UNIVERSITY OF SOUTHAMPTON

FACULTY OF CIVIL ENGINEERING AND THE ENVIRONMENT

Transportation

Freight Transport, Routing Software and Time-Dependent Vehicle Routing Models

by

Nicolas Rincon-Garcia

Thesis for the degree of Doctor of Philosophy

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ABSTRACT

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Routing and scheduling software is part of the Information and Technology systems available to support the transport industry, and uses complex algorithms along with geographical representations of the road network to allow better planning of daily collection and delivery schedules. This research reviews the evolution of routing and scheduling software, the algorithms used along with reported barriers to wider take-up and potential industry driven improvements that could be made. A survey of transport companies in the United Kingdom was conducted in order to validate and prioritize the software capabilities that require the most development according to the new challenges that the industry is facing. Responses suggested that companies required improved route optimization to tackle congestion based on time-dependent data and models, and greater accuracy in the representation of the road network. Not considering congestion leads to the underestimation of travel times and the production of inaccurate schedules. Literature shows that operational research techniques are available to solve problems that represent real world conditions, but research into the relative merits of using time-dependent models needs to be undertaken.

Although exact methods have been developed to solve the Vehicle Routing Problem, they cannot cope with large instances and rich variants that are required by the industry. Therefore, metaheuristic algorithms are usually implemented in routing software. A reported barrier in metaheuristic algorithms is the lack of accuracy (the difference between optimal or best-known values and the result of the proposed algorithm). In this research an algorithm was developed using elements of Large Neighbourhood Search that is capable to substantially improve the state of the art for the time-dependent Vehicle Routing Problem. Comparison of results with available test instances shows that the proposed algorithm is capable of obtaining a reduction in the number of vehicles (4.15%), travel distance (10.88%) and travel time (12.00%) compared to previous implementations in reasonable time. A variant that considers the Rules on Drivers' hours required in the scheduling of vehicles over 3.5 tons in the European Union and the UK is also introduced. Analysis of results show result improvements in number of vehicles (19.0%), travel distance (17.7%) and route duration (4.4%) compared to previous implementations.

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To my supervisors, family and friends for their support,
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UNIVERSITY OF Southampton

Academic Thesis: Declaration Of Authorship

I, NICOLAS RINCON-GARCIA [please print name]

declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

[title of thesis] FREIGHT TRANSPORT, ROUTING SOFTWARE AND TIME-DEPENDENT VEHICLE ROUTING MODELS

I confirm that:

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List of acronyms and abbreviations

AFMS: Advanced Fleet Management
ATIS: Advanced Traveller Information
CNV: Cumulative number of vehicles
CTD: Cumulative travel distance
CVRP: Capacitated Vehicle Routing Software
CVRS: Computerized Vehicle Routing Software
DSS: Decision Support Systems
EC-UW: European regulation on driving and working hours and The Road Transport (Working Time) Regulation 2005 required in the UK)
ERP: Enterprise Resource Centre
FIFO: first-in-first-out
FSM: Fleet Size and Mix Vehicle Routing Problem
FSMD: Fleet size and mix VRPTW with Routing Costs
FSMF: Fleet size and mix VRPTW with Fixed Cost
FSMFD: Fleet size and mix VRPTW with Fixed Cost and Routing Costs
GIS: Geographical Information System
GPS: Global Positioning System
HGV: Heavy Goods Vehicle
HVRP: Heterogeneous Vehicle Routing Problem
HVRPD: Heterogeneous VRPTW with Routing Costs
ICT: Information and Communication Technologies
IT: Information Technology
ITS: Intelligent Transport System
KPI: Key Performance Indicator
LGV: Light Goods Vehicle
LTL: Less-than-load (multi-drop deliveries)
LNS: Large Neighbourhood Search
MDVRP: Multi-depot Vehicle Routing Problem
NP-Hard: Non-deterministic Polynomial-time Hard
NV: Number of vehicles
OVRP: Open Vehicle Routing Problem
PDVRP: Pickup and Delivery Vehicle Routing Problem
PVRP: Periodic Vehicle Routing Problem
Sat-Nav: Satellite and Navigation System
SDVRP: Site-dependent Vehicle Routing Problem
TDVRP: Time-dependent Vehicle Routing Problem
TDVRPTW: Time-dependent VRPTW
TDVRP-EC: Time-dependent VRPTW and Rules on Drivers' hours (European Union Regulation)
TDVRP-EC-UW: Time-dependent VRPTW and Rules on Drivers' hours (European Union Regulation and The Road Transport (Working Time) Regulation 2005)
TMS: Transportation Management Systems
TS: Tabu Search
TSP: Traveling Salesman Problem
VNS: Variable Neighbourhood Search
VRPTW: Vehicle Routing Problem with Time Windows
VED: Vehicle Excise Duty
VRP: Vehicle Routing Problem
WTD: Working Time Directive

Chapter 1

Introduction

1.1. Motivation

Logistics and transportation are considered key activities that contribute to business success and environmental mitigation, where both technology and innovation are vital to obtain better use of the network (European Commission, 2011). Companies must design and manage freight transport operations, taking into consideration the specific characteristics of their Supply Chain, the provision of available infrastructure, and regulations, where supply chain is defined by the relation between sources, logistic provisions and customer (Allen et al., 2000, Chopra and Meindl, 2007).

Congestion and new transport policies have brought new challenges to the freight industry, as companies are being affected by travel time variability and low speed due to congestion (Golob and Regan, 2001). Travel time variations during a time of day may result from congested roads and other circumstances related to accidents, road maintenance, weather, etc., however recurrent delays due to congestion are responsible for up to 80% of total delays in peak hours (Skabardonis et al., 2003). Not including time variation on routing decisions might lead to overtime and missed deliveries (Haghani and Jung, 2005, Kok et al., 2012). Additionally, measures imposed by authorities to tackle the negative impacts of transport, such as access restriction and rules pertaining to drivers' hours, impose additional costs on the industry. Nevertheless, customers expect continuously improving and reasonably priced service, rather than a deteriorating service; this requires a higher level of scheduling reliability (Ehmke et al., 2012). The importance of providing effective and efficient solutions to the industry is paramount, bearing in mind that the profit margin in the sector is a mere 3% (FTA, 2015).

Decision support systems that aid planners in providing vehicle schedules are available, called computerized vehicle routing software (CVRS). The benefits of implementation not only consist of reducing transportation costs—savings are estimated to be in the area of 5% to 20% (Toth and Vigo, 2001)—but also of ameliorating human calculations and providing a graphical interface of the routes, which takes into consideration the road representation (Tarantilis and Kiranoudis, 2002). With the previously mentioned challenges that the industry is facing, new technologies in communication and data processing have emerged and been implemented in CVRS, along with models to support vehicle scheduling in order to provide solutions to the industry.

1.2. Information and technology systems in the freight transport industry

Affordable technologies that are present in everyday devices, such as mobiles, are being used in the transport industry to provide information to planners and drivers. In fact, the most frequently used information and technology system in the freight transport industry is the satellite and navigation system (Sat-Nav) (DFT, 2010). By using the Global Positioning System (GPS), drivers can obtain their current location on a digital map of the road network (DFT, 2010).

Due to recent technological breakthroughs, decision support systems for vehicle scheduling have evolved from stand-alone applications to more sophisticated tools that involve the utilization of a range of technologies such as computers and telecommunication devices, portable or not, to store, retrieve, transmit and manipulate data. Nowadays, planners can obtain the current location of vehicles and communicate in real time with drivers to make changes in the routes, e.g. new collections. Additionally, drivers can get information about road conditions even in real time from intelligent transportation systems (ITS), e.g. predicted congestion, current congestion, accidents or road closures.

Although a lot of new data and devices that provide solutions to the industry are available, and vendors offer a range of capabilities in their software, the shortcomings of these technologies are still not quite clear. It is in the interest of the industry and researchers to understand the barriers of these technologies in order to provide improved solutions to the industry.

1.3. Models to support vehicle scheduling

Among the main components of CVRS are the mathematical models and different solution techniques to solve the Vehicle Routing Problem (VRP) (Drexl, 2012). The VRP is the set of models that look for the optimal series of routes to be followed by a fleet of vehicles to serve a number of locations (Toth & Vigo, 2001).

