delivery to clients with known needs on low-cost vehicle routes beginning and ending at a depot is the norm. Operations research is devoted to solving the Vehicle Routing Problem (VRP). VRP's popularity stems from the fact that it is both useful in the real world and extremely difficult to implement. Using it in real-world systems that distribute goods and deliver services of demand to customers is what makes it so important. Variations of the VRP literature include time windows, different depots, a diversified fleet of vehicles, split delivery and pickups and deliveries as well as precedence and complex loading limits as well as customer satisfaction, to name just a few of the variables.

A notable quest to reduce pollution and delivery cost to obtain customer satisfaction augmented more research in the optimization of e-commerce delivery. Some earlier researchers considered demand management, $CO_2$ emission, fuel consumption, and time management.

## 2.1 Demand management

According to Agatz et al [2], selecting a time slot is an important consideration when creating an attended home delivery system. Each zip code in a service area was examined in terms of the number of available time slots. The delivery time slot offerings were generated using two automated processes (Continuous Approximation Approach and Integer Programming Approach). There is still a need for more research on real-time management in attended home delivery, even if the paper's numerical results show that using service requirements and the Optimization model saves a lot of money compared to merely offering all time slots.

Punakivi M. et al [105], identified, modeled, and analyzed existing and emerging e-grocery home delivery operation models. He used the interview method to obtain his data. Factors affecting home delivery operations were considered. He examined the cost of vehicles and labour, vehicle capacity, customer density, location of the depot, etc., which were key in the decision making on the delivery cost. Drop-off time was taken to be the same (2 minutes) for all delivery models analyzed. However, it may vary in different cultures and settings.

Yan and Oppewal [64], examined the delivery charge and other situational factors that could affect the choices of a consumer in grocery shopping. The study was conducted by using the convenience sampling method. The convenience sampling technique is a non-probability sampling method that does not give each respondent a chance to be selected. The result of this study can therefore be said to be biased.

Hays T. et al [110], "Strategies and challenges of e-groceries retailing logistics", analyzed e-groceries past and present, different business models employed (pure play online, brick and mortar going online, and partnership between brick and mortar and pure-play online) as well as order fulfilment and delivery strategies. The paper concluded with the failures and successes of e-groceries.

Klein R. et al [79] "On the approximation of opportunity cost for dynamic pricing in attended home delivery", presented an approximation based on mixed integer programming that integrated into the dynamic pricing approach proposed by Yang X. et al [134], a choice-based demand management and vehicle routing in e-fulfilment. It evaluated the proposed approaches in practice and concluded on implications for practical use of the approach especially when real-time pricing decisions are required. Mkansi et al [94], examined the e-grocery challenges and remedies regarding global market leaders' perspectives. The study expanded existing knowledge of the challenges of e-grocery and employed semi-structured interviews to gather data on the online global market. The study concluded that factors that affect the e-grocery market are basically at the managerial level. As a result, e-grocery retailing practitioners must focus on this specific management area to achieve meaningful improvement in performance.

E-grocery retailing is unlikely to take over the entire grocery business any time soon, but its market share could yet increase significantly. E-grocery It has been suggested by the authors that the management of supply and distribution for e-groceries [65] [102], is one of the major obstacles to e-grocery operations, and they believe that this is the case. Most of the order transaction concerns have been overcome by Internet-based solutions in recent years, making ordering easier, cheaper, and faster. The e-grocery industry, on the other hand, is still plagued by numerous issues. Inefficient home delivery is one of the most significant challenges.

## 2.2 $CO_2$ Emission

Industrial development leads to a surge in the discharge of greenhouse gases, $CO_2$ to be specific. One of the utmost imperative cradles of this greenhouse gas is running locomotives used in the carriage, heavy machines, and other equipment. One more aspect closely linked to the process of combustion engines is exhaust discharges. In a report circulated in 2012 the Intercontinental Agency for Research of Cancer (IARC), one of the World Health Organization (WHO) agencies made known that exhaust fume from diesel engines breeds cancer (Press Release 2012). Before the publication, diesel exhaust fumes were categorized as possibly cancer-causative. Upon examination of the most recent ecological research, the WHO researchers openly indicated that diesel exhaust fumes are a cause of cancer (Silverman et al. 2012) [9]. White et al. (2010) in the Report of EPA (Environmental Protection Agency) based on years of investigation on humans and animals ratifies that

particulate substance is hazardous and ominously leads to the development of sarcoma, and lung cancer (Ecological Protection Agency 2002).
Greenhouse gas discharged by the transport sector over the world is a solemn issue of concern. To abate such discharge the vehicle engineers have been working persistently. Scientists have been trying hard to shift fossil fuels to substitute fuels and trying to drive various approaches to make traffic movement smooth and ease traffic jamming and the discharge of greenhouse gas. Vehicles emit an enormous number of contaminants such as Carbon Monoxide, hydrocarbons, carbon dioxide, particulate matter, and oxides of nitrogen. Undeniably, $CO_2$ emissions have a negative impact on both the environment and human health. In recent TSP and VRP publications, the reduction of $CO_2$ emissions has been a topic of interest, with the focus on minimizing the routing costs and polluting emissions. There have been numerous studies on green vehicle routing over the last few decades, using a variety of terms, including Pollution Vehicle Routing Problem (PVRP), Eco-Vehicle Routing Problem (EVRP), Green Vehicle Routing Problem (GVRP), etc. There have been some investigations on how carbon emissions in the supply chain are identified, measured, and analyzed. Using a concave minimization problem, Elhedhli and Merrick [46], examined the link between $CO_2$ emissions and vehicle weight in a supply chain network design challenge.
In Pattara et al [104], an objective and standard methodology for determining a carbon footprint were developed. Sundarakani et al [121], developed an analytical and finite difference approach to approximate a three-dimensional infinite carbon footprint model and used this tool in a wine supply chain using the life cycle assessment (LCA) methodology. Using a generic methodology, Rizet et al [111], compared the energy consumption and $CO_2$ emissions across the supply chains of various products as well as supply chains and nations. Carbon dioxide ($CO_2$) is the most significant contributor to global warming pollution, according to Cole V. (1996)[33]. According to Wang et al (2017) [84], total $CO_2$ emissions are inversely proportional

to fuel use.

The optimal vehicle routing model developed by Li et al (2016) [82], was based on reducing carbon dioxide emissions, and it was assumed that $CO_2$ emissions occurred as a result of the entire combustion of fuel during transportation. This necessitates a reduction in fuel use during e-grocery delivery. A carbon tax's environmental impact was taken into account by Li et al [83]. Ant colony optimization (ACO), an algorithm developed by the Massachusetts Institute of Technology Media Laboratory, was used to fine-tune their design. They also ran simulations based on various actual situations, in which electricity prices change over time and carbon fees are also taken into account. Multi-tiered distribution systems have also incorporated emission-free technologies. E-VRP variants that take into account both battery life and battery swapping stations are also studied by Li et al [83]. Energy efficiency is achieved through the application of an adaptive genetic algorithm (GA) based on scaling optimization and neighbourhood search.

Using computer simulations, researchers found that optimising energy usage and travel times reduces both carbon emissions and overall logistical delivery costs. As part of their efforts to reduce transportation-related $CO_2$ emissions, Dantzig's traditional vehicle routing model was extended to include the option of using vehicles of varying sizes to complete routes. Although $CO_2$ emissions can be reduced greatly, the overall travel distances and the number of routes taken by the vehicles used have increased dramatically, according to their model.

Sustainable Parcel Delivery (SPD) is a model that compares economic savings and $CO_2$ emissions from delivery between electric vehicles (EVs) and fossil fuel vehicles (FFVs). With respect to a certain route, it assessed the costs and $CO_2$ emissions of the two alternatives, in addition to other elements such as the cost of purchase and maintenance of fuel, operation, and fixed costs such as the daily ticket, all depending on the vehicle performance.

Many models and methods to obtain routings for optimizing vehicle routes have been adapted considering their characteristics such as battery autonomy, shortage of recharging stations, and elevated time of charge. An electric vehicle (EV) with substantially lower pollutant $CO_2$ emission than a fuel-efficient vehicle (FFV) should be considered for production in the struggle to achieve zero emissions of $CO_2$. However, the impact of the weather on the performance of electric vehicles (EVs) must also be taken into account. Because they are more expensive, electric vehicles (EVs) are less self-sufficient in terms of distance travelled and, therefore, more difficult to obtain.

In addition, Arnold et al [7], compared and evaluated the efficacy of several distribution mechanisms before deployment. There were several outcomes from the employment of cargo bikes for last-mile deliveries: In the zone outside the city limits, driving time increased up to 134%, but the external expenditures per parcel are decreased by 40%. Freight cycles on urban traffic energy efficiency and carbon emissions were studied by Mello and colleagues (Mello et al, 2000) [93]. Cargo bikes were put to the test in a Portuguese city to see how effective they are. Comparison of freight bikes vs diesel vehicles on public roads.

A vehicle's economic and environmental efficiencies were evaluated using factors like road taxes, insurance costs, depreciation costs, and energy costs. Using parameters such as delay time, average speed, and wheel-to-wheel energy consumption, an analytical tool, AIMSUN (an established international leader in mobility planning and transportation management technology) simulated traffic flow. Traffic flow efficiency could be improved by replacing a large number of diesel cargo vans with cargo bikes, according to research. Delivery trucks could be replaced with cargo bikes and cargo cycles to improve traffic efficiency and minimise $CO_2$ emissions and costs. However, perishable items, especially in large quantities, may have a different narrative to tell. According to Kirby et al [78], the amount of $CO_2$ emitted during transportation is directly proportional to the amount of gasoline utilized by the vehicle. For gasoline vehicles, the estimation of $CO_2$ emissions under the constant speed assumption can differ by up to 20%, while for diesel vehicles, the variation can be up to 11%. Additionally, they noted that the disparity could widen during times of high traffic.

## 2.3 Fuel Consumption

Palmer [101],established an average diesel fuel consumption per kilogram of $CO_2$ emissions of 2.7 gallons. An approximation based on fuel consumption data from cars and trucks up to 2.7 tonnes of gross mass was provided by the Australian Greenhouse Office [10], and the coefficient value is comparable. The total amount of fuel used can also be estimated in other ways. The set of variables impacting fuel usage is where the major distinction can be found. Frey et al [56] classified explanatory variables into two groups: the physical properties of the vehicle, such as engine speed and manifold absolute pressure. This was followed by the externally observable variables that define the driver's behaviour and road circumstances, such as speed, accelerating, and the road grade.

