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Optimising an eco-friendly vehicle routing problem model using regular and occasional drivers integrated with driver behaviour control

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ABSTRACT

Vehicle routing problem (VRP) research has recently improved dramatically to simulate more real-life circumstances. Nevertheless, the typical VRP models proposed have been isolated from the most important factor determining the success of the VRP plan on the ground, i.e. the human factor (driver). Thus, this research investigates the effect of drivers' behaviours on the optimal VRP plan by integrating the level of autonomy of both planner and drivers as represented by risk-taking parameters. To enhance the model configuration's practicability, the concept of 'ridesharing' – which has been introduced before – has also been integrated to expand the logistical services, improve customer satisfaction, and compensate for shortages in service. Moreover, to ensure environmentally-friendly logistical practices, a velocity maximisation policy and environmental penalty enforcement on the chosen velocity range have been considered. In general, the model improves drivers' satisfaction, customers' perceived quality, and the firm's financial objectives. Additionally, it achieves a better supply chain strategic fit by planning at the three levels: strategic, tactical, and operational. A numerical example was solved using the Eclipse Java 2018-09 solver through two heuristic methods, the Greedy and the Intra-route neighborhood heuristic, and both revealed the same near-optimal solutions. Sensitivity analyses showed that the resulting insignificant increase in the VRP costs due to assigning autonomy for drivers is still reasonable, and the total costs' objective function weight has an insignificant effect on the total near-optimal solution, while that of the energy consumption objective function has the largest impact.

1. Introduction

One of the most popular applications of operation research science is the VRP, which was defined by Clarke and Wright (1964) as serving customer networks distributed at different geographic points, using fleets of trucks from different capacities. VRP-related studies have exponentially grown by around 6% per year in the research literature (Eksioglu et al., 2009). Furthermore, VRP has grasped its importance due to its wide usage in logistic and transportation aspects. Moreover, the literature has concentrated on different variants related to VRP, in which scholars set models and solutions for many real-life problems to control difficulties associated with different stages of transportation, such as travel times, pick-up and delivery time windows, and information input (Braekers et al., 2016).

Paraskevopoulos et al. (2017) stated that the routing and scheduling planning processes confront some challenges in allocating scarce resources for certain services. On the other hand, the VRP topic has been widely analysed due to its impact on various industries (Lahyani et al., 2017). Based on a taxonomic review related to the VRP topic during the period 2009–2015, it was revealed that the literature focused on some important VRP aspects, and different models were suggested to solve the problems of different objectives, including the capacitated VRP, periodic VRPs, the VRP with time windows, and others (Braekers et al., 2016). Additionally, a very crucial aspect that considerably affects the near-optimal results required for such a VRP case is augmenting the human factor in VRP models. More specifically, Jabbour et al. (2015)

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published a study related to the importance of integrating Green Human Resources Management (GHRM) to optimise the use of a Green Supply Chain Management (GSCM), improving the effectiveness of supply chains and the efficiency of inventory systems, integrated with the routing planning process, ensures a comprehensive and sustainable strategy.

It is critical that the drivers who manage the transportation process are considered while analysing a VRP model. Controlling the drivers' behaviours fundamentally improves the sought goals when optimising any VRP model. Accordingly, a literature review has been conducted by Alam and McNabola (2014) who found that controlling drivers' behaviour in a green manner can reduce fuel consumption by 45%. In the same vein, Liimatainen (2011) developed a study of the utilisation of fuel consumption data to be used in an incentive system for drivers of heavy-duty vehicles as a practical solution for use by logistical companies to motivate drivers to stick to energy-efficient routing plans. He also mentioned that such behaviours are variable with individual differences, by which the fuel consumption could vary up to 30%. A study conducted by Archetti et al. (2016) discussed the VRP topic with a special case, in which occasional drivers serve different logistical companies. Based on that, this work focuses 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 near optimal velocity range accompanied by the lowest environmental penalty imposed on certain fuel consumption rates. Also, the effects of drivers' differences on the driving pattern are being understood to introduce representative parameters that could be integrated with the VRP model to optimise its results. Such differences are: driver's ages and fatigue relationship, their level of skills and performance, and the training and awareness sessions they are exposed to.

This research contributes to the literature by introducing a comprehensive rich VRP model in terms of its objectives and heuristic solution, which released more practical and realistic characteristics. Compared to previous VRP models, their suggested variants and developed models were being introduced in isolation from the drivers' behaviour. Whereas, accounting for the drivers' autonomy ensures that they can make timely decisions when unexpected conditions emerge. Drivers will be more satisfied when they are treated as humans who can think and make decisions, rather than a robot or vehicle that needs to apply the assigned plans, regardless of the emergent matters occurring. This research could be used as an evidence for the logistical firm; assigning autonomy to drivers maintaining a reasonable VRP plan, which is still cost effective and efficient. Considering that occasional driver autonomy will increase the willingness of such drivers to serve even though their compensation rate does not increase, occasional drivers used to satisfy shortages in delivery services, including speed and route decisions, will be tolerant of 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. So, analysing such results sensitively will help in determining drivers' proper level of autonomy.

This paper is organised as follows: Section Two briefly introduces the reviewed literature. Section Three presents the research problem and the proposed mathematical model. The numerical instance and the hypothetical data set are presented in Section Four with the results discussion, while the conducted sensitivity analyses are explained in Section Five. Section Six presents the managerial implications. Finally, Section Seven discusses the conclusions and future research.

2. Literature review

Since the focus of this research is developing and optimising a rich VRP model that incorporates real-life configurations, the available suggested VRP models have been reviewed to identify the emerged gaps and scan future work suggested in recent literature. Miscellaneous literature of variants and contributions of the proposed VRP models are classified as related to the following topics: Multi-level Supply Chains and Classical VRP, Green VRP, Rich VRP, and VRP and Drivers' Behaviour.

2.1. Classical VRP

The case of a gasoline truck 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 totally satisfy the demand of all stations with minimum possible covered mileage, by solving the problem as a linear programming formulation. Later on, Clarke and Wright (1964) generalised the problem into the case of solving the best network of customers spread around a central depot point. However, both researches had not considered real-life aspects, which are associated with real, large-scale problems. Nevertheless, it becomes an easier challenge to create more practical solutions to serve reality. The technological revolution, as well as the telecommunications industry, helped vigorously in applying the idea of the truck 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 to keep track of the topic in a much easier and less discriminatory manner. Dependent on their work (2009), another detailed review was accomplished by Braekers et al. (2016), in which they analysed the various trends of VRP found in literature between 2009 and 2015. A review of 277 articles revealed that academic researchers have focused on different variants of the VRP topic and various important points were discussed. Such a rich topic brought the opportunity to study different real-life problems associated with VRP. For instance, the Heterogeneous 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 30 years of studying the HFVRP and its 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 minimum vehicle costs. Also, Lai et al. (2016) studied a multi-graph Heterogeneous VRP with time constraints, and solved the mixed integer linear programming model with a Tabu search heuristic, which provided enhanced routing costs and better customer service. Other related variants were widely studied in the literature, such as VRP with Time Windows (VRPTW) (related to 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).

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, regarding VRPTW, which refers to the time elapsed between serving the customer and ending the service, various literature discussed that variant. Lahyani et al. (2015) presented a taxonomic review and compared the soft times windows in which penalties are given for vehicles' late service, while with hard time windows the vehicle is not allowed to arrive late at all.