Different VRP variants have been proposed in the literature to represent the different logistic configurations found in the industry, such as: a Vehicle Routing Problem with time windows (VRPTW), where each customer has a demand, a time window to be served and each visit has duration; a capacity constrained problem for heterogeneous vehicle fleets (HVRP), where different vehicle types with different costs and characteristics are available (Taillard, 1999); a pickup and delivery Vehicle Routing Problem (PDVRP), where goods are picked up at one location and delivered to other location (Parragh et al, 2008); a multi-depot Vehicle Routing Problem (MDVRP), where multiple depots are allowed (Pisinger & Ropke, 2007); a site-dependent Vehicle Routing Problem (SDVRP), where certain customers can only be served by certain vehicles and vehicles do not need to have the same capacity; an open Vehicle Routing Problem (OVRP), where vehicles do not need to return to the depot at the end of the delivery day (Pisinger & Ropke, 2007); and a periodic Vehicle Routing Problem (PVRP), where the planning period is extended to several days (Yu & Yang, 2011).

The VRP is a hard combinatorial problem (a non-deterministic polynomial-time hard problem) and some VRP variants such as the VRPTW have been studied thoroughly by the scientific community and efficient solutions techniques have been achieved. Although exact algorithms that guarantee optimality are computationally too demanding to be used for the industry, metaheuristic algorithms have been developed to execute “intelligent” searches and provide results near optimality with little computational effort, where algorithm analysis, comparison and improvement have been performed with available benchmark instances (an instance is a concrete set of input data necessary to solve a problem) (Bräysy & Gendreau, 2005a; Bräysy & Gendreau, 2005b; Cordeau et al, 2002; Drexl, 2012). Nevertheless, some variants that might be required by the industry have received less attention; such is the case of time-dependent VRP variants (TDVRP), where travel time varies according to departure time due to congested roads during different periods of the day (Kok et al, 2012).

The development of algorithms for VRP variants with more complex restrictions is a challenging task as is the case, for example, with the Vehicle Routing Problem with time windows and driving time regulations in the European Union (the set of rules that dictate the maximum number of driving hours in a weekly planning horizon, resting periods, and the maximum driving time without a break in a working day). After its first formal formulation, along with benchmarking instances and a solution method based on a large neighbourhood search metaheuristic (LNS) by Goel (2009), results with a different LNS tailoring proposed by Prescott-Gagnon et al (2010) obtained highly improved results, namely a reduced number of vehicles (31.7%) and travel distance (17.2%).

A number of critiques of the research on algorithms have been mentioned in the literature, as the most current efficient methods for VRP variants are intricate and difficult to reproduce (Vidal et al, 2013). Furthermore, some metaheuristic implementations have been tailored to work well in specific test instances by tuning parameters so specifically to consider the best random seed that provides high accuracy (Sörensen, 2015). There is a need for general and simple algorithms, applicable to practical settings required by the industry (Vidal et al, 2013), and capable of producing good results independently of the instance.

There is a gap between VRP research and industry requirements, where VRP models that take into consideration the multiple restrictions that companies face are called rich models (Hartl et al, 2006). The present research aims to understand the requirements of the industry and provide knowledge regarding VRP models that are capable of coping with industry necessities.

1.4. Research justification

The situation of the freight industry is shifting due to innovation (new technologies that provide data and devices), the evolution of customer expectations (e-commerce and home delivery), and changes in road conditions (regulation, congestion, etc.). Although the VRP has been the subject of intensive research due to the challenge that finding optimal solutions presents and due to the possible benefits that it might bring to the transport industry. In the industry, a number of efficient techniques have been developed to solve some variants; however, algorithms for some richer variants that consider the new situation have received less attention from the scientific community and research with adequate evaluation accuracy remains scarce.

As was previously mentioned, exact algorithms are not viable in real operations and implementations of metaheuristic approaches which might provide solutions that are far from optimal, if not adequately tailored. Consequently, CVRS might provide poor quality schedules. A test carried out by an academic group using different providers of software for vehicle routing showed a significant difference in the quality of solutions, up to 10% between the best vs. the worst schedule in instances of only 100 customers, where a higher difference was found in larger problems (Hallamaki et al., 2007; Bräysy & Hasle, 2014). Therefore, an understanding of available technology along with its shortcomings via a literature review, the necessities of the industry through direct discussion with companies that operate vehicles making use of CVRS, and understanding the capabilities that offer the current theories in solutions techniques to provide high accurate solution for the VRP variants that are required by the industry.

As an example congestion data. By using ITS, it is possible to estimate the different travel times between locations on highways or urban roads according to the departure time (peak hours present longer travel times). If congestion is not considered, vehicle schedules will be inaccurate and may lead to the violation of the expected delivery time to customers. Additionally, a lack of attention to the rules pertaining to drivers’ hours, may give schedules that do not comply with the regulations.

Therefore, it is important to understand the necessities of the industry and to focus research efforts on developing algorithms capable of providing near optimal solutions that mitigate the impact of new conditions in a market that every day demands more efficiencies with tighter restraints.

1.5. Objectives

- To understand the needs of the industry regarding vehicle routing models and Computerized Vehicle Routing Software.

- To better understand theory about models and solution techniques for vehicle routing and to understand if the algorithms are capable to solve the necessities of the industry.

- To explore new approaches to better satisfy the industry needs.

1.6. Results and products of the thesis

The results presented in this thesis are the following:

- Identification of Computerized Vehicle Routing Software capabilities that require improvements according to freight companies.
- Presentation of a literature review of algorithms to solve Vehicle Routing Problems and technological advances that have been incorporated in Computerized Vehicle Routing Software.
- Design of an algorithm for the Time-dependent Vehicle Routing Problem with Time Windows capable of obtaining a reduction in the number of vehicles (4.15%), travel distance (10.88%) and travel time (12.00%) compared to previous implementations.
- Design of an algorithm for the Time-dependent Vehicle Routing Problem with Time Windows and Rules on Drivers' hours (European Union Regulation) capable of obtaining a reduction in the number of vehicles (19.0%), travel distance (17.7%) and route duration (4.4%) compared to previous implementations.
- Design of an algorithm for the Time-dependent Vehicle Routing Problem with Time Windows and Rules on Drivers' hours (European Union Regulation and The Road Transport (Working Time) Regulation 2005 in the UK).
- Application of the designed algorithms in a set of instances that resemble a home delivery case. Results show the effects on costs and emissions of different levels of congestion, densities of customers and lengths of time windows.

The list of research products that have been produced in this research are listed below as follows:

Published

Conference papers:

- Rincon-Garcia Nicolas, Waterson Ben and Cherrett Tom (2013) When academic theory meets industry reality: The case of Vehicle Routing Problems. In, 18th Annual Logistics Research Network Conference. Birmingham, GB, 04 - 06 Sep 2013.

- Rincon-Garcia Nicolas, Velazquez-Abad Anthony, Waterson Ben and Cherrett Tom (2015). Improved Algorithms For Routing Urban Delivery Vehicles. In, 20th Annual Logistics Research Network Conference. Derby, GB, 9-11 Sep 2015.

Submitted for review

Papers in refereed journals:

- Rincon-Garcia Nicolas, Waterson Ben and Cherrett Tom (2016) Requirements from Vehicle Routing Software: Perspectives from literature, developers and the freight industry. Journal: Transport Reviews

- Rincon-Garcia, Nicolas, Waterson, Ben and Cherrett, Tom (2016) A hybrid metaheuristic for the Time-Dependent Vehicle Routing Problem with Hard Time Windows. Journal: International Journal of Industrial Engineering Computations.

Chapter 2

Vehicle scheduling, software and industry requirements

> “*Time conscious customers demand flexible and reliable deliveries and these demands can be costly if driver’s routes and schedules are not optimised…*
>
> *For delivery drivers, it is frustrating to be within a mile of a delivery point and to then take another 10 minutes to get to the final destination because they are not familiar with the local road network …* ”
>
> \- DFT (2010) -

Vehicle scheduling is a complex activity that requires human expertise, in fact only a few cases of full scheduling automation are found in the industry, namely taxi scheduling solutions (Cegarra et al., 2012). However, a number of IT systems are available to support drivers and planners, among these are Computerized Vehicle Routing and Scheduling Systems (CVRS) (DFT, 2010). Rochat and Semet (1994) illustrate the benefits of supporting schedules with CVRS in a Swiss company producing pet food and flour, by using software it was possible to produce routes, in a matter of minutes, that comply with Rules on Drivers’ hours, weight restrictions, access restriction and reduction of travelled distance, something that is time consuming and difficult to achieve manually.

