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Integrating the Differences among Drivers in Determining the Optimal Path for Green Vehicle Routing

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Dedication

I dedicate my work to my husband and soul mate, Ayham, and my sweet twins, Hamza and Rawad.

To my father and mother and siblings

To my sincere relatives & friends

Thanks for their love, encouragement and prays to bring this work to the light.

I also dedicate this work to all souls who are inspired with knowledge and creativity, to all those who struggle to success, to the science lovers and seekers.

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To all friends and relatives who have sounded so genuinely pleased and interested over my studying period.

الإقرار

أنا الموقعة أدناه مقدمة الرسالة التي تحمل العنوان:

Integrating the Differences among Drivers in Determining the Optimal Path for Green Vehicle Routing Problem

أقر بأن ما اشتملت عليه هذه الرسالة إنما هي نتاج جهدي الخاص، باستثناء ما تمت الإشارة إليه حيثما ورد، وان هذه الرسالة ككل، أو أي جزء منها لم يقدم من قبل لنيل أية درجة علمية أو بحث علمي أو بحثي لدى أية مؤسسة تعليمية أو بحثية أخرى.

Declaration

The work provided in this thesis, unless otherwise referenced, is the researcher's own work, and has not been submitted elsewhere for any other degree or qualification.

Student's Name: **الإسم:**

Signature: **التوقيع:**

Date: **التاريخ:**

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Abbreviations

BBMO: Bumble Bees Mating Optimization Algorithm.

CMEM: Comprehensive Modal Emission Model.

CTRP: Combination Tuck Routing Problem.

CVRP: Capacitated Vehicle Routing Problem

DVRP: Dynamic VRP.

EOL: End of Life.

FPVRP: Flexible Periodic VRP.

GPS: Global Positioning System.

GVRP: Green VRP.

GVRPOD-DB: Green VRP model with Occasional Drivers Integrated with Drivers' Behavior.

GVRPPD: Green VRP with Pickup and Delivery.

HFVRP: Heterogonous Fleet VRP.

IRP: Inventory Routing Problem.

3L-VRPCB: Clustered with Three Dimensional Loading Problem.

MDFSMVRP: Multi-Depot Fleet Size and Mix VRP.

MDVRP: Multi Depot VRP.

MOVRPM: Multi-Objective Vehicle Routing Problem Model**.**

MINLP-MOM: Mixed Integer Non Linear Programming and Multi-Objective Model

OVRP: Open VRP.

OVRPTW: Open VRP Model with Time Windows.

PRP: Pollution Routing Problem.

PVRP: Periodic VRP.

RPA: Route-Path Approximation.

RVNS: Reduced Variable Neighbourhood Search.

RVRP: Rich VRP

TDPVRP: Time-Dependent Pollution VRP.

TDVRP: Time-Dependent VRP.

TDVRP-PS: Time Dependent VRP with Path Selection.

VRP: Vehicle Routing Problem.

VRPB: VRP with Backhauls.

VRPOD: VRP with Occasional Drivers.

VRPODTW: Vehicle Routing Problem with Occasional Drivers with Time Window.

VRPPD: VRP with Pickup and Delivery.

VRPTW: VRP with Time Windows.

2E-VRPPD: 2 Echelon VRP with Pickup and Delivery.

3L-VRPCB: Clustered with Three Dimensional Loading Problem.

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Abstract

Vehicle Routing Problem (VRP) is one of the most common real-world operations research applications that grasped a rich attention from researchers in order to develop as much realistic models as possible. Although researches have been conducted to solve different variants of VRP model, richer models are still required to simulate more real-life circumstances. For instance, the emerging unexpected conditions (i.e.: accidents, or unexpected congestion); and dealing with over-capacitated acquired fleet of trucks. More importantly, VRP models have been proposed as isolated from the most effective factor on the success of VRP plan on ground; who is the driver. Therefore, this research spots the light on the effect of driver behavior on the optimal VRP plan, and evidences are given by figures to convince decision makers with the possibility of integrating such factor provided with the significance of the accompanying effects. The level of autonomy of making logistical decisions such as speed or route changing decisions for both planner and drivers have been represented in the model by involving risk taking parameters, and the effect of changing the level of autonomy on VRP total costs has been investigated using a sensitivity analysis. Also, in order to enhance the model configurations' practicability; the idea of "ride sharing" is introduced by involving not only full time regular drivers to serve, but also occasional drivers set to be available to serve when shortages happens in logistical services, or when remote orders are received from rural or country-side areas as uncommon destinations for regular drivers. For the purpose of ensuring environmental friendly logistical practices, the policy of velocity maximization has been used as well as imposing environmental penalties on the chosen rate of velocity associated with certain fuel consumption rate. Whereas the proposed VRP model satisfies both the driver by assigning a certain level of autonomy; and the firm's financial objectives via total costs minimization; it additionally accounts for the consumed energy during serving customers in order to optimize the service time. A numerical instance with a hypothetical data set has been solved by Eclipse Java 2018-9 solver by using two heuristic methods which are adaptive solving algorithms and are able to find a local optimal solution (i.e.: the Greedy, and the Intra-route neighborhood heuristic), both revealed the same near-optimal solutions. Such VRP modeling and results have been used as a proof of concept to verify the proposed VRP model. Ultimately, the results are analyzed sensitively and show that the resulted insignificant increase in VRP costs due to assigning different levels of autonomy for drivers are still reasonable, as the total costs' objective function weight has a mere effect on the total optimal solution, while that for the energy consumption function has the largest effect.

Chapter One
Introduction

1.1 General Background

One of the most popular applications of the operation research science is Vehicle Routing Problem (VRP). VRP; which was defined by Clarke and Wright (1964) as serving customers' network distributed in different geographic points, using different capacities' fleet of trucks. VRP-related studies have been exponentially grown about six percent per year in the literature researches (Eksioglu et al., 2009). Besides, VRP has grasped its importance due to its wide usage in the logistics and transportations' aspects. Moreover, the literature has concentrated on different variants related to VRP, in which the scholars set models and solutions for many real life problems to control difficulties associated with different stages of transportation. Such difficulties are the travel times of transportation, pick up and deliveries time window and input information (Braekers et al. , 2016).

Paraskevopoulos et al. (2017) stated that the routing and scheduling planning process confront some challenges with allocating scarce resources for certain services. On the other hand, VRP topic has widely been analyzed due to its impact on various industries (Lahyani et al., 2017). Based on taxonomic review related to VRP topic since 2009 up to 2015, it reveals that the literature focused on some important VRPs' aspects, and different models were suggested to solve different objectives' problems, for instance, the capacitated VRP, periodic VRPs, VRP with time windows and others (Braekers et al., 2016). Additionally, a very crucial side which considerably affects the optimal results required for such a VRP case is human factors. Jabbour et al. (2015) published a study relating to the importance of integrating green human resources (GHRM) in order to optimize the use of a Green Supply Chain Management (GSCM) that considers using a certain green policy when applying the supply chain stages. The drivers who are the subjects that manage the transportation process are critical to be considered while analyzing a VRP model. Controlling those drivers' behaviors would fundamentally improve the sought goals when applying any VRP model. Accordingly, a literature review has been made by Alam and McNabola (2014) and found that controlling the driver behavior in a green manner can reduce the fuel consumption by 45%. In the same vein, Liimatainen (2011) developed a study of utilization of fuel consumption data to be used in an incentive system for the heavy-duty vehicles' drivers as a practical solution to be used by logistical companies to motivate drivers to stick to the energy-efficient routing plan. He also mentioned that such behaviors are variable with the individual differences, by which the fuel consumption could vary up to 30%.

A study conducted by Archetti et al. (2016) discussed VRP topic with a special case, when using occasional drivers as a ridesharing concept to serve different logistical companies. Based on that, this work will focus on developing a multi criteria approach for solving a VRP model, which takes into consideration the green policy; by which the environmental issues are being studied and solved by accounting for the optimal velocity range accompanied with the lowest environmental penalty imposed on certain fuel consumption rate. Also, the effects of drivers' differences on the driving pattern will be understood in order to introduce representative parameters that could be integrated with VRP model to optimize its results. Such differences are; level of autonomy, drivers ages and fatigue relationship, their level of skills and performance, and the training and awareness sessions they exposed to, are all intended to be studied in examine the possibility of integrating a human factor which is able to optimize VRP solutions realistically on ground. The occasional drivers who are the third external partners to be used for excess or remote customers' orders as a safety procedure are the third issue to be studied in this research. The model is assumed to produce the minimum travelling costs and fuel consumption. The following literature review systematically compares between the different contributions and the developed solving methods. Also, the research problem as well as research significance, questions and objectives are finally defined clearly. Consequently, the main aim of this research is to develop a model that can consider several aspects of green VRP such as occasional drivers and drivers' differences.

1.2 Problem Statement

VRP topic has been widely discussed in the literature. The challenge on providing a realistic model that reflects the real-life aspects is being adapted by multiple academic researchers. Though, it is clear that the variants used to be studied while considering that there are no differences between drivers, and so, all the near optimal results are idealized regardless the driver behavior pattern (Srinivas and Gajanand, 2017). Different objectives had been analyzed such as minimizing the routing travelling costs, travelling time and distance as well as reducing the air pollution levels resulted from such logistical activities. Recently, other persistent necessities have emerged as a result of the accelerated development of the technological and transportation industries. For instance: adopting a green policy when modeling for VRPs' different variants, integrating drivers' behavior with VRPs models, including occasional drivers in the routing plan, considering the route status such as congestions issues as an important factor to be planned for and taking into consideration the required customer service level. Consequently, this study aims to develop and near optimally solve an eco-friendly VRP model integrated with driver behavior controlling parameters, involving both regular and occasional drivers. To the best of our knowledge, as can be shown from the reviewed literature, those topics had been studied individually and VRP models have been studied as isolated from the driver's behavior pattern.

1.3 Research Significance

From what has been discussed above, the necessity is being emerged to develop a rich VRP model which is able to quantitatively and qualitatively improve the three pillars of sustainability; the economy, the environment, and the society. Developing a VRP model that improves the perceived quality of the value-chain stakeholders (i.e.: from the corporate management down to the customer) is expected to prosper the logistical firm’s outcomes. More specifically, the society members from rural areas to city-center dwellings will be satisfied with VRP services offered not only by capacitated regular drivers’ set, but also by occasional drivers. Recently, the logistical practices and industrial activities are being aggressively developed, not only locally but also globally across continents, and the routing planning system becomes more complex and forked. Therefore, the idea of ridesharing is considered as a safety method for over-capacity delivery requirements. The concept of ridesharing has been defined as sharing the individual travelers of the travelling costs for riding others’ vehicles for a trip when they have similar time schedules, such idea has been introduced in the state of art by Furuhata et al. (2013). This concept has been developed later by Walmart to be their vision in using in-store customers to make delivery for on-line customers who are close to their destination (Archetti et al., 2016). On the other hand, such service will load additional compensation costs on VRP costs; however, they are optimized by the proposed model. Furthermore, controlling the drivers’ behavior; who significantly affects the routing process desired outcomes on ground; will sustain that the drivers' behaviors' variations are controlled, and the effect on the routing expenses is optimized as well. However, integrating the driver behavior concept in VRP model; represented by controlling the assigned level of autonomy for drivers; is expected to improve the driver satisfaction level. This in turn would help in achieving the strategic objectives of the firm by mitigating variance between the planned and on ground achievements. Finally, the recent orientation toward a green environment and sustainable world has imposed an urgent attention from researchers and practitioners; a service as logistics are considered as major sources for pollution and so, VRP model would never be comprehensive unless accounting for a green policy.

Consequently, an eco-friendly VRP model is developed by controlling the routing optimum velocity and enforcing an environmental penalty on fuel consumption rate; while considering at the same time both society satisfaction and firms' economy prosperity.

1.4 Research Objectives

This work aims to achieve the following objectives:

1. To identify the best configurations of VRP model to be a rich and realistic model that simulates real circumstances of logistical firms' activities. The proposed model is intended to be sustainable by optimizing the economic objectives of VRP plan; improving the society satisfaction level, and accounting for a green logistical policy. Such VRP configurations are involving the use of a third part to cover

shortages in logistical services to improve the service level as well as incorporating the driver’s behavior when designing the logistical services’ network. Such objectives are intended to be optimized financially and environment-friendly.

2. To develop a comprehensive and solvable mathematical model that consists of the required multi-objectives function that satisfies the required VRP model configurations. This then is verified as a proof of concept in line with the intended objectives of VRP model.

1.5 Proposed Methodology

This study is following the analytical operations research’s methodology in order to achieve the objectives of this research. Firstly, in order to determine the required configurations of VRP model to be a rich and realistic and to identify the current problems and the suggested future works; a systematic literature review is conducted. This will ensure a comprehensive understanding of the limitations and gaps of the available VRP model. As a result, the problem that will be solved in the proposed VRP model could be determined and defined in terms of its required objectives to be achieved by the model, as well as understanding the accompanying constraints to solve the model. Such problem definition is important to be thoroughly understood and confirmed as it comprehensively covers the total features of the intended VRP variants and characteristics; this is necessary to ensure that the representing mathematical model which will be formulated later on consists of all the required preliminaries and functions, and to know the necessary configurations for applying VRP model on ground. And as such, all the obtained knowledge will be integrated for defining the best configurations and specifications for the intended VRP model.

Secondly, a mathematical model that accounts for the obtained VRP configurations is formulated as a comprehensive and solvable VRP model, and then it is coded using the suitable language in a way that integrates all the approved VRP model specifications. After that, the proper solving algorithms are determined; depending on the model characteristics; and the model is solved by using the proper solver. More specifically, the heuristics algorithms are examined to solve the model as they are usually able to solve different real-life aspects' VRP models even for a large scale size, such algorithm could improve the quality of the solutions in short computing time, Juan et al. (2015). As VRP is NP-Hard problem, heuristics are used to solve it until finding a local optimal solution. Two specific algorithms are intended to be used; the Greedy method, and Intra-Route Heuristic Neighborhood Search method; the first algorithm initializes the near optimal solution, which might be improved by using the second algorithm. Both methods are adaptive and iteratively improve the candidate solutions until find the local optimal solution. Such heuristics' algorithms could not find the global optimal solution in comparison with the exact methods. Therefore, solving the model by two methods might improve the obtained near-optimal solution, as the used heuristics could not maintain that the solution is global such as the case when using exact algorithms.

Thirdly, in order to validate the proposed model, a numerical instance is solved using the proper solver and algorithms. Furthermore, sensitivity analyses are conducted to test the affective relationships on the model results. Such results could be used to influence important decisions related to logistical firms' activities and will be evidences to convince decision makers towards the required changes on the available logistical systems. Figure 1 presents flow chart of the proposed methodology.