Meanwhile, VRP was expanded in a way that served industrial applications; Gribkovskaia et al. (2008) studied the case of satisfying only the demands of profitable pickup points. In their study, a mixed integer linear programming formulation was designed to minimise the total cost associated with the covered routes with totally delivered orders, and partially satisfied pickups. They argue 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 accomplished simultaneously, with the same vehicle delivering all of the orders from the depot to the destinations, and from destinations back to the depot point. Both a Node-based mathematical model and a hybrid heuristic algorithm were used to solve the 2E-VRPPD in medium and large sizes.

When considering the fleet's trucks' differences, the capacity of the truck/vehicle is one of the important decisions that affects the optimal VRP network choices. Lahyani et al. (2015) mentioned that the Capacitated Vehicle Routing Problem (CVRP) provides a solution with 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 light on the combination-vehicle attributes as a Combination Truck Routing problem (CTRP), in which vehicle types and travelled distances were considered in a survey, and a heuristic algorithm was applied to solve a real logistical case.

However, a challenging variant other 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) published a literature review about the MDVRP considering different VRP variants. They also presented different approaches to solving the problem. Consequently, research was extended on the topic of the MDVRP and it was deemed to be realistic and served real applications as effectively as possible. Lahyani et al. (2017) introduced 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 considerably achieved.

Referring to the PVRP, which has been defined by Campbell and Wilson (2014) as a VRP with multiple periods' service, the customers' orders are being scheduled to be met during 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), in which the objective function here minimises the total routing costs, while allowing some flexibility to customer satisfaction frequencies and quantity, during the planning horizon, rather than fixed frequencies and quantity. Also, the FPVRP considers the inventory costs accompanied by the objective function, which is modelled in the Inventory Routing Problem (IRP). The results of their work reveal that the costs were minimised better than when using PVRP or IRP.

According to the route types 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) analysed different VRPB literature and compared the exact and heuristic algorithms. Also, the literature 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 clusters with a three dimensional loading problem (3L-VRPCB). Here, the line-haul customers should be served before the backhaul 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 minimises the number of vehicles, travelling costs, and the un-serviced backhauls. Therefore, 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). These 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 obtain 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) suggests a new developed Bumble Bees Mating Optimisation (BBMO) algorithm to solve the OVRP. A comparative analysis was conducted between the other meta-heuristic, evolutionary and other nature-inspired algorithms. They argue that the results were satisfactory and better solutions were revealed. According to the important variant, the DVRP, wide researches were conducted and accompanied by a different mix of other variants. The DVRP grasped its importance from the fact that the real life aspects are mostly dynamic in their nature and requirements. Pillac et al. (2013) published a review paper that comprehensively studied various DVRP works from different perspectives. Specifically, two dimensions are important to understand when studying the DVRP, from which the dynamicity degree comes; these 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 emerges from the uncertain demand of available data. As the recent technological revolution provides an easier follow up system for the routing planning process, as the complexity of the DVRP increases and the need for richer VRP models emerges.

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 was static in relation to vehicle speed and journey time. On the contrary, traffic congestion will aggressively affect the optimal solution of planned routes from cost and distance overviews. Therefore, the study of VRP would be more realistic when considering the current traffic prosperities. Nowadays, on-point information about traffic on a certain route would help to identify the expected time to cross a certain route. Thus, using the TDVRP would greatly improve the optimal solution of the routing plan with minimum cost and time. Moreover, the optimal solution is expected to be enhanced not only in minimising time durations for planned routes but also in CO_2 emissions of the travelled journey. A case study conducted by Maden et al. (2010) describes a heuristic algorithm that minimises 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, conducted on a south western sample in the United Kingdom, shows that 7% of CO_2 emissions were reduced compared to the traditional VRP model with an emissions saving objective.

Franceschetti et al. (2013) presented an integer linear programming formulation, which considers minimising the costs of the travelled journey in both emissions and drivers' costs. Such a model is referred to as a Time-Dependent Pollution VRP (TDPVRP). They document that using the assumption of a fixed speed rate when planning for a VRP optimal solution would deviate from the expected CO_2 emissions by 20% for gasoline vehicles. Both congestion and free flow cases were studied and a complete characterisation 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 meant that the model provided a solution with an 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 a near optimal solution, taking into consideration stochastic traffic conditions.

On the other hand, developing effective and sustainable VRP models is important and dramatically affects the success of supply chain management and the inventory planning process. Achieving a high fit level between strategic planning and supply chain requires the existence of a strong integration between supply chain levels, inventory management process, and route planning. Due to the impact of the optimal routing plan on supply chain efficiency and success, more literature are discussed below.

2.2. VRP and supply chain and inventory systems' management

Referring to the integrated supply-chain systems' development, Gharaei et al. (2019a) developed an optimal supply chain batch sizing policy, which is integrated with a green policy, a vendor-managed inventory, and consignment stock agreement. The provided model can determine the optimal number of vendor batches and the volumes of batches for each product. The presented multi-product, multi-buyer model with realistic constraints can minimise the total costs of the integrated supply chain. An outer approximation with equality relaxation and an augmented penalty technique has been used to solve the mixed integer nonlinear programming problem and has achieved excellent results. Another work has been published by Shekarabi et al. (2018), who have optimised a lot-sizing policy for an integrated multi-level, multi-wholesaler supply chain under limited warehouse space. A generalised outer approximation technique, based on decomposition principles, has been used to solve the mixed integer nonlinear programming model. Besides, for the purpose of optimising the replenishment process, which has a cumulative effect on economic production quantity models, Gharaei et al. (2019c) have solved a mixed integer nonlinear programming model, using the generalised cross decomposition technique, with the aim of optimising the inventory system management. The total inventory costs have been minimised and the profit was maximised by optimising the lot-size of the replenishments. From the achieved optimistic results of the presented models, it could be inferred that optimising the integrated supply chain levels and inventory management process is expected to improve the routing planning objectives. Studies should focus more on integrating between different levels of planning process.

The integrated supply chain is highly affected by what is known as Joint Economic Lot-Sizing Problem (JELP). This relationship has been investigated by Gharaei et al. (2019b). A four-level supply chain has been studied as referring to the improved cooperation due to the effect of the JELP. The suggested model aims to minimise the inventory costs by ordering the optimal lot size, which is coordinated over the four levels of the supply chain: the suppliers, the producers, the wholesalers, and the retailers, producing the joint economic lot size: a MINLP model with stochastic constraints, including space limitation, procurement costs, the number of orders, and joint economic lot size. To solve such a large scale and hard MINLP model, the Generalised Bender Decomposition technique (GBD) has been used. The exact solving method reveals the best performance in terms of the optimum solution, the number of taken iterations, the dual infeasibility, the constraint violation, and the complementarity. Additionally, the sensitivity analysis shows low sensitivity between the change rate of inventory costs and lot size, while on the other hand, it shows an inverse relationship between the change rate of the inventory costs and the change rate of the period length of the product. As such, these results infer that an important relationship exists between the optimum period length and the optimal routing plan, affecting, in turn, the total inventory costs.

Investigating the impact of the routing and distribution process on the success of supply chain planning could be conducted considering variable issues. The demand probability distribution, the considered number of levels of the supply chain, the variability of the transferred products, the quality, the price, and the availability of the products are all important parameters to be considered when issuing routing and production strategies, although demand uncertainty substantially affects the chains' profit. Different works have studied different levels of supply chains, considering demand variation.