Despite the many benefits reported either by the industry and the scientific literature, adoption rate of CVRS in the industry is rather low, a survey conducted in 335 companies in 2010 by the Department for Transport in the UK found that adoption rate in companies with less than 10 vehicles is 11% and for companies with more than 10 vehicles is 17% (DFT, 2010). The reasons to reject IT systems are: not suitable (49%), too expensive (33%), pointless (9%) and too complex (2%).

In this chapter it is intended to understand the evolution of CVRS, the new reported benefits obtained by the implementation of new technologies and the barriers that have to be overcome to provide better IT systems to support vehicle scheduling. In order to do so, it is necessary to review current routing practices and routing characterization as long as to review CVRS architecture. Additionally, a survey conducted in companies in the UK to identify the reasons to implement CVRS and the software components that require improvement is presented. Literature dealing with IT systems for the freight transport industry usually is focused on adoption rates (e.g., research presented by Davies et al. (2007) and Golob and Regan (2003)) or vendors perspective (e.g., research presented by Drexl (2012) and OR/MS-Today (2014)).

This chapter focuses on CVRS and the components that require further development according to industry users. A relevant CVRS component is the routing model (Drexl, 2012), VRP variants have been subject of considerable interest among researchers since its first formulation in 1959 (Dantzig and Ramser, 1959), with over one thousand papers found in a recent overview of scientific databases dealing with its variations, solution techniques and reported implementations (Eksioglu et al., 2009). Unfortunately, despite the immense attempt to provide high-efficient solutions for theoretical models, there remains (at least anecdotally) a feeling that theoretical models cannot be used in reality as they do not reflect the real constraints imposed by real life logistics and legislation. Routing characterization in this chapter follows the taxonomy proposed for VRP variants in order to identify relevant VRP variants that are of special interest to the industry.

2.1. Routing decisions in practice and new challenges in the road freight industry

Although all logistics operations (both in-house and third-party) face the same basic problem of using the available fleet of vehicles to serve the demand, the diversity of fleet sizes and compositions, and the diversity of demand constraints and predictability have led to a diverse range of scheduling approaches within the industry.

For example, (Golob and Regan, 2003) surveyed 712 transport companies in California and categorized route methods in manual routing (63%), followed by software supported (23%) and fixed schedules (15%). A more recent survey of 312 companies in Washington about route construction and prioritization of factors (Rowell, 2012) found that majority of companies either have daily-dynamic routes or fixed schedules, where 65% of companies had 10 vehicles or less, prioritization of factors is shown in Figure 1. Similar results have been found in the European Union (ECORYS, 2006) with the main priority of carrier operators still being to satisfy customer requirements at the minimum possible cost, where the three main transportation costs are: labour, fuel and depreciation.

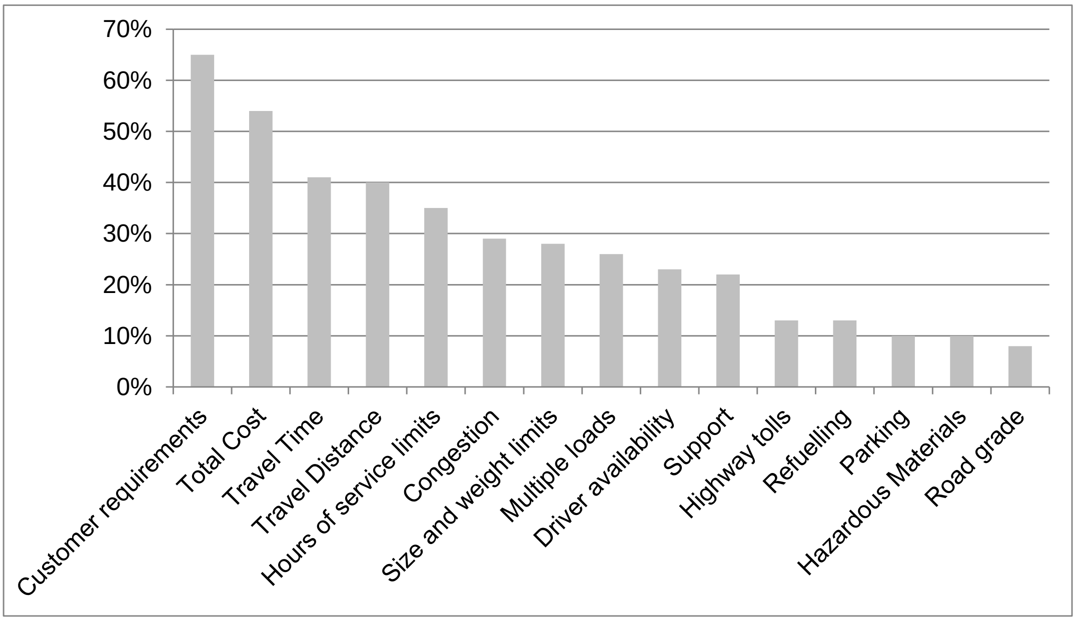


Figure 1. Prioritization of routing factors according to percentage of companies that ranked the factor with the highest grade in the state of Washington, 312 freight carriers.
Source: Rowell (2012)

A common practice in the industry is to plan drivers and vehicles that will deliver to specific customers and allow drivers to decide the final sequence, the function of the planners is to find feasible plans that minimise operational costs (DFT, 2011c). Planners face complex decisions involving multiple constraints such as: personal (e.g., driver's experience and knowledge of the route, language), environmental (e.g., weather, congestion, traveling time) and infrastructure (e.g., tolls, parking, access restrictions). Planners are vital to the operation in order to prioritize and relax constraints according to extensive knowledge in order to provide efficient solutions. Although full automation in vehicle scheduling is found in certain operation such as taxis, it is highly uncommon to find goods routing with full automation (Cegarra et al., 2012).

The reported attributes in the literature review to describe transport operations and its relation with routing requirements are summarized in Table 1.

Table 1. Attributes to describe transport operations and reported routing requirements.

Attribute	Vehicle size and regulation		Length of journey	Type of visit	Fleet Size	Type of ownership
Classification	• Light goods vehicles • Heavy goods vehicles		• Urban • Regional • Long-Haul	• Goods • Services • Others	• Less than 10 vehicles • 10 or more vehicles	• Transport provider • Private fleet
Technical requirements	**Driving regulation** Time windows Multiple periods Time-dependent models Drivers assignment	**Access Restrictions** Time windows Road representation Heterogeneous fleet Detailed geographical data	Time Windows Urban: Congestion Data Time-dependent models Rerouting (Communication) Long Haul: No necessarily use of Less-Than-Load (multi-drop deliveries) models Detailed geographical data	Time Windows Heterogeneous fleet Services: Requirement to provide useful information to derive useful probability distributions Models to deal with optional or complex request in extended planning horizons		
Reported benefits	Decrease impact of driving regulation costs.	Decrease impact of access restrictions Accurate road information to planners and drivers	Improve reliability Information of fuel and parking for long-haul operators	Routing under uncertainty		

Policy and Regulation in the UK and the European Union has enforced different measures according to vehicle size such as speed limitations, Rules on Drivers' hours and access restriction. Goods vehicles over 3.5 tonnes are defined as Heavy Goods Vehicles (HGV), since 2002 speed limitation for HGV is recommended to 90 km/h (European-Commission, 2007), driving time regulation and access restriction depend on the characteristics of the vehicle, therefore imposing new challenges in route planning.

Rules on Drivers' hours

Rules on Drivers' hours are the set of rules that dictate maximum number of driving hours in a weekly planning horizon, resting periods (uninterrupted period where a driver may freely dispose of his time "at the end of the working day"), and maximum number of driving time or working time without breaks (periods "within the working day" which is used exclusively for recuperation) in a working day. Limiting driving times improves road safety by reducing drivers' fatigue and drowsiness (Jensen and Dahl, 2009). Regulation 561/2006 (EC) applies to driving and working hours of road haulage vehicles over 3.5 tons in members of the European Union (European Union, 2006), with supplementary regulations sometimes found in particular countries (e.g. in the UK, The Road Transport (Working Time) Regulation 2005 imposes additional restrictions to drivers such as the introduction of mandatory breaks after six hours of working time even in situations where only a small portion of that time has actually been driving (DFT, 2005)).