An extension of the VRP with time windows, the Pollution-Routing Problem (PRP) was developed by [20]. It entails allocating a set of consumers to a specific set of cars and setting their pace along each leg of the route to reduce the cost of fuel, pollution, and driver expenses. The authors used a simplified version of the emission and fuel consumption model provided by Barth et al [19] and [18] to determine the amount of fuel burned. An arc is assumed to have the same parameters, however, the load and speed can vary from one arc to another. Since fuel consumption and greenhouse gas emissions are intimately linked, this means that the PRP goal approximates the overall amount of energy used on a particular road section.

Xiao et al. (2012) [133] proposed the Fuel Consumption Rate (FCR) which is a dynamic that is reliant on load purpose. They applied FCR to a typical CVRP and called it the FCR considered Fuel Consumption VRP (FCVRP) and formulate the mathematical model for this type of problem. After that, an algorithm based on Simulated Annealing incorporating a fusion exchange rule is established and tried by using well-known yardsticks. Numerical consequences illustrate that the planned FCVRP can lessen fuel consumption by 5% on usual as associated with the CVRP model.

Many well-known models were studied by Demir E. et al [39]. For example, models like Bowyer et al's four-mode elemental fuel consumption model and the instantaneous fuel consumption model [23], include both sorts of variables, but the models' many factors make them more suited for short-distance trips. Additionally, it discussed the average travel speed model that uses linear regression to predict fuel consumption per unit mile using the inverse of average travel speed. Urban driving, where the speed limit rarely exceeds 50 kilometres per hour, is a popular application for this vehicle. Despite the model's simplicity, it has a drawback: it ignores critical factors such as idle time, acceleration, and deceleration cycles when constructing an effective delivery routing. Speed limits on public roads are frequently established by the federal or municipal governments (Wikipedia, 2015). They play a critical role in ensuring the general public's safety and the safety of those using the roads (UK Government, 2014). Arc-specific speed limits are common in most cities, however in some, they are separated into speed zones (e.g. Dublin City Council, 2015). Speed zones improve traffic flow and reduce the risk of collisions. Unnecessary overtaking, delays, and rear-end incidents can all be reduced with the implementation of reasonable speed limits.

Additionally, speed limits provide environmental advantages. When 40 km/hr speed limits are in place, the most efficient route is also the least polluting. Zones with speed limits of 20 mph (32 km/h) have been shown to have a positive impact on residents' quality of life while also promoting more environmentally friendly and healthful modes of transportation. Unless an unduly low gear is utilised, a study conducted by the UK's Department for Transport (DfT, 2013) shows that speed limits encourage slower driving, save fuel, and lower pollutants than other methods (DfT, 2013). Speed adjustments have a considerable impact on $CO_2$ emissions in metropolitan environments, according to Van Woensel et al. (2001) [128].

Stochastic shortest pathways were recently examined by Ehmke et al. (2014) [45] with a goal to reduce emissions. The scientists determined that to reduce emissions, automobiles should take a more winding route rather than a more direct route. A city's quickest route may not always be the most cost-effective or environmentally friendly one. A 40 km/h speed limit in urban areas means that the fastest route is also the least polluting.

As part of the MEET project (Methodologies for estimating air pollutant emissions from transportation), Jabali O. et al [69], used a methodology described by Hickman et al [4], which allowed them to model $CO_2$ emissions directly based on the average vehicle speed, but the focus was not on time management. In Koc et al, 2016 [80], a more application-oriented perspective is offered, which also incorporates fuel usage, emissions, and operating expenses. Total costs including depot running costs, vehicle fixed costs, and fuel and $CO_2$ emissions costs were the focus of the research. When driving, the vehicle's speed is determined by the arcs it crosses. An algorithm named P-L-HALNS (Pollution and Location-Heterogeneous Adaptive Large Neighborhood Search) was developed to address the issue. The Adaptive Large Neighborhood Search (ALNS) framework developed by Demir et al. serves as a foundation for this method (2012).

## 2.4 Time Minimization

The Green Vehicle Routing Problem's Greenhouse Gas (GHG) emissions may be time-dependent due to the unpredictability of journey speed. Various factors impacting travel speed and congestion, such as increased speed and increased $CO_2$ emissions, are considered in this form [114]. The time-dependent travelling salesman problem (TDTSP) was studied by Malandraki et al. (1996) [90]. There were time windows, capacities, and waiting at the customer location in the mixed integer linear programming formulations offered by them to calculate journey times, step functions were used. A branch-and-cut approach for solving minor problems with 10–25 nodes was proposed, along with nearest-neighbour (greedy) heuristics for the TDTSP without time windows.

The TDTSP was first addressed by Malandraki et al (1996) [90], who offered a dynamic programming approach to finding a solution. Although it was suggested that their technique could handle a wide variety of journey time functions, results were only given for step functions like those obtained in Malandraki et al [89]. The time-dependency components in Brown et al models were easily incorporated using straightforward procedures. Customer orders for gasoline were processed using a decision support system that first provided a solution that ignored changes in travel time and then sequenced the loads for each vehicle in consideration of things like traffic congestion during rush hours, road and weather conditions, etc., Brown et al [27]. A multiplier factor has been employed by other studies to reflect changes in trip times [62] and [68].

Some academics investigated the use of drones for delivery in an effort to further reduce delivery time and cost. In light of the merits and cons of drone delivery, Murray and Chu [98], proposed two popular concepts on how to fairly employ drones in the last-mile delivery process. The central depot serves as a launch pad for drones, which are then sent on a round-trip journey to their final destination. In densely populated urban areas, where drones can only fly for around 20 kilometres at a time, this notion necessitates an extensive and expensive depot network. The second approach uses delivery trucks as mobile launching platforms for drones [125], which are more suited for delivering goods to people who are home at the time. The most basic approach for using drones in the last mile is to launch them from a depot directly toward clients. Even though drones have a restricted flight range, they must be housed in metropolitan areas, where land is unquestionably expensive, so either a single depot or a network of dispersed depots must be built in an urban region. Cost-oriented considerations for depot installation and drone purchase are discussed in Shavarani et al (2020) [24].

In contrast to much of the research, Sung and Nielsen (2020) [122], address the safety concerns that arise from the coexistence of drones in the same airspace. Genetic algorithms can be used to divide the service area into separate zones, each of which can be served by a single drone. Recharging stations can be introduced into the distribution network in order to bridge the gap between depot and client. Hong et al. (2018) [63] presents the site planning problem for drone recharge stations. Maximum weighted coverage for a discrete set of possible sites is achieved through a combination of mixed integer programming (MIP) and heuristic solution approaches. Using a single depot, a truck, and a group of drones, Murray and Chu [98] were the first to create the parallel drone scheduling Travel Salesman Problem (PDSTSP). Choosing which customers would be better served by drone and which would be better served by truck to reduce the overall make-span was the task at hand. Flying the drones between the depot and specific consumers was accomplished using a MIP and a simple heuristic. In a single travel Salesman Problem (TSP) tour, the truck serves all the remaining customers without capacity constraints Additional depots, multiple trucks, and time windows were added to the PDSTSP by Ham [59]. They use constraint programming as a technique for solving their problems. For the instance where drones can deliver many items concurrently. Dorling et al [42], looked at a MIP and a simulated annealing technique.

A MIP and boundary approaches were provided by Torabbeigi et al. (2020) for the customer-to-drone assignment and optimization. However, whereas [119] and [47], assume a single depot, other articles explore a depot network and allow drones to transfer depots. [125] proposes a stochastic and dynamic form of the problem. A single depot was able to optimize the number of customers served by trucks and drones operating independently. Using the example of on-demand meal delivery by drone, Liu (2019) [85], offers a rolling horizon strategy to deal with the dynamic setting. Securing drones from being grounded due to bad weather or failures due to accidents is another concern, which is why Sawadsitang et al. [115], suggest a three-stage stochastic programming model.

An exact branch-and-bound process,because exact dynamic programming (DP) approach, and another DP if the customer sequence is given have been proposed to tackle this problem. According to Bouman P. et al. [22], dynamic programming can be utilised to combine trucks and drones to expedite supermarket delivery times. There is still a long way to go before drones may be used for business purposes. Concept has been proven to be a viable alternative for delivery, especially during critical periods like pandemics. Despite the fact that drone delivery is faster than land vehicles due to the fact that they are not subject to road traffic, depending on their operational concept, processing a significant amount of load may require a significant drone fleet size, so it is still uncertain whether drones can contribute to handling large volumes of load and minimising delivery costs.

There are also performance issues, privacy concerns and complications to consider when using it. Considering that drones are still in their infancy and that many operational specifics remain a mystery. Deliveries to people's homes that are present are still done the old-fashioned way, with a human being there. Without the use of a drone, the driver can provide service to customers.

On generic networks with many vehicles and dynamic pickup and delivery, Voccia et al developed a Markov decision procedure for the problem of same-day delivery [130]. Deliveries with time windows and various vehicles were introduced by Van Heeswijk et al[127] . Additionally, whenever a vehicle departs from the depot, it is permitted to return to the depot to pick up urgent orders, even if the current tour has not yet been completed. Travel time and delivery costs will go up in this scenario, according to Ulmer et al [125].

Cargo bikes are compared to standard vans and self-service models by Arnold et al [7]. Based on data from Antwerp (Belgium), a simulation study is used. The Clark–Wright savings algorithm is used to determine bike, vehicle, and human travel routes. Failed deliveries are taken into consideration in the calculation as well (11%). Cargo bikes can reduce external costs, such as emissions, noise, and congestion, by 40% when compared to vans, according to the findings. The combined distribution of regular vans and cargo bikes using micro-depots is the subject of yet another simulation research [49].

A heuristic approach to solving the vehicle routing problem was proposed in 1959 [36], and many specific search methods have been developed for the vehicle routing problem. The optimal insertion heuristic is used to identify vehicle paths in an agent-based simulation. Determining where to place your micro-distribution centre may involve upfront fees as well as ongoing operating expenses. Selecting micro-depot locations can also become a short-term choice challenge and have high facility costs depending on which of these expenses are applicable. Micro-depots, delivery windows, and electric cargo bikes all have unique characteristics that may be of interest to potential clients. Deliveries take longer while travelling slowly, but energy usage is lower, saving time when recharging [41]. Cargo bikes were specifically addressed in [31]. This study compares several types of cargo bikes with delivery vehicles by using time frames to solve the routing problem. A heuristic technique is used to solve the optimization issue, which tries to minimise routing costs. The net present value of e-trikes is the lowest, according to the results [25]. Short periods are preferred by customers since it decreases their waiting time. As a result, longer zigzag trips could be a danger to logistics providers due to a smaller window of opportunity [88].