Giri and Bardhan (2014) have developed a supply chain, which consists of a single supplier and a single retailer and suggested a reliable backup supplier as a solution for mitigating the effects of the disruption that might occur due to uncertain demand. The assumed backup supplier has enhanced the profit of the retailer when there is no coordination with the primary supplier, which, even if allowed with the primary supplier, it remains effective up to a certain range of the chain's disruption probability before it collapses. Different scenarios have been investigated on the effect of the contract nature between retailer and supplier with retailer profitability. The results have shown that a reliable backup supplier, who might be costlier than the primary supplier, will enhance disruption resistance and profitability. Accordingly, securing a sustainable routing plan will ensure receiving orders on time, whether considering the primary or backup supplier, which, in turn, is expected to mitigate the chain disruption probability by using sustainable an on-hand inventory during highly fluctuating demand. Another work discussing supply chain planning has been introduced by Giri and Masanta (2018). They developed a closed-loop supply chain model consisting of a manufacturer, two suppliers, and a retailer. The demand has assumed to be dependent on the retail price and quality in a stochastic environment. It is assumed that the production process is related to the learning process. The developed closed-loop supply chain model has shown positive results in profitability when considering the human factor effect during the manufacturing process, which is the learning effect. Such work that integrates supply chain planning and the human factor effect can indicate the importance of studying the human factor effects on the planning and executing of results over other strategic decisions, such as distribution and the outing planning process. On the other hand, other factors that could affect the profitability of the supply chain are investigated by Yin et al. (2016). They introduced a game theoretic model that integrates a two-level supply chain and a manufacturer, whose decisions lead multiple suppliers with an uncertain level of quality and demand rate. The model has been considered as a non-cooperative game and analysed by Stackelberg equilibrium and has shown that manufacturer profitability is dramatically affected by the expected defective rate as well as demand stability.

Securing a stable and optimal routing plan also plays a substantial role in Just-In-Time (JIT) manufacturing within variable lead time, during which an inventory system highly affects the efficiency and effectiveness of the JIT profitability. Sarkar and Giri (2018) developed a stochastic supply chain model that aims to minimise the ordering cost inventory and imperfect production for a better integration between vendor and buyer within a JIT manufacturing and variable lead time inventory system. Dramatic savings were attained due to the reduction in lead time and ordering costs, as well as defective rates. Integrating the VRP with JIT is expected to enhance the profitability of both vendor and buyer in a stochastic supply chain model. Another inventory system model has been developed on the three stages of a supply chain: a manufacturer, a distributor, and a retailer. In this work, Shah et al. (2018) assumed a quadratic demand rate for deteriorate items allowing for a downstream credit payment given by the distributor to the retailer, to minimise the joint total costs by solving the optimal shipments, replenishment time, and downstream credit period, which substantially affects demand and production rates.

Based on the above publications, demand rate distribution aggressively affects the success of the incurred supply chain management and profitability for all sharing levels. Also, monitoring and controlling an effective inventory system plays a substantial role in increasing the chains' profitability. Therefore, optimising the routing process, which has impact on, first, the lead time, second, the inventory total costs and even all the chains' players profitability and satisfaction downstream to the consumer is an important success factor, which reflects coordinated and cooperated managerial decisions over strategic, operational, and tactical planning levels.

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 green awareness towards sustainable VRP models. A survey conducted by Lin et al. (2014) comprehensively reviews the different available literature on Green VRP (GVRP). The suggested models were analytically compared and categorised into GVRP and Pollution Routing Problems (PRPs). Suggestions were presented considering the GVRP with other VRP variants. The philosophy of this work considered the traditional VRP researches and a survey on the GVRP, and presented how traditional VRP could interact with the GVRP in the coming inspired research topics. This work could be used as a starting point for researchers and logistics practitioners to create sustainable VRP work that considers the important variants, combining the most important real-life aspects with continual green needs.

One of the available rich works that combines green issues with VRP has been recently published by Niu et al. (2018). The 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 minimise the routing costs regarding both the fuel and CO_2 emissions. The results of realistic instances computed on a Chinese sample revealed that such an open VRP model approximately reduced both fuel costs by 20% and CO_2 emissions costs by 30%.

For the purpose of controlling environmental pollution caused by distribution process emissions, a paper has recently been published by Hosseini-Nasab and Lotfalian (2017) classifying the selected route type by the fuel consumption level, depending on the average velocity level. They argue in their work that many researchers solved the green VRP by considering the fuel consumption rate minimisation (Zhong et al., 2004; Gurtu et al., 2015), 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 implemented. Therefore, they suggest that studying the effects of road type on average velocity and the accompanying fuel consumption rate would be effective in reducing fuel costs and emissions (Fagerholt et al., 2010). A three-objective mathematical model has been proposed, which: 1) minimises the travelling costs and consumed energy; 2) minimises the fuel consumption rate by minimising the incurred environmental penalty; and 3) maximises customer satisfaction levels in terms of maximum possible average velocity. After running the model, the results revealed that an improvement opportunity exists for reducing environmental pollution and planning eco-friendly routes, by considering the relationship between route type and certain fuel consumption rates associated with CO_2 emissions. This, in turn, would save non-renewable natural resources. They also suggest that, as the model is NP-Hard programmed and will be time consuming for solving large instances, it would be more realistic to solve the model 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 and 2015 considering the real life aspects of VRP as individual cases, considering only a few variants. As a result, the suggested models cannot be easily generalised for real cases and applications. Therefore, future works were suggested, considering multiple variants to have richer VRP models. The RVRP is defined as a 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 analyse the available literature about RVRP. They also provide the requirements that should be available to consider it to be a RVRP study. An important matter they mention is the gap between the suggested RVRP models in the literature and the complexity of the real-life aspects. They argue that most researches focus on providing a mathematical model with solutions rather than adjusting the real-life characteristics with the suggested model. In their paper, they provide the requirements as optimisation criteria, constraints, and preferences that should be available to produce an 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 location service, different starting and ending points, and route restrictions. According to the provided highly constrained model, an iterative improvement approach is required, such as the Reduced Variable Neighborhood Search (RVNS) algorithm and a tour relatedness measure. The results of the computational experiments reveal that the suggested algorithm would work effectively under dynamic planning systems. In the same vein, a case study on the semi-conductor 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 minimise the related route and schedule costs related to the semi-conductor supply chains. The results were compared with other suggested models in literature; they had less computing time and performed well in solving different problem instances.

Similarly, Soleimani et al. (2018) studied the collection and distribution (pick-up and delivery) of 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, such as travelling costs (fuel cost), cost of setting up the distribution centres, and minimising the supplying vehicles and air pollution levels. The multi-objective non-linear programming model has been linearised and solved using a fuzzy approach. Testing the model on a real case study proved 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 in the previous review, different researches published on VRP variants (Gribkovskaia et al., 2008). The topic still attracts academic researchers in a way that meets the logistical practitioners' needs. The suggested VRP models with various combinations of the variants, mainly focus on minimising travelling costs as well as time, such as García-Nájera et al. (2015) and Soleimani et al. (2018). New gaps have emerged that, when filled, would make VRP models more practical and beneficial. Specifically, enhancing customer satisfaction, creating more realistic models by adding new operational planning characteristics, such as the cross docking process, connecting a constrained scheduling process with a routing problem, considering road environments when planning for a VRP model, using occasional drivers as an economic sharing concept, and studying the most effective human factors related to the 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: the collection of arrived goods from the coming inbound trucks, classifying products into same type categories, and dispatching each category to the defined destination points. Implementing the cross-docking processes is possible on different choices of route networks available on the ground to arrive at supplier and delivery destinations. The proposed model assigns products, suppliers, cross-docks, and the optimal route networks and schedules. They presented a hybrid genetic algorithm that was applied to several examples to minimise the purchasing, distribution, and holding in storage costs. Studying reverse logistics operations was suggested as a further research point. Furthermore, the optimisation of VRP solutions not only include the minimisation of related costs and time, but would also 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 synchronising the important resources schedules with the routing plans. Although some literature was found using the variants as Skill VRP or Technician Routing Problem in their study, the topic is still not mature enough. The mentioned taxonomic review claimed that a paper published by Tozlu et al. (2015) presents the idea from both a product and service planning view, as a Variable Neighborhood Search Algorithm (VNS) was suggested to solve a routing model for assigning limited healthcare service providers to different patients. The review also suggested different gaps as an opportunity for future research.