Drivers of Light Goods Vehicles under 3.5 Ton (LGV) in the UK have to comply with GB domestic Rules on Drivers' hours (VOSA, 2011). By 2008 driving time regulation for LGV seemed to be not clear to operators, where only 13% declared full knowledge, see Table 2 (DFT, 2009).

Table 2. Understanding and knowledge of drivers' hours regulations.

None	24%
A little	22%
Some	31%
Extensive	13%
Not specified	9%

Source: DFT (2009)

The sets of Rules on Drivers' hours according to the type of vehicle in the UK are shown in Table 3.

Table 3. Sets of Rules on Drivers' hours according to the type of vehicle in the UK.

<table>
<tr><th>Vehicle Type</th><th>Regulation 561/2006 (EC) (European Union, 2006)</th></tr>
<tr><td rowspan="5">over 3.5 Ton</td><td>• Daily driving period shall not exceed 9 hours, with an exemption of twice a week when it can be extended to 10 hours.
• Total weekly driving time may not exceed 56 hours and the total fortnightly driving time may not exceed 90 hours.
• Daily rest period shall be at least 11 hours, with an exception of going down to 9 hours maximum three times a week. Daily rest can be split into 3 hours rest followed by 9 hour rest to make a total of 12 hours daily rest.
• Weekly rest is 45 continuous hours, which can be reduced every second week to 24 hours. Compensation arrangements apply for reduced weekly rest period. Weekly rest is to be taken after six days of working, except for coach drivers engaged in a single occasional service of international transport of passengers who may postpone their weekly rest period after 12 days in order to facilitate coach holidays.
• Breaks of at least 45 minutes (separable into 15 minutes followed by 30 minutes) should be taken after 4 ½ hours at the latest.</td></tr>
<tr><td>The Road Transport (Working Time) Regulation 2005 (VOSA, 2011)</td></tr>
<tr><td>• Mobile workers must not work more than 6 consecutive hours without taking a break.
• If working hours total between 6 and 9 hours, working time should be interrupted by a break or breaks totalling at least 30 minutes.
• If working hours total more than 9 hours, working time should be interrupted by a break or breaks totalling at least 45 minutes.
• Breaks should be of at least 15 minutes' duration.
• Weekly working time must not exceed an average of 48 hours per week over the reference period. A maximum working time of 60 hours can be performed in any single week providing the average 48-hour limit is not exceeded.
• Night work: if night work is performed, working time must not exceed 10 hours in any 24-hour period. Night time is the period between 00.00 and 04.00 for goods vehicles and between 01.00 and 05.00 for passenger vehicles. The 10-hour limit may be exceeded if this is permitted under a collective or workforce agreement.

Working time definition (GB, 2005): time during which the mobile worker cannot dispose freely of his time and is required to be at his workstation, ready to take up normal work, with certain tasks associated with being on duty, in particular during periods awaiting loading or unloading where their foreseeable duration is not known in advance.</td></tr>
<tr><td>Provisions under the Working Time Regulations 1998 (VOSA, 2011)</td></tr>
<tr><td>• An entitlement to 4.8 weeks' paid annual leave (increased to 5.6 weeks from 1 April 2009).
• Health checks for night workers.</td></tr>
<tr><td rowspan="4">under 3.5 Ton</td><td>GB Domestic Drivers Hours (VOSA, 2011)</td></tr>
<tr><td>• Maximum driving limit is 10 hours per day in any 24 hour period.
• Maximum duty is 11 hour maximum in a 24 hour period beginning at the start of the duty time.

Duty definition (VOSA, 2011): In the case of an employee driver it includes all periods of work and driving, but does not include rest or breaks.</td></tr>
<tr><td>Provisions under the Working Time Regulations 1998 (VOSA, 2011)</td></tr>
<tr><td>• Weekly working time, which must not exceed an average of 48 hours per week over the reference period (although individuals can 'opt out' of this requirement if they want to).
• An entitlement to 4.8 weeks' paid annual leave (increased to 5.6 weeks from 1 April 2009).
• Health checks for night workers.
• An entitlement to adequate rest.</td></tr>
</table>

Driving time regulation constraints in the VRP have obtained recent attention in order to mitigate its economic cost in transport operations (Goel et al., 2012, Kok et al., 2010a, Kok et al., 2010c, Xu et al., 2003), time windows and driver schedules must be considered where modelling the complete set of restrictions into solution algorithms has imposed new challenges to modellers (Kok et al., 2010c). Kok et al. (2010c) show major improvements in the required numbers of vehicles and travelled distance if the planning horizon considers multiple days and the full set of regulations is modelled when scheduling long-haul operations.

Access Restrictions

Access restriction to certain zones and roads has changed due to congestion and noise; additionally, specific regulations must be considered. In the case of Paris city centre restriction is based on the area of the vehicle rather than on weight (Browne et al., 2007). Access restriction includes time restrictions, which has impacted transport operations, a clear example is the London Lorry Control Scheme enforced to protect Londoners at nights and weekends from noise where HGV over 18 tons can only access certain roads, imposing an estimated extra cost to the industry of 30 million (FTA, 2002).

Modelling these kinds of restrictions require detailed road representation, time windows and considering multiple characteristics of different types of vehicles (heterogeneous fleet models). In order to handle in an effective way all the geographical data, Geographical Information Systems (GIS) are recommended. However, the majority of research has considered separately operational research models for the VRP and GIS data manipulation, leaving a gap of knowledge to analyse if routing decisions can be improved when data processing is integrated into solution algorithms (Keenan, 2008).

Detailed geographical information for freight transport is an issue identified by transport operators worldwide, navigational systems have been focused on the car segment; therefore, lorries were directed to unsuitable roads and travel speed was based on car specification rather than in freight vehicles, it might lead to inaccurate travel time estimations and other issues (DFT, 2010, Rowell, 2012).

Length of journey

Golob and Regan (2003) and Rowell (2012) present length characterizations; however both can be summarized in the second approach:

- Urban
- Regional (Up to 480 km)
- Long-Haul (Over 480 Km)

Urban companies are more likely to miss schedules and reroute due to congestion (Golob and Regan, 2003). The concept of city logistics addresses the technical requirements to routing in congested urban environments where time-dependent models with time windows might improve service level and reduce costs; developments in communications allow rerouting to reduce impact of non-predictive congestion (Ehmke et al., 2012). Shorter length journeys seem to affect vehicle size, Light Goods Vehicles account for 42 per cent of urban deliveries in the south of the UK (Cherrett et al., 2012).

Drivers in urban operations are expected to expend less time driving than other drivers, a characterization of urban deliveries performed by (Allen et al., 2000) shows possible impacts of parking restriction and delivery procedures in urban operations, Table 4.

Table 4. Delivery activities and proportion of time in city centres.

Activity	Percentage
• Driving	12%
• Parked at the roadside with driver present	1%
• Parked at roadside without driver present	87%
• Total	100%

Source: Allen et al. (2000)

It seems that regional companies are less demanding in terms of routing, they are less likely to use routing software and to reroute due to congestion, the number of missed schedules in regional companies is higher than in long-haul companies but lower than in urban companies (Golob and Regan, 2003).

Long-haul companies seem to have heavier vehicles and require equally all the routing factors to support the routing decision. Rules on Drivers' hours, overnight parking and petrol stations might be considered; therefore, detailed geographical information is required, maximizing loading factor is an important issue to reduce costs. Software for this kind of companies not necessarily provides Less-than-truck-load (multi-drop deliveries) solutions (Rowell, 2012), multi-drop is the term in the industry when vehicles perform a number of deliveries before returning to the depot e.g, parcels, mail, home delivery.

Type of visit

Allen et al. (2000) presented the following characterization for urban deliveries that can be applied to different type of journeys:

- Goods
- Services
- Others (e.g.: post, waste, ancillary)

Multiple requirements in goods and services are found in the literature (e.g., time windows, heterogeneous fleets). However, stochastic functionalities in routing software for service operations are reported to be the subject of possible improvement, they have not been fully implemented in commercial applications (Drexl, 2012). At the moment, gathering sufficient data to derive useful probability distributions in real operations is considered a difficult task, offering a research gap to improve this situation (Drexl, 2012). Additionally, literature dealing with optional or complex requests in extended planning horizons is rather scarce (Drexl, 2012).