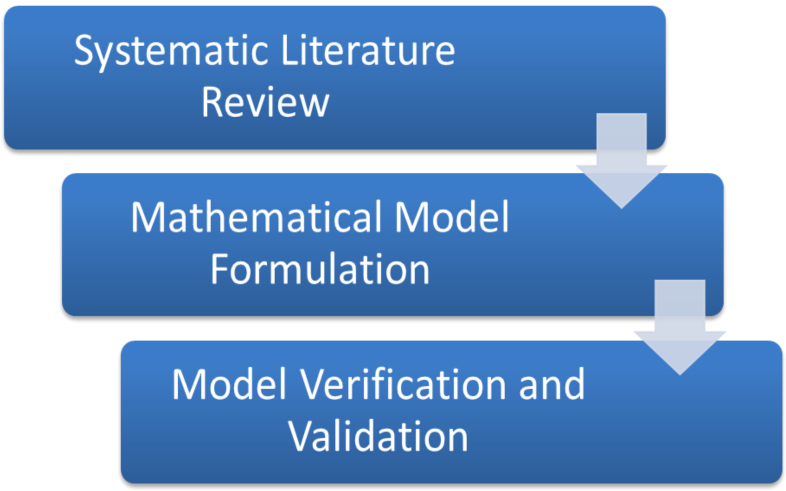

Figure 1: Flowchart of the proposed Methodology**.**

1.6 Thesis Organization

This thesis has been organized as following:

Chapter Two includes the literature that has been reviewed systematically in order to get a comprehensive understanding about the available VRP models, and to define their gaps and limitations. Chapter Three describes the proposed mathematical model in terms of its formulation, preliminaries, decision variables, parameters, assumptions, objective functions' and constraints' formulations and descriptions, as well as the linearization process. Chapter Four introduces results of the proposed numerical instance that has been used with hypothetical data set, in order to verify the solvability and validity of the model. Those results release an optimal VRP routing solution, including the optimal consumed energy, the optimal velocity, the optimal environmental penalty, and the optimal total costs. Also, the model decision variables solutions present the decision to choose either regular or occasional driver; the optimal loaded quantity, and the optimal choice of velocity rate. Chapter Five discusses the sensitivity analyses that are conducted on risk taking parameters and total costs and on the effect of each objective function weight on the total optimal solution. Finally, conclusions, limitations, and future works are presented in Chapter Six.

Chapter Two
Literature Review

2.1 Overview

This chapter presents the systematic literature review related to VRP topic. Since the focus of this research is developing a rich VRP model that incorporates real-life configurations, the available suggested VRP models have been understood in order to identify the emerged gaps and scan the future works as have been suggested in recent literature. Miscellaneous literatures of variants and contributions of the proposed VRP models are classified as related to the following topics:

- Classical VRP
- Green VRP
- Rich VRP
- VRP and drivers’ behavior

2.2 Classical VRP

The case of a gasoline trucks’ fleet serving multiple stations had firstly been considered as a Truck Dispatching Problem by Dantzig and Ramser (1959). In their paper, they were seeking to satisfy all stations demand totally with the minimum possible covered mileage, by solving the problem as a linear programming formulation. Later on, Clarke and Wright (1964) had generalized the problem into the case of solving the best network of customers spread around a central depot point. However, both researches had not considered the real life aspects which are associated with the large scale real problems. Nevertheless, it becomes an easier challenge to create more practical solutions to serve the reality. The technological revolution as well as the telecommunications industry helped vigorously in applying the idea of the trucks dispatching problem considering different real life requirements.

In relation to VRP research topics, different taxonomic reviews and classification studies were executed. Eksioglu et al. (2009) explained the methodology to classify VRP-pertinent literature, they argued that VRP related literature were disjointed over time and an all-encompassing review study is needed in order to keep track of the topic much easier and in discriminating manner. Depending on their work (2009), another detailed review was accomplished by Braekers et al. (2016), in which they analyzed the various trends of VRP found in literature between (2009- 2015). A review of 277 articles revealed that academic researchers have focused on different variants of VRP topic and different important points were discussed. Such a rich topic brought the opportunity to study different real life problems associated with VRP. For instance, the Heterogonous Fleet VRP (HFVRP) in which the capacity of the trucks was variable; Koç et al. (2016) presented a comparative analysis of the literature presented through thirty years of studying the HFVRP and the related variants and meta-heuristic algorithms, the HFVRP has been defined as serving a set of customers with known demands by a limited or unlimited capacitated fleet of trucks, with the minimum vehicle costs. Also, Lai et al. (2016) studied a multi-graph HVRP with time constrained, and solved the mixed integer linear programming model with a Tabu search heuristic, which provided an enhanced routing costs and better customer service. Moreover, other related variants were widely studied in the literature such as: VRP with Time Windows (VRPTW) which is related with the different service time for each customer, VRP with Pickup and Delivery (VRPPD), the Multi Depot VRP (MDVRP), the Periodic VRP (PVRP) and Backhauls VRP (VRPB).

In order to understand the different variants of VRP, some studies in the literature were reviewed regarding each variant and the contributions were analytically compared. More specifically, VRPTW; which refers to the time collapsed when serving the customer until ending the service; various literatures discussed that variant. Lahyani et al. (2015) presented a taxonomic review and compared between the soft times windows in which penalties are given for late vehicles' service, while with hard time windows the vehicle is not allowed to arrive late.

Meanwhile, VRP were expanded in a way that serving the industrial applications, Gribkovskaia et al. (2008) studied the case of satisfying only the profitable pickup points' demands. In their study, a mixed integer linear programming formulation has been designed to minimize the total cost associated with the covered routes with totally delivered orders, and partially satisfied pickups. They argued that it is sometimes more beneficial to serve the same customer twice rather than creating a full route circle. Recently, Belgin et al. (2018) published a study regarding VRPPD with two-echelon (2E-VRPPD), in which the pickup and delivery operations are being accomplished simultaneously, with the same vehicle delivering the orders totally from depot to the destinations, and from destinations back to the depot point. Both Node-based mathematical model and a hybrid heuristic algorithm were used to solve the 2E-VRPPD in medium and large size.

When considering the fleet's trucks differences, the capacity of the truck/vehicle is one of the important decisions that affect the optimal VRP network choices. Lahyani et al. (2015) mentioned that the Capacitated Vehicle Routing Problem (CVRP) provides a solution with the minimum costs with a closed route circle, one time customer service by one vehicle, and the route total demand must not exceed the assigned vehicle capacity. Also, Li et al. (2016) shed the light on the combination-vehicle attributes as a combination Tuck Routing problem (CTRP), in which the vehicle types and the travelled distances were considered in a survey, and a heuristic algorithm was applied to solve a real logistical case.

However, another challenging variant rather than the regular single VRP is the MDVRP. In this setting, the final clients; who are not clustered around each single depot; are being served from different depots. Montoya-Torres et al. (2015) have published a literature review work about the MDVRP considering different VRP variants' works. Also, they presented different approaches which had been suggested to solve the problem. Consequently, researches were extended on the topic of the MDVRP to be as realistic and serve the real applications as effectively as possible. Lahyani et al. (2017) introduced in their work a combination of Multi-Depot Fleet Size and Mix VRP (MDFSMVRP). Both Branch-and-Cut and Branch-and-Bound algorithms were used to solve the suggested formulations with different indexes. An improvement on the lower and upper bounds on the tested instances has been achieved considerably.

Referring to the PVRP which has been defined by Campbell and Wilson (2014) as a vehicle routing problem with multiple periods' service; the customers orders' are being scheduled to be met on multiple periods, with the same fixed quantity. A recent study presents the PVRP as a flexible characteristic, in which Archetti et al. (2017) discussed the Flexible PVRP (FPVRP) where the objective function here minimizes the total routing costs while giving some flexibility of the customer orders' satisfaction frequencies and quantity, during the planning horizon, rather than fixed frequencies and quantity. Also, the FPVRP considers the inventory costs accompanied with the objective function, which is modeled in the Inventory Routing Problem (IRP). The results of their work revealed that the costs were minimized better than using PVRP or IRP.

According to the routes' types that are planned to be covered by the available fleet of trucks, another variant emerged; VRP with Backhauls (VRPB) in which both delivery and pickup are available on the same routes. A study conducted by Koç and Laporte (2018) analyzed the different VRPBs literature and compare between the exact and heuristic algorithms. Also, the literatures available about the standard VRPB as well as the different variants are tabulated in the study, with the defined mathematical model and solution. Accordingly, Bortfeldt et al. (2015) had extended VRPB into clustered with three dimensional loading problem

(3L-VRPCB). Here, the line-haul customers should be served before the backhauls ones. Two hybrid algorithms were suggested to plan for the packing and routing procedures. Also, García-Nájera et al. (2015) suggested a multi-objective model that minimizes the number of vehicles, the traveling costs and the un-serviced backhauls. And so, the suggested similarity–based evolutionary algorithm brought solutions for real life applications.

Recently, it has been noticed that three VRP variants are more important to consider in a combined VRP model, in order to be a Rich VRP (RVRP), those are the Open VRP (OVRP), the Dynamic VRP (DVRP) and the Time-Dependent VRP (TDVRP) (Braekers et al., 2016). Various researches concentrated on those variants and suggested different algorithms to solve the optimal solution. For instance, the OVRP, which supposes that vehicles should not return to the depot after making deliveries. A work presented by Marinakis and Marinaki (2014) suggested a new developed Bumble Bees Mating Optimization (BBMO) Algorithm to solve the OVRP. A comparative analysis was conducted between the other meta-heuristic, evolutionary and other nature inspired algorithms. They argued that the results were satisfactory and better solutions were revealed. According to the important variant; the DVRP, wide researches were conducted as accompanied with different mix of other variants. The DVRP grasped its importance from the fact that the real life aspects are mostly dynamic in their natures and requirements. Pillac et al. (2013) published a review paper which comprehensively studied the different

DVRP works from different perspectives. Specifically, two dimensions are important to understand when studying the DVRP; from which the dynamicity degree comes; which are the evolution and quality of the information being transferred across the planning horizon. Regarding the evolution, the information could be changed after the planners defined a routing plan, while the quality of the information immerses from the uncertain demand available data. As the recent technological revolution provides an easier following up system for the routing planning process, as the complexity of the DVRP increases and the need for richer VRP models is emerged.

Furthermore, another important variant of VRP is the Time-Dependent VRP (TDVRP). Accordingly, Maden et al. (2010) mentioned that the previous VRP variants were being studied supposing that the routing plan is static regarding to the vehicles speeds and journey time. On the contrary, the traffic congestion will aggressively affect the optimal solution of the planned routes from costs and distances overviews. Therefore, the study of VRP would be more realistic when considering the current traffic prosperities. As nowadays, on point information about traffic on a certain route would help in identifying the expected time to cross a certain route. Thus, using the TDVRP would highly improve the optimal solution of the routing plan with minimum costs and time. Moreover, the optimal solution is expected to be enhanced not only in minimizing time durations for the planned routes but also in CO_2 emissions of the travelled journey. A case study conducted by Maden et al. (2010) described a heuristic algorithm which minimizes the total travel time of VRP, taking into account the variation caused by the expected traffic congestion, which is usually higher during rush hours. The results of the study which were conducted on a south western sample in the United Kingdom shows that 7% of CO_2 emissions were reduced comparing with the traditional VRP model with emissions' saving objective.

Franceschetti et al. (2013) presented an integer linear programming formulation which considers minimizing the costs of the travelled journey in both emissions and drivers' costs. Such a model is referred to a Time-Dependent Pollution VRP (TDPVRP). They documented that using the assumption of a fixed speed rate when planning for VRP optimal solution would deviate from the expected CO_2 emissions by 20% for the gasoline vehicles. Also, both congestion and free flow cases were studied and a complete characterization of the optimal solution was derived which prescribes all the speed and congestion properties. Another interesting work considering the TDVRP including the path selection decision was presented by Huang et al. (2017). Here, the conventional assumption of the given customer location and arcs was improved by providing a path selection choice explicitly in the road network, this means that the model provides a solution with optimal route and path selection decision depending on both departure times and congestion levels related to the suggested network. A variant called Time Dependent VRP with Path Selection (TDVRP-PS) has been solved using The Route-Path Approximation (RPA) method which provides near optimal solution taking into consideration a stochastic traffic conditions.

2.3 Green VRP

The logistics and distribution processes world are highly crossed with the persistent need of green policy applications worldwide. For this point, different researches have considered the green awareness toward having a sustainable VRP models. A survey conducted by Lin et al. (2014) comprehensively reviewed the different available literature on the Green VRP (GVRP). The suggested models were analytically compared and categorized into GVRP and Pollution Routing Problem (PRP). Suggestions were presented about considering the GVRP with other VRP variants. The philosophy of this work considered the traditional VRP researches, a survey on the GVRP and presented how the traditional VRP could interact with the GVRP in the coming inspired researches' topics. This work could be used as a starting point in order to help researches and logistics practitioners in creating a sustainable VRP work that considers the important variants combining the most important real life aspects and the green continual needs.

One of the available rich works that combines green issues with VRP has been recently published by Niu et al. (2018). Authors considered an Open VRP model with Time Windows constraint (GOVRPTW). A hybrid Tabu Search Algorithm was suggested depending on the Comprehensive Modal Emission Model (CMEM). The suggested model aimed to minimize the routing costs regarding both the fuel and CO_2 emission costs. The results of realistic instances computed on a Chinese sample revealed that such an open VRP model reduced both fuel costs by 20% and CO_2 emissions costs by 30% approximately.

For the purpose of controlling the environmental pollution caused by the distribution process emissions, a paper has recently been published by Hosseini-Nasab and Lotfalian (2017) classifying between the selected route type by the fuel consumption level depending on the average velocity level. They argued in their work that many researchers solved the green VRP with considering the fuel consumption rate minimization (Gurtu et al., 2015; Zhong et al., 2004), the case that impedes a similar route planning in terms of sticking to a certain route type and average velocity during the routing plan, which is not practical when implementation. Therefore, they have suggested that studying the effect of road type on average velocity and the accompanying fuel consumption rate would be effective in reducing fuel cost and emissions (Fagerholt et al., 2010). A three objectives' mathematical model has been proposed which; 1) minimizing the travelling costs and the consumed energy, 2) minimizing the fuel consumption rate by minimizing the incurred environmental penalty, and 3) maximizing customer satisfaction level in terms of maximum possible average velocity. After running the model on numerical instances, the results revealed that an improvement opportunity is existed for reducing the environmental pollution and planning for an eco-friendly routing plans; by considering the relation between the route type and certain fuel consumption rates associated with CO_2 emission. This in turn would save the non-renewable natural resources. Also, they suggested that as the model is NP-Hard programming and will be time consuming for solving large instances; it would be more realistic to solve the model by using heuristics, meta-heuristics or an exact method, such as; Spatial branch-and-bound, and Branch-and-reduce (Burer and Letchford, 2012).