The VRP topic would considerably serve the logistics practitioners who are stuck with definite partners, with whom they need to maintain their required service level, with contractual obligations, as agreed. 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 the required service level with 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 should include as many rich variants as possible. Subsequently, studying factors affecting the service level is important when preparing a routing plan. Such factors are the drivers' behaviours, which significantly affect routing decisions such as speed and route choices. An analytical framework for studying the relationship between drivers' behaviour and VRP is presented by Srinivas and Gajanand (2017). They claim that the available literature studied VRP variants as separate to the topic of drivers' behaviours, although, the planner behaviours of VRP were also considered. This work motivates researchers to integrate the drivers' behaviours factors within the familiar objectives of VRP: minimising costs, time, and pollution. This inspiring work might bring new thinking in modelling VRPs and facilitate their application easily in real life.

As noticed from the latter mentioned topics, many factors affect the suggested optimal solution found by the chosen VRPs models. 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 using 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) suggested using a third-party logistical service to cover the shortage happening in the assigned fleet of trucks, or received orders from far destinations for better customer satisfaction and increased service efficiency and availability. Since implementing such a solution would increase routing plan costs, optimal planning for VRP modelling is required. Therefore, Archetti et al. (2016) presented a multi-start heuristic approach that minimises 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 occasional drivers, in a way that will improve the availability and flexibility of the drivers. On the other hand, more challenges associated with the other VRP variants exist and need to be considered to optimise the practical benefits of crowd-shipping. Recently, a work presented by Macrina et al. (2017) claimed that using occasional drivers with multiple deliveries within a time window constraint (VRPODTW) would positively serve logistical companies regarding both routing plan and costs savings, although more variants should be considered to optimise a 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 a VRPOD plan as an eco-friendly plan, and optimising the usage of occasional drivers by controlling their behaviour. Section 2.5 spotlights the literature published about drivers' behaviours and the encountered effects on the routing plan.

2.5. VRP and driver behaviour

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

Srinivas and Gajanand (2017) believe that whatever the VRP objective was, it is important to think about drivers' sentiment when setting the routing plan. In cases such as VRP with a time window, circumstances would be different in reality and the driver might need frequent or infrequent breaks to achieve the plan objectives. Other cases for which minimising pollution was their objective, it would be lower cost 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 the ground. As a result, driver satisfaction would be better in a way that can 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 behaviour in a VRP model in terms of reducing total VRP costs, by sharing the routing plan decisions between the driver and the planner.

A study had discussed the idea of studying driver behaviour and its effects on risk homeostasis towards speed selection and accident rates was published by Janssen and Tenkink (1988), and under general conditions, it is believed that safety engineering measures would be reduced by shifts in behaviour. In the same regard, Iversen (2004) has studied the relationship between perceived attitude and driving behaviour patterns. The results show a strong correlation, as attitudes toward rule violation, speeding, and careless driving are strongly related to reckless driving, drinking, and seat belt use, which, in turn, could capture risk taking behaviour and help to predict a driver's driving pattern in the future. Additionally, he reflected the results of two theories that discussed the effect of perceived attitude on a person's control over performance, i.e. 1) the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975); and 2) the Theory of Planned Behaviour (TPB) (Ajzen, 1985). Both theories have been studied in relation to driving behaviour research such as, speeding, drunk drivers, and aggressive driving patterns, to predict risky driving behaviour and its effect on accidents in the future.

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

From what had been discussed above, it is expected to enhance VRP results on the ground when considering drivers' behaviour. Since this research includes two types of drivers, i.e. regular drivers, and occasional drivers, both drivers' behaviours are considered and the effect of their behaviours on the routing costs is monitored and analysed through sensitivity analysis. This, in turn, will help in deciding the proper level of autonomy as assigned between the planner and the driver, increase driver satisfaction, and achieve better customer satisfaction levels due to higher service availability for both nearby and remote customers. As such, evidence that the VRP model is solvable and practical will be a motivation to control the effect of drivers' behaviour patterns on different related issues as stated above in the literature.

3. Problem presentation

The VRP topic has been widely discussed in the literature. The challenge in providing a realistic model that reflects the real-life aspects is being adapted by multiple academic researchers. However, it is clear that the variants were studied while considering that there are no differences between drivers, so all the near optimal results are idealised regardless of drivers' behaviour patterns (Srinivas and Gajanand, 2017). Different objectives were analysed, such as minimising the routing travel costs, travel time and distance, and reducing air pollution levels, which resulted from such logistical activities. Recently, other persistent necessities have emerged as a result of the accelerated development of technological and transportation industries. For instance, adopting a green policy when modelling VRPs' variants, integrating drivers' behaviour with VRP models, including occasional drivers in the routing plan, and considering the route status, such as congestion issues, are important factors that require planning and when considering the required customer service level. Consequently, this study aims to develop, and near optimally solve, an eco-friendly VRP model integrated with driver behaviour controlling parameters, involving both regular and occasional drivers. To the best of our knowledge, as can be shown from the reviewed literature, these topics have been studied individually and VRP models have been studied in isolation from the drivers' behaviour patterns. Therefore, a more comprehensive and realistic model for solving a VRP that employs the ridesharing concept is developed. The concept of ridesharing has been defined as sharing individual travellers' costs by riding others' vehicles for a trip when they have similar time schedules. Such an idea has been introduced by Furuhata et al. (2013). This concept was developed later by Walmart to be its vision in using in-store customers to make deliveries for online customers who are close to their destination (Archetti et al., 2016), while, first, studying drivers' behaviour patterns, and second, accounting for the environment, would considerably serve real applications, and would be, more convincingly, adopted by logistical firms. Furthermore, investigations into different driver behaviour patterns highlight their effect of one of the objective functions: the near optimal VRP total costs. Such behaviour patterns include: 1) risky driving pattern; 2) neutral driving pattern; and 3) averse driving pattern. Each pattern is represented in the model by choosing different values for the risk-taking parameters. For example, assigning a high value to the risk-taking parameter for the driver means that the planner is risky, and the driver responsibility is significant when making decisions related to the near optimal route or speed according to the real circumstances, and vice-versa; when the risk taking parameter of the driver is medium or low, this means that the planner is neutral or risk averse, and, as such, the level of autonomy for the driver will not be high when making speed or route choice decisions (Srinivas and Gajanand, 2017). Different scenarios are sensitively analysed to investigate the effects of changing the model parameters on the routing plans.

The ability to monitor and control human differences between different drivers improves the stability of the results of the executed routing plans. Also, the proposed strategies and performance could be evaluated and measured more easily and precisely when referring to human performance and its effect on the plan, rather than to only the results of routing plans. Comparing the effects of different scenarios on routing plan weather costs, energy, or other outputs will ensure adjusting the plan to the best configurations. The importance of the human factor should never be neglected and should be integrated whenever the human's effect on the plan's output is significant. In addition, the expected positive impact on the supply chain profit and minimised inventory costs are other factors promoting the VRP-conducted plan.