An additional consideration is the quantity of possible time frames for customers to select from [2]. Customers naturally want more options, and Van Duin et al [126], emphasise the significance of incorporating customers when creating time windows. They demonstrate that customers are more likely to receive their orders on the first try if they are not just given a defined delivery window. As a result of this, logistics providers are more likely to face the risk of clients selecting time periods that do not fit into their short delivery tours. Delivering goods under time limitations and a limited vehicle fleet is the primary goal of a VRP with Time Windows (VRPTW). For residential delivery services, delivery timings may be restricted to certain periods agreed upon by clients. Commercial clients with limited operating hours, or consumers who live in access-restricted pedestrian streets, are two more prominent reasons for time windows in an urban context. [8] and [16] are examples of recent work on a TSPTW with time windows. New developments in TSPTW algorithms can be found in [24], and [6], [32]. The logistics provider may offer incentives like a delivery discount or free delivery to nudge consumers toward the precise time windows it prefers [28], [134], to cope with the issue of time window agreements.

As a result, some studies have addressed some of the questions that arise when it comes to a customer's specific needs. Deterministic requests but stochastic journey durations were studied by Boysen and colleagues [14] who worked on deterministic demands but stochastic travel times, [69], and [129] examined the case of self-imposed time windows in which time slots are supplied by a carrier but not by customers. Using heuristics Campbell et al [29], approximation methodologies, and simulation studies, researchers [45], [1], and Boyer et al. (2009) [24], their findings support the time window management's cost/benefit analysis. Virtual Route Planning with Time Window (VRPTW) is a variant of the Vehicle Routing Problem (VRP) that adds a time window for each customer to be supplied with vehicles. Distribution and transportation system expenses are heavily dependent on vehicle route and schedule. For a fleet of vehicles, the vehicle routing problem (VRPTW) comprises a design of a set of minimum-cost routes starting and terminating at a depot for clients with known needs. When it comes to this particular group of clients, it only happens once for every one of them. As a further requirement, all customers must be assigned to a vehicle that does not exceed the vehicle's capacity. A solution method to reducing exhaust emissions is presented in our study, which focuses on reducing fuel usage by minimising delivery times.

# 3 Mixed Integer Linear Programming (MILP)

In practice, the most imperative objective of the Vehicle Routing Problem (VRP) is to minimize the total transference rate. As almost all the carriage charges are deeply dependent on the itinerant distance, hence, various literature that tried to minimize the itinerant distance has been put out. In some circumstances where the total consignment (or weight) allotted to each distribution van varies due to the drop-off action (or supply at a visiting point), the total charge attained from load overall with distance will be in distress. In the part of the VRP, there are several studies related to the minimization of the roaming distance, carriage cost and fuel consumed. The Vehicle Routing Problem (VRP) is a delinquent that is extensively studied since it was first presented by Dantzig Ramser in 1959 [36]. VRP is pains taken as a combinatorial problem and is a NP-hard problem (Lenstra, RinnooyKan, (1981)). The objective of a VRP is to find the least equivalent cost of the total routes dispensed. These charges might be the overall itinerant distance, the least number of vans used and the overall time of roaming. The Vehicle Routing Problem with Time Window (VRPTW) is described as the problem of designing minimum-cost routes from one depot to a set of scattered points in a geographical region. The routes are designed to ensure each point is visited only once by exactly one vehicle within a given time interval. All routes start and end at the depot, and the total demands of all points on one route must not exceed the capacity of the vehicle.

Exact methods are currently applied to find an optimal solution for a few customers with limited capacity and fixed time windows [16]. Popular exact procedures include direct tree search, dynamic programming, Mixed-integer linear programming, etc. In this section, we present the MILP model which seeks to minimize the time used in offering grocery delivery service to customers on a service day, thereby reducing the fuel consumed in the delivery process. In all the VRP variants, the 'Capacitated VRP' (CVRP) occupies a central position.

Using the MILP model, we aim to minimize the cost and the cost the amount of delivery by minimizing the time it takes to deliver groceries to consumers on a given service day. In all the VRP variants, the Capacitated VRP (CVRP) occupies a central position. It was defined by Dantzig and Ramser in 1959 [36] as follows. The input consists of a set of $n+1$ points, a depot, and the number of customers; an $(n+1)(n+1)$ matrix $d = d_{ij}$ with the distances between every pair of points $i$ and $j$; an n-dimensional demand vector $q = q_i$ giving the amount to be delivered to customer $i$; and a vehicle capacity $Q$. A solution is a set of routes, starting and ending at the depot, that visit every customer exactly once in such a way that the sum of the demands of the customers of each route does not exceed the vehicle capacity. This is a capacitated vehicle routing Problem with Time Windows (VRPTW) [13], [15], [118], in which the time window is the optimal time slot for delivery. The focus is on constructing an optimal routing plan of travel for given vehicles based on specified time slot allocation with known customer demands (number of orders) to be served in specified areas. Section 3.2 spells out the general model and detailed description of the variables used in the process of modeling.

## 3.1 Problem Statement

We consider the problems concerning the distribution of ordered groceries between depots and final users (customers). This study focuses on the problem of time slot allocation to different service areas, providing both an acceptable level of service to customers' satisfaction and minimizing exhaust emission by reducing fuel consumption by minimizing the travel time used in the delivery process. We can therefore find the minimization of the delivery time for a service day by optimizing the route to every customer [52].

Even though the number of stops a vehicle makes during a service day may be large, the number of time slots in a service day can be small; no more than four in the case of Albert.nl. Our approach aims to increase the demand density within a time slot for each zip code. Therefore, it tends to construct large zip code clusters for each time slot. Because the integer programming model explicitly considers the individual vehicle routes, it is more concerned with the zip code groups that can be visited by individual vehicles over the entire period.

In our study, 3 time slots are considered. Based on the available information given by the consumer, the data on postcodes of all customers are known. The various postcodes are grouped into several areas based on their location in the delivery region. Afterwards, we define a unique traffic situation for each specific area through the speed assigned at a certain time of service day. A homogeneous fleet of vehicles is used to serve the customers as used in Agatz et al [1].

### 3.1.1 Key Assumptions

Assume all delivery services for a day starts from the depot and end at the depot and all orders to be served are known. We assume that the distance from area $i$ to area $j$ equals the distance from $j$ to $i$.

### 3.1.2 Parameters

We set the time bounds for a day's service. The service region is divided into areas where each area is represented by $i \in \mathbf{I} = \{1, ..., a+1\}$ with depot inclusive, where $a$ is the number of service areas. Let $w_i$ be the distance between each pair of orders in area $i$. At the beginning of service at the depot, $i = 1$ and $s = 1$ whilst at the end of service, $i = 1$ and $s = m+2$ where $m$ is the number of time slots for service delivery.

We also let $d_{ij}$ be the distance traveled from area $i$ to area $j$. Theoretically, each area could be denoted by a a point (x, y) as in the Cartesian coordinate system.

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{3.1}$$

Since we assume that the distance from area $i$ to area $j$ equals the distance from $j$ to $i$ which yields a symmetric distance matrix below:

| | $Area1$ | $Area2$ | $Area3$ | $Area4$ |
|---|---|---|---|---|
| $Area1$ | 0 | $d_{12}$ | $d_{13}$ | $d_{14}$ |
| $Area2$ | $d_{21}$ | 0 | $d_{23}$ | $d_{24}$ |
| $Area3$ | $d_{31}$ | $d_{32}$ | 0 | $d_{34}$ |
| $Area4$ | $d_{41}$ | $d_{42}$ | $d_{43}$ | 0 |

Vehicles travel with different velocities at different times and in different areas, for instance, the morning 'rush' hours compared to the afternoons and evenings 'non-rush' hours, busy areas as compared to non-busy areas, $u_{ijs}$ is introduced to be the velocity of the vehicle from area $i$ to area $j$. The speed from $i$ to $j$ is mostly not the same which gives the asymmetric matrix below:

| | $Area1$ | $Area2$ | $Area3$ | $Area4$ |
|---|---|---|---|---|
| $Timeslot1$ | $v_{11}$ | $v_{12}$ | $v_{13}$ | $v_{14}$ |
| $Timeslot2$ | $v_{21}$ | $v_{22}$ | $v_{23}$ | $v_{24}$ |
| $Timeslot3$ | $v_{31}$ | $v_{32}$ | $v_{33}$ | $v_{34}$ |
| $Timeslot4$ | $v_{41}$ | $v_{42}$ | $v_{43}$ | $v_{44}$ |
| $Timeslot5$ | $v_{51}$ | $v_{52}$ | $v_{53}$ | $v_{54}$ |

Similarly, $v_{is}$ the velocity of travel in area $i$ at time slot $s$ differs from one time slot to the other.

Let $b_1$ represent the time for the start of service at the depot and $b_{s+1}$ be the time for the end of service at the depot. We also let $n_i$ be the number of orders in area $i$ in a service day, and $\tau$ is the service time per customer.

$I = \{2,...,a+1\}$ is the set of areas to be served, where $a$ is the number of service areas

$\underline{I} = I \cup \{1\}$ is the set of areas to be served including the depot which is the service starting and ending point.

$S = \{2,...,m+1\}$ is the set of time slots

$s \in \underline{S} = \{1,...,m+2\}$ is the set of time slots including the beginning of service day $s = 1$, end of service day is $s = m+2$, and $m$ is the number of service time slots.

$K = \{1,...,h\}$ represents a homogeneous fleet of vehicles.

### 3.1.3 Decision variables

The optimal routing plan,

$$x_{isk} = \begin{cases} 1, & \text{if truck k is located to an area i in time slot s} \\ 0, & \text{otherwise} \end{cases}$$

$$y_{ijsk} = \begin{cases} 1, & \text{if truck k travels from area i to area j in time slot s} \\ 0, & \text{otherwise} \end{cases}$$

$o_{isk} \in N^+$ is the number of orders served by truck $k \in K$ at time slot $s \in S$ in the area $i \in I$.

$z_i \in N^+$ is the number of unsatisfied orders in area $i$ due to current load capacity.

$t_{isk} \in R \geq 0$ is the starting time of service for truck $k \in H$ at time slot $s \in S$ at area $i \in I$.

## 3.2 Time/Fuel-consumption minimization model

Following earlier research works [13], [15], [118], in which the time window is the optimal time slot for delivery, we propose a Mixed Integer Linear Programming (MILP) model for the capacitated VRPTW. Given a set of customers $N = 2, \ldots, m+1$ with known demands (number of orders) for any $i \in N$, we have a fleet of homogeneous vehicles of capacity Q to deliver those orders, from a central depot ($i = 1$) to individual customers.