2.4 Rich VRP

As mentioned by Braekers et al. (2016), the reviewed researches between (2009-2015) were considering the real life aspects of VRP as individual cases, or only considering some variants. As a result, the suggested models cannot be easily generalized for real cases and applications. Therefore, future work considering multiple variants to have a richer VRP models were suggested. The RVRP is defined as VRP model that considers various real life complexities (Goel and Gruhn, 2008). Related to the available published rich VRPs models, Lahyani et al. (2015) presented a taxonomic review to analyze literature available about RVRP. They also provided the proper requirements that should be available to consider a study as a RVRP study. An important matter they mentioned was the gap between the suggested RVRP models in the literature and the complexity of the real life aspects. They argued that most researches focused on providing a mathematical model with solution rather than adjusting the real life characteristics with the suggested model. In their paper, they provided the requirements as the optimization criteria, constraints and preferences that should be available in order to produce a RVRP model. One more work on the RVRP was presented by Goel and Gruhn (2008). The variants that were studied as combined are: time windows restrictions, heterogamous fleet of trucks with variable travel times, travel costs and capacity, multi-dimensional capacity constraints, multiple pickups and delivery locations' service, different starting and ending point and route restrictions. According to the high constrained provided model, an iterative improvement approaches such as Reduced Variable Neighbourhood Search (RVNS) algorithm and a tour relatedness measure. The results of the computational experiments revealed that the suggested algorithm would work effectively under dynamic planning systems. In the same vein, a case study on the semiconductor supply chain released two mixed integer linear programming formulations (Madankumar and Rajendran, 2018). The model which considers a Green VRP with Pickup and Delivery variants (G-VRPPD-SCC) aims to minimize the related routes' and schedules' costs related to the semi-conductor supply chains. The results were compared with other suggested models in literature and had a less computing time and performed well in solving different problems instances.

Similarly, Soleimani et al. (2018) studied the collection and distribution (pick-up and delivery) of the original and remanufactured, End of Life (EOL) products. A Green VRP with Pickup and Delivery (GVRPPD) model was suggested to reduce the collection and distribution processes-related costs as travelling costs (fuel cost), cost of setting up the distribution centers as well as minimizing the supplying vehicles and air pollution levels. The multi-objective non-linear programming model has been linearized and solved by a fuzzy approach. Testing the model on a real case study proofed the achieved improvement on the objectives. Therefore, such a GVRPPD model would highly increase the efficiency of the related businesses working on reverse logistical chains.

As shown from the previous literature review, different researches were published on VRP variants (Gribkovskaia et al., 2008). Recently, the topic is still attracting academic researchers in a way that meets the logistical practitioners' needs. Mostly, the suggested VRP models with various combinations of the variants focus on minimizing travelling costs as well as time, such as: García-Nájera et al. (2015) and Soleimani et al. (2018). New gap has been emerged in order to make VRP models more practical and beneficial. Specifically; enhancing customer satisfaction, creating more practical models by adding new operational planning characteristics such as cross docking process, connecting constrained scheduling process with routing problem, considering road environment when planning for a VRP model, using occasional drivers as an economic sharing concept and studying the most effective human factors related to VRP topic.

The cross docking process was studied by Ahmadizar et al. (2015) as a two level VRP. The process which includes three main activities named as collection of arrived goods from the coming inbound trucks, classifying products into same kind categories and finally dispatching each category to the defined destination points. Implementing the cross docking processes is possible on different choices of routes' network available on ground to arrive to the suppliers and delivery destinations. The proposed model assigns products, suppliers, cross-docks as well as the optimal routes' network and schedules. They presented a hybrid genetic algorithm that was applied on several examples to minimize the purchasing, distribution and holding in storage costs. Studying the reverse logistics operations was suggested as further research point. Furthermore, the optimization of VRP solutions not only include minimization of related costs and time, but also would be extended to include the availability of required resources which are considered as scarce and important to sustain the required VRP plans. Paraskevopoulos et al. (2017) reviewed the literature executed on synchronizing the important resources schedules with the routing plans. Although some literature were found using the variants as Skill VRP or Technician Routing Problem in their study, the topic is still not enough matured. The mentioned taxonomic review claimed that a paper published by Tozlu et al. (2015) has presented the idea from both product and service planning view, as a Variable Neighborhood Search Algorithm (VNS) was suggested to solve a routing model for assigning a limited health care service providers to different patients. The review also suggested different gaps as an opportunity for future researches.

Additionally, VRP topic would serve considerably the logistics practitioners who are stick to definite partners and with whom they need to maintain their required service level as agreed with contractual obligations. VRP with service level constraints has recently been studied by Bulhões et al. (2018). A compact mathematical formulation, a branch and cut algorithm, and a hybrid genetic algorithm were proposed to balance between the required service level with a minimum costs. Therefore, planning for a VRP with an acceptable level of service would highly increase the profit of a certain logistics company, such a topic is important for academic researchers to study, and include as much rich variants as possible. Subsequently, studying factors affecting the service level is important when preparing a routing plan. Such factors are the drivers' behaviors which significantly affect the routing decisions such as speed and routes choices. An analytical framework for studying the relationship between the drivers' behavior and VRP is presented by Srinivas and Gajanand (2017). They claimed that the available literature studied VRP variants as separated from the topic of drivers' behaviors, though, the planner behaviors of VRP were also considered. This work motivates researchers to integrate the drivers' behaviors factors within the familiar objectives of VRP; minimizing costs, time and pollution. This inspiring work might bring new thinking in modeling VRPs and facilitate applying them easily in real life.

As been noticed from the latter mentioned topics, there are many factors affecting the suggested optimal solution found by the chosen VRPs models. And as such, the proposed solution method should be innovated as accounts for the surrounded conditions as last-mile and same-day delivery capability. Amazon and Walmart have introduced the idea of crowd-shipping by assigning orders to people interested in serving by their own vehicles for customers not far away from their own destinations for certain compensation (Barr and Wohl, 2013; Bensinger, 2015). Accordingly, a new variant has been proposed as a practical solution for the rigid capacitated vehicle routing plan in the name of occasional drivers. Archetti et al. (2016) have suggested using a third party logistical service to cover the shortage happening in the assigned fleet of trucks, or received orders from far destinations, in order to satisfy better customer satisfaction and increase service efficiency and availability. Since implementing such a solution would increase the routing plan costs, an optimal planning for VRP modeling is required. Therefore, Archetti et al. (2016) have presented a multi-start heuristic approach that minimizes the total costs associated with assigning orders for both regular and occasional drivers. The results revealed that a dramatic cost saving could be achieved when applying an economic compensation scheme for the company and the occasional drivers, the way that will improve and the availability and flexibility of the drivers to serve. On the other hand, more challenges associated with the other VRP variants are existed and need to be considered in order to optimize the benefits of crowd-shipping practically. Recently, a work presented by Macrina et al. (2017) claimed that using the occasional drivers with multiple deliveries with time window constraint (VRPODTW) would positively serve the logistical companies in both routing plan and costs savings, though, more variants are important to be considered in order to optimize VRPODTW solution.

Depending on the previous discussion, this work extends the idea of using occasional drivers, by studying it with other important variants; i.e.: developing VRPOD plan as an eco-friendly plan, and optimizing the usage of occasional drivers by controlling their behavior. Section 2.5 spots the light on the literature published about drivers' behaviors and the encountered effects on the routing plan.

2.5 VRP and driver behavior

Studying VRP with different variants will definitely improve the routing plan and reveal a rich VRP model. Though, there is a gap exists between the planning stage for the optimal VRP and the real implementation stage, for instance, the driver behavior is such an important factor that affects VRP solution on reality. In general, literature had spot the light on the human factors which affect the driving behavior; such as: the effect of fatigue rate due to overload work (Murray and Park, 2013;Ting et al., 2008; Zhang et al., 2016), the effect of driver age, gender and personality on risky driving behavior (Zuckerman and Kuhlman, 2000), and the level of autonomy assigned for the driver who executes the routing plan on ground (Srinivas and Gajanand, 2017). Nevertheless, when reviewing the published VRP modeling researches, it is been argued by Srinivas and Gajanand (2017) that the different VRP variants' researches have been presented over years as isolated from driver behaviors and its effect on the real optimal solution. They supported their claim by reviewing the existing studies on driver behavior; such as Ting et al. (2008) and Tran et al. (2011), as well as reviewing different published researches of various variants of VRP models (Qian and Eglese, 2016).

Srinivas and Gajanand (2017) have believed that; whatever VRP objective was, it is important to think about the driver sentiment when setting the routing plan. In cases such as VRP with time window, circumstances would be different in reality and the driver might need frequent or infrequent break to be able to achieve the plan objectives. Other cases which minimizing pollution was their objective, it would be lower costs-plan if the driver had an autonomy level in route or speed choices in a matter that reduces emissions, or even reducing travel time on ground. And as a result, the driver satisfaction will be better in a way that will improve the environmental, economic and social performance of the logistical firm. The presented framework could be used as a starting point to include the driver behavior in a VRP model in terms of reducing total VRP costs, by sharing the routing plan decisions between driver and planner.

A study had discussed the idea of studying the driver behavior and its effect on the risk homeostasis towards speed selection and the accident rate was published by Janssen and Tenkink (1988), and under general conditions, it is been believed that safety engineering measures would be reduced by shift in behavior. In the same regard, Iversen (2004) has studied the relation between the perceived attitude and the driving behavior pattern. The results had shown a strong correlation, as attitude toward rule violation, speeding and the careless driving are strongly related to reckless driving, drinking and seat belt use, which in turn could capture the risk taking behavior and help to predict driver's driving pattern in the future. Additionally, he reflected the results of two theories that discussed the effect of the perceived attitude on person's control over performance, i.e.: 1) Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975); and 2)

Theory of Planned Behavior (TPB) (Ajzen, 1985). Both theories have been studied as related to driving behavior research such as: speeding, drunk drivers, and aggressive driving pattern, in order to predict risky driving behavior and its effect on accidents in the future.

In the same vein, Møller and Gregersen (2008) have examined other relations of risk driving behavior rather than safety motives, those that had positive significant effect were: 1) the psychosocial function of driving 2) other driving related interaction with friends; and 3) leisure time activities pattern such as playing PC-games. Doing body building and partying with friends were also found to be related to increased risky driving pattern. They recommended that other motives rather than safety issues are required to control driving pattern, such as behavioral related issues and activities.

From what had been discussed above, it is expected to enhance VRP results on ground when considering the driver's behavior. Since this research includes two types of drivers; (i.e.: regular drivers, and occasional drivers), both drivers' behaviors are considered and the effect of their behaviors on the routing costs is monitored and analyzed through sensitivity analysis. Which in turn will help in; deciding the proper level of autonomy as assigned between planner and driver; increasing the driver satisfaction; as well as achieving better customer satisfaction level due to higher service availability for both the nearby and remote customers. And as such, the evidence that VRP model is solvable and practical will be a motivation to control driver's behavior pattern's effect on different related issues as stated above in the literature.

2.6 Summary

This chapter provides a comprehension understanding of VRP topic and introduces a wide range of the related variants available in literature. More specifically, the classical VRP definitions and its developments overtime have been presented, in order to provide knowledge to understand the topic of VRP thoroughly. Also, gaps that have been found in the reviewed literature are identified and analyzed in order to construct this research's objectives after determining the problem statement and concluding its significance. According to the fact that the intended VRP model in this research is required to be an eco-friendly model, the literature about green VRP have been reviewed.

Furthermore, rich VRP models that were found in literature have been discussed according to their contributions and limitations. Ultimately, as the focus of this study is to consider the driver behavior when modeling a VRP plan; the available literature that discusses the driver behavior effects generally on driving have also been covered.

Chapter Three
Model Formulation

3.1 Overview

As the previous sections have discussed the published literature about VRP variants in order to determine the rational research gaps and manage the future researches' suggestions; this section presents the proposed mathematical model which translates this research objectives. A Mixed Integer Non Linear Programming Multi-Objective Model (MINLP-MOM) has been developed in terms of objective functions and constraints, in order to be solved into near optimal VRP network. Also, the Fixed-Charge modeling has been used to control one choice of route type. Later on, the MINLP-MOM is linearized in order to facilitate solving the proposed model. Understanding the research objectives comprehensively would lead to a mature realization of the proper model components.

3.2 Mixed Integer Non Linear Programming (MINLP) and VRP modeling

VRP is classified as undirected graph, that has a depot (o) and customers' source and destinations nodes (i , j) ; to be satisfied through an optimal route, without allowing for sub tours (i.e.: either routes that do not satisfy capacity constraint, or route that do not include depot on their route), and also, imposes demand and capacity constraints; this in turn could be formulated as an Integer Program as a basic VRP model (Rader, 2010). In this research, further decision variables have been added to the basic version of VRP model; accounting for releasing an optimal routing solution integrated with decisions; related to the assignment of the driver type associated with the minimum costs (i.e.: regular (X) or occasional (O), and C: the assigned driver costs), and the decision to choose the optimal route type and carried load (i.e.: Y, and Q, respectively). And as such, the model includes binary variables as well as continuous variables in terms of objective functions and constraints; as there will be a multiplication of two binary variables in the fourth objective function, which results in a Mixed Integer Non Linear Programming (MINLP).