Fleet Size

A frequent classification of fleet size is the division between less-than or more-than 10 vehicles. A characteristic of the freight UK market is that a large number of companies have few vehicles and a reduced number of companies have a large number of vehicles, reaching up to thousands of vehicles. Therefore, 93% of small firms (less than 10 vehicles) have 46% of the total vehicle fleet and 7% of large firms have 54% of the total vehicle fleet (Davies et al., 2007). Studies of Information and Communication Technologies (ICT) adoption in freight road providers and studies dealing specifically with routing software including companies with private fleets consistently find a positive relation between fleet size and adoption ratio (Davies et al., 2007, Golob and Regan, 2003).

Type of ownership

- Transport provider
- Private fleet.

Transport providers have played a major role in the transport industry, in the case of the UK traditionally more goods have been transported by transport providers than by private fleets (DFT, 2011a). Performance indicators of transport providers and private fleets vary in some aspects, vehicles of transport providers present higher utilisation and travel longer distances; however, lading factor and empty running indicators are similar for both type of operations (DFT, 2011b). Although Golob and Regan (2003) suggest that transport service providers are more like to utilise routing software, no differences regarding software requirements are identified in the literature review.

2.2. Evolution of Computerized Vehicle Routing and Scheduling Systems

“Decision Support Systems (DSS) are computer technologies that can be used to support complex decision making and problem solving” (Shim et al., 2002). Since the 1970’s, major technological breakthroughs have offered innovative solutions for vehicle planners and more recently for drivers. In this section, a review of CVRS capabilities and the respective technological components that support them are presented.

The three main components of DSS are a database, a model and a user interface. Since the early 1970's, the evolution of DSS has been influenced by data processing, the microcomputer and network communication developments (Shim et al., 2002). Supporting the routing decision might require an additional element to represent the road network, Geographical Information Systems (GIS) allow the manipulation and visualization of geographical data (road characteristics) such as streets, roads, intersections, velocities, congestion times, street names, length, and address ranges (Bozkaya et al., 2010, Ioannou et al., 2002, Sadeghi-Niaraki et al., 2011, Weigel and Cao, 1999). Among the reported benefits in the implementations of CVRS are (Tarantilis and Kiranoudis, 2002):

- Transport cost reduction
- Reduction in fuel consumption and environmental impact
- Improved customer service
- Effective strategic planning
- Less reliance on individual skills
- Tighter control of distribution

Although CVRS has advanced considerably since its first inception, manual intervention in route and schedule design is still vital to the operation in order to prioritize or relax certain constraints using the real-world knowledge of the logistics planner to provide the most efficient solutions (Cegarra et al., 2012). Despite this, many technologies have aided the development of CVRS tools particularly GIS for enabling detailed road characterisation and mobile technologies to allow the tracking of vehicles in real-time and the transfer of routing information emanating from CVRS systems to the driver, see Figure 2 (Jung et al., 2006).

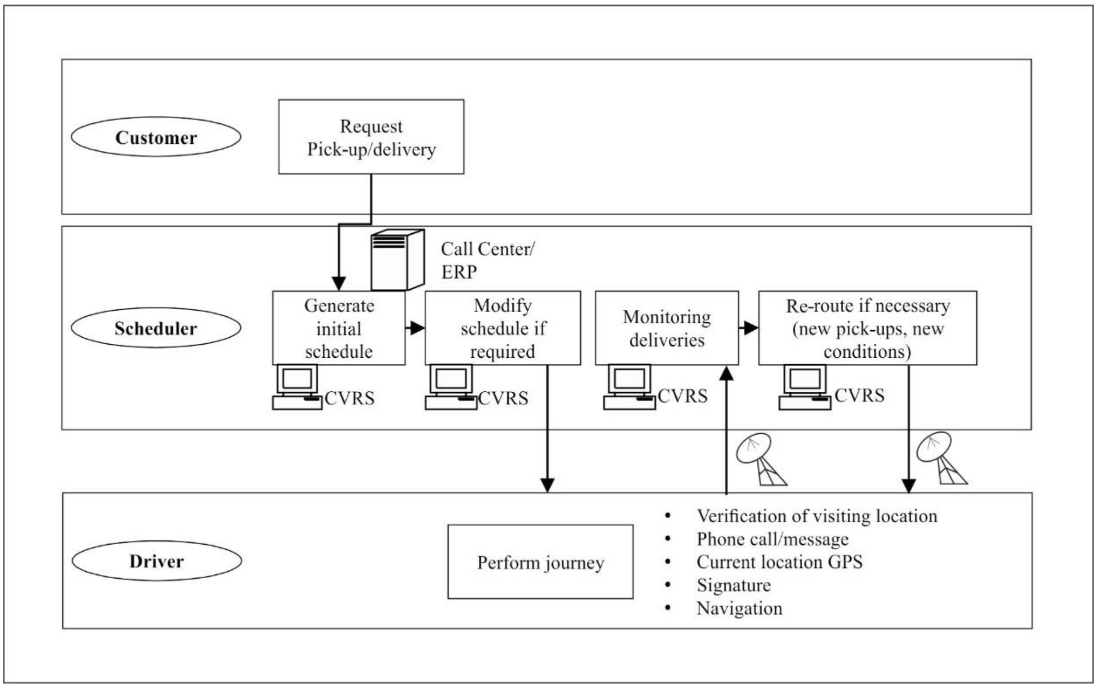


Figure 2. Flowchart of the planning/delivering process with re-routing.
Source: Jung et al. (2006)

The evolution of CVRS is presented in Figure 3. Initial schedules were based on obtaining a minimum distance/time route that satisfied all the customer service requests. In this way, Dantzig and Ramser (1959) proposed a theoretical model for determining the minimum distance routes for petrol tankers travelling between customers, so that each site was only visited once while satisfying all demands and not exceeding the vehicles capacities.

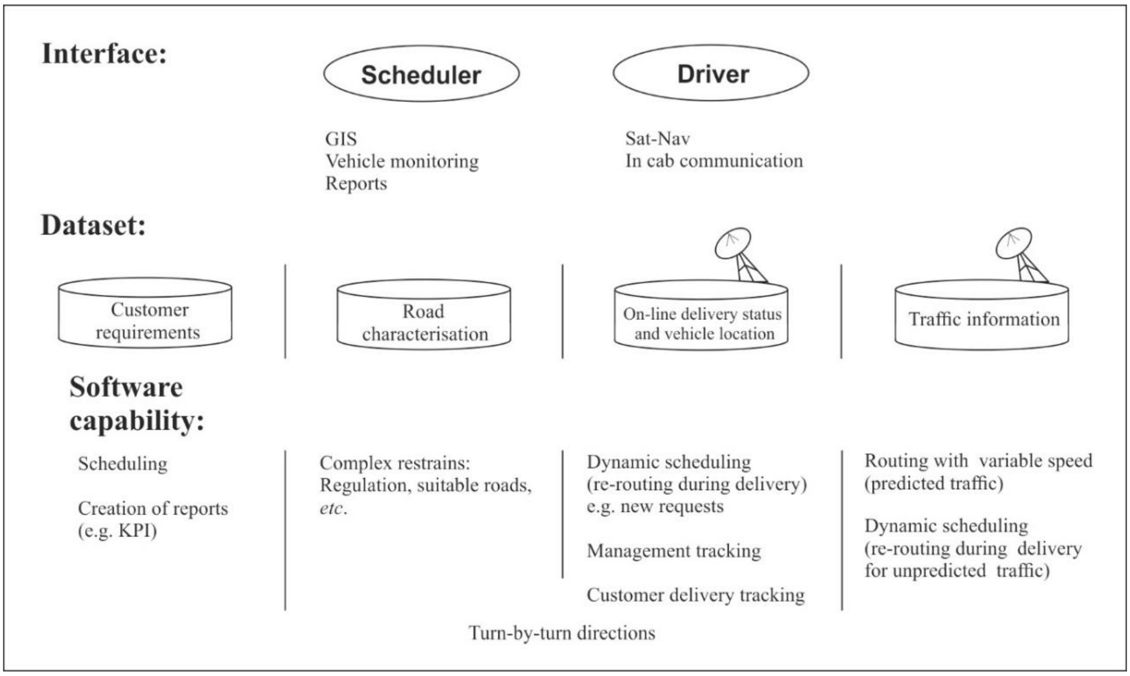


Figure 3. Development of CVRS

The development and adoption of GIS by businesses and government in the late 90s (Keenan, 1998), allowed the inclusion of detailed road characteristics into commercial CVRS. In a survey conducted in 2010 to CVRS providers, 86% reported GIS capabilities e.g., displaying routes and maps, editable routes, address geocoding, turn-by-turn directions (where routes between locations are described by presenting the road segments and the turns) (OR/MS-Today, 2010). Road characterization offers the possibility to include into the model legal restrictions. Additionally, calculation of shortest paths between customers taking under consideration the road network geometry and restrictions becomes an automatized task with the adequate algorithm (Jung et al., 2006).