The directed graph is G(N, A), where N is the set of nodes and A is the set of arcs $(i, j)$ that connects pairs of nodes from N. Each arc $(i, j) \in I$ is associated with a travel distance $d_{ij}$. Each customer in $i \in N$ is associated with a service time $\tau$. Let $\rho$ be the penalty for unserved orders. The objective is to minimize the travel time used to serve all customers while satisfying the capacity and time window constraints.

We aim to minimize the fuel consumed in the delivery of groceries by finding an optimal plan that will minimize the travel time used in the delivery process, thereby minimizing the greenhouse gas ($CO_2$) emission. Minimizing the travel time used in the delivery process also leads to the minimization of the delivery cost.

Akcelik et al [3] modeled fuel consumption considering three key components. The first component considered was the distance of travel. This encompassed the travel distances from the depot to the service centers (areas of service), the travel distances within the areas of service while delivering the orders, and the travel distances from the last areas of service back to the depot. The second component considered was the stops. The total number of stops made to serve the orders during the service day. Lastly, the time component dealt with the serving time in delivering the orders to the individual customers.

Following Akcelik's approach, this study seeks to minimize the fuel consumed by minimizing the travel time used in the delivery process for a service day.

**The travel time component**. The time of travel for all vehicles used on the service day across all areas and in all time slots is estimated by:

$$\sum_{k=1}^{h}\sum_{s=2}^{m+2}\sum_{i=1}^{a+1}\sum_{j=1}^{a+1}\frac{d_{ij}}{u_{ijs}}y_{ijsk}+\sum_{i=2}^{a+1}\sum_{s=2}^{m+1}\sum_{k=1}^{h}((\frac{w_i}{v_{is}})*o_{isk}) \tag{3.2}$$

**The stops time component**. The total number of stops made by all vehicles on the service delivery day during the delivery process is estimated by:

$$\sum_{i=2}^{a+1}\sum_{s=2}^{m+1}\sum_{k=1}^{h}(o_{isk}*x_{isk}) \tag{3.3}$$

**The services time component**. Each stop requires service delivery. The time used to serve all customers in all areas in all time slots is also estimated by:

$$\sum_{i=2}^{a+1}\sum_{s=2}^{m+1}\sum_{k=1}^{h}\tau*o_{isk} \tag{3.4}$$

The total time used for the service delivery on a service day is given by:

$$T = \sum_{k=1}^{h}\sum_{s=2}^{m+2}\sum_{i=1}^{a+1}\sum_{j=1}^{a+1}\frac{d_{ij}}{u_{ijs}}y_{ijsk} + \sum_{i=2}^{a+1}\sum_{s=2}^{m+1}\sum_{k=1}^{h}(\tau + \frac{w_i}{v_{is}}) * o_{isk}. \tag{3.5}$$

From the insight drawn from Arigliano et al (2015) [6] and Sun et al (2015) [120], we present our formulation as shown below:

$$FC = \alpha T + \sum_{i=2}^{a+1}\rho z_i \tag{3.6}$$

Where $\alpha$ is fuel cost per unit time, $\rho$ is the penalty for unsatisfied orders, and $\tau$ is the service time per customer.

## 3.3 The Exact Approach

The above model was subject to constraints. We now describe the constraints that give a possible solution to the problem as follows:

It is assumed that all service starts from the depot $i = 1$ which implies all loaded trucks are at the depot in the first time slot $s = 1$ and progressively travel to all feasible areas of assignment until the end of service is reached where all trucks then return to the depot in the time slot $s = m+2$ at the end of service (end of its assignment) as proposed by Arigliano et al (2015) [6], [120]. Each vehicle performs exactly one trip on a service day. The number of routes is equal to the number of vehicles used for the service delivery.

Firstly, a vehicle/truck $k \in H$ can serve one and only one area $i \in I$ in a time slot $s \in S$.

$$\sum_{i=1}^{a+1} x_{isk} = 1, \forall k = 1,...,h, \forall s = 2,...,m+1. \tag{3.7}$$

Secondly, the number of orders that can be served in the area $i \in I$ in a time slot $s \in S$ by truck $k \in H$ should never exceed the total number of orders in the area for the service day.

$$o_{isk} \leq n_i x_{isk}, \forall i = 2, ..., a+1, \forall s = 2, ..., m+1, \forall k = 1, ..., h. \tag{3.8}$$

Next, the summation of all served and unserved orders in the area $i \in I$ after the service day must be the same as the total number of orders in the area $i \in I$.

$$z_i + \sum_{s=2}^{m+1} \sum_{k=1}^{h} o_{isk} = n_i, \forall i = 2, ..., a+1. \tag{3.9}$$

Also, as stated earlier, at the beginning of a service day $s = 1$, all trucks must be at the depot $i = 1$.

$$x_{11k} = 1, \forall k = 1, ..., h. \tag{3.10}$$

So must it be that, at the end of service $s = m+2$, all trucks must return to the depot $i = a+1$.

$$x_{1(m+2)k} = 1, \forall k = 1, ..., h. \tag{3.11}$$

The two binary variables used are linked by:

$$y_{ijsk} \geq x_{i(s-1)k} + x_{jsk} - 1, \forall i, j = 1, ..., a+1, \forall s = 1, ..., m+2, \forall k = 1, ..., h. \tag{3.12}$$

A set of a homogeneous fleets of vehicles/trucks is used. The capacity of the vehicles should not be exceeded.

$$Q \geq \sum_{i=2}^{a+1} \sum_{s=2}^{m+1} o_{isk}, \forall k = 1, ..., h. \tag{3.13}$$

The start time of a proceeding time slot $s+1$ by truck $k$ must be higher than the total time used for the current time slot $s$.

$$t_{j(s+1)k} \geq t_{isk} + \tau o_{isk} + \frac{w_i}{v_{is}} o_{isk} + \frac{d_{ij}}{u_{ij(s+1)}} y_{ij(s+1)k}, \forall i \neq j = 1, \ldots, a+1, \forall s = 1, \ldots, m+2, \forall k = 1, \ldots, h. \tag{3.14}$$

The start time for the beginning of service in a preceding time slot $s-1$ must be lower than the start time of current time slot $s$.

$$b_{s-1} \leq t_{isk}, \forall i = 1, \ldots, a, \forall s = 1, \ldots, m+2, \forall k = 1, \ldots, h. \tag{3.15}$$

Lastly, the finishing time of current time $s$ must be less than the start time of the next time slot $s+1$.

$$t_{isk} + \tau o_{isk} + \frac{w_i}{v_{is}} o_{isk} \leq b_{s+1}, \forall i = 1, \ldots, a+1, \forall s = 1, \ldots, m+2, \forall k = 1, \ldots, h. \tag{3.16}$$

The objective function (3.6) is to minimize the fuel consumption by finding the total time used for the delivery (3.5) which was obtained from the total time of travel (3.1) and the corresponding stops made to make delivery in (3.3) and (3.4). (3.7) ensures that a truck is located in exactly one service area per each time slot. (3.8) and (3.9) ensure that when a truck is located in a certain area in a specific time slot, it can serve non-zero customers in it. (3.10) and (3.11) also ensure every truck starts at the depot and ends at the depot. (3.12) links $x$ and $y$ variables. (3.13) ensures vehicle capacity is not exceeded and (3.14), (3.15), and (3.16) serve as the time boundaries for the service day.

### 3.3.1 Numerical Results of the Exact Algorithm

A mathematical model is designed with appropriate constraints for the decision variables. The resulting optimization problem is cast as an instance of Mixed-Integer Linear Programming (MILP) with the use of Matlab and Cplex MILP solver. Sets of simulated data were used through the study to obtain the number of orders in each area of service, the speed, and distances between each pair of areas, and each pair of customers' postcode/orders in an area. With a known number of vehicles/trucks and number of areas available, we fixed the time slots available to 3. The offer of few time slots forces demands to be concentrated in these fewer time slots, which results in a balanced workload. Earlier researchers, for example, Koc et al, 2016 [80] and Fischetti et al, 2005 [50] used the commercial software ILOG-CPLEX for Linear Programming problems (LP). Similarly, does this study follow the use of ILOG-CPLEX in solving the LP. The model is implemented in the mathematical programming language MATLAB and solved using the commercial software ILOG-CPLEX 12.9.0 solver with laptop-ANS8H2QD whose processor is AMD Rysen 3 3250U with Radem Graphics with RAM of 8GB.

Table 1: Results of the Exact Algorithm

| Run | # of Trucks | # of time slots | # of Areas | Orders served | Run time(s) | Exit flag | T(hrs) | fval |
|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 3 | 20 | 0.1146 | 1 | 3.3938 | 5.0907 |
| 2 | 2 | 3 | 4 | 26 | 0.1433 | 1 | 4.3226 | 6.4839 |
| 3 | 2 | 3 | 5 | 24 | 0.1880 | 1 | 4.4688 | 6.7032 |
| 4 | 2 | 3 | 6 | 24 | 0.1860 | 1 | 4.1863 | 6.2795 |
| 5 | 3 | 3 | 6 | 35 | 0.5760 | 1 | 5.95095 | 8.9264 |
| 6 | 3 | 3 | 7 | 28 | 0.5102 | 1 | 4.6883 | 7.0324 |
| 7 | 3 | 3 | 8 | 21 | 0.5040 | 1 | 3.8070 | 5.7104 |
| 8 | 4 | 3 | 8 | 36 | 1.4073 | 1 | 6.1404 | 9.2106 |
| 9 | 4 | 3 | 9 | 40 | 1.6613 | 1 | 6.9493 | 10.4240 |
| 10 | 4 | 3 | 10 | 30 | 0.6063 | 5 | 4.9599 | 7.4398 |
| 11 | 5 | 3 | 10 | 50 | 3.5310 | 5 | 8.0811 | 12.1216 |
| 12 | 5 | 3 | 11 | 58 | 2.5124 | 5 | 9.8700 | 14.8050 |
| 13 | 5 | 3 | 12 | 39 | 5.0072 | 5 | 6.5785 | 9.8678 |
| 14 | 6 | 3 | 12 | 42 | 5.1270 | 5 | 7.4359 | 11.1538 |
| 15 | 6 | 3 | 13 | 59 | 6.6528 | 5 | 10.1722 | 15.2583 |
| 16 | 6 | 3 | 14 | 57 | 3.6484 | 5 | 9.8959 | 14.8438 |
| 17 | 6 | 3 | 15 | 59 | 11.2201 | 5 | 10.3550 | 15.5325 |
| 18 | 6 | 3 | 16 | 79 | 5.5958 | 5 | 13.2375 | 19.8562 |
| 19 | 6 | 3 | 17 | 65 | 22.1564 | 5 | 11.2214 | 16.8321 |
| 20 | 9 | 3 | 18 | 72 | 35.2261 | 5 | 14.3719 | 21.5578 |

Note: All computations in this study are obtained using Matlab R2019b version 9.7.T = total time
fval is the value of the objective function.