The MINLP model is formulated as a basic example as following:

$$\text{minimize or maximize} \sum_{i,j}^{n} C_{ij} X_{ij} * Y_{ij} + d_{ij} Q_{ij}$$

Where: $X_{ij}, Y_{ij} \in \{0,1\}, \text{and } Q_{ij} \geq 0 \;\; (\text{for all } i,j = 1,2,\ldots N; i \neq j)$

3.2.1 Fixed-Charge Model

In order to integrate the decisions of the four types of routes, Fixed-Charge modeling has been used (Rader, 2010). Such formulation allows for one-time charge when a certain activity is performed and so its value is not equal zero. The formulation of this type of model requires adding number of binary variables equals to the number of the associated decisions. In this research, as there are four routes' types, and only one route type is assigned for either the chosen regular driver or the chosen occasional driver. And so there are four representative binary variables represented by the summation of the binary variable Y_{ijr} have been included in the model, while *"r"* represents the chosen route type. Each variable refers to the chosen optimal velocity during the routes' network. In order to integrate the fixed charged model in the mathematical model, the summation of the binary variables refers to the available decisions such as the chosen routes type; are multiplied as following:

$$\text{minimize or maximize} \sum_{i,j}^{n} (C_{ijr}X_{ijr} * \sum_{r=1}^{4} Y_{ijr} + d_{ij}Q_{ij})$$

Where:

$X_{iir}, Y_{iir} \in \{0,1\}, \text{and } Q_{ii} \geq 0 \; \forall \; r = 1,2,3,4; i = 0,1, \ldots N, j = 1, \ldots, N$

Such arrangement requires that another constraint that connects between the decisions to choose one of the available routes' types only if the regular driver (X_{ii}) has been assigned. The same criterion is applied on the occasional driver decisions(O_{ii}). Such constraint could be formulated for example; by multiplying the binary variable of choosing the route type one (Y_{ii1}) by a sufficiently large value which is known as M; (i.e. mathematically M: ∞). This will ensure that the binary variable (Y_{ii1}) equals one if and only if the associated driver type binary variable equals one as well. In order to ensure choosing only one route type, the summation of routes' variables should equal one. The model will be as following:

minimize :

$$\sum_{i,j}^{N} \left(C_{ij}X_{ij} * \sum_{r=1}^{4} Y_{ijr} + C_{ij}\, O_{ij} * \sum_{r=1}^{4} Y_{ijr} \; + d_{ij}Q_{ij} \right)$$

Subject to:

$$\sum_{r=1}^{4} Y_{ijr} = 1$$

$$X_{ij} \leq M * \sum_{r=1}^{4} Y_{ijr}$$

$$O_{ij} \leq M * \sum_{r=1}^{4} Y_{ijr}$$

Where:

$$X_{ij}, O_{ij}, Y_{ijr} \in \{0,1\}, \text{and } Q_{ij} \geq 0$$

$$(\text{for all } i = 0,1, \dots N; j = 1, \dots, N, r = 1,2,3,4)$$

3.3 Model description

The MINLP-MOM model has been designed as a set of regular and occasional drivers’ logistics service. Accordingly, a set of customers from i to j is generated randomly in terms of locations coordinates and demands. The suggested model has managed three important issues related to VRP which are:1) improving the service level by using a third party as occasional driver in order to satisfy customers located far from the regular drivers’ destinations network,2) sustaining green driving behaviors through controlling the chosen velocity range, and imposing environmental penalty, 3) considering the drivers’ behavior when planning for VRP by studying the effect of the driver’s choice on the total transportation costs by inserting a risk-taking probability.

Sets of arcs (i, j), occasional drivers (K), and regular drivers (D) were proposed to be used in generating solutions. Four objective functions have been composed in order to manage: 1) minimization of energy consumption level associated with traversing VRP plan (denoted by Z_1), 2) maximization of velocity level to a certain upper limit in order to reduce CO_2 emissions (denoted by Z_2), 3) minimization of penalty associated with velocity choice (denoted by Z_3), and 4) minimization of total travelling costs incorporating the driver's behavior effect (denoted by Z_4). And as such, four decision variables have been proposed, i.e.: 1) assigning a regular driver to implement the suggested VRP plan, 2) assigning an occasional driver to implement the suggested VRP plan, 3) the quantity carried by the vehicle which satisfies the demands of customers associated with VRP plan and minimizes the energy consumed by the vehicle through each VRP trip, and 4) the near optimal route type choice referring to the near optimal average velocity range. The model mathematical formulation is presented in the following section. The first three objective functions have been adopted from the work conducted by Hosseini-Nasab and Lotfalian (2017), while the forth objective function have been developed from the formula introduced by Srinivas and Gajanand (2017); by including the occasional drivers in all objective functions and constraints.

3.4 Model Preliminaries

This section provides the used indices, sets, decision variables, parameters, and assumptions; in order to understand the proposed mathematical model components.

3.4.1 Indices and sets

o: Depot point.

i: Customer node, i = 0, 1,…,N.

j: Destination node, j = 1,…,N.

D: set of regular drivers to be assigned.

K: set of occasional drivers to be hired.

r: Index of routes' types associated with an allowable velocity range, r = 1,2,3,4. (adopted from: Hosseini-Nasab and Lotfalian, (2017)

3.4.2 Decision Variables

X_ijdr:1,if a regular driver d travels from node i to node j through route type r; otherwise: 0.

Q_{iir}: Load carried by the vehicle from node i to node j through route type r (Kg).

O_(ijkr):1,if an occassioanl driver k travels from node i to node j through route type r; otherwise:0.

Y_{iir} : 1, if the vehicle travels from node i to node j along route type r ; otherwise: 0, r=1,2,3,4.

3.4.3 Parameters

Table 1 presents the parameters that have been used in the proposed VRP model.

Table 1: The parameters of the proposed VRP model

M: a sufficiently large positive value (mathematically, M: ∞)
PEN_r: The environmtal penalty associated with the fuel consumption rate imposed on route type r (\$), where $PEN_r \geq 0 \quad, \forall r = 1,2,3,4$:
d_{ij} : Distance travelled from node i to node j(km).
d_{0i} : Distance travelled from depot o to customer i (Km)
d_{ik}:Distance travelled from customer i to occasional driver destination k (Km).
d_{0k}: Distance travelled from depot o to occasional driver destination k (Km).
x_i: X-Coordinate for node i.
x_j: X-Coordinate for node j.
y_i: Y-Coordinate for node i.
y_j: Y-Coordinate for node j.
VEL_{ijr} : Velocity of travel from node i to node j along route type r (Km/hr), where $VEL_{ijr} \neq 0, \forall i = 0,1,\dots,N, j = 1,\dots,N, r = 1,2,3,4$
DEM_i: Demand at node i (Kg), where DEM_0 = 0.
CAP: Capacity of the vehicle (Kg).
α_r: Fuel consumption factor for route type r
γ : Occasional driver distance factor representing willingness of driver to serve, $\gamma \geq 1$
V_r^*: The maximum velocity limit allowed on route type r (Km/hr).
ρ: Occasional driver compensation scheme's factor, $\rho \geq 1$
β: Parameter of risk-taking behavior by the planner in order to determine level of autonomy of the planner.
Δ: Parameter of risk-taking behavior by a regular or occasional driver in order to determine the level of autonomy for the assigned driver.
C_{ijd} : Cost of traversing arc (i,j) by a regular driver d (\$).
TR_{dr}: Training cost for a regular driver d for route type r driving pattern (\$).
SC_{dr}: Salary cost for a regular driver d through route type r (\$/Period).
TC_{ijdr} : Total Cost of travel from node i to node j by a regular driver d including training costs, through route type r(\$).
C_{ijk} : Cost of traversing arc (i,j) by an occasional driver k (\$).
C_{oik}: Cost of travel from depot o to customer i by the occasional driver k(\$).
C_{ik}: Cost of travel by the occasional driver k from customer i to the occasional driver k destination (\$).
C_{ko}: Cost of travel by an occasional driver k from his/her destination to the depot o (\$).
TR_{kr}: Training cost for an occasional driver k for route type r driving pattern (\$).
TC_{ijkr} : Total Cost of travel from node i to node j by an occasional driver k including training costs through route type r(\$).
W_{Z_i}: Target weight for each objective function (Z_i) which would be determined by the planner.
Z_{opt}: Total value of the near optimal solution ($Z_{opt} = \sum_{i=1}^{4} W_{Z_i} * Z_i^*$).

3.4.4 Model Assumptions

1. All vehicles are identical in terms of load and capacity limit.
2. All vehicles depart from the depot carrying the total quantity required to satisfy the demand of all received orders.
3. Customers' demand and locations are known in advance and all customer demands should be satisfied
4. Regular drivers serve up to a known radius-distance of customers' nodes (1 Km-200 Km).
5. There are one or more route types existing between every pair of nodes.
6. There are four types of routes depending on the allowable average velocity range (Hosseini-Nasab and Lotfalian, 2017; Samaras, 2012):

Type One: for velocities below 30 Km/hr, this has the highest fuel consumption rate, such as riding vehicles in city-urban environment)

I. Type Two: for velocities between 31 Km/hr and 55 Km/hr, the fuel consumption rate decreases, such as driving in the sub-urban or rural areas.

II. Type Three: for velocities between 56 Km/hr and 80 Km/hr, fuel consumption rate also decreases, such as driving in rural or high ways.

III. Type Four: driving with these average velocities' range will increase the fuel consumption rate, such as freeways driving conditions.

7. Depending on the velocity ranges rule, the following assumption has been proposed: $\alpha_1 > \alpha_4 > \alpha_2 > \alpha_3$ (Samaras, 2012).
8. The distances along the different route types between the same pair of nodes could be different and measured as a rectilinear distance.

9. The proposed model accounts for optimizing the service time by finding the least amount of summation of the traversed distances. While the other methodology which solves for time window constraints and requires using other fuzzy logic Lin et al. (2014); has been relaxed.
10. $\alpha_r \geq 0.05, \forall\, r = 1,2,3,4$, as the minimum average fuel consumption rate on the near optimal velocity is found to be at least around 5 L/100Km for a particular vehicle type (Samaras, 2012)
11. Regular and occasional drivers are trained to stick to the announced velocity policy and the assigned route.

12. Regular and Occasional drivers are given a certain amount of autonomy (Δ) in taking route and velocity-related decision, as compared to the planner autonomy level (β) according to the following conditions: $\mathbf{0 \leq \Delta \leq a \leq \beta \leq b}$ **,** a , b ≥ 0 :i.e.: Parameter of risk- taking behavior by the planner is larger than the one taken by the driver, this is because planner has a wider perspective from strategic point view rather than the driver who has a tactical or operational perspective.

13. The occasional driver k is willing to serve through a route type r, if the extra distance travelled to reach driver destination is less than or equal to ($\gamma - 1$) times the direct distance from the depot to the occasional driver destination:

14. $d_{0i} + d_{ik} \leq \gamma\, d_{0k} \quad , \forall\, i = 0,1,\ldots,N\,, \forall\, k = 1,\ldots,K.$

15. All costs of traversing an arc (i, j) are measured as cost of a rectilinear distance, for each regular driver d, and occasional driver k; this is to

ensure that the associated costs of VRP plan are used regarding to a specific formula rather than using estimated costs which vary from case to other; the used formula is shown in equation (1). Other networks' types could be adaptive in the model depending on the real case data.

$$C_{ij,l} = \left|x_i - x_j\right| + \left|y_i - y_j\right| \tag{1}$$

i, j =1,…..,N, i≠j, *l*=d (regular), k (occasional).

16. Occasional drivers are paid according to the following compensation scheme adopted from Archetti et al. (2016) , $(C_{0ik} + C_{ik} - C_{k0}) * \rho, \ \rho \geq 1$.

17. Training costs are assumed to be paid to train drivers on different driving pattern, training costs follow a uniform distribution from 10$ to 30$ according to the required driving pattern (Asrawi et al., 2017).

3.4.5 Objective Function

The four objective functions in the model are given as follows. The first objective function is given in equation (2).

- Energy consumption minimization:

$$Min: Z_1 = \sum_{i=o}^{N} \sum_{j=1}^{N} \sum_{r=1}^{4} \left((Q_{ijr} * d_{ij}) \right) \tag{2}$$

Description of equation (2): minimizes the summation of: the quantity loaded from node i to node j ×distance from node i to j through route type r.

The first objective function minimizes the consumed energy during serving destinations, by VRP routing in terms of traversed distances and load quantity for each route. This will help in minimizing customer service time. The second objective function is given in equation (3).

- Velocity maximization

$$Max: Z_2 = \sum_{i=o}^{N} \sum_{j=1}^{N} \sum_{r=1}^{4} (VEL_{ijr} * Y_{ijr}) \tag{3}$$

Description of equation (3): maximize the summation of: (the velocity of route type r from node i to node j multiplied by binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise).

The second objective function maximizes the chosen velocity rate up to the maximum allowed velocity limit that ensures the possible minimum fuel consumption rate (120 Km/h), and so, pollution rate is decreased for each near optimal route. The third objective function is given by equation (4)

- Penalty related to velocity policy minimization

$$Min: Z_3 = \sum_{i=o}^{N} \sum_{i=1}^{N} \sum_{r=1}^{4} (PEN_r * Y_{i\,ir}) \tag{4}$$

Description of equation (4): Minimize the summation of: (the penalty of route type r from node i to node j× binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise).

The third objective function minimizes the environmental penalty of fuel consumption imposed on the chosen velocity rate for each route. The fourth objective function is given by equation (5).

- Total travelling costs minimization

Min

$$Z_4 = \sum_{i=o}^{N} \sum_{j=1}^{N} \sum_{r=1}^{4} \left(\sum_{d=1}^{D} \left(X_{ijdr} * Y_{ijr} * TC_{ijdr} \right) + \sum_{k=1}^{K} \left(O_{ijkr} * Y_{ijr} * TC_{i,j,k,r} \right) \right) \quad (5)$$

Where:

$$TC_{ijdr} = E[C_{ijdr} + SC_{dr} + TR_{dr}] + \beta * \sqrt{\Delta^2 * Var\left(C_{ijdr} + SC_{dr} + TR_{dr}\right)}$$

, and

$$TC_{ijkr} = E[TR_{kr} + (C_{0ik} + C_{ik} - C_{k0}) * \rho] + \beta * \sqrt{\Delta^2 * Var(TR_{kr} + (C_{0ik} + C_{ik} - C_{k0}) * \rho)}$$

Description of equation (5): minimize the summation of: binary variable (1 if regular driver d assigned to serve from node i to node j through route type r; 0 otherwise) × binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise) × the total costs of travelling from node i to node j by regular drivers set (D) through route type r + the summation of: binary variable (1 if occasional driver k assigned to serve from node i to node j through route type r; 0 otherwise) × binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise) × the total costs of travelling from node i to node j by occasional drivers set (K) through route type r.