Mobile technologies, defined as portable devices that encompass hardware, software and communications (Jarvenpaa and Lang, 2005), that utilise GIS concepts and Global Positioning Systems (GPS) with real time communication have brought a range of products to the transport industry. Satellite navigation systems offer drivers turn-by-turn directions when negotiating unfamiliar roads and 44% of companies with more than 10 vehicles in their fleet reported using it (DFT, 2010). In-cab communications and GPS provide vehicle tracking and status of deliveries in real time in order to re-route vehicles if necessary (e.g., courier pick-ups and deliveries, food distribution) (Montemanni et al., 2005). Additionally, it provides control over the operation with customers able to access the system and get information in real time about the status of the delivery and the location of the vehicle.

The technologies previously mentioned have made possible the collection and communication of data depicting the status of the road network; concepts like Intelligent Transportation Systems (ITS) and Advanced Traveller Information (ATIS) are based on obtaining, processing and communicating information in order to make a better use of transportation resources (Crainic et al., 2009, Khattak et al., 2004). Changing road conditions such as speed due to congestion is an issue for transport companies where schedules become unreliable if congestion is not considered when planning (Haghani and Jung, 2005, Kok et al., 2012). In a survey of transport managers in California, more than 80% considered congestion “serious” or “critically serious” due to unreliable travel times, increased costs and driver frustration (Golob and Regan, 2001), CVRS providers report the utilisation of traffic information for routing (OR/MS-Today, 2014), which provides more reliable schedules, not considering congestion might lead to the underestimation of travel time and missed deliveries (Haghani and Jung, 2005, Kok et al., 2012). Although congestion can be predicted to a certain extent, recurrent delays due to congestion are responsible for up to 80% of the total delays in peak hours (Skabardonis et al., 2003), mobile technologies can allow drivers to receive road information in real time in order to avoid unpredicted congestion (Cohn, 2009).

An important element in CVRS is the ability to provide control over the operation, where creation of reports with a statistical module is a common capability (Drexl, 2012). A new challenge in the industry involving data storage is the driving time regulation. The Tachograph is used to record the activities of drivers, and can be paired to CVRS in order to provide driving times and smooth out driver workloads (Paragon, 2009).

In the UK, the main CVRS providers are: DiPS, LogiX, Optrak, Paragon, Roadnet, Descartes, Truckstops (DFT, 2005) and 5 out of the 7 are participants of the software survey conducted by OR/MS-Today (2014). Software characteristics (routing functions, features and type of fleet) are shown in Table 5. Most of the vendors provide capabilities to utilise historical traffic by road segments (OR/MS-Today, 2014), turn-by-turn directions is supported by the 5 vendors along with capabilities for handling driving time regulations and re-routing during delivery (messaging to driver and real time vehicle tracking). Vendors offer support to different types of fleets, each type might have special requirements, e.g., long haul requires information about driving time regulation with restrictions for the week, overnight parking and resting, petrol stations, cost of petrol, tolls, etc. (Rowell, 2012), Descartes is the only vendor that supports bus routing.

Table 5. Software characteristics of main CVRS vendors in the UK.

			Routing Function						**Features**									**Type of fleet**					
Characteristics		Number of companies using software	Same day re-routing	Daily Routing	Weekly Routing	Real-time traffic info for routing	Historical travel time for routing	Consider driver skills	Geographic restrictions	Driver hour rules	Assigns individual drivers	Tur-by-turn directions	Electronic driver display	Integration to Sat-Nav	Messaging to driver	Real time vehicle tracking	Local pick-up and delivery	Long-haul LessThanLoad	Long-Haul	Courier	Buses	Service fleets
Software	Optrak	1-100	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		
	Paragon	101-500	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x	x		x
	Roadnet	+1001	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x
	Descartes	+1001	x	x	x		x	x	x	x	x	x	x		x	x	x	x		x	x	x
	TruckStops	+1001	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x

Source: OR/MS-Today (2014)

Although it seems that from the vendor perspective, there are a range of capabilities to support the transport industry, there remain questions about the components that require further improvements from a user perspective. The following section introduces a survey conducted to companies with freight operations that made use of CVRS in order to understand the requirements of the industry.

2.3. Survey

The survey was designed to be answered by planners and transport managers in companies in the UK with freight transport operations that have implemented CVRS using an on-line structured questionnaire (see Appendix A). Companies were identified by business social networks, business directories and the database for HGV operators. Nine hundred companies were contacted initially by phone in order to request information regarding characteristics of transport operation and willingness of being part of the study. In many cases it was stated that as a company policy, no information could be provided to researchers. It is important to highlight that only companies with CVRS could participate in the survey and the adoption rate in the industry is low (11% in companies with less than 10 vehicles and 17% in companies with more than 10 vehicles). In total 19 responses were gathered, 10 companies are 3PL and 9 support private operations where the core business is other than freight services. Characteristics of transport operations in surveyed companies are presented in Figure 4.