# 4 The Heuristic Approach

Heuristic methods are used to resolve the vehicle routing problem according to the specific knowledge of the problem, which is in most cases sub-optimal or close enough to a reliable solution [40]. In this study, we have proposed a solution for vehicle routing using an Exact approach approach in section 3. The major drawback with the Exact approach is the computing run time, which is often longer, we, therefore, try to use the Heuristic to solve the routing problem, which must perform much faster. Section 4.1 gives the additional parameters used in the Heuristic approach. 4.1.1 gives the flowchart which is the diagrammatic representation of the Heuristic algorithm. Section 4.2 presents the numerical results of the Exact and Heuristic algorithms with fixed parameters. Section 4.2.3 presents how the trucks move in each scenario considered.

A challenge specific to the vehicle routing problem is to minimize the number of routes, the violation, and the total cost of the routes simultaneously. Foreknowledge of the minimum number of routes is necessary to avoid the complexities. This study uses a set of homogeneous vehicles with known capacity; therefore, the minimum number of routes can be easily computed as the total demand divided by the capacity of the vehicles. Our local search employed the construction method that consists in building a solution by adding new elements iteratively to an initial empty solution. In the case of the VRP, it typically consists in starting from a solution with empty routes and adding customers to routes one by one. The number of routes is incremented by 1 and a new search is performed, the process is repeated until a feasible solution is found.

As earlier stated, the objective is to propose a routing plan that minimize the time used in the grocery delivery process which in turn minimizes the fuel consumption and also minimizes delivery costs. Heuristics may help in finding a feasible solution or an improved and possibly optimal solution to large and difficult mixed integer programs. Intuitively, one could model the total time used in the delivery process by introducing variables that represent, for each vehicle, the sequence of stops at various areas within each time slot. Therefore, we determine the approximate total time used in the delivery process and the associated delivery costs by optimizing the route to each customer.

In our study, we again consider 3 time slots. We present a heuristic approach for this problem of minimizing the time used for the delivery of groceries with an objective function that approximates the time used in the delivery execution on a service day and the associated delivery cost.

Research done by Arigliano et al [6], Sun et al [120], Fischetti et al [51] and Fleszar et al [54], used heuristic approaches to solve MILP, we also approach solving the model heuristically by allowing all services to start from the depot $i = 1$ in the first time slot $s = 1$ and progressively travel to all feasible areas of assignment until the end of service is reached where all trucks then return to the depot) in $s = m+2$ at the end of service (its assignments).

## 4.1 Parameters

The neighborhood search considers the area with maximum speed or, the area with the closest distance from $i$ to $j$. The optimal routing plan is that:

A vehicle/truck $k \in H$ can serve one and only one area $i \in I$ in a time slot $s \in S$. At the beginning of a service day $s = 1$, all trucks must be at the depot $i = 1$. All trucks, at the end of service $s = m+2$, must return to the depot $i = a+1$. A set of homogeneous fleets of vehicle/trucks are used. The capacity of the vehicle (Q) should not be exceeded. Let $N_i$ be the current total number of orders served, then at the start of service at the depot, $N_i = 0$, since no order is served. The sum of all served and unserved orders in an area $i \in I$ after the service day must be the same as the total number of orders in the area $i \in I$. Time of Service in area $i$ in time slot $s$ by truck $k$ is obtained from $\tau * o_{i,s,k}$, the travel time from area $i$ to area $j$ is $d_{ij}/u_{ijs}$, and the time of travel within an area $i$ is $w_i/v_{is} * (o_{i,s,k})$. We can therefore deduce the start time and finish time for each time slot $s$.

The start time of service in a current time slot $s$ in area $i$ by truck $k$ is obtained from the finish time of $k$ in its previous area and the time used to travel from the previous area to the current area of service.

$$T_k = \sum_{k=1}^{h} \sum_{s=1}^{nS-1} \sum_{i=1}^{a+1} \sum_{j=2}^{a+1} (t_{finish_{i,s,k}} - t_{start_{i,s,k}}) \tag{4.1}$$

$$T_f = \sum_{i=2}^{a+1} (d_{i1}/u_{i1(nS)}) \tag{4.2}$$

$$T = T_k + T_f \tag{4.3}$$

$$FC = \alpha T + \sum_{i=1}^{a+1} \rho * z_i \tag{4.4}$$

where $\alpha$ is the fuel cost per unit time and $\rho$ is the penalty for unsatisfied orders.

### 4.1.1 Flowchart

Figure 3 shows the flow chart of the Heuristic algorithm. Firstly, initialization of the parameters needs to be performed with the number of areas that must be visited. In the flow chart, the task is carried out till the visit to all the possible visit areas is completed before its termination.

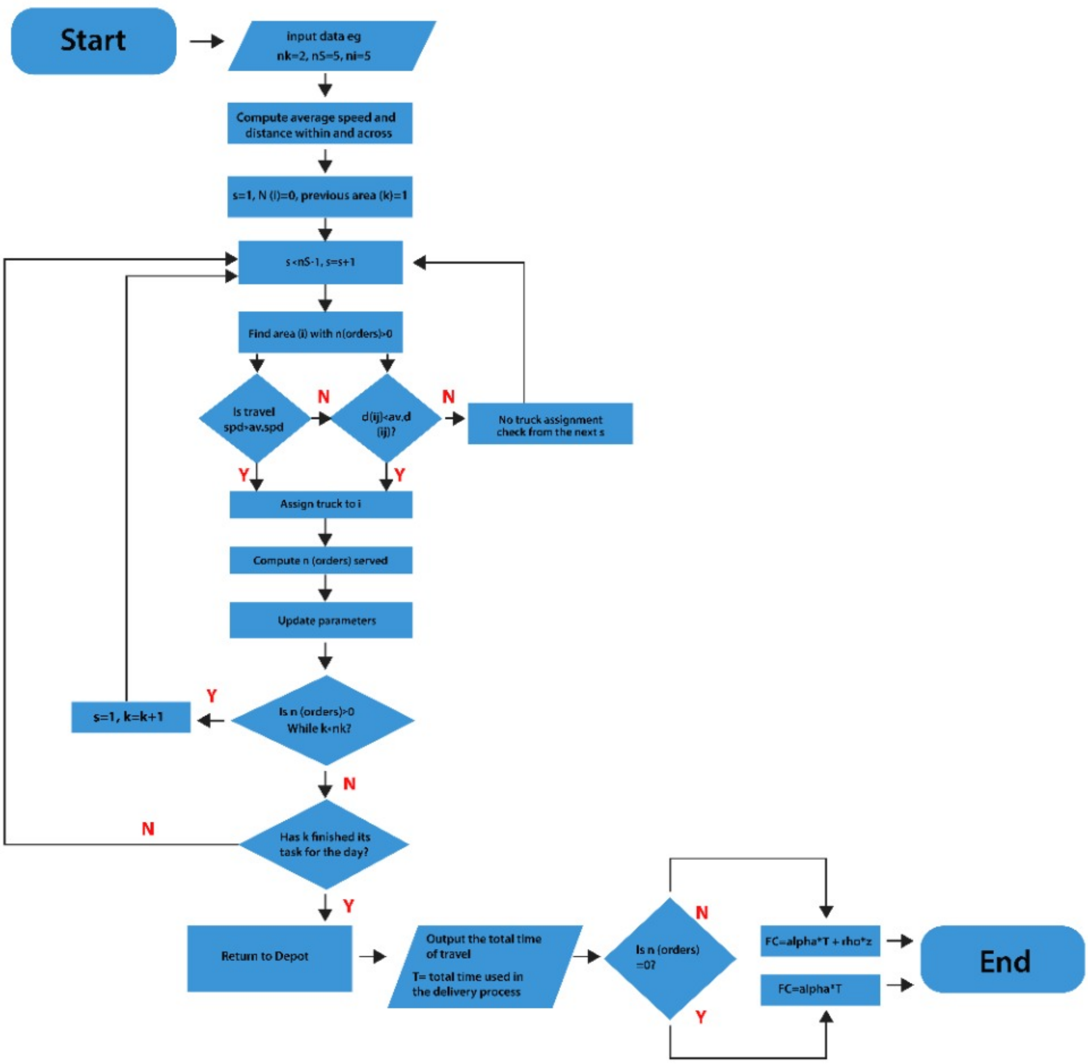



Figure 3: Overview of heuristic solution

A flowchart is used to present the heuristic process. The description of the steps used in solving the delivery problem is given below.

**Steps of the flowchart:**

1. Initialization.
2. Insert the number of areas to be visited in the service region [Data].
3. While (number of orders $>0$ and time slot $<$ final time slot)
4. Assign a truck (consider the capacity of the truck) to an area if the speed within the area is high or the speed from the present location to the next area of the visit is high in the time slot under consideration. If not, find the next closest area to the present location and assign the truck, else, go to step 3 in the next time slot until conditions are met.
5. Compute the total number of orders served ($N_i$) and update parameters.

   $N_i = N_i + o_{isk}$

   $n_{orders} = n_{orders} - N_i$
6. While (number of trucks used $<$ total number of trucks and number of orders $>0$).
7. Assign another truck and go to step 3.
8. If the capacity of the truck is exhausted, or if all orders are served in all possible areas to be visited then stop and return to the depot. Else go to step 3 in the next time slot.
9. End the while in step 6.
10. End while in step 3.
11. Compute the time used by all trucks for the delivery and the objective value.
12. Stop.

Heuristics can be effective for making immediate decisions; however, they often result in irrational or inaccurate conclusions. Additionally, heuristic underlies the illusion of validity. The illusion of validity lies in the tendency to overestimate the accuracy of making decisions. Nonetheless, there are many situations where heuristics can yield accurate predictions or result in good decision-making. However, in our study, the value of the objective function obtained by the heuristic approach will be compared with the Exact objective function value to determine the gab to check the performance of the heuristic. Here, same sets of simulated data (as used for the Exact approach) were used to obtain the number of orders in each area of service, the speed, and distances between each pair of areas, and each pair of customers' postcode/orders in an area. With a known number of vehicles/trucks and number of areas available, we fixed the time slots available to 3. The worst scenario of our test case is the situation where there are still some unserved orders after all the time slots are exhausted on a service day. This situation is dealt with by the introduction of the penalty for unsatisfied orders ($\rho$) which will increase the value of the objective function in such scenarios.