3.1. Mathematical model

A Mixed Integer Non-Linear Programming Multi-Objective Model (MINLP-MOM) has been developed in terms of objective functions and constraints, to be solved into a near optimal VRP network. Also, fixed-charge modelling has been used to control one choice of route type. Later on, the MINLP-MOM is linearised to facilitate solving the proposed model. Understanding the research objectives comprehensively would lead to a mature realisation of the proper model components.

The MINLP-MOM model has been designed a logistics service for a set of regular and occasional drivers. 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 the VRP, which are: 1) improving the service level by using a third party as occasional driver to satisfy customers located far from the regular drivers' destinations network; 2) sustaining green driving behaviours through controlling the chosen velocity range, and imposing environmental penalty; and 3) considering the drivers' behaviour when planning for the 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 for use in generating solutions. Four objective functions have been composed to manage: 1) the minimisation of energy consumption levels associated with traversing the VRP plan (denoted by Z_1); 2) the maximisation of velocity level to a certain upper limit to reduce CO_2 emissions (denoted by Z_2); 3) the minimisation of penalties associated with velocity choices (denoted by Z_3); and 4) the minimisation of total travelling costs incorporating the driver's behaviour effect (denoted by Z_4). 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 the VRP plan and minimises 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's 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 fourth objective function has been developed from the formula introduced by Srinivas and Gajanand (2017), by including the occasional drivers in all objective functions and constraints.

3.2. Model preliminaries

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

3.2.1. Indices and sets

o: Depot point.
i: Customer node, i = 0, 1, …,N.
j: Destination node, j = 1, …,P.
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).).

3.2.2. Decision variables

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

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

O_{ijkr} :1, if an occasional driver k travels from node i to node j through route type r; otherwise: 0.

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

3.2.3. 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, $M \rightarrow +\infty$)
PEN_r :The environmental penalty associated with the fuel consumption rate imposed on route type r ($), where $PEN_r \geq 0$,∀ $r = 1,2,3,4$:
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 $VEL_{ijr} \neq 0$, ∀ $i = 0, 1, \ldots, N$, $j = 1, \ldots, P$, $r = 1,2,3,4$
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 behaviour by the planner in order to determine level of autonomy of the planner.
Δ: Parameter of risk-taking behaviour 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 ($Z_{opt} = \sum_{i=1}^{4} W_{Z_i}^* Z_i^*$).

3.2.4. 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):
   I. Type one (0–30 Km/hr): for velocities below 30 Km/hr, which has the highest fuel consumption rate, such as riding vehicles in city-urban environment.
   II. Type two (31–55 Km/hr): 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.
   III. Type three (56–80 Km/hr): for velocities between 56 Km/hr and 80 Km/hr, fuel consumption rate also decreases, such as driving in rural or high ways.
   IV. Type four (81–120 Km/hr): driving with these average velocities' range will increase the fuel consumption rate, such as highways 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. There is no time window for delivery specified at any of the nodes.
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/100 Km 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. 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: $0 \leq \Delta \leq \mathrm{a} \leq \beta \leq \mathrm{b},\ \mathrm{a},\ \mathrm{b} \geq 0$: i.e.: Parameter of risk-taking behaviour by the planner is larger than the one taken by the driver.
13. The occasional driver k is willing to serve through a route type r, if the driver's destination is less than or equal to (γ − 1) times the direct distance from the depot to the occasional driver destination:

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

14. 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; as shown in equation (1)

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

$i = 1 \ldots N,\ j = 1, \ldots,\ P,\ \mathrm{i} \neq \mathrm{j},\ l = d$ (regular), k (occasional).

15. Occasional drivers are paid according to the following compensation scheme,

$$(C_{0ik}\ + C_{ik} - C_{k0}) * \rho, \quad \rho \geq 1.$$

16. 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).

3.3. Objective function

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

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

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

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

The second objective function maximises 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 will be decreased for each near optimal route. The third objective function is given by equation (4)

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

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

$$\begin{aligned} \mathrm{Min}\ Z_4 = & \sum_{i=o}^{N} \sum_{j=1}^{P} \sum_{r=1}^{4} \Bigg(\sum_{d=1}^{D} \Big(X_{ijdr} * Y_{ijr} * TC_{ijdr} \Big) \\ & + \sum_{k=1}^{K} \Big(\ O_{ijkr}\ *\ \ Y_{ijr} * TC_{ijkr} \Big)\ \Bigg) \end{aligned} \tag{5}$$

where

$$\begin{aligned} TC_{ijdr} = & E\Big[C_{ijd} + SC_{dr} + TR_{dr}\Big] \\ & + \beta * \sqrt{\Delta^2 * Var\Big(C_{ijd} + SC_{dr} + TR_{dr}\Big)}, \text{ and} \end{aligned}$$

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

The fourth objective function minimises the total costs of the VRP routing plan associated with choosing either regular or occasional driver, integrated with minimising 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).

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

Notice that the total near optimal solution depends on the chosen weights for each objective function. The following are the constraints of the model.

$$\sum_{d=1}^{D} \sum_{r=1}^{4} X_{ijdr} \leq 1 \quad \forall\ i = 1, \dots N,\ \forall\ j = 1, \dots, P \tag{7}$$

$$\sum_{k=1}^{K} \sum_{r=1}^{4} O_{ijkr} \leq 1 \forall\ i = 1, \dots N,\ \forall\ j = 1, \dots, P \tag{8}$$

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

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

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

$$\sum_{r=1}^{4} Q_{ijr} \geq \sum_{r=1}^{4} \left(X_{ijdr} * Y_{ijr} * DEM_j \right) \forall\ i = 0, 1, \dots, N, j = 1, \dots, P\ \ \forall\ d = 1, \dots, D, \tag{12}$$

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

$$\forall\ i = 0, 1, \dots, N, j = 1, \dots, P, i \neq j\ \ \forall\ k = 1, \dots, K \tag{13}$$

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

$$\forall\ i = 0, 1, \dots, N, j = 1, \dots, P,\ \forall\ d = 1, \dots, D,\ r = 1,2,3,4 \tag{14}$$

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

$$\forall\ i = 0, 1, \dots, N, j = 1, \dots, P,\ \forall\ k = 1, \dots, K,\ r = 1,2,3,4 \tag{15}$$

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

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

$$\forall\ i = 0, 1, \dots, N, j = 1, \dots, P, \quad \forall\ d = 1, \dots, D,\ r = 1,2,3,4 \tag{17}$$

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

$$\forall\ i = 0, 1, \dots, N, j = 1, \dots, P, \quad \forall\ k = 1, \dots, K,\ r = 1,2,3,4 \tag{18}$$

$$\sum_{r=1}^{4} O_{ijkr} + \sum_{r=1}^{4} X_{ijdr} = 1$$

$$\forall\ i = 0, 1, \dots, N,\ j = 1, \dots, P, \forall\ k = 1, \dots, K,\ \ \forall\ d = 1, \dots, D \tag{19}$$

$$\sum_{r=1}^{4} Y_{ijr} = 1, \forall\ i = 0, 1, \dots, N, j = 1, \dots, P$$

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

$$\forall\ i = 0, 1, \dots, N, j = 1, \dots, P, \forall\ d = 1, \dots, D,\ \forall\ r = 1,2,3,4, \tag{21}$$

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

$$\forall\ i = 0, 1, \dots, N, j = 1, \dots, P, \forall\ k = 1, \dots, K,\ \forall\ r = 1,2,3,4 \tag{22}$$

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

$$Q_{ijr} \geq 0\ \forall\ i = 0, 1, \dots, N,\ j = 1, \dots, P,\ r = 1,2,3,4 \tag{24}$$

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

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

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

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 will not be considered. Furthermore, constraint (23) guarantees that vehicle returns empty to the depot. Constraints (24) refers to the non-negative 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.