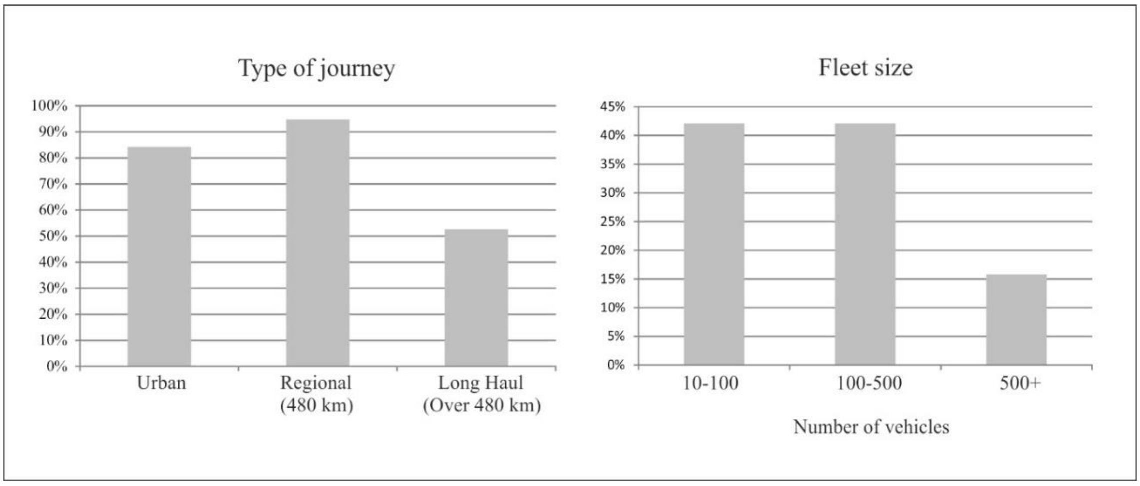
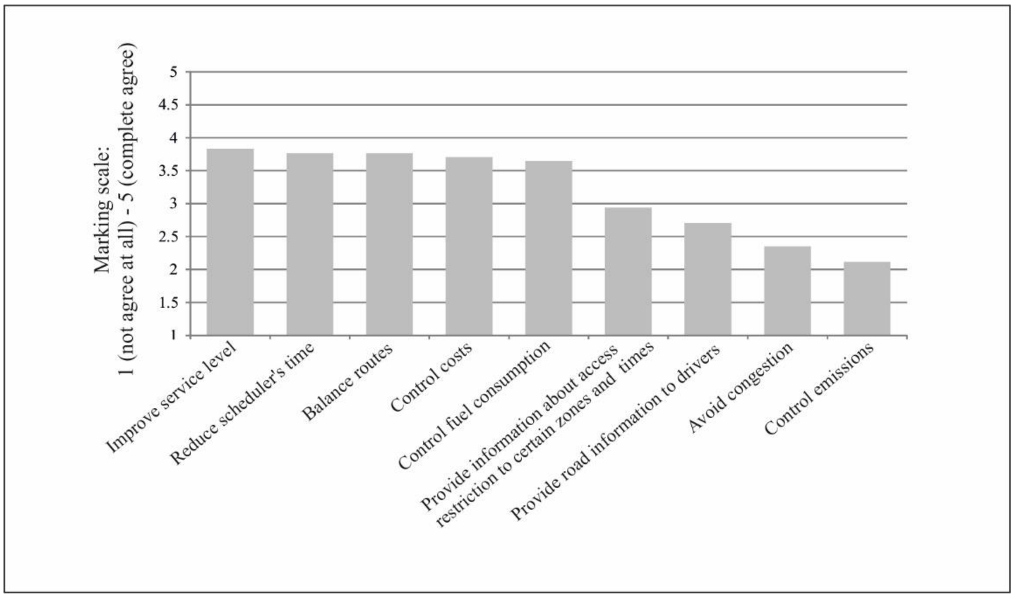
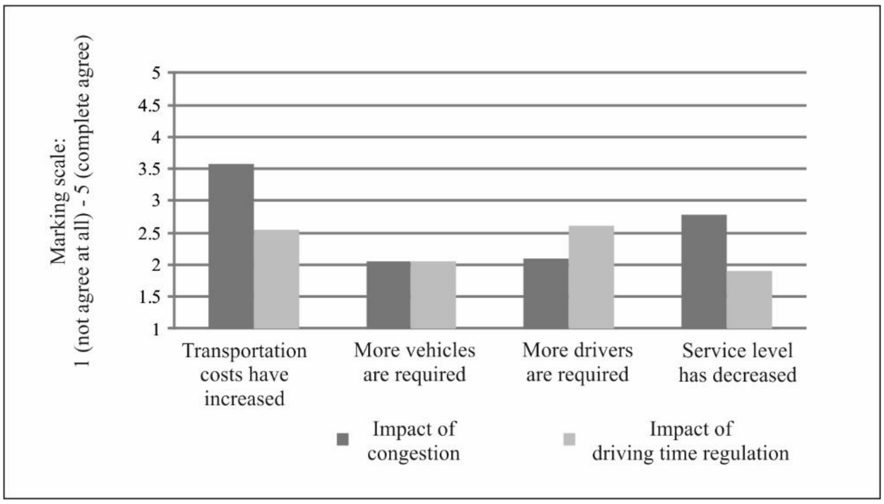


Figure 4**.** Characteristics of transport operations in surveyed companies (n=19)

Among the main reasons to adopt CVRS are: improvement of service level, reduction of scheduler’s time, balance routes and control costs, see Figure 5. Surveyed companies reported that the financial impact of congestion and service level have been higher than the impact of driving time regulation, where more drivers are required to comply with driving time legislation when compared to schedules prior to the implementation of the regulation, see Figure 6.

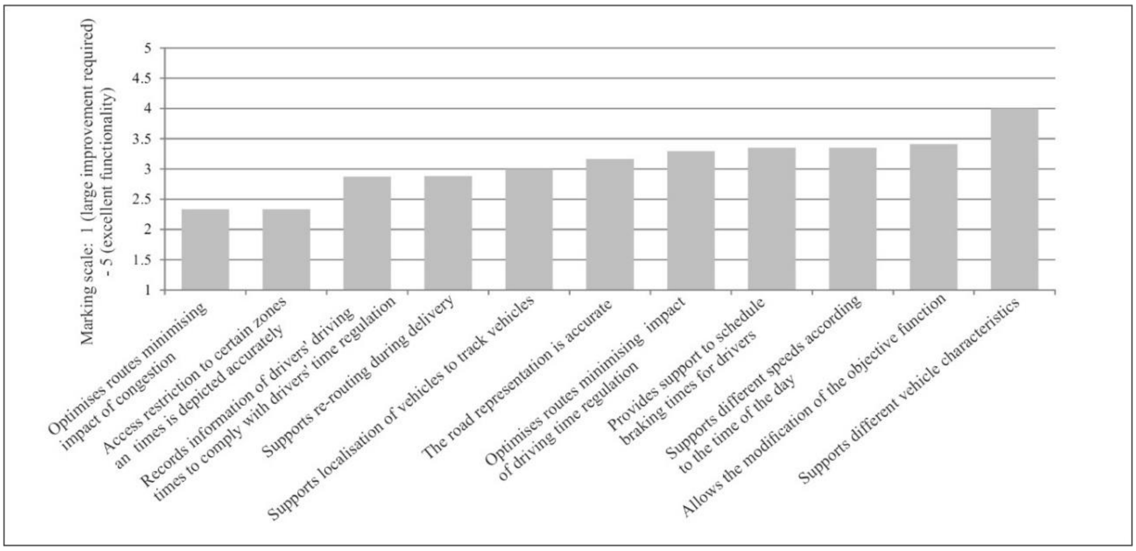


(See appendix A, question 13)
Figure 5. Reasons to adopt CVRS (n=19)



(See appendix A, questions 9 and 10)
Figure 6. Impact of new challenges in the industry (n=19)

The reported capabilities that require the most improvement, according to interviewed users are optimisation of routes minimising impact of congestion and accuracy of information regarding vehicle restriction to certain zones and times. Accuracy of road representation obtained an average marking, where capabilities to provide support to driving time directives is marked above average, support to different vehicle characteristics obtained the highest marking, a capability reported as a must have in CVRS according to Drexl (2012), see Figure 7.



(See appendix A, question 15)
Figure 7. Evaluation of CVRS capabilities according to users (n=18)

Although main vendors report capabilities for routing with historical travel time and to some extent with real-time traffic information, surveyed companies state the necessity of improving related capabilities. The elements of information systems to provide capabilities are data, software and hardware. In the following section the reported issues on technologies that support CVRS are introduced.

2.4. Issues and considerations in technologies that support CVRS capabilities

Data

The two capabilities that require the most development are optimisation of routes minimising impact of congestion, where patterns of traffic are needed, and accuracy of information regarding vehicle restriction to certain zones and times, additional capabilities related to data are re-routing, where real-time congestion might be required, and accuracy of road representation.

Within road characterization, it is reported in the literature the lack of accurate, detailed road information for freight transport, leading software to provide incorrect solutions, e.g., inefficient planning and vehicles on unsuitable roads (DFT, 2010). Furthermore, maps become out-of-date rather quickly. Gathering, processing and distributing data requires policy and resources, much of the information required by CVRS is obtained by local authorities and some initiatives have been put in place in order to openly share datasets in order to promote app development for transport users (Shrestha et al., 2014), for example, the city of Reading shares the links of the road network and estimation in real-time of road conditions based on loop detectors in selected links[1]. However, the freight industry requires a number of road characteristics such as: allowed height, allowed weight, allowed width, road gradient, allowed turns according to vehicle characteristics, tolls and petrol stations (Rowell, 2012). This level of detail is expensive to achieve and responsibility is not clear, available datasets are in different stakeholders, road information and characterization might be argued that relies on councils and government, but by 2008 approximately 58% of total road length was unclassified in the UK (DFT, 2010). Road classification consists of identification of roads that are best suited for traffic where unclassified roads are intended for local traffic, but still there is not a clear standard and it relies on local government characterization (DFT, 2012).

Different mapping strategies and products have come up in the market. In the car segment, traditional Sat-Nav providers have decreased sales due to nearly free mobile apps, such is the case of TomTom. The strategy of Waze, map-navigation app provider, is to rely on users to update maps, at the moment there are 140.000 volunteer map editors (Gibbs, 2014). The freight industry requires highly detailed information and Waze is an example of how to use and communicate driver's knowledge.

Regarding traffic patterns, currently some applications provide travel time estimations even considering real-time conditions, such as TomTom in some European Countries (Switzerland, UK and The Netherlands) (Cohn, 2009) and Google Traffic, some of the initiatives to obtain traffic information are the following:

i) Obtaining road congestion data from users: It makes use of mobile technologies and GPS to get information of multiple drivers in order to estimate network conditions (Marfia et al., 2013). Marfia et al. (2013) named Google Traffic as an example of this initiative and suggest that data should be used carefully due to lack of information about accuracy (Marfia et al., 2013). Privacy issues are also mentioned in the literature regarding user consent, data security and anonymization (Laurila et al., 2012).