Table 2: Results of the Heuristic Algorithm

| Run | # of Trucks | # of time slots | # of Areas | Orders served | Run time(s) | T(hrs) | FC |
|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 3 | 20 | 0.0251 | 4.7267 | 7.0901 |
| 2 | 2 | 3 | 4 | 26 | 0.0261 | 5.5442 | 8.3163 |
| 3 | 2 | 3 | 5 | 24 | 0.0251 | 5.2716 | 7.9073 |
| 4 | 2 | 3 | 6 | 24 | 0.0186 | 5.3083 | 7.9625 |
| 5 | 3 | 3 | 6 | 35 | 0.0321 | 6.4264 | 9.6396 |
| 6 | 3 | 3 | 7 | 28 | 0.0184 | 7.1082 | 10.6623 |
| 7 | 3 | 3 | 8 | 21 | 0.0156 | 6.2689 | 9.4034 |
| 8 | 4 | 3 | 8 | 36 | 0.0282 | 9.2226 | 13.8339 |
| 9 | 4 | 3 | 9 | 40 | 0.0267 | 9.6032 | 14.4048 |
| 10 | 4 | 3 | 10 | 30 | 0.0265 | 8.9366 | 13.4049 |
| 11 | 5 | 3 | 10 | 50 | 0.0268 | 12.5507 | 18.8261 |
| 12 | 5 | 3 | 11 | 58 | 0.0264 | 13.2859 | 19.9289 |
| 13 | 5 | 3 | 12 | 39 | 0.0274 | 10.8991 | 16.3487 |
| 14 | 6 | 3 | 12 | 42 | 0.0140 | 11.9453 | 17.9179 |
| 15 | 6 | 3 | 13 | 59 | 0.0125 | 13.8005 | 20.7053 |
| 16 | 6 | 3 | 14 | 57 | 0.0328 | 14.5207 | 21.7811 |
| 17 | 6 | 3 | 15 | 59 | 0.0481 | 15.4824 | 23.2236 |
| 18 | 6 | 3 | 16 | 79 | 0.0263 | 15.5847 | 23.3771 |
| 19 | 6 | 3 | 17 | 65 | 0.0181 | 15.2719 | 22.9078 |
| 20 | 9 | 3 | 18 | 72 | 0.0332 | 18.6300 | 27.9450 |

Note: All computations in this study are obtained using Matlab R2019b version 9.7

# 5 Analysis of Results of the Exact and Heuristic Approaches

In this section, we present the results of fixed parameters for both the Exact and the Heuristic approaches. This study's objective is to obtain a routing plan or time slot allocation that will minimize the time used in the grocery delivery which in turn minimizes the fuel consumption and the delivery costs. This implies both code have the same set of data. We consider 20 different scenarios for the two approaches in the table below. Each Run test used the same set of parameters. We illustrate our experiment in two scenarios. The first scenario is an instance of having 2 trucks, 3 time slots, and 3 areas of service. This implies 4 areas, thus depot inclusive, 5 time slots are involved here, thus $a+1$, $S+2$. And the second scenario is an instance of having 3 trucks, 3 time slots and, 6 areas of service as Run 1 in table 1.

## 5.1 Parameters Used

For all our test cases, 3 time slots were used. The service time per customer $\tau = 0.1$(hours) and the penalty cost for unsatisfied orders $\rho = 1.5$. The value of $\rho$ is subject to the price of fuel at the time of consideration. Starting time at the depot $s = 1$ is 0.00. The length of each time slot is 1 hour. The capacity of each truck is 30.

**Demand simulation**

In all our test cases, the number of orders (customers) is simulated by randomly taking random integers ranging from 0 to 10.

**Distance simulation** We also let $d_{ij}$ be the distance traveled from area $i$ to area $j$. The distance from one area $i$ to the next area $j$ is randomly generated by considering real numbers from 0 to 10 km.

**Speed simulation** Speed of driving differs from one area to the other and also from one time slot to the other. Therefore, driving across and within areas must factor in the various speed changes accordingly. While stimulating, we set a lower speed bound for the speed within an area as 5km/h and that of speed across areas as 30km/h. The lower bound for speed from area $i$ to $j$ is 15km/h and 45km/h as the upper bound.

Two scenarios of the simulated sets of parameters are displayed in the Appendix. In the first scenario (Run 1), the generated number of orders, the simulated distances between the areas under consideration, the widths of each of the 4 areas (depot inclusive), and the generated driving speed within the areas considered in each time slot are shown in Appendix A.

The second scenario (Run 5), a test case where there were 3 trucks, three time slots, and 6 areas of service.

The generated number of orders to be served in the areas, the distances generated between each pair of areas, and the widths of the 7 areas (depot inclusive) are given in Appendix B.

## 5.2 Comparison of results for the Exact and Heuristic Approaches

To implement the two algorithms described in the earlier sections, the algorithms were programmed in MATLAB. The Exact algorithm had an additional solver CPLEX to the MATLAB. The exact solutions can be used as benchmark solutions to evaluate and calibrate the heuristics approaches on small-sized instances before the heuristics are applied to large-sized instances [26]. The use of exact benchmark solutions and evaluation of heuristics on these benchmarks will provide the researchers in the city logistics field with more confidence and they will be in a better position to appraise and support city logistics-related policies, which are assessed using the heuristics solutions of the VRPTW.

We present the computational results for both the Exact and the Heuristic approaches in Table 1 below.

In the table, each test case (Run) is represented in column one. Columns two, three, and four represent the number of trucks, the time slots, and the number of areas to be served appropriately. Column five highlights the number of orders served for both approaches. The Run time in seconds, the Exit flag which denotes optimality, the total time used for the delivery process, and the values of the objective function are appropriately highlighted in columns six, seven, eight, and nine for the Exact approach. Columns ten, eleven, and twelve represent the Run time (in seconds), the total time used for the service process (in hours), and the objective function of the Heuristic approach. Column thirteen represents the relational gap (Gap) between the Heuristic to the Exact approach.

Table 3: Table of Results for the Exact and Heuristic Approaches

| | Exact Approach | | | Heuristic Approach | | | |
|---|---|---|---|---|---|---|---|
| Run | Run time(s) | T(hrs) | fval | Run time(s) | T(hrs) | FC | Gap |
| 1 | 0.1146 | 3.3938 | 5.0907 | 0.0251 | 4.7267 | 7.0901 | 0.39 |
| 2 | 0.1433 | 4.3226 | 6.4839 | 0.0261 | 5.5442 | 8.3163 | 0.27 |
| 3 | 0.1880 | 4.4688 | 6.7032 | 0.0251 | 5.2716 | 7.9073 | 0.18 |
| 4 | 0.1860 | 4.1863 | 6.2795 | 0.0186 | 5.3083 | 7.9625 | 0.27 |
| 5 | 0.5760 | 5.95095 | 8.9264 | 0.0321 | 6.4264 | 9.6396 | 0.08 |
| 6 | 0.5102 | 4.6883 | 7.0324 | 0.0184 | 7.1082 | 10.6623 | 0.52 |
| 7 | 0.5040 | 3.8070 | 5.7104 | 0.0156 | 6.2689 | 9.4034 | 0.65 |
| 8 | 1.4073 | 6.1404 | 9.2106 | 0.0282 | 9.2226 | 13.8339 | 0.50 |
| 9 | 1.6613 | 6.9493 | 10.4240 | 0.0267 | 9.6032 | 14.4048 | 0.38 |
| 10 | 0.6063 | 4.9599 | 7.4398 | 0.0265 | 8.9366 | 13.4049 | 0.80 |
| 11 | 3.5310 | 8.0811 | 12.1216 | 0.0268 | 12.5507 | 18.8261 | 0.55 |
| 12 | 2.5124 | 9.8700 | 14.8050 | 0.0264 | 13.2859 | 19.9289 | 0.35 |
| 13 | 5.0072 | 6.5785 | 9.8678 | 0.0274 | 10.8991 | 16.3487 | 0.66 |
| 14 | 5.1270 | 7.4359 | 11.1538 | 0.0140 | 11.9453 | 17.9179 | 0.61 |
| 15 | 6.6528 | 10.1722 | 15.2583 | 0.0125 | 13.8005 | 20.7053 | 0.36 |
| 16 | 3.6484 | 9.8959 | 14.8438 | 0.0328 | 14.5207 | 21.7811 | 0.47 |
| 17 | 11.2201 | 10.3550 | 15.5325 | 0.0481 | 15.4824 | 23.2236 | 0.50 |
| 18 | 5.5958 | 13.2375 | 19.8562 | 0.0263 | 15.5847 | 23.3771 | 0.18 |
| 19 | 22.1564 | 11.2214 | 16.8321 | 0.0181 | 15. 2719 | 22.9078 | 0.36 |
| 20 | 35.2261 | 14.3719 | 21.5578 | 0.0332 | 18.6300 | 27.9450 | 0.30 |
| Average | 5.3287 | | | 0.0254 | | | 0.386 |

Note: All computations in this study are obtained using Matlab R2019b version 9.7

The Gap in table 3 was obtained from the relation below:

$$Gap = \frac{FC - fval}{fval}.$$

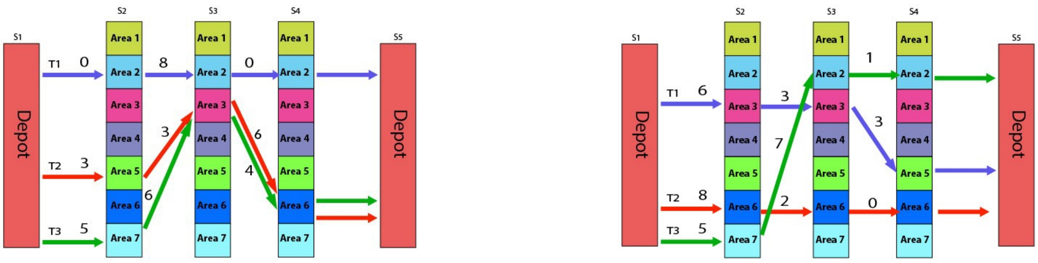
For each instance, we again look out for test cases where all orders available are served in both approaches. The first nine instances gave an exit flag value of 1 which indicates an optimal solution is obtained and the remaining had an exit flag value of 5 which implies the objective value obtained is close to the optimal value. As the number of areas of service increases with the increasing number of orders, the Run time, Time used, and the fval/FC also increases. The computing time (Run time) for the Heuristic approach is generally far faster than the Exact approach. The Exact approach uses less time for the delivery and therefore has minimum values for the objective function as compared to the Heuristic approach.