Where:

The total cost of travelling from node i to node j through route type r associated with the regular driver d = the summation of : the expected value of: (the cost of traversing arc i, j by regular driver d + salary cost for a regular driver d + training cost for a regular driver d through type r) + risk taking behavior sensitivity value by the planner multiplied by the square root of the quadrate of risk taking behavior sensitivity by the regular driver d × the variance of : (the cost of traversing arc i, j by regular driver d + salary cost for a regular driver d + training cost for a regular driver d through type r) , and:

The total cost of travelling from node i to node j through route type r associated with the occasional driver k = the summation of : (the expected value of: the training costs of an occasional driver k + cost of travelling depot o to customer i through route type r + cost of travelling customer i to an occasional driver k through route type r − cost of travelling from occasional driver k to depot o through route type r) multiplied by compensation factor of an occasional driver k) + risk taking behavior sensitivity value by the planner multiplied by the square root of the quadrate of risk taking behavior sensitivity by the occasional driver k × the variance of : (the training costs of an occasional driver k + cost of travelling depot o to customer i through route type r + cost of travelling customer i to an occasional driver k through route type r − cost of travelling from occasional driver k to depot o through route type r) multiplied by compensation factor of an occasional driver k).

The fourth objective function minimizes the total costs of VRP routing plan associated with choosing either regular or occasional driver, integrated with minimizing the costs of assigning a certain level of autonomy for the chosen type of driver; for each route. Collectively, the total multi-objective function is given in equation (6).

- Total optimal solution

$$Z_{opt} = \sum_{i=1}^{4} W_{Z_i} * Z_i^{*} \qquad (6)$$

Description of equation (6): optimize the summation of (the target weight W_i for objective function i × the optimal solution of the objective functionZ_i).

3.5 Constraints

The following are the constraints of the model:

$$\sum_{d=1}^{D} \sum_{r=1}^{4} X_{ijdr} \leq 1 \qquad \forall\, i,j = 1, \dots N, i \neq j \qquad (7)$$

Description of equation (7): the summation of the chosen route types from node i to j by a regular driver d should be less than or equal 1; for each destination node j; $i \neq j$.

$$\sum_{k=1}^{K} \sum_{r=1}^{4} O_{ijkr} \leq 1 \quad \forall\, i,j = 1, \dots N, i \neq j \qquad (8)$$

Description of equation (8): the summation of the chosen route types from node i to node j by an occasional driver k should be less than or equal 1; for each destination node j; $i \neq j$.

$$\sum_{\substack{i=0\\ i\neq l}}^{N}\sum_{r=1}^{4} X_{ildr} - \sum_{\substack{j=0\\ j\neq l}}^{N}\sum_{r=1}^{4} X_{ljdr} = 0 \qquad \forall l = 1, \dots \dots, N \ , \ \forall\, d = 1, \dots \dots, D \qquad (9)$$

Description of equation (9): the summation of the binary variable value (1 if regular driver d assigned to serve from node i to node l through route type r; 0 otherwise) associated with choosing a regular driver d to serve from node i to node l through route type r − the summation of the binary variable value (1 if regular driver d assigned to serve from node i to node l through route type r; 0 otherwise) associated with choosing a regular driver to serve from node l to node j through route type r = 0; for each node destination l, and regular driver d.

$$\sum_{\substack{i=0\\ i\neq l}}^{N}\sum_{r=1}^{4} O_{ilkr} - \sum_{\substack{j=0\\ j\neq l}}^{N}\sum_{r=1}^{4} O_{ljkr} = \quad 0 \qquad \forall l = 1, \dots \dots, N \, , \ \forall\, k = 1, \dots \dots, K \qquad (10)$$

Description of equation (10): the summation of the binary variable value (1 if occasional driver k assigned to serve from node i to node l through route type r; 0 otherwise) associated with choosing an occasional driver k to serve from node i to node l through route type r − the summation of the binary variable value (1 if occasional driver k assigned to serve from node i to node l through route type r; 0 otherwise) associated with choosing an occasional driver to serve from node l to node j through route type r = 0; for each node destination l, and occasional driver k.

$$\sum_{\substack{i=0\\i\neq l}}^{N}\sum_{r=1}^{4} Q_{ilr} - \sum_{\substack{j=0\\j\neq l}}^{N}\sum_{r=1}^{4} Q_{ljr} = DEM_l \qquad \forall l = 1, \dots \dots, N \qquad (11)$$

Description of equation (11): the summation of the load carried from node i to node l through route type r −the summation of the load carried from node l to node j through route type r should equal the demand of node l; for each node l.

$$\sum_{r=1}^{4} Q_{ijr} \geq \sum_{r=1}^{4} (X_{ijdr} * Y_{ijr} * DEM_j)$$

$$\forall\, i = 0,1,\dots,N\,, j = 1,\dots,N, i \neq j; \forall\, d = 1,\dots,D \qquad (12)$$

Description of equation (12): the summation of the load carried from node i to node j through route type r is larger than or equal to the summation of: (binary variable value (1 if regular driver d assigned to serve from node i to node j through route type r; 0 otherwise); for each node i, j, $i \neq$j, and regular driver d multiplied by binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise) multiplied by the demand of node j through route type r; for each r = 1,2,3,4.

$$\sum_{r=1}^{4} Q_{ijr} \geq \sum_{r=1}^{4} (O_{ijkr} * Y_{ijr} * DEM_j)$$

$$\forall\, i = 0,1,\dots,N\,, j = 1,\dots,N, i \neq j, \forall\, k = 1,\dots,K \qquad (13)$$

Description of equation (13): the summation of the load carried from node i to node j through route type r is larger than or equal to the summation of: (binary variable value (1 if occasional driver k is assigned to serve from node i to node j through route type r; 0 otherwise); for each node i, j, $i \neq$j, and occasional driver k multiplied by binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise) multiplied by the demand of node j through route type r; for each r = 1,2,3,4.

$$Q_{ijr} \leq (CAP - DEM_i) * X_{ijdr} * Y_{ijr}$$
$$\forall i = 0,1,\dots,N, j = 1,\dots,N, \ \forall d = 1,\dots,D, \ r = 1,2,3,4 \qquad (14)$$

Description of equation (14): the load carried from node i to node j through route type r is less than or equal to the subtract of the capacity of the vehicle and the demand of node i ⨉ binary variable value (1 if regular driver d assigned to serve from node i to node j through route type r; 0 otherwise); for each node i, j, $i \neq$j, regular driver d, and route type r multiplied by binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise).

$$Q_{ijr} \leq (CAP - DEM_i) * O_{ijkr} * Y_{ijr}$$
$$\forall i = 0,1,\dots,N, j = 1,\dots,N, \forall k = 1,\dots,K, r = 1,2,3,4 \qquad (15)$$

Description of equation (15): the load carried from node i to node j through route type r is less than or equal to the subtract of the capacity of the vehicle and the demand of node i ⨉ binary variable value (1 if occasional driver k is assigned to serve from node i to node j through route type r; 0 otherwise); for each node i, j, $i \neq$j, occasional driver k, and route type r multiplied by binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise).

$$\sum_{j=1}^{N} \sum_{r=1}^{4} O_{ijkr} \leq 1 \quad \forall i = 0,1,\dots,N, \forall k = 1,..,K \qquad (16)$$

Description of equation (16): the summation of binary variable value (1 if occasional driver k is assigned to serve node j through route type r; 0 otherwise) is less than or equal 1; for each node i, and occasional driver k.

$$X_{ijdr} \leq V^*{}_r * \alpha_r * \frac{Y_{ijr}}{PEN_r}$$

$$\forall\, i = 0, 1, \dots, N\,, j = 1, \dots, N,\;\; \forall\, d = 1, \dots, D, r = 1,2,3,4 \qquad (17)$$

Description of equation (17): binary variable value (1 if regular driver d assigned to serve from node i to node j through route type r; 0 otherwise) ≤ maximum allowed velocity for regular driver × fuel consumption factor for route type r × binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise÷ the penalty associated with travelling through route type r; for each node i, j, $i \neq$j, regular driver d, and route type r.

$$O_{ijkr} \leq V^*{}_r * \alpha_r * \frac{Y_{ijr}}{PEN_r}$$

$$\forall\, i = 0, 1, \dots, N\,, j = 1, \dots, N,\;\; \forall\, k = 1, \dots, K, r = 1,2,3,4 \qquad (18)$$

Description of equation (18): binary variable value (1 if occasional driver k assigned to serve from node i to node j through route type r; 0 otherwise) ≤ maximum allowed velocity for occasional driver k × fuel consumption factor for route type r × binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise) ÷ the penalty associated with travelling through route type r; for each node i, j, $i \neq$j, occasional driver k, and route type r.

$$\sum_{r=1}^{4} O_{i\,ikr} + \sum_{r=1}^{4} X_{i\,idr} = 1$$

$$\forall\, i = 0,1,\dots,N,\ j = 1,\dots.,N, \forall\, k = 1,\dots,K\,,\ \forall\, d = 1,\dots,D \qquad (19)$$

Description of equation (19): the summation of the binary variable value (1 if occasional driver k is assigned to serve from node i to node j through route type r; 0 otherwise) + the summation of the binary variable value (1 if regular driver d is assigned to serve from node i to node j through route type r; 0 otherwise) = 1; for each node i, and j, $i \neq$j, occasional driver k, and regular driver d.

$$\sum_{r=1}^{4} Y_{ijr}=1$$
$$\forall\, i = 0,1,\dots,N, j = 1,\dots,N \qquad (20)$$

Description of equation (20): the summation of binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise) = 1; for each node i, and j, $i \neq$j, and route r.

$$X_{ijdr} \leq M * Y_{ijr}$$

$$\forall\, i = 0,1,\dots,N, j = 1,\dots,N, \forall\, d = 1,\dots,D, \forall\, r = 1,2,3,4 \qquad (21)$$

Description of equation (21): binary variable value (1 if regular driver d assigned to serve from node i to node j through route type r; 0 otherwise) should be less than or equal M multiplied by binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise; for each node i, destination node j; $i \neq j\ , regular\ driver\ d, route\ type\ r,$ M ≈ ∞.

$$O_{ijkr} \leq \text{M} * Y_{ijr}$$

$$\forall\, i = 0,1,\dots,N, j = 1,\dots,N, \forall\, k = 1,\dots,K, \forall\, r = 1,2,3,4 \qquad (22)$$

Description of equation (22): binary variable value (1 if occasional driver k assigned to serve from node i to node j through route type r; 0 otherwise) should be less than or equal M multiplied by binary variable (1 if route type r is chosen to serve from node i to node j; 0 otherwise); for each node i, destination node j; $i \neq j\ , occasional\ driver\ k, route\ type\ r,$ M ≈ ∞.

$$Q_{i0r} = 0 \qquad \forall\, i = 0,1,\dots,N\ , r = 1,2,3,4. \qquad (23)$$

Description of equation (23): the load carried from node i to the depot o through route type r equals zero; for each node i, and route type r.

- Non-negativity constraint:

$$Q_{ijr} \geq 0 \quad \forall\, i = 0,1,\dots,N,\ j = 1,\dots,N, r = 1,2,3,4 \qquad (24)$$

- Binary variable for assigning a regular driver :

$$X_{ijdr} \in \{0, 1\} \forall\, i = 0,1,\dots,N, j = 1,\dots,N, r = 1,2,3,4, \forall\, d = 1,\dots,D \quad (25)$$

Binary variable for assigning an occasional driver:

$$O_{ijkr} \in \{0,1\} \ \forall\, i = 0,1,\dots,N, j = 1,\dots,N, r = 1,2,3,4,\ \forall\, k = 1,\dots,K \quad (26)$$

- Binary variables for choosing route type:

$$Y_{ijr} \in \{0, 1\} \; \forall \, i = 0, 1, \ldots, N, j = 1, \ldots, N, r = 1,2,3,4. \tag{27}$$

The implications of the above-mentioned constraints are as follows: constraints (7) & (8) ensure that the assigned regular or occasional driver can choose at most one route type to travel from node i to node j. Constraints (9) & (10) imply the flow conservation law of the chosen route type by both the regular and the occasional drivers. Constraint (11) implies the flow conservation law of goods carried during a certain route. Demands' constraints for both regular and occasional driver are controlled by constraints (12) & (13), respectively, while capacity constraints are presented by constraints (14) & (15) for regular and occasional driver, respectively. According to the assumption that an occasional driver can at most serve the same customer only once, constraint (16) guarantees this assumption. The maximum allowed velocity for regular or occasional driver which is lower than the velocity upper bound are controlled by constraints (17) & (18), respectively. Additionally, in order to ensure that each customer is served by either regular or occasional driver; constraint (19) is employed. In the same vein, only one route type choice is possible either by the assigned regular or occasional driver as presented by constraint (20). Constraints (21) & (22) ensure that the chosen route type could only be assigned to a regular or an occasional driver, respectively; if and only if the driver is assigned to serve from node i to j; otherwise the route type is not considered. Furthermore, constraint (23) guarantees that vehicle returns empty to the depot. Constraints (24) refers to the nonnegative loaded quantity, and finally constraints (25), (26), and (27) imply choosing binary variables for the decisions of the regular driver, the occasional driver, and the route type, respectively.

3.6 Linearization

Despite that the practical problems like transportation model are naturally modeled as Mixed Integer Non Linear Programming (MINLP) (Burer and Letchford, 2012), which would allow to mathematically model it to be more representative by involving more reality conditions and decision variables; it will be linearized in order to be solved as a MIP model, which in role facilitates the optimization and solving process and improve its solvability for larger instances; especially that there are quite effective exact and heuristic algorithms by using the available MIP solvers (Burer and Letchford, 2012).This process will be conducted by proposing two auxiliary variables that represent the product of the two binary variables in the fourth objective function (Z_4), as well as the other related non-linear constraints' expressions (i.e.: constraints; 12,13,14, and 15) (Coelho, 2013). The following auxiliary variables have been defined in order to linearize the nonlinear expressions in the proposed VRP model:

XY_{ijdr}: 1, if the regular driver d is assigned to serve from node i to node j along route type r; otherwise: 0.

OY_{ijkr}: 1, if the occasional driver k is assigned to serve from node i to node j along route type r; otherwise: 0.