3.4. Linearization

Despite that the practical problems like transportation model are naturally modelled 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 real conditions and decision variables; it will be linearised in order to be solved as a MIP model, which in role facilitates the optimisation 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 nonlinear 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)

$$\text{Min } Z_4 = \sum_{i=o}^{N}\sum_{j=1}^{P}\sum_{r=1}^{4}\Big(\sum_{d=1}^{D}\big(X_{ijdr}*Y_{ijr}*TC_{ijdr}\big) + \sum_{k=1}^{K}\big(O_{ijkr}*Y_{ijr}*TC_{i,j,k,r}\big)\Big)$$

Linear equivalent of Z_4 :

$$\text{Min } Z_4 = \sum_{i=o}^{N}\sum_{j=1}^{P}\sum_{r=1}^{4}\Big(\sum_{d=1}^{D}\big(XY_{ijdr}*TC_{ijdr}\big) + \sum_{k=1}^{K}\big(OY_{ijkr}*TC_{ijkr}\big)\Big) \tag{28}$$

$$XY_{ijdr} \le X_{ijdr} \tag{29}$$

$$XY_{ijdr} \le Y_{ijr} \tag{30}$$

$$XY_{ijdr} \ge X_{ijdr} + Y_{ijr} - 1 \tag{31}$$

$$OY_{ijkr} \le O_{ijkr} \tag{32}$$

$$OY_{ijkr} \le Y_{ijr} \tag{33}$$

$$OY_{ijkr} \ge O_{ijkr} + Y_{ijr} - 1 \tag{34}$$

$$\sum_{r=1}^{4} Q_{ijr} \ge \sum_{r=1}^{4}\big(X_{ijdr}*Y_{ijr}*DEM_j\big) \quad \forall\, i = 1,\ldots N,\ \forall\, j = 1,\ldots,P; \quad \forall\, d = 1,\ldots,D \quad \text{Nonlinear expression}$$

$$\sum_{r=1}^{4} Q_{ijr} \ge \sum_{r=1}^{4}\big(XY_{ijdr}*DEM_j\big) \quad \forall\, i = 1,\ldots N,\ \forall\, j = 1,\ldots,P, \forall\, d = 1,\ldots,D \quad \text{Linear equivalent} \tag{35}$$

$$\sum_{r=1}^{4} Q_{ijr} \ge \sum_{r=1}^{4}\big(O_{ijkr}*Y_{ijr}*DEM_j\big) \quad \forall\, i = 1,\ldots N,\ \forall\, j = 1,\ldots,P, \quad \forall\, k = 1,\ldots,K \quad \text{Nonlinear expression}$$

$$\sum_{r=1}^{4} Q_{ijr} \ge \sum_{r=1}^{4}\big(OY_{ijkr}*DEM_j\big) \quad \forall\, i = 0, 1,\ldots, N, j = 1,\ldots, P\ \forall\, k = 1,\ldots,K \quad \text{Linear equivalent} \tag{36}$$

$$Q_{ijr} \le (CAP - DEM_i)*X_{ijdr}*Y_{ijr}\ \forall\, i = 0, 1,\ldots, N, j = 1,\ldots, P, \forall\, d = 1,\ldots,D,\ r = 1,2,3,4 \quad \text{Nonlinear expression}$$

$$Q_{ijr} \le (CAP - DEM_i)*XY_{ijdr} \quad \forall\, i = 0, 1,\ldots, N, j = 1,\ldots, P, \forall\, d = 1,\ldots,D,\ r = 1,2,3,4 \quad \text{Linear equivalent} \tag{37}$$

$$Q_{ijr} \le (CAP - DEM_i)*O_{ijkr}*Y_{ijr} \quad \forall\, i = 0, 1,\ldots, N, j = 1,\ldots, P, \forall\, k = 1,\ldots,K,\ r = 1,2,3,4 \text{Nonlinear expression}$$

$$Q_{ijr} \le (CAP - DEM_i)*OY_{ijkr} \quad \forall\, i = 0, 1,\ldots, N, j = 1,\ldots, P, \forall\, k = 1,\ldots,K,\ r = 1,2,3,4 \quad \text{Linear equivalent} \tag{38}$$

The fourth objective function (i.e.: total costs minimisation) has been linearised 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.

4. Results and discussion

This section presents a numerical instance using data set adopted from the literature in order to verify the solvability and the validity of the proposed VRP model. The proposed set of data is presented in Section 4.1 where all the data that have been generated randomly are analysed and optimised using the proposed model. Eclipse Java 2018–9 is used to code the mathematical model and to solve it using the proper solving algorithms. Section 4.2 presents the solver characteristics and information related to the chosen solving methods. Finally, Section 4.3 discusses the numerical results that have been obtained by solving the proposed VRP model using the suggested numerical example.

4.1. 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, 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, suburban, 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 minimises 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.

In order to assess the capability of the proposed model in optimising a VRP problem encountered with the proposed conditions, a numerical instance has been proposed. Sets of **5** customers; **4** identical vehicles, $\mathbf{K = 3}$ occasional drivers, and $\mathbf{r = 4}$ types of routes; have been used as inputs to solve the 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.

4.2. Eclipse Java solver and algorithms

Eclipse Java 2018-09 software has been used for coding the mathematical model and solving the VRP proposed problem. As the VRP is one of the classic Operations Research application and discrete optimisation 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 the 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-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 the 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 behaviour, 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 will be able to produce the optimal routing plan with the optimal minimum travel distance and minimum number of vehicles to complete the distribution service, this will ensure that every assigned route will be balanced in terms of the assigned

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: $\mathbf{0 \leq \Delta \leq a \leq \beta \leq b}$	U [0,5]
β (a = 5, b = 10), where: $\mathbf{0 \leq \Delta \leq a \leq \beta \leq b}$	U [5,10]
$\gamma \geq 1$	U [1,3]
TR_{kr}	U [10,30] $
TR_{dr}	U [10,30] $
SC_{dr}	U [7, 9] $

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

driver type, the assigned route type, the optimal velocity, penalty and consumed energy (Liu et al., 2006).

4.3. Numerical results

The model was coded by Java and solved via Eclipse 2018–09 on a PC *Intel*® *Celeron*®*M inside*™*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.

4.3.1. Green routing plan with occasional drivers' assignment incorporated with both regular and occasional drivers' behaviour control

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. Fig. 1 describes the near optimal traversed routes.