We next consider the illustration of scenarios under consideration from Table 1 (Run 1 and Run 5) to illustrate the observations made in terms of the truck movements. The first scenario is Run 1, a test case of having 3 trucks, three time slots, and 3 different areas of service, there were 9 orders in Area 2, 1 order in Area 3, and 10 orders in Area 4 which makes up the 20 orders. The second scenario is Run 5, a test case of having 8 orders in Area 2, 9 orders in Area 3, 0 orders in Area 4, 3 orders in Area 5, 10 orders in Area 6, and 5 orders in Area 7 which yields a total of 35 orders as shown on Tables 1, 2, and 3.

### 5.2.1 Truck Movements in test cases


(a) Exact Approach (b) Heuristic Approach

Figure 4: Scenario 1: 2 trucks, 3 time slots and 3 areas of service




(a) Exact Approach (b) Heuristic Approach

Figure 5: Scenario 2: 3 trucks, 3 time slots and 6 areas of service

In the first scenario (Run 1), with the Exact approach, Truck 1 moves from the depot in time slot 1, goes to Area 2, and serves 3 orders in time slot 2. It remains at Area 2 in time slot 3 to serve 6 more orders and returns to the depot in the last time slot. Truck 2 moves from the depot in time slot 1, goes to Area 3 and serves 1 order in time slot 2. It moves to Area 4 in time slot 3, and serves 4 orders, remains at Area 4 to serve 6 more orders in time slot 4 and then moves back to the depot. But with the Heuristic approach, Truck 1 moves from the depot in the time slot 1, goes to Area and serves 6 orders in time slot 2. It remains at Area 2 in time slot 3 and serves 3 more orders. It moves to Area 3 in time slot 4 to serve 1 order and finally returns to the depot. Truck 2 moves from the depot in time slot 1, goes to Area 4, and serves 7 orders in time slot 2. It remains at Area 4 in the time slot 3, and serves 3 orders and then moves to the depot.

In the second scenario (Run 5), with the Exact approach, Truck 1 moves from the depot in time slot 1, goes to Area 2 and serves 0 orders in time slot 2. It remains at Area 2 in time slot 3 and serves 8 orders, and then moves back to the depot. Truck 2 moves from the depot in time slot 1, goes to Area 5 and serves 3 orders in time slot 2. It moves to Area 3 in time slot 3 and serves 3 orders, and further moves to Area 6 to serve 4 orders in time slot 4, and then returns to the depot. Truck 3 moves from the depot in time slot 1, goes to Area 7 and serves 5 orders in time slot 2. It moves to Area 3 in time slot 3 and serves 6 orders, and further moves to Area 6 to serve 6 orders in time slot 4, and then moves back to the depot. While with the Heuristic approach, Truck 1 moves from the depot in time slot 1, goes to Area 3 and serves 6 orders in time slot 2. It remains at Area 3 in time slot 3 and serves 3 more orders. It moves to Area 5 in time slot 4 to serves 3 orders and finally returns to the depot. Truck 2 moves from the depot in time slot 1, goes to Area 6, and serves 8 orders in time slot 2. It remains at Area 6 in time slot 3 and serves 2 more orders, and then moves to the depot. Truck 3 moves from the depot in time slot 1, goes to Area 7 and serves 5 orders in time slot 2. It then goes to Area 2 in time slot 3 and serves 7 orders. It remains at Area 2 in time slot 4 to serve 1 more order and finally returns to the depot.

In each scenario above, the Exact approach has an exit flag value of 1 which indicates an optimal solution is found.

### 5.2.2 Graphical representation of results

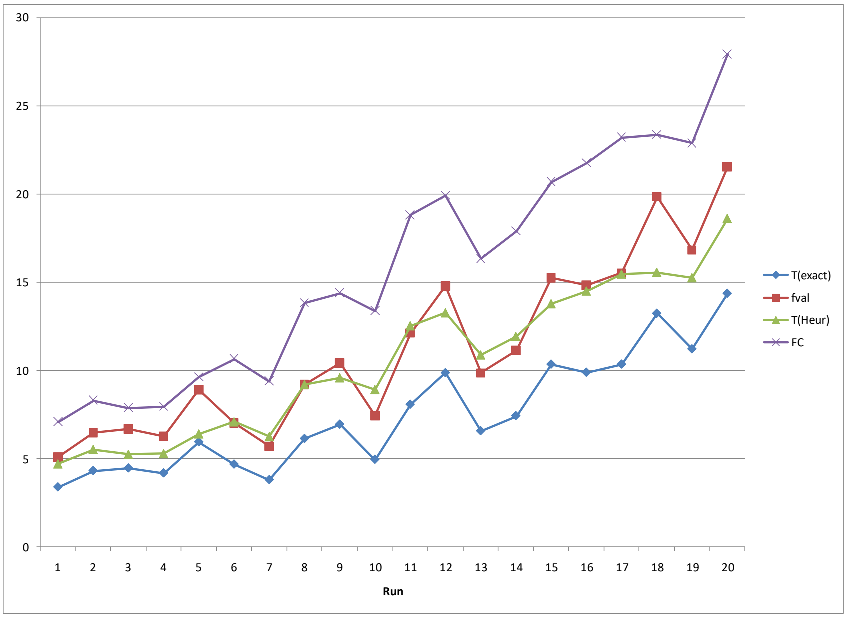



Figure 6: The Graph of the results of the fixed parameters

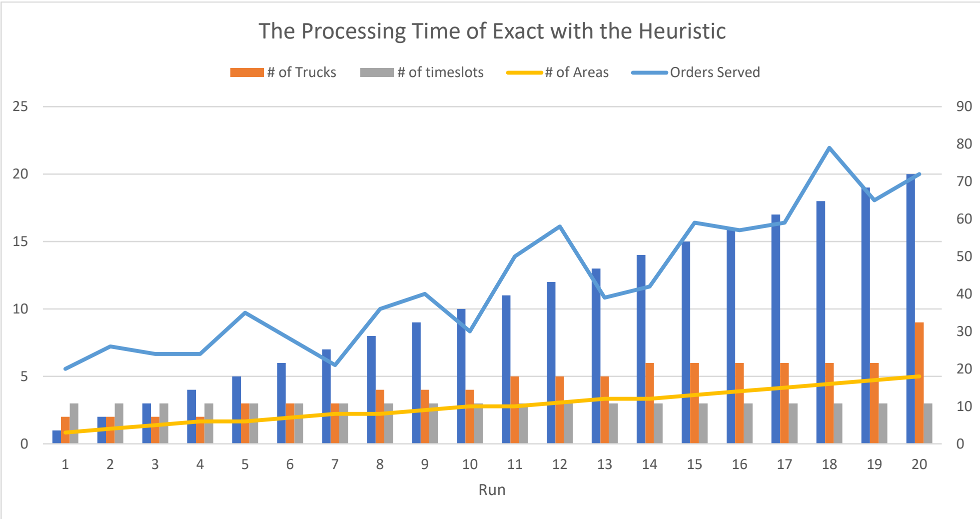



Figure 7: The Graph of Run time versus Run for the Exact and Heuristic algorithms

The objective of this thesis was to propose Exact and Heuristic algorithms for a routing plan to minimize the time of travel for e-grocery delivery which tends to minimize delivery cost and the fuel consumed. The background of the study is given in section one. Earlier research works in section two. We have presented the model in section 3.2, an exact approach in section 3.3, and a heuristic approach in 4.0. The time slot allocation and assignment of customers' orders to vehicles is obtained by solving a generalized assignment problem with an objective function that minimizes the time used in the delivery leading to the minimization of the fuel consumption and delivery cost in sections three and four. And finally, section five presents the summary, conclusion and further research of the study.

In this section, we have presented the result obtained by our proposed algorithms algorithm. We already have the information about the number of areas. We experimented by changing the number of areas and then compared the results of the Exact algorithm with the Heuristic algorithm. We have analyzed the time taken by the proposed Exact algorithm and Heuristic algorithm to visit each area exactly once, and back to the depot. We observed results of the Exact approach that gave optimal solution or near-optimal solution for all the 20 instances of the experiment. The objective values of the Exact and Heuristic approach were compared, and the corresponding relation gabs were found for the experiments.

## 5.3 Summary of Results, Conclusion, and Recommendation

### 5.3.1 Summary of Results

E-grocery home delivery service is chosen as the subject of this study because of the potential contribution of e-grocery delivery in reducing GHG emissions. We proposed an Exact and Heuristic algorithm and illustrate the two approaches to the solution of the MILP model in chapters 3 and 4. The comparison of the processing time of Exact with the Heuristic is described in Table 1. We report the solution of the objective function as fval and FC appropriately for the two approaches. Moreover, we report the computing time (sec) needed to solve an instance for both versions of the algorithm. However, the Heuristic shows greater potential power in terms of computation time to solve the instances. Clearly, in all instances, the Run time for the Heuristic is a far faster than that of the Exact algorithm. Both algorithms were solved within the available system memory.

Each of the 20 instances is solved once with the MIP model described in chapter

3 by using Matlab with a Cplex solver and the proposed Heuristic algorithm was solved with Matlab in section 4. Table 1 indicates that the Matlab with a Cplex solver can find the optimal solution or 'near optimal solution', but in a substantially larger amount of time than the Heuristic algorithm. Considering the 20 instances for which we know the solutions, both the Exact and the Heuristic algorithm solved the VRP with 18 service areas. Our algorithms can be extended to solve larger areas with adjustments or the number of trucks available for use on the service day. As expected, the Heuristic algorithm has a far shorter computing time than the Exact algorithm. The average Run time required by Exact is approximately 5.3287 seconds whiles the Run time of the Heuristic to produce the reported solutions is approximately 0.0254 seconds. The average gap between the value of the objective function for the Exact and the Heuristic algorithms obtained is 0.386

### 5.3.2 Conclusion and Recommendation

**Conclusion** Vehicle routing problem forms an integral part of supply chain management, which plays a significant role in productivity improvement in organizations through efficient and effective delivery of orders to customers. This paper presents the time-dependent vehicle routing problem with time windows, which incorporates the characteristics of the traveling salesman problem with delivery. The time-varying travelling speed is considered to capture the real-world problem of road congestion. Considering time-dependent travel times increases the complexity of the problem. The results depend on the speeds, paths taken, and the starting time of the journey. Getting the minimum cost is useful for vehicle operators to improve their operational performance so that they can minimize the environmental and economic costs.