Fourth Objective Function Nonlinear Expression (Z_4)

$\text{Min}Z_4 =$

$\sum_{i=o}^{N}\sum_{j=1}^{N}\sum_{r=1}^{4}\left(\sum_{d=1}^{D}\left(X_{ijdr} * Y_{ijr} * TC_{ijdr}\right) + \sum_{k=1}^{K}\left(O_{ijkr} * Y_{ijr} * TC_{ijkr}\right)\right)$

Linear equivalent of Z_4 :

$\text{Min}Z_4 =$

$$\sum_{i=o}^{N}\sum_{j=1}^{N}\sum_{r=1}^{4}\left(\sum_{d=1}^{D}\left(XY_{ijdr} * TC_{ijdr}\right) + \sum_{k=1}^{K}\left(OY_{ijkr} * TC_{ijkr}\right)\right) \quad (28)$$

$$XY_{ijdr} \leq X_{ijdr} \quad (29)$$

$$XY_{ijdr} \leq Y_{ijr} \quad (30)$$

$$XY_{ijdr} \geq X_{ijdr} + Y_{ijr} - 1 \quad (31)$$

$$OY_{ijkr} \leq O_{ijkr} \quad (32)$$

$$OY_{ijkr} \leq Y_{ijr} \quad (33)$$

$$OY_{ijkr} \geq O_{ijkr} + Y_{ijr} - 1 \quad (34)$$

$\sum_{r=1}^{4} Q_{ijr} \geq \sum_{r=1}^{4} \left(X_{ijdr} * Y_{ijr} * DEM_j\right) \forall\, i = 0,1,\dots,N\,, j = 1,\dots,N, i \neq$

j;

$\forall\, d = 1, \dots, D$ Nonlinear expression

$\sum_{r=1}^{4} Q_{ijr} \geq \sum_{r=1}^{4} \left(XY_{ijdr} * DEM_j\right) \forall\, i = 0,1,\dots,N\,, j = 1,\dots,N, i \neq$j;

$\forall\, d = 1, \dots, D$ Linear equivalent (35)

$\sum_{r=1}^{4} Q_{ijr} \geq \sum_{r=1}^{4} (O_{ijkr} * Y_{ijr} * DEM_j) \,\forall\, i = 0,1,\dots,N, j = 1,\dots,N, i \neq j,$

$\forall\, k = 1,\dots,K$ Nonlinear expression

$\sum_{r=1}^{4} Q_{ijr} \geq \sum_{r=1}^{4} (OY_{ijkr} * DEM_j)$

$\forall\, i = 0,1,\dots,N, j = 1,\dots,N, i \neq j, \forall\, k = 1,\dots,K$ Linear equivalent (36)

$Q_{ijr} \leq (CAP - DEM_i) * X_{ijdr} * Y_{ijr} \forall\, i = 0,1,\dots,N, j = 1,\dots,N,$

$\forall\, d = 1,\dots,D,\ r = 1,2,3,4$ Nonlinear expression

$Q_{ijr} \leq (CAP - DEM_i) * XY_{ijdr}$

$\forall\, i = 0,1,\dots,N, j = 1,\dots,N, \forall\, d = 1,\dots,D, r = 1,2,3,4$

Linear equivalent (37)

$Q_{ijr} \leq (CAP - DEM_i) * O_{ijkr} * Y_{ijr}$

$\forall\, i = 0,1,\dots,N, j = 1,\dots,N, \forall\, k = 1,\dots,K, r = 1,2,3,4$ Nonlinear expression

$Q_{ijr} \leq (CAP - DEM_i) * OY_{ijkr}$

$\forall\, i = 0,1,\dots,N, j = 1,\dots,N, \forall\, k = 1,\dots,K, r = 1,2,3,4$ Linear equivalent (38)

The fourth objective function (i.e.: total costs minimization) has been linearized by defining two auxiliary variables with the support of constraints 29 to 34. Constraints 29 and 30 will ensure that XY_{ijdr} will be zero if either X_{ijdr} *or* Y_{ijr} are zero. Constraint 31 will make sure that XY_{ijdr} will take value 1 if both binary variables are set to 1. Similarly, Constraints 32 and 33 will ensure that OY_{ijkr} will be zero if either

O_{ijkr} or Y_{ijr} are zero. Constraint 34 will make sure that OY_{ijkr} will take value 1 if both binary variables are set to 1.

3.7 Summary

This chapter has presented the formulation of the proposed VRP model that involves both regular and occasional drivers; integrated with risk taking behaviors' parameters encountered within eco-friendly logistical practice. This model has been formulated as MINLP using the Fixed Charge problem in order to achieve the intended objectives of the proposed VRP routing plan. And then, the model has been linearized in order to be solved by the available Mixed Integer Programing (MIP) solvers. And as such, the proposed model as it is constructed with the associated constraints will allow optimizing the routing plan to serve set of destinations using both regular and occasional drivers' set; controlling simultaneously their driving behavior by assigning a pre-determined level of autonomy for both the planner and the driver. This in turn allows the driver to make decisions related to speed or route in case there is unexpected condition emerged, such as accidents or unexpected congestions. For the purpose of ensuring a green logistical practice, the model ensures choosing the optimal possible velocity rate accompanied with the optimal lowest environmental penalty. Also, by controlling the driver behavior through assigning a certain level of autonomy, it would be possible to define the rational extent to which the drivers can make decisions, and then verify their performance on ground. Additionally, such optimized routing plan prevails the optimal loaded quantity for each destination and the related total costs required to serve it by the cost-effective driver type. Such arrangements ensure having a comprehensive VRP model which is expected to improve the firm obtained objectives; the driver satisfaction, and the customer satisfaction level. Chapter Four introduces a numerical instance that has been solved as a proof of concept in order to verify the validity and solvability of the proposed model. The numerical instance results, as well as the solving algorithms are also discussed.

Chapter Four
Model Results

4.1 Overview

This chapter introduced a numerical instance using hypothetical data set in order to verify the solvability and the validity of the proposed VRP model. The proposed hypothetical set has been presented in Section 4.2; where all the stochastic data have been generated randomly and are analyzed and optimized using the proposed model. Eclipse Java 2018-9 is intended to be used for coding the mathematical proposed model and to solving it using the proper solving algorithms. Section 4.3 presents the solver characteristics and information related to the chosen solving methods. Finally, section 4.4 discusses the numerical results that have been obtained by solving the proposed VRP model using the suggested numerical example.

4.2 Numerical Example

For the purpose of assessing the proposed mathematical model as compared to other previous literature models, a hypothetical example with a data set is borrowed from literature, namely, from Hosseini-Nasab and Lotfalian, (2017). More specifically, four sets have been proposed to be used in solving the model, i.e.: 1) a set of customers (N), 2) a set regular drivers' (D) 3) a set of occasional drivers (K) 4) a set of route types (R). The problem has been tested on an identical fleet of vehicles. At each edge there is a certain allowed velocity; according to the available road type (i.e.: urban areas, sub-urban, rural areas, and highways); that follows a uniform distribution given by U [1,120] Km/hr. such a velocity average decision is identified according to the available route type on ground, and then the model chooses the near optimal velocity that minimizes the environmental penalty. Since the demand of the customers changes every day, it was assumed that the distance of customers' coordinates from the depot point follows also a uniform distribution given by U [10,300] Km for each customer node. Customer's demand has also been generated randomly from a uniform distribution given by U [200, 1000] Kg in order to initialize values for the parameter DEM_i assigned to the proposed coordinates. Table 2 presents the parameters proposed values to be used in solving the model.

Table 2: Numerical example data for the model parameters

Parameter	**Value**
Period	Per day
M	100
d_{ij}	U [10,200] Km
d_{ik}	U [50,200] Km
VEL_{ijr}	U [1,120] Km/hr
DEM_i	U [200,1000] Kg
CAP	1000 Kg
α_r	>.05
$\rho \geq 1$	U [1,3]
Δ (a=5,b=10), where: **$0 \leq \Delta \leq a \leq \beta \leq b$**	U [0,5]
β (a=5, b=10), where: **$0 \leq \Delta \leq a \leq \beta \leq b$**	U [5,10]
$\gamma \geq 1$	U [1,3]
TR_k	U [10,30] $
TR_d	U [10,30] $
SC_{dr}	U [7 , 9] $

In order to assess the capability of the proposed model in optimizing a VRP problem encountered with the proposed conditions, a numerical instance has been proposed. Sets of **5** customers; **4** identical vehicles, K=3 occasional drivers, and **r = 4** types of routes; have been used as inputs to solve VRP model. Tables (3 & 4) present, respectively, the customers' coordinates and demands data; as been generated randomly by Eclipse software according to the given ranges. Table 5 presents the occasional drivers' destinations coordinates from depot point which is assumed to have (0,0) coordinates.

Table 3: The proposed customers' coordinates

Coordinate (X , Y)	**Customer ID**				
	(1)	(2)	(3)	(4)	(5)
X-coordinate	54	120	186	85	113
Y-coordinate	114	46	23	126	57

Table 4: Proposed customers' demands (Kg)

Customer ID	(1)	(2)	(3)	(4)	(5)
Demand(Kg)	600	400	200	300	300

Table 5: Occasional drivers' destinations' coordinates from depot point

K / **Depot**	(1)	(2)	(3)
(0,0)	(114,81)	(63,146)	(198,102)

4.3 Eclipse Java Solver and Algorithms

Eclipse Java 2018-09 software has been used for coding the mathematical model and solving VRP proposed problem. As VRP is one of the classic Operations Research and discrete optimization problems; it is solved by heuristic methods, such methods are based upon rules of thumb, common sense or refinement s of exact methods. A heuristic algorithm usually results in a near-near optimal solution as compared with exact algorithms, which are able to find a global-near optimal solution (Rader, 2010).

The Greedy algorithm solves VRP by constructing the routes for the drivers using a sequential greedy insertion algorithm, which inserts customers into the active route in non-decreasing order of their distance to the depot, and then starts a new route when violating the vehicle capacity constraint, and, when all customers have been inserted as initial solution, this method improves each route using a 2-exchange neighborhood. On the other hand, the Intra-Route Heuristic Neighborhood Search method has the ability to solve large instances and is preferable for the real-case problems such as VRP-related models (Hosseini-Nasab and Lotfalian, 2017). Both methods are classified as adaptive-local search heuristic algorithms that incorporate random elements into the classic local search method; by choosing candidate solutions outside the selection rule and then repeat the process until finding the best near-optimal solution. Accordingly, in this research, the proposed converted MIP model is solved by the two heuristic-methods (i.e.: The Greedy solution and The Intra-Route Heuristic Neighborhood Search in order to assess the near optimality of the resulted solutions.).

Such algorithms are suitable to solve a multi-objective combinatorial problem as VRP considering that the highest priority objective to solve is finding the minimum cost rout in terms of optimal traversed distances (optimal route) while considering the driver behavior, which leads to the optimal cost-effective choice of the driver type. And then, the resulted consumed energy as well as the optimal velocity type, and the associated environmental penalty solutions are being developed using the adaptive local search heuristics algorithms. This multi-objective heuristics' solving methodology is able to initialize the initial near optimal routing plan using the Greedy algorithm, and then to improve the near optimal routing plan by using the Intra-route local search algorithm using 1-0 exchange move. And so, the proposed model is able to produce the optimal routing plan with the optimal minimum travel distance and minimum number of vehicles to complete the distribution service, this ensures that every assigned route will be balanced in terms of the assigned driver type, the assigned route type, the optimal velocity, penalty and consumed energy (Liu et al., 2006).

4.4 Numerical Results

The model was coded by Java and solved via Eclipse 2018-09 on a PC $Intel^{®}\ Celeron^{®} M\ inside^{TM} CPU$ 440 @1.86 GH_z and 2.00 GB RAM. This section presents the results of solving the numerical instance introduced previously in the hypothetical data set.

4.4.1 Green Routing Plan with Occasional and Regular Drivers' Assignment

After solving the model using the introduced algorithms; the routing travelling costs, the model decision variables as well as the near optimal solution for the objective functions have been prevailed. The near optimal routing solution has shown that the 5 customers would be served by only 2 identical vehicles among the available 4 vehicles in the following two routes; (3 – 5 -2), and (4 – 1). Both algorithms have revealed the same near optimal routing plan, which supports the proposition that this is the optimal possible routing plan within such objectives and constraints. Figure 2 describes the near optimal traversed routes.

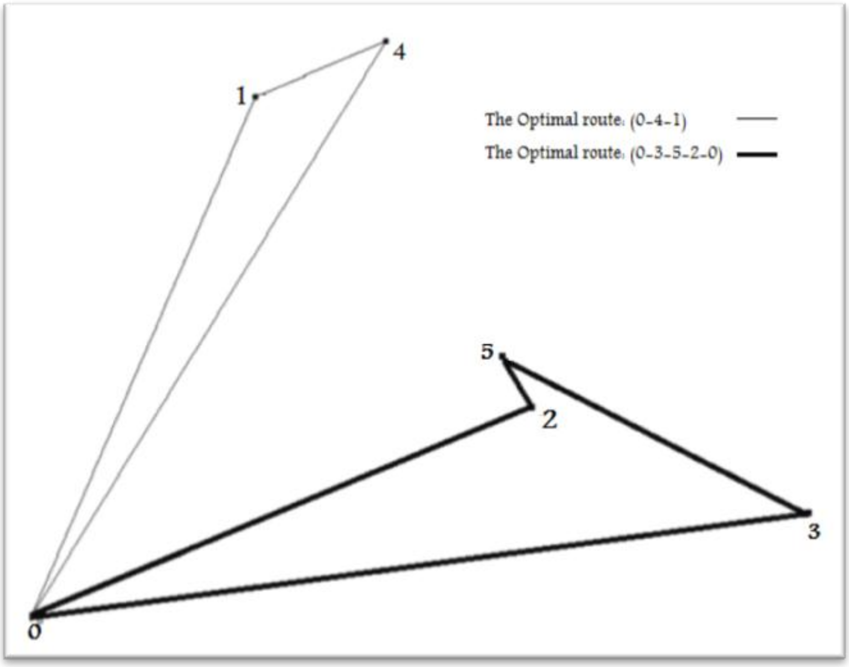

Figure 2: The near optimal VRP Routing Plan produced by the Greedy and Intra-route Neighborhood heuristic algorithms.

4.4.2 Near optimal Routing Plan in terms of Routes' Classification and Driver Type

Table 6 illustrates the values of the model decision variables given in terms of choosing a regular or occasional driver to serve during the trip from node i to node j ($i.e.: XY_{ijdr}$ and, OY_{ijkr} respectively). Also, the near optimal quantities that would be loaded from node i, to node j along the distance between nodes i and j are shown in the same table ($i.e.: Q_{ij}$ and, d_{ij} respectively). And as a result, the near optimal energy which is consumed during each trip has been known, which indicates for the customer satisfaction level. Additionally, the resulted near optimal total travelling costs for each trip are also displayed according to the chosen driver type ($i.e.: TC_{ijdr}$ and,TC_{ijkr}). For instance, the trip from depot node 0 to node 3 is assigned for a regular driver ($i.e.: XY_{ijdr} = 1$ and, $OY_{ijkr} = 0$) with the total associated cost of 255.46 \$. The near optimal load to be carried by the regular driver equals to 200 Kg in order to satisfy the demand of node 3. This quantity would be transferred along a distance of 504 Km resulting in a near optimal energy of 100800 (Kg.Km). Overall, the results of the proposed numerical instance have shown that all the chosen drivers where among the regular drivers' set, despite that the occasional driver compensation scheme's factor has chosen to be the minimum allowable value (i.e.: ρ =1). However, using different data set with different destinations' coordinates would probably produce different assignment plan. Also, developing a cost effective compensation scheme is expected to increase the probability that the model chooses the occasional drivers.