4.3.2. 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 ($i.e.: Q_{ijr}$ 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

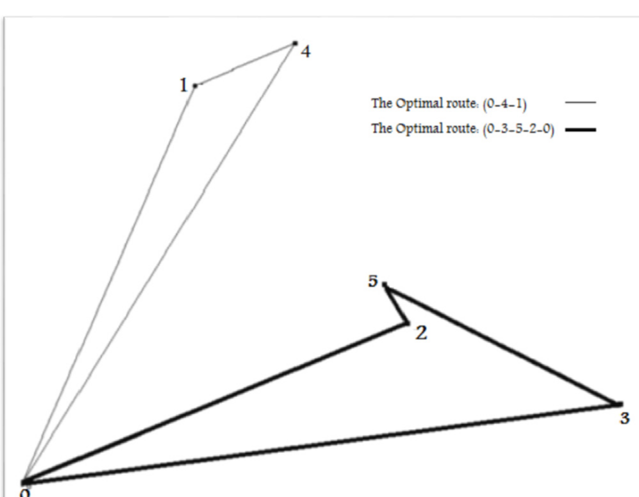

Fig. 1. The near optimal VRP Routing Plan produced by the Greedy and Intra-route Neighborhood heuristic algorithms.

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 been chosen to be the minimum allowable value (i.e.: $\rho = 1$). 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 will choose 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 a near optimal velocity of 21 Km/h, and so the associated binary decision variable ($i.e.: \mathbf{Y}_{351}$) 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 a near optimal penalty of 3 $.

4.3.3. 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 optimisation 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. 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 behaviour is being taken into consideration; it is an important matter that needs to be strategically planned.

5. Sensitivity analyses

For the purpose of analysing the effects of the risk level in the plan when assigning levels of autonomy to drivers regarding 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 Δ respectively). To analyse the weight of the total cost 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 analysis results.

5.1. The effects 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,

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 Q_{ijr} (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: $\beta = 8$, $\Delta = 4$, $\gamma = 1$, $\rho = 1$.

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_{ijr}	y_{ij4}			
(0,3)	69	0	0	1	0	3	0.07	4
(3,5)	21	1	0	0	0	1	0.15	3
(5,2)	30	1	0	0	0	1	0.06	1
(0,1)	48	0	1	0	0	2	0.08	3
(1,4)	2	1	0	0	0	1	0.14	0.28

Table 8
Near optimal values for objective functions.

Objective Function	Greedy Solution	Intra-Route Heuristic Neighborhood Search
Total penalty (Z_3)	11.28	11.28
Total velocity (Z_2)	170	170
Total energy (Z_1)	323300.0	323300.0
Total costs (Z_4)	1156.32	1156.32
(Z_{opt})	**324637.6**	**324637.6**

although, such a process would affect the total cost of the routing plan, and as such, the relationship should be sensitively analysed to determine the best trade-off between the driver's satisfaction level and the firm's satisfaction level. Initially, it has been proposed that both the planner and driver have zero value for both the planner and the driver β, and Δ, respectively, which is the traditional VRP model, for which driver behaviour is not considered. The results have shown that the total costs were minimal in this arrangement. Another three scenarios of different values of β, and Δ have been examined to represent the three possible scenarios for risk level from the planner's perspective: 1) the neutral-risk level as seen in scenario two; 2) the risk-seeker level as seen in scenario three; and 3) the risk-averse level as seen in scenario four. 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 levels of autonomy combinations (i.e. different risk patterns from the planner's perspective), and their associated total VRP routing costs. As expected, relaxing the model from such parameters (scenario one) would result in the minimum total costs of the VRP plan (1064$), while assigning equal level of autonomy for the driver in making decisions related to speed or route choice (scenario two) has slightly increased the total costs of the 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 behaviour when planning for a rich and realistic VRP model would ensure applying the model effectively on the ground. Also, driver satisfaction would be enhanced, while maintaining 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 are associated with the risk-seeker planner due to assigning a high level of autonomy for the driver (i.e. $1150.54) is larger than the risk-averse planner scenario, when $\beta = 8$, and $\Delta = 1$, by 5.3%. 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 levels due to the higher and efficient level of service availability. However, the risk-seeking planner's scenario, when $\beta = 6$, and $\Delta = 5$, opposes that the responsibility of driver is important and his/her decisions will be effective, and the driver may exhibit a risk seeking, risk-neutral, or risk-averse behaviour, depending on his/her nature. The nature of the driver could be determined by using a driver's behavioural survey, which should be updated regularly from the previous route and speed decisions to predict their actions. This would help in determining the proper level of autonomy assigned to the driver. Fig. 2 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 units of dollars. More specifically, the trajectory shows a growth in the total VRP costs when the parameters' values were gradually increased from the relaxed condition, in which there is no risk (i.e. $\beta = 0$, and $\Delta = 0$, when driver behaviour had not been considered) before decreasing again, when reducing the driver's level of autonomy of the driver (scenario four).

Such a relationship 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

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

Experiment no.	Risk Pattern of the planner	β	Δ	($\boldsymbol{Z_4}$) ($)	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	–

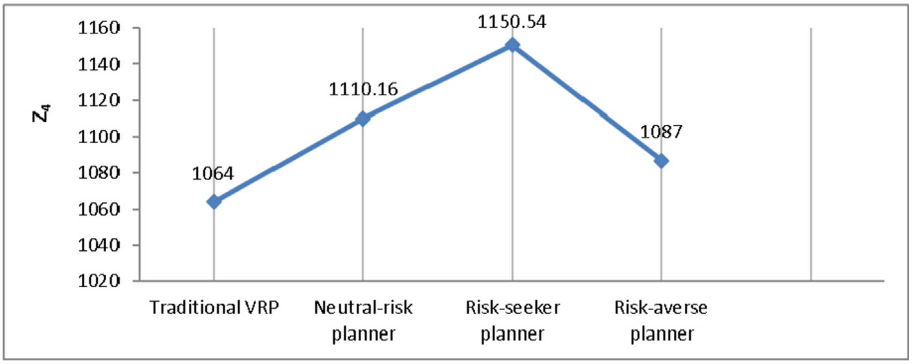

Fig. 2. The relationship of the effect of different scenarios of risk level against the total VRP costs' near optimal solution.

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	324586.3
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

effect of the total VRP costs on the total multi-objective function solution will rationally help in planning for the best near optimal VRP plan to satisfy the logistical firm's strategic objectives. The following section discusses the effect of each objective function qualitatively on the total near optimal solution, to get a clearer explanation about the effect on each function on the total near optimal solution of the VRP plan.

5.2. The effects of the objective functions weights on the total near optimal solution

To understand the effect of each objective function on the total near optimal solution qualitatively, related weights have been changed by interchangeably assigning different values for each objective function. 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. Analysis of the results shows that the objective function of energy consumption minimisation (Z_1) has the highest effect on the total near optimal solution ($Z_{opt} = 647882.32\$$), whereas other trials of assigning different weights for the objective functions did not significantly change the total near optimal solution. Fig. 3 describes the trajectory for the five scenarios of changing the weights' values associated with each objective function. It is apparent that the objective functions associated with velocity maximisation (Z_2), penalty minimisation (Z_3), and total costs minimisation (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 minimising the energy consumption (Z_1) has dramatically affected the total multi-objective function near optimal solution from 324586.3 up to 647882.32; these results are similar to those obtained by Hosseini-Nasab and Lotfalian (2017), which, in role, required that serious attention should be given by the firm's management to introducing effective planning for the locations of their warehouses and the chosen occasional drivers, to control the resulting energy. This will ensure the improvement of customer satisfaction levels by minimising 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 cost component has a minor effect on the total near optimal solution. Therefore, this is an opportunity for the logistical firm's management to incorporate drivers' behaviour when planning for a VRP even though the related total costs would increase.