Logistics companies need not only to consider improving service quality and reducing operating costs but also take a certain corporate social responsibility: reducing greenhouse gas emissions. Vehicle route optimization helps improve fuel efficiency and driver productivity, reduce transportation time, and improve customer retention, which is important to make a business thrive, yielding economic growth with an eco-friendly environment. This study modelled a relative optimization model for a VRPTW with synchronized visits and scenarios considering greenhouse gas emissions. Considering the problem is NP-hard, a heuristic algorithm is developed to solve the optimization model.

This study demonstrates two approaches (The Exact and Heuristic approaches) to minimize the time used in the delivery of groceries. The Exact approach serves as a benchmark to verify the performance of the heuristic method. In our study, both the exact and heuristic methods are examined. Computational results show that in our test cases of 20 instances, the values of the objective functions were found for both the Exact and the Heuristic. All instances were solved to optimality or 'near optimality' within the given memory limit for the Exact algorithm. Though the Exact gives the best solution for all the 20 instances, the heuristic finds its solutions with very good and reasonable computational time (on average 0.0254 seconds) than the Exact. The new algorithms could generate sets of road schedules that can be stored for solving the full vehicle routing problem in grocery delivery providing significant alternatives to e-grocers within a minimum time yielding minimum delivery cost. The Exact model, which was used as a benchmark outperformed the Heuristic model. The performance of the heuristic needs to be revisited due to the wide gap.

**Recommendation** Practically, the computer-based solution system allows adjustments to the problem parameters and generates new solutions easily, therefore, it can be used to facilitate logistics service providers' decision-making process in the urban distribution of groceries. Heuristic methods may work better in some cases when more unpredictable events happen and work on such cases can be used in future research. We recommend that e-grocers adapt the model in real practice.

**Further Study** To improve the accuracy of the heuristic approach, we suggest two future research directions:

1. future studies (research) will seek to improve the performance of the heuristic approach.
2. future research will consider using real-world data from a UK e-grocery company for the proposed algorithms to solve the full vehicle routing problem of e-grocery in the presence of a limited time.
3. also, the success of both exact and approximate methods (Heuristics) suggest that hybrid methods could be an important area of research.

**Appendix A**

In the first scenario (Run 1), the generated number of orders is presented below.

| *Area* | *Area*1 | *Area*2 | *Area*3 | *Area*4 |
|---|---|---|---|---|
| *Width* | 0 | 9 | 1 | 10 |

The simulated distances between the areas under consideration are given in the matrix below:

| | *Area*1 | *Area*2 | *Area*3 | *Area*4 |
|---|---|---|---|---|
| *Area*1 | 0 | 4.1984 | 2.4383 | 1.9890 |
| *Area*2 | 4.1984 | 0 | 5.3861 | 5.0109 |
| *Area*3 | 2.4383 | 5.3861 | 0 | 4.3010 |
| *Area*4 | 1.9890 | 5.0109 | 4.3010 | 0 |

The widths of each of the 4 areas (depot inclusive) are given by:

| *Area* | *Area*1 | *Area*2 | *Area*3 | *Area*4 |
|---|---|---|---|---|
| *Width* | 0 | 0.0259 | 0.5497 | 0.4353 |

The generated driving speed within the areas considered in each time slot is given as:

| | *Area*1 | *Area*2 | *Area*3 | *Area*4 |
|---|---|---|---|---|
| *Timeslot*1 | 15 | 15 | 5 | 15 |
| *Timeslot*2 | 15 | 15 | 15 | 5 |
| *Timeslot*3 | 15 | 15 | 5 | 5 |
| *Timeslot*4 | 15 | 5 | 15 | 5 |
| *Timeslot*5 | 5 | 15 | 5 | 15 |

The driving speed within the areas considered in each time slot is given as:

| | $Area1$ | $Area2$ | $Area3$ | $Area4$ |
|---|---|---|---|---|
| $Timeslot1$ | 15 | 15 | 5 | 15 |
| $Timeslot2$ | 15 | 15 | 15 | 5 |
| $Timeslot3$ | 15 | 15 | 5 | 5 |
| $Timeslot4$ | 15 | 5 | 15 | 5 |
| $Timeslot5$ | 5 | 15 | 5 | 15 |

The speed for driving in each time slot from $i$ to $j$ is mostly not the same as from $j$ to $i$ which gives the asymmetric matrix below:

| $s1$ | | | | $s2$ | | | |
|---|---|---|---|---|---|---|---|
| 45 | 45 | 45 | 45 | 30 | 30 | 45 | 45 |
| 45 | 45 | 45 | 30 | 45 | 45 | 30 | 45 |
| 30 | 45 | 30 | 45 | 30 | 45 | 45 | 45 |
| 45 | 30 | 30 | 30 | 45 | 45 | 45 | 45 |

| $s3$ | | | | $s4$ | | | |
|---|---|---|---|---|---|---|---|
| 30 | 30 | 30 | 30 | 30 | 45 | 45 | 30 |
| 45 | 30 | 30 | 45 | 30 | 30 | 45 | 30 |
| 30 | 45 | 30 | 45 | 30 | 45 | 30 | 30 |
| 45 | 30 | 45 | 30 | 45 | 45 | 30 | 45 |

| $s5$ | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 |

**Appendix B** In the second scenario (Run 5), test case where there were 3 trucks, three time slots, and 6 areas of service.

The generated number of orders to be served in the areas are:

| $Area$ | $Area1$ | $Area2$ | $Area3$ | $Area4$ | $Area5$ | $Area6$ | $Area7$ |
|---|---|---|---|---|---|---|---|
| $Number of orders$ | 0 | 8 | 9 | 0 | 3 | 10 | 5 |

The distances generated between each pair of areas are given as:

| | $Area1$ | $Area2$ | $Area3$ | $Area4$ | $Area5$ | $Area6$ | $Area7$ |
|---|---|---|---|---|---|---|---|
| $Area1$ | 0 | 4.2060 | 8.0481 | 4.0157 | 4.6129 | 8.2625 | 5.3974 |
| $Area2$ | 4.2060 | 0 | 7.7884 | 7.9993 | 2.7375 | 8.0825 | 7.8511 |
| $Area3$ | 8.0461 | 7.7884 | 0 | 11.2699 | 5.0540 | 0.3044 | 5.0288 |
| $Area4$ | 4.0157 | 7.9993 | 11.2699 | 0 | 8.6018 | 11.4231 | 7.1449 |
| $Area5$ | 4.6129 | 2.7375 | 5.0540 | 8.6018 | 0 | 5.3499 | 6.0054 |
| $Area6$ | 8.2625 | 8.0825 | 0.3044 | 11.4231 | 5.3499 | 0 | 5.0530 |
| $Area7$ | 5.3974 | 7.8511 | 5.0288 | 7.1449 | 6.0054 | 5.0530 | 0 |

The widths of the 7 areas (depot inclusive) are given by:

| $Area$ | $Area1$ | $Area2$ | $Area3$ | $Area4$ | $Area5$ | $Area6$ | $Area7$ |
|---|---|---|---|---|---|---|---|
| $Width$ | 0 | 0.0259 | 0.5497 | 0.4353 | 0.4204 | 0.3303 | 0.2046 |

The driving speed within the areas considered in each time slot is given as:

| | $Area1$ | $Area2$ | $Area3$ | $Area4$ | $Area5$ | $Area6$ | $Area7$ |
|---|---|---|---|---|---|---|---|
| $Timeslot1$ | 5 | 5 | 15 | 5 | 5 | 15 | 15 |
| $Timeslot2$ | 5 | 5 | 5 | 15 | 5 | 5 | 15 |
| $Timeslot3$ | 5 | 15 | 15 | 5 | 5 | 5 | 5 |
| $Timeslot4$ | 15 | 5 | 5 | 5 | 5 | 5 | 15 |
| $Timeslot5$ | 5 | 15 | 5 | 15 | 15 | 15 | 15 |

The speed for driving in each time slot from $i$ to $j$ is mostly not the same as from $j$ to $i$ which gives the asymmetric matrix below:

| | | | $s1$ | | | |
|---|---|---|---|---|---|---|
| 30 | 45 | 30 | 30 | 45 | 30 | 45 |
| 45 | 45 | 30 | 30 | 45 | 30 | 30 |
| 30 | 30 | 30 | 30 | 30 | 45 | 45 |
| 45 | 45 | 45 | 30 | 30 | 45 | 45 |
| 45 | 30 | 30 | 30 | 45 | 45 | 30 |
| 30 | 30 | 30 | 45 | 30 | 30 | 45 |
| 30 | 30 | 45 | 30 | 30 | 30 | 45 |

| | | | $s2$ | | | |
|---|---|---|---|---|---|---|
| 30 | 45 | 45 | 45 | 30 | 30 | 30 |
| 30 | 45 | 30 | 30 | 45 | 45 | 45 |
| 45 | 30 | 45 | 45 | 30 | 30 | 45 |
| 45 | 30 | 45 | 45 | 45 | 30 | 45 |
| 45 | 30 | 30 | 30 | 45 | 30 | 45 |
| 45 | 30 | 30 | 45 | 30 | 30 | 30 |
| 30 | 30 | 30 | 45 | 45 | 45 | 30 |

| | | | $s3$ | | | |
|---|---|---|---|---|---|---|
| 30 | 30 | 30 | 30 | 45 | 45 | 45 |
| 45 | 45 | 30 | 30 | 30 | 30 | 30 |
| 30 | 30 | 30 | 45 | 45 | 45 | 30 |
| 45 | 30 | 45 | 45 | 45 | 45 | 45 |
| 45 | 45 | 45 | 30 | 45 | 30 | 45 |
| 30 | 30 | 30 | 45 | 45 | 45 | 30 |
| 45 | 30 | 45 | 45 | 45 | 30 | 30 |

| *s*4 | | | | | | |
|---|---|---|---|---|---|---|
| 30 | 45 | 45 | 30 | 30 | 45 | 45 |
| 30 | 45 | 30 | 30 | 45 | 45 | 45 |
| 30 | 30 | 45 | 45 | 30 | 30 | 30 |
| 45 | 30 | 45 | 45 | 30 | 45 | 45 |
| 30 | 45 | 45 | 30 | 45 | 45 | 45 |
| 45 | 45 | 45 | 45 | 30 | 45 | 45 |
| 45 | 45 | 30 | 45 | 30 | 45 | 30 |

| *s*5 | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |

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