On the other hand, the decisions to choose one of the possible four routes' types are presented in Table 7 where the values of the decision variables are shown incorporated with the near optimal chosen velocity; penalty, and fuel consumption factor (α) during each trip. For example, the second trip between node 3 and node 5 would be executed by an near optimal velocity of 21 Km/h, and so the associated binary decision variable $(i.e.:\ \boldsymbol{Y_{351}})\ equals\ 1;$ whereas the other binary variables associated with the rest of routes' type equal zero; such decision variable value indicates for the first classification of routes' types with a fuel consumption factor α equals 0.15, resulting in an near optimal penalty of 3 $.

Table 6: Near optimal values of the model decision variables and parameters

Near optimal Served Destinations	XY_{ijdr}	OY_{ijkr}	$\boldsymbol{TC_{ijdr}}$ **($)**	$\boldsymbol{TC_{ijkr}}$ **($)**	**Near optimal values of $\boldsymbol{Q_{ij}}$ (Kg)**	$\boldsymbol{d_{ij}}$ **(Km)**	**Near optimal values of Energy (Kg.Km)**
(0,3)	1	0	255.46	0	200	504	100800.0
(3,5)	1	0	216.46	0	300	221.3	66400.0
(5,2)	1	0	212.46	0	400	104.5	41800.0
(0,1)	1	0	214.46	0	600	105.5	63300.0
(1,4)	1	0	257.46	0	300	170	51000.0

*Note: β=8, **Δ**=4, $\boldsymbol{\gamma}$=1, ρ=1

4.4.3 Objective Functions' Components' Near Optimal Results

After solving the proposed numerical instance by Eclipse Java 2018-09 software using Greedy and Intra-Route algorithms; it has been revealed that both methods had the same near-near optimal solutions and routings, and so, it is the best solution for such a discrete optimization problem. Table 8 displays the solutions of the objective functions as resulted from both methods.

However, all the results of this numerical instance have been obtained by considering that all the weights of the four objective functions are equal subjectively from importance perspective (i.e.: W_{Z_i} *equals* 1; for each i =1,2,3,4), such proposition is used as a qualitative indicator for the firm decision makers to be able to alter the preferences depending on the firm strategy.

Table 7: Near optimal values of the decision variables of choosing route type, and the associated near optimal velocities, penalties and α values.

Near optimal Served Destinations	Near optimal VEL_{ijr} (Km/hr)	Near optimal Route Type				Near optimal route type (r)	Near optimal α value	Near optimal penalty ($)
		y_{ij1}	y_{ij2}	y_{ij3}	y_{ij4}			
(0,3)	69	0	0	1	0	3	0.07	4.0
(3,5)	21	1	0	0	0	1	0.15	3.0
(5,2)	30	1	0	0	0	1	0.06	1.0
(0,1)	48	0	1	0	0	2	0.08	3.0
(1,4)	2	1	0	0	0	1	0.14	0.3

By comparing the results of the objective functions' components; it could be inferred that the energy component accounts for the largest percentage of the total near optimal solution with a percent of 99.58 %; which is the same result got from the work accomplished by Hosseini-Nasab and Lotfalian, (2017). And after that, the total costs' component refers to 0.35% from the total near optimal value. Other components have low contributions; i.e.: penalty with 0.0035 %, and velocity with 0.05 %). Consequently, it is apparent that the consumed energy is important to be managed wisely by the logistical firm management and should acquire an important attention. Besides, as the total costs' component has an acceptable percent of contribution even that driver's behavior is being taken into consideration; it is an important matter that needs to be strategically planned.

Table 8: Near optimal values for objective functions

Objective Function	**Greedy Solution**	**Intra-Route Heuristic Neighborhood Search**
Total penalty (Z_3)	11.3	11.3
Total velocity (Z_2)	170.0	170.0
Total energy (Z_1)	323300.0	323300.0
Total costs (Z_4)	1156.3	1156.3
(Z_{opt})	**324637.6**	**324637.6**

4.5 Summary

For the purpose of assessing the solvability of the proposed mathematical model which incorporates using the concept of ride sharing, while controlling the driver's behavior for both occasional and regular drivers; within a green logistical practice; this chapter analyzed a numerical instance with hypothetical data. Accordingly, the model has been solved using Eclipse Java 2018-9 program. As a result, the model was able to release an eco-friendly VRP routing plan, incorporated with controlling the risk level in assigning the autonomy for drivers. The optimal routing has been obtained in order to optimally serve the proposed set of customers, by trading off between the associated optimal velocities; penalties, energy, and total VRP costs. Moreover, the results have shown that the energy consumption as well as the total VRP costs have been reported as the largest percent of the total optimal solution, which in turn requires that more intensive analyses are needed in order to investigate the effect pattern of such objective functions on the optimal solution. Therefore, sensitivity analysis is conducted and discussed in the next chapter on different relations in order to get a better understanding and to use such results to rationally introduce effective optimal logistical strategies.

Chapter Five

Sensitivity Analysis

5.1 Overview

For the purpose of analyzing the effect of the risk level in the planner plan when assigning level of autonomy to drivers on the near optimal total costs; this section presents the results of sensitivity analysis on the risk taking parameters for both planner and driver (i.e.: β, and $\boldsymbol{\Delta}$ respectively). Besides, in order to analyze the weight of the total costs' objective function component as well as the other components, sensitivity analysis is also conducted on the effect of such weights on the total near optimal solutions. The following sections present the analyses results.

5.1.1 The Effect of Risk Taking Parameters on the Near Optimal Total Costs

Changing the level of autonomy for both planner and drivers could be achieved by changing the risk-taking parameters. Though, such process would affect the total costs of the routing plan, and as such, this relationship should be sensitively analyzed in order to determine the best trade-off between driver satisfaction level and the firm satisfaction level. Initially, it has been proposed that both planner and driver have zero value for both the planner and the driver β, and $\boldsymbol{\Delta}$, respectively, which is the traditional VRP model where driver behavior is not considered. The results have shown that the total costs were the minimum in this arrangement. Another three scenarios of different values of β, and $\boldsymbol{\Delta}$ have been examined to represent the three possible scenarios for the risk level from the planner perspective: 1) the neutral-risk level as seen in scenario 2, 2) the risk-seeker level as seen in scenario 3, and 3) the risk-averse level as seen in scenario 4. All the proposed scenarios have been studied with their effects on the total costs' objective function (Z_4). Table 9 presents the four scenarios of different level of autonomy combinations (i.e.: different risk patterns from planner perspective), and their associated total VRP routing costs. As expected, relaxing the model from such parameters (scenario 1) would result in the minimum total costs of VRP plan (1064.00$), while assigning equal level of autonomy for the driver in making decisions related to speed or route choice (scenario 2) has increased the total VRP costs have slightly increased the total costs of VRP plan by 4.3% (i.e.: 1110.16 $). This change is due to the increased amount of the variance in the total costs' function (see equation 5). However, the importance of incorporating the driver's behavior when planning for a rich and realistic VRP model would ensure applying the model effectively on ground. Also, driver satisfaction would be enhanced while maintaining at the same time a cost-effective VRP plan.

Comparing the sensitivity analysis results for the four scenarios shows an acceptable change in the total VRP costs; as the highest costs is associated with the risk-seeker planner due to assigning a high level autonomy for the driver (i.e. : 1150.54$) is larger than the risk-averse planner scenario (4); when $\beta = 8$, and $\boldsymbol{\Delta} = 1$; by 5.8%. Such difference is still accepted as long as other perceived characteristics of the model are going to be improved, in terms of driver satisfaction level, as well as customer satisfaction level due to the higher and efficient level of service availability. Though, the risk-seeker planner's scenario; when $\beta = 6$, and $\boldsymbol{\Delta} = 5$; opposes that the responsibility of driver is important and his decisions will be effective, and the driver may exhibit a risk seeking, risk-neutral, or risk-averse behavior depending on his nature. The nature of the driver could be determined by using behavioral survey of the driver which should be updated regularly from the previous route and speed decisions in order to predict their actions. This helps in determining the proper level of autonomy as assigned to the driver.

Figure 3 displays the pattern of the effect of changing the risk level on the total VRP costs. The four scenarios are shown on the X-axis while the resulted total VRP costs are reported on the Y-axis in dollars' unit. More specifically, the trajectory shows a growth in the total VRP costs when the parameters' values where gradually increased from the relaxed condition where there is no risk (i.e.: $\beta=0$, and $\boldsymbol{\Delta}=0$; where driver behavior have not been considered) before decreasing again when reducing the level of autonomy of the driver (scenario 4).

Such a relation requires an extended explanation of the effect that the total VRP costs' component has on the total near optimal solution. Obtaining a better comprehension of the real effect of the total VRP costs on the total multi-objective function's solution will rationally help in planning for the best near optimal VRP plan for satisfying the logistical firm strategic objectives. The following section discusses the effect of each objective function qualitatively on the total near optimal solution in order to get a clearer explanation about each function effect on the total near optimal solution of VRP plan.

Table 9: Sensitivity analysis results the effect of five scenarios of risk patterns on the total VRP near optimal solution

Experiment no.	Risk Pattern of the planner	β	Δ	(Z_4) ($)	Percentage Change (%)
Scenario.1	No risk	0	0	1064.00	-
Scenario.2	Risk-neutral planner	4	4	1110.16	+4.3 % from scenario 1
Scenario.3	Risk-seeker planner	6	5	1150.54	+5.8 from scenario 4
Scenario.4	Risk-averse planner	8	1	1087.00	-

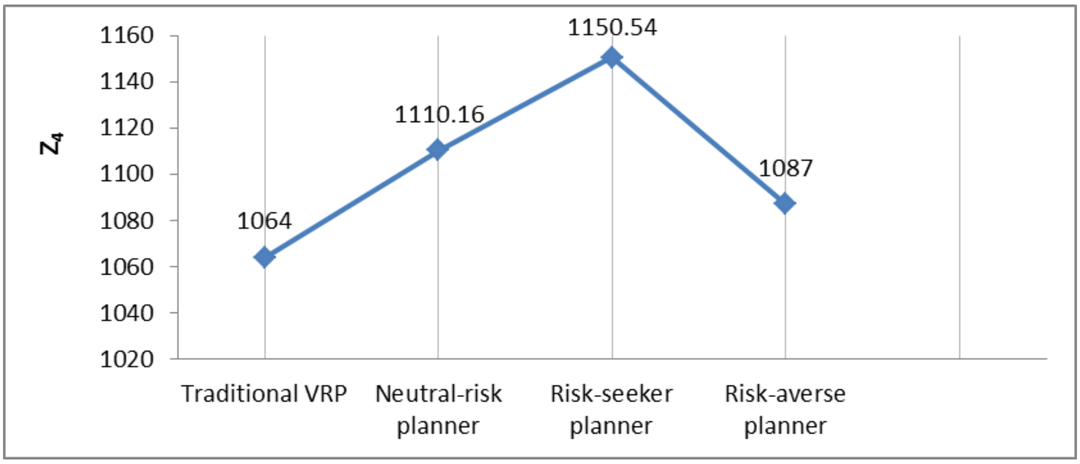

Figure 3: The relationship of the effect of different scenarios of risk level against the total VRP costs' near optimal solution.

5.1.2 The Effects of the objective Functions Weights on the Total Near optimal Solution

In order to understand the effect of each objective function on the total near optimal solution qualitatively; related weights have been changed by assigning different values for each objective function interchangeably. Table 10 presents the resulted near optimal values of the total multi-objective function for five different scenarios including the equivalence status that has been conducted in the numerical instance. By analyzing the results; it is shown that the objective function of energy consumption minimization (Z_1) has the highest effect on the total near optimal solution ($Z_{opt} = 647882.32\$$). Whereas the other trials of assigning different weights for the objective functions did not change the total near optimal solution considerably. Figure 4 describes the trajectory for the five scenarios of changing the weights' values associated with each objective functions. It is apparent that the objective functions associated with; the velocity maximization (Z_2), penalty minimization (Z_3), and total costs minimization (Z_4); all have nearly the same effect on the total multi-objective function by merely changing its value when increasing their weights. In comparison, the first objective function of minimization the energy consumption (Z_1) has dramatically affected the total multi-objective function near optimal solution from 324586.30 up to 647882.32; similar to the results obtained by Hosseini-Nasab and Lotfalian, (2017), which in role requires that a serious attention should be existed from the firm management for introducing effective planning for the locations of their warehouses and the chosen occasional drivers, in order to control the resulted energy. This ensures improving the customer satisfaction level by minimizing the consumed energy, as well as releasing a better near optimal solution for the whole VRP model. Consequently, this is evidence that the total VRP costs' component has a minor effect on the total near optimal solution. So, this is an opportunity for the logistical firm management to incorporate drivers' behavior when planning for a VRP even though the related total costs would be increased.