First, the issue of minimising the total VRP costs as a cost-effective service network has been optimised in terms of all the associated service costs, including destination, driver training, and

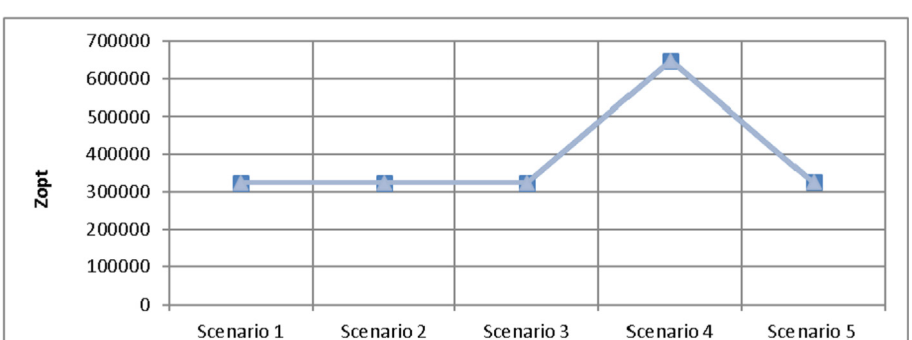

Fig. 3. The relationship of the weights of the objective functions and the total near optimal solution.

salary costs. Second, customer satisfaction levels have been improved by optimising the consumed energy used during service to the customer, affecting the service time, which depends on optimising the carried load along the distance of a near optimal routing network. Customer satisfaction has not only has been improved from the service time, but also from improving the probability of the service's availability. This issue has been manipulated by considering the idea of ridesharing by incorporating the occasional drivers as a third logistical party that serves when there is either a shortage in the firm's hired regular drivers, or when the customer's location is far away from the regular drivers' assigned destinations, such as rural and country-side areas (i.e. represented by the binary variable OY_{ijkr}), although such a process would increase VRP costs due to the compensation paid to the occasional drivers and the model also optimises those costs. Third, the proposed model optimises the total costs even when controlling the driver's behaviour in terms of controlling the level of autonomy assigned to the driver by the planner as a technique to determine the risk levels of a certain logistical firm. More specifically, the model has incorporated risk-taking parameters to adjust drivers' behaviour, which is represented by their ability to make decisions related to speed or routes on the ground. However, the sensitivity analysis on the relationship between risk-taking parameters and the VRP total costs prevailed that such an arrangement has a positive effect on VRP total costs, as increasing the assigned level of autonomy for drivers 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 function's weights on the total near-optimal solution. It has been shown that doubling the weight of the objective function that minimises the VRP total costs did not significantly affect the total near optimal solution. On the other hand, the objective function associated with minimising consumed energy has the largest effect when doubling its weight, by increasing the total near-optimal solution to almost double (note that such a procedure checks the effects qualitatively). Based on that, incorporating driver behaviour parameters when designing a delivery network such as VRP, is still reasonable even though the total costs have increased slightly.

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's strategy and the drivers' and customers' satisfaction. By using such a multi-objective 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. Through this, a new contribution has been added to the VRP modelling, taking into consideration the effect of human differences on the routing decisions.

6. Managerial implications

The conducted sensitivity analyses are used to support the managerial implications and insights. The relationships that have been studied in the sensitivity analyses are based on first, the focus of the study, i.e. the effect of involving the drivers' behaviour in the VRP costs, and second, clarifying the managerial impact on the firms' management, decision makers, and stakeholders. Table 9 and Fig. 2 show the mere impact of the assigned levels of autonomy to drivers on the total VRP costs; this supports the decision of integrating drivers' behaviours into the VRP plan, while sustaining a cost-effective routing plan. Using certain methods for evaluating and measuring the effectiveness of the proposed strategy, such as methods suggested by Sobhanallahi et al. (2016a, 2016b), would eliminate the probability of change resistance on the current strategy followed by logistics firms. Comparing revenues, drivers' performance, perceived quality of customers, number of loyal customers, and customers' destination distribution, before and after conducting the proposed model, helps in verifying the benefits of the proposed model. The second part of the sensitivity analysis has been conducted to check the effects of the cost-objective function on the total optimal solution; this has been done to provide managers with evidence that a mere increase in the routing plan costs due to the assigning of autonomy to drivers, will not significantly affect the total optimal solution. Table 10 and Fig. 3 present the effect of assigning different levels of autonomy on the total routing plan. Nevertheless, the worst case, in which the driver has the highest autonomy level, had an insignificant effect. Therefore, such results justify that considering the differences among drivers does not affect optimal plans negatively, and vice-versa, the expected benefits to the environment, economy, and society are magnified.

From the discussed sensitivity analyses results above, the importance of considering the human factor impact on the optimal routing plan could not be neglected. Moreover, as seen from the conducted literature on optimising different supply chain models, i.e. referring to Section 2.2, it could be concluded that the optimal routing plan affects also the success of managing the supply chain at different stages in single and multi-level chains, and as such, the supply chain's profitability and inventory total costs should be optimised. Future researches that integrate the VRP topic with supply chain management in one comprehensive optimisation model are recommended.

7. Conclusions

This research has introduced an eco-friendly VRP with an occasional driver's service integrated with driver behaviour control, which can enhance the perceived quality and efficiency of the near optimal VRP plan stakeholders. More precisely, the firm's financial objectives and the customer satisfaction level, by expanding the logistics service from city-dwellings up to rural residents, and driver satisfaction levels have been studied and included in one eco-friendly VRP model, achieving the three pillars of sustainability. In addition, monitoring the various driver behaviour effects, represented by the level of the assigned autonomy, allows the controlling of the driving pattern by analysing the associated risk characteristics of the driver using behavioural surveys and historical data, i.e. risky driving pattern, neutral driving pattern, and averse driving patter, maintaining that the proposed model will optimise the resulted increase in total VRP costs.

The incorporation of the use of occasional drivers and driver autonomy levels requires that the model accounts for dynamicity. Therefore, dynamic programming would ensure the updating of the routing plan input data. Also, the integration of other human characteristics in the mathematical model, such as fatigue, age, and experience level would improve the reality of the proposed model, and allow the development of effective VRP plans.

The model results could be also optimised by improving the available reward-driven systems and maintenance, which help in improving drivers' behaviour, reducing transportation emissions, and environmental penalties, and, therefore, the VRP total costs.

For future studies, this work could be extended by adding parameters referring to the optimisation of the rewards given to drivers for their performance, considering that the routing and logistics processes are reward-driven systems (Gharaei et al., 2015). For instance, the timeliness and learning pattern of driving behaviour could be monitored and controlled by integrating parameters in the proposed VRP model. Another future research could include the maintenance process in the proposed model as a way to reduce the failure rate of the vehicles and increase the accuracy of the logistic services in terms of time and cost. The model could be adapted to the idea of releasing an optimal selective maintenance schedule over the breaks periods, which minimise maintenance costs under stochastic constraints (Duan et al., 2018). Another interesting research topic is updating the proposed model in a way that enables firms' management to evaluate the effectiveness and performance rate of the applied strategies before, and after, applying the proposed VRP model, which considers the driver behaviour. Such a study would confirm the actual benefits of the applied model. One available research has provided an improved dimensional analysis technique with the name of the Freeman model, which has been approved as an accurate and valid evaluation technique for the effectiveness and performance rate of the supply chain's stakeholders (Sobhanallahi et al., 2016a). Also, the dimensional analysis method has been developed by using the weighted value of evaluators for the scoring performance of stakeholders, separately, rather than using simple averaging (Sobhanallahi et al., 2016b). This technique could be integrated with the proposed VRP model to measure the effectiveness of modified firms' strategy, with the ability of changing the number of evaluators and their weighted value.

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