Table 10: The Sensitivity analysis results of the effect of objective functions' weights on the total near optimal solutions

Experiment no.	W_1	W_2	W_3	W_4	Total value of the near optimal solution (Z_{opt}) ($)
Scenario 1	1	1	1	1	324586.30
Scenario 2	1	1	2	1	324634.32
Scenario 3	1	2	1	1	324734.32
Scenario 4	2	1	1	1	647882.32
Scenario 5	1	1	1	2	325746.46

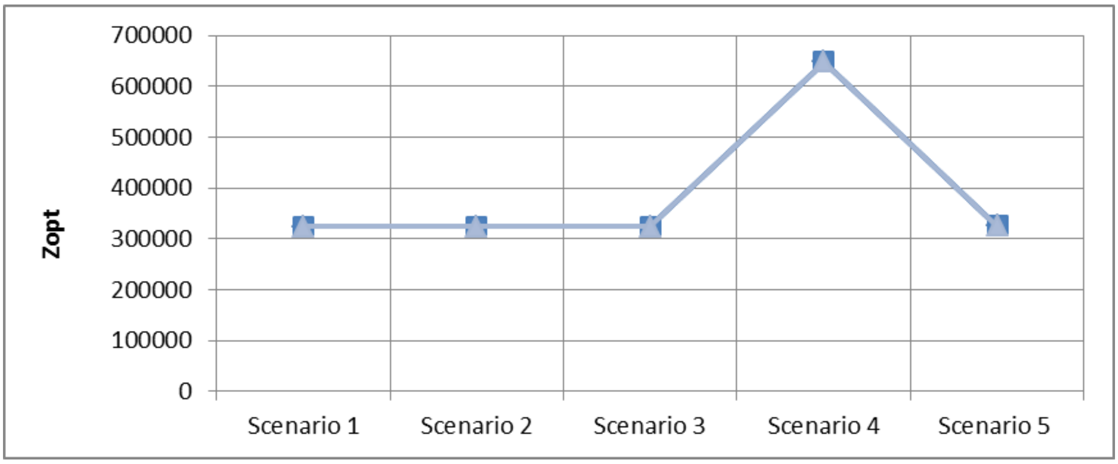

Figure 4: The Relationship of the Weights of the Objective Functions and the Total Near optimal Solution

5.2 Summary

This chapter has introduced the sensitivity analyses that have been conducted for, firstly; studying the effect of changing the assigned level of autonomy to control the driver behavior on; the total optimal VRP costs, and secondly; studying the significance of the effect of each objective function on the total objective function optimal solution; by the changing the associated weights. This in turn would be used by decision makers in setting strategies and plans for an optimal the logistical decisions. In general, the risk taking behavior parameters have a positive relationship on the total optimal VRP costs; as the level of autonomy for the driver increased, as the total costs also increased. Though, by conducting the second sensitivity analysis, it was apparent that the total costs' objective function has a minor effect on the total objective function near-optimal solution, and so, such increase in total costs could be rationally traded off when assigning a certain level of autonomy for drivers, while maintaining at the same time a cost effective VRP plan. Additionally, the energy consumption level should grasp higher attention from the firm management in order to optimally serve customers and improve VRP total solution.

Chapter Six

Conclusions and Recommendations

6.1 Summary

This research has answered the question of formulating a rich VRP model to be as realistic when is applied on ground as possible. In order to introduce a rich VRP model that has comprehensive characteristics improving the perceived quality and efficiency of the model for the value-chain stakeholders. More precisely, the firm financial objectives, the customer satisfaction level, as well as the driver satisfaction level have been studied and included in one VRP model. Moreover, the environment sustainability issue has been considered by both reducing fuel consumption level and maintaining a green driving behavior. This altogether contributed to the three components of sustainability effectively.

As the model solves different issues, it has been constructed using both continuous and binary integer variables, and so MINLP approach has been used in order to manage all the mode’s objectives. The model formulation and the related objective functions; constraints, assumptions, parameters, decision variables, and sets have all been identified in details. Also, in order to assess the validity and applicability of the proposed model; a hypothetical data set has been used to solve a numerical instance using Eclipse Java 2018-9 solver, which optimized the model solutions using the Greedy and Intra-route heuristic neighborhood algorithms. Those solutions have been reported and analyzed illustrating VRP plan with the four objective functions (i.e.: energy consumption minimization, velocity maximization, penalty minimization, and total costs minimization), in order to satisfy the research objectives. Firstly, the issue of minimizing the total VRP costs as to be a cost-effective service network has been optimized in terms of all the associated service costs including destinations' cost, driver's training cost, and salary cost. Secondly, the customer satisfaction level has been improved by optimizing the consumed energy during serving the customer that affects the service time; which depends on optimizing the carried load along the distance of a near optimal routing network. Also, the customer satisfaction not only has been improved from the service time, but also by improving the service availability probability. This issue has been manipulated by considering the idea of ridesharing by incorporating the occasional drivers as a third logistical party that serves when either there is a shortage in the firm's hired regular drivers, or when customer's location is located far away from the regular drivers' assigned destinations, such as rural and country-side areas (i.e.: represented by the binary variable $OY_{i\,ikr}$). Although such process would increase VRP costs due to the compensation paid to the occasional drivers, the model optimizes those costs as well. Thirdly, the proposed model optimize the total costs even when controlling the driver's behavior in terms of controlling the level of autonomy that is assigned to the driver by the planner, as a technique to determine the risky level of a certain logistical firm. More specifically, the model has incorporated risk-taking parameters in order to adjust the drivers' behavior which is represented by their possibility in making decisions related to speed or route on ground. However, the sensitivity analysis on the relationship between risk-taking parameters and

VRP total costs prevailed that such arrangement has a positive effect on VRP total costs, as increasing the assigned level of autonomy for driver has increased the model total costs due to the increased variance. Nevertheless, this issue has been justified by conducting a sensitivity analysis on the effect of the objective functions' weights on the total near optimal solution. It has been shown that doubling the weight of the objective function that minimizes VRP total costs did not affect the total near optimal solution considerably. On the other hand, the objective function associated with minimizing the consumed energy has the largest effect when doubling its weight; by increasing the total near optimal solution just about the double; (Note that such procedure checks the effects qualitatively). Based on that, incorporating driver behavior parameter when designing a delivery network such as VRP; is still reasonable even though the total costs have increased merely.

Ultimately, such results show the importance of the model, and they could be used as a justification for the ability of designing a VRP model that serves the firm strategy; the driver satisfaction, and the customer. By using such multi-objectives VRP model, it could be ensured that the affective factors that contribute to a certain network success have been considered in terms of controlling the level of autonomy of the assigned drivers. By this, a new contribution has been added to VRP modeling taking into consideration the human differences' effect on the routing decisions.

6.2 Research Contribution

This research contributed to the literature by introducing a comprehensive rich VRP model in terms of its objectives and heuristic solution that released more practical and realistic characteristics. As compared to previous VRP models, their suggested variants and the developed models were being introduced as isolated from the driver behavior. Whereas accounting for the driver autonomy ensures that the driver can makes decision on time when unexpected conditions are emerged. Besides, the driver will be more satisfied when dealing with him as a human who can think and make decisions, rather than as a robot or a vehicle that needs to apply the assigned plans whatever emergent matters happen. And so, this research could be used as an evidence for the logistical firm; that assigning autonomy to drivers maintains a reasonable VRP plan which is still cost effective and efficient. Also, according to the idea of using the occasional drivers to satisfy shortages in delivery service; considering the occasional driver autonomy will increase the willingness of such drivers to serve even though their compensation rate does not increased, as the speed and route decisions will be tolerant with their conditions.

By adopting the proposed model by a certain logistical company, there will be a chance for reviewing the collected data released from applying the model for a certain trial period, the proposed model's results could be assessed and verified if the expected objectives have been achieved. And so, analyzing such results sensitively will help in determining the proper level of autonomy of drivers.

6.3 Limitations and Recommendations

- While the model has been programmed and solved successfully releasing the same near-optimal solution by two algorithms; the Greedy and Intra-route neighborhood heuristic; such heuristic approach cannot guarantee that such solutions are global. This is due to the fact that such a discrete optimization problem is difficult to be solved by an exact method (Rader, 2010).
- The model has been assumed as a static model, while such incorporation of occasional drivers' use and driver autonomy level requires that the model accounts for dynamicity. And so, dynamic programming languages e.g. Python will ensure updating the routing plan input data such as new received orders close to the assigned network, or even newly emerged route conditions such as unexpected congestion or accident that requires updated level of autonomy for the driver.
- The model has been solved by assuming that the fleet of vehicles is homogenous, and so, all the vehicles are assumed to have the same driving characteristics, in terms of fuel consumption rate and speed.
- Although the model is behaving eco-friendly by accounting for the velocity and environmental penalty, there is no gas emission index that could be used to optimize its level.
- Involving occasional drivers require that approved list of drivers are known in advance, this is important for controlling the level of autonomy assigned to them. Otherwise, their driving patterns would be

fluctuated in in a way that minimizes the probability to expect the suitable level of autonomy and their driving risk level characteristics.

6.4 Future work

Applying the model using real cases will improve its reliability and validity. Additionally, better realistic results will be obtained which can be used by decision makers more effectively. For example, using different compensation scheme for the occasional drivers would modify the model propositions and reveal different assignment plans. The driver behavior has been studied in this research to investigate the possibility to involve representative parameters (i.e.: risk taking behavior parameters), in VRP model while maintaining a reasonable and cost effective VRP plan. On the other hand, such parameters could be studied by investigating their effect on different objective functions in VRP model, such as their effect on reducing service time, or producing different driving patterns. Moreover, verifying the actual validity as well as the model practicability requires that the model should be applied on ground. This will ensure that the proposed VRP plan has achieved actual improvements on the firm; driver, and society satisfactions. This could be conducted by comparing results before and after applying the model. Acquiring real verified data by a certain logistical firm is expected to increase the probability that other firms will adopt the model as well. In addition, integrating other human characteristics such as: fatigue, age and experience level will improve the reality of the proposed model and allow obtaining better effective VRP plans. More specifically, studying the effect of such human factors on VRP plan allows determining precisely the drivers' differences and the resulted effects on the routing plan. Including such important parameters could be used as a comprehensive assessment tool for the used human resources, and help the human resource management in setting development, training, and awarding plans. Finally, using the Global Positioning System (GPS) when applying the proposed model on real cases would improve the obtained VRP plans, considering that on-time communication between drivers and firm's operation' planner would ensure assigning the proper level of autonomy. This maintains the driver behavior with autonomy under monitoring and control.

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جامعة النجاح الوطنية

كلية الدراسات العليا

دمج الاختلافات بين السائقين في تحديد المسار الأمثل لمشكلة توجيه المركبة الخضراء

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قدمت هذه الاطروحة استكمالاً لمتطلبات الحصول على درجة الماجستير في الادارة الهندسية، بكلية الدراسات العليا، في جامعة النجاح الوطنية، نابلس- فلسطين.

2019

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الملخص

مشكلة توجيه المركبة تعتبر إحدى أهم تطبيقات علوم بحوث العمليات المعاصرة، وقد حظيت باهتمام كبير من الباحثين نظراً لأهميتها الكبيرة في تطبيقات تصميم شبكات النقل اللوجستية. على الرغم من ذلك، تم تطوير النماذج الخاصة بهذه المشكلة وحلها باستخدام علم بحوث العمليات بمعزل عن تأثير العوامل البشرية المتعلقة بالعنصر الأهم المطبَق للخطة على أرض الواقع وهو السائق. في هذا البحث تم دراسة إمكانية إضافة العامل البشري ودراسة تأثيره على الخطة اللوجستية الأمثل. تم ذلك من خلال فرض متغيرات متعلقة بمستوى المخاطرة التي يتخذها المخطط عند قيامه بتوكيل السائق بما يسمى " مستوى السيطرة" بنسبة معينة ، بحرية اتخاذ قرارات متعلقة بالنقل مثل تغيير السرعة او الطريق المخطط لهما أثناء مرحلة التخطيط، و ذلك تبعا لظروف طارئة يتعرض لها أثناء تنفيذه لخطة النقل وتوصيل البضائع، مثل حدوث أزمة غير متوقعة في غير أوقات الذروة المتوقعة أو حدوث حادث سير قد يعيق من إكمال الخطة بالطريق و السرعة المخطط لها، مما يؤثر على تلبية طلبات الزبائن و إرضائهم بالوقت المطلوب. يهدف النموذج المقدم أيضاً لتحقيق متطلبات الديمومة على ثلاث مستويات، أولاُ على المستوى الاقتصادي من خلال تصميم نموذج رياضي قادر على تقليل تكاليف النقل المتعلقة بالخطة المثلى، وعلى المستوى البيئي من خلال قدرة النموذج على تحديد السرعة المثلى و تقليل الغرامة المالية المترتبة عليها و المعتمدة على نسبة استهلاك الوقود. أما بالنسبة لتحقيق الديمومة على الصعيد المجتمعي، فقد تم استخدام فكرة التشارك الاقتصادي التي تتضمن استخدام مجموعة من السائقين الاحتياط من أجل تلبية طلبات الزبائن المتواجدين في المناطق النائية البعيدة عن نقاط توصيل السائقين التابعين لشركة النقل، أو من الممكن استخدامهم في حالة حصول نقص بخدمة سائقي الشركة،

بهذا يمكن تحسين الخدمة المقدمة للزبائن من حيث توافرها وفعاليتها. أيضاً، من خلال إضافة التحكم بالعامل البشري رياضياً من قبل النموذج المقدم، يمكن تحسين مستوى الرضا الوظيفي لسائقي الشركة، وأيضا عند إعطاء السائق الاحتياط حرية اتخاذ القرار بنسبة معينة، سيصبح إمكانية توافرهم أكبر حيث سيكون هناك مرونة باختيار الطريق و السرعة المناسبة لهم. إضافة إلى ذلك، تم استخدام دالة الهدف المتعلقة بتقليل الطاقة المبذولة بالنقل والمعتمدة على المسافة والحمولة، حيث يمكن استخدامه كمؤشر لتحسين جودة خدمة النقل من أجل تحسين الجودة للزبائن. كل هذه النتائج ستعود بفائدة على عائدات الشركة وستجعل تحقيق أهدافها الاستراتيجية أفضل، وستزيد من شبكة الزبائن الخاصة بها من أقصى المناطق النائية حتى ساكني مركز المدن. بالمقابل، من المتوقع أن تؤدي إضافة العنصر البشري إلى النموذج المقدم لزيادة تكاليف النقل بسبب زيادة الانحراف المعياري عن التكلفة المتوقعة، لذلك، تم عمل تحليلات الحساسية لدراسة العلاقة بين زيادة مستوى السيطرة للسائق التابع للشركة والاحتياط على حدٍ سواء، وبين التكاليف المتعلقة بالخطة الأمثل للنقل. أظهرت نتائج دراسة الحساسية أن العلاقة إيجابية وأن الزيادة الحاصلة بالتكلفة كانت بسيطة. ولكن، من أجل التأكد من مدى تأثير هذه الزيادة على الحل الكلي الأمثل المتعلق بكل دالات الهدف، تم عمل دراسة حساسية لفحص تأثير وزن كل دالة هدف على الحل الأمثل، و قد أظهرت النتائج أن دالة الهدف المتعلقة بتقليل تكاليف النقل كان لها تأثير بسيط على تكاليف النقل حتى عند مضاعفة الوزن الخاص بها، بينم مضاعفة وزن دالة الهدف المتعلقة بتقليل الطاقة المبذولة بالنقل كان له التأثير الأكبر. النموذج الرياضي المطور هو نموذج غير خطية مكون من متغيرات صحيحة وغير صحيحة تم تحويله لاحقاً إلى نموذج خطي لتسهيل إمكانية حله. تم إجراء برمجة النموذج المقدم باستخدام لغة الجافا باستخدام برنامج الحل (Eclipse Java 2018-9)، باستخدام خوارزميات الحل (Heuristics) والتي أظهرت تطابقاً لنفس الخطة المثلى مما يرجح أن تكون هي الخطة الأمثل.