[1] http://opendata.reading-travelinfo.co.uk/

ii) Automatic Vehicle Identification: Plate video recognition systems are used to identify vehicles by their plates and estimate travel time between locations when the same vehicle is identified in two different locations in a period of time (Dion and Rakha, 2006).

iii) Spot speed measurement systems: Speed detectors measure the speed of the vehicles at the location of the sensor (e.g., loop detectors, radar and infrared technologies) (Dion and Rakha, 2006). However, travel time estimations might be inaccurate due to the complexities involved in calculations based on speed on location of the sensor and not considering traffic dynamics and queue evolution in the studied stretch (Soriguera and Robusté, 2011).

Traffic information is used to predict travel times on congested roads, it requires continuous data collection across the day in order to tailor the speed model (Kok et al., 2012), gathering traffic information on minor roads and all the links on urban networks is a difficult task due to prohibitive investment cost in the case of loop detectors and cameras, where road congestion data from users is emerging due to the fact that it leverages mobile network infrastructure providing a cost-effective way to collect traffic data (Herrera et al., 2010).

Nevertheless, data managing is an expensive task that still is a matter of controversy regarding who should be responsible for it, local councils, map providers, public agencies, etc. (DFT, 2010). There are no definitive standards governing how road database information should be collected, updated or distributed (DFT, 2010, DFT, 2008). Recommendations to improve these issues are: joined-up working between authorities, mapping providers, and software vendors; resolve compatibility issues between telematics, Sat-Nav and any other IT freight solutions; and standardisation and collaboration (DFT, 2010). Cooperation and standardisation between stakeholders is required in order to provide accurate data. Still, there is the concern about price, should this information be free and government subsidise it or it should come at a price. Nevertheless, government has started to address these issues due to the possible benefits in users of transport systems (Shrestha et al., 2014).

Software

Computer programmes on CVRS usually have 5 components: i) interface to a database or enterprise resource centre (ERP) (system that support cross-functional processes in companies) (Mabert et al., 2003) ii) GIS tools for geocoding addresses, calculating shortest paths in road networks (distance and travel time between locations), geolocation, etc. iii) a planning module to support automated/manual interactive planning (the core analytic tool), iv) a telematics module that allows data exchange between dispatchers and vehicles, v) statistic module to provide KPIs and reports (Drexl, 2012).

According to Drexl (2012) the most challenging component is the automated planning module that makes use of VRP models to find close to optimal schedules. It is important to highlight that finding the shortest route between locations could be also a non-deterministic polynomial-time hard (NP-Hard) problem, but different applications in network transport optimisation can be solved in polynomial times such as the Time-dependent quickest path problem in FIFO networks and the Time-dependent least consumption path problem (minimisation of fuel consumption and driver wage) (Gendreau et al., 2015).

The VRP has been subject to extensive research, where a large number of variants that consider different logistic configurations have been proposed (Eksioglu et al., 2009). However a number of critiques have been addressed to VRP research. In many cases results cannot be replicated, proposed algorithms make use of highly tailored parameters and focus on improving best-known results, the industry requires parameter-free algorithms capable to consistently solve real-life problems. According to Drexl (2012) “The last 0.1 % in solution quality to be gained from an additional complex algorithmic device are insignificant, since the data available in practice are never 100 % accurate”.

Despite the large number of publications in the topic, recent literature reviews on VRP algorithms highlight the importance of providing solutions for dynamic problems (where some of the information is revealed during the execution of the route), stochastic models (where a level of uncertainty in the data is present and probabilistic distribution is known) (Hoff et al., 2010, Laporte, 2009, Pillac et al., 2013), more complex instances to account for realistic situations with richer models (Hoff et al., 2010) and integrated and synchronized models to account for multi-modal transport and a range of operations where routes depend on each other (Drexl, 2012).

Regarding the necessities stated by the surveyed companies in this research for route optimisation minimising the impact of congestion, Gendreau et al. (2015) conducted the most recent literature review in time-dependent routing problems. Some of the mentioned problems are the “*time-dependent point-to-point route planning*” (which is obtaining the optimal path between two locations in a road network) and the “*time-dependent vehicle routing*” (time-dependent VRP variants). The challenge in the point-to-point route planning relies on providing efficient algorithms on-line for the next-generation web-based travel information systems that require results in milliseconds or microseconds. Although, it is required to use this problem to establish time-dependent travel times in the TDVRPTW, shortest paths might be determined in a pre-processing phase (Kok et al., 2012) prior to the execution of solving the actual schedule due to the fact that forecasted travel-times are used and there is no need of on-line applications when designing the routes for the following planning period. Gendreau et al. (2015) highlight the requirement of additional contributions of the Operational Research community in time-dependent routing problems, where techniques for constant-speed classic network optimisation problems exist but it is required research for their time-dependent counterparts.

Hardware

CVRS might receive information from and make use of different ITS technologies, where there are potential benefits from device interconnectivity such as retrieving actual driving times from the Tachograph in order to provide schedules for next day accommodating driving time regulation, telematics and analysis of driver behaviour, downloading detailed turn-by-turn schedule into the Sat-Nav for driver knowledge, etc. However, standardization and collaboration are required to improve device connectivity (DFT, 2010).

An additional barrier mentioned in ITS related to routing and driving is accuracy of vehicle location, where there is signal loss of GPS due to the “city canyon” effect; tall building in city environments, trees and hills might bounce radio signals from satellites and derive inaccurate GPS location (Gong et al., 2012). Although it is a key issue in systems that require high accuracy, e.g., driverless car, different solutions have been created for the freight industry such as the integration of road characteristics to estimate the position of the vehicle when no signal is received (DFT, 2010, Gong et al., 2012).

2.5. Discussion of the chapter

The concept of business logistics is more frequently recognized as a core capability that enables companies to gain and maintain competitive advantage based on offering better customer value, defined as the relation between perceived benefits and customer’s costs, where effective planning and operation in logistics is able to improve both elements and create value to customers (Christopher, 2010). When routing, it seems that companies maintain these objectives, in the prioritisation of key routing factors reported by Rowell (2012), meeting customers’ requirements and the minimisation of total cost (travel time and travel distance) appear among the most important factors. Something according to the prioritisation of reasons to adopt CVRS reported by companies in this research, additional reasons are reduction of scheduler’s time and balancing workloads. Available processor capacity allows the creation of feasible optimised routes that take under consideration a range of restrictions in a fraction of the time that is required by manual schedules. Still, it is reported in the literature that human interaction is required to verify and modify routes, Erdoğan et al. (2013) exemplify it in a charity organization that adopted a prototype VRP model for bank charity collection and shop delivery, transport manager yet has to modify routes in order to minimise the risk of time window violations due to heavy traffic, balancing workloads, clustering, inclusion of urgent requests, forced or delayed collections and unavailability of vehicles or staff. When additional restrictions not supported in the model have to be considered or a relaxed schedule is required, manual route modifications should be easily performed and evaluated with an adequate CVRS interface design based on GIS (Cegarra et al., 2012).

The freight transport industry has some special characteristics, low margin profits (up to 3%) (FTA, 2015), a large number of operators with very few vehicles and a small number of companies with a large number of vehicles (7% of operators control 54% of the total goods vehicles in the UK) (Davies et al., 2007), and a large range of logistic configurations to support different business models. Therefore the low CVRS adoption rate, in many companies it does not support the specific type of operation or bring enough benefits to compensate the investment of its implementation. Nevertheless, big players are implementing and improving computerized routing such as UPS and its ORION project (On-Road Integrated Optimisation and Navigation), it saves more than 1.5 million gallons of fuel, reduces the environmental impact of the operation and has shown in preliminary tests the possibility to save millions of dollars. It will enable the next generation of software capabilities by allowing customers to see on-line their incoming deliveries and actively choose drop preferences and reroute shipment if necessary (UPS, 2015), it is an example of how ITS has transformed the industry and will continue to do so.

There is the necessity to provide improved solutions to the industry, companies have stated that optimisation under congestion and accuracy of road characteristics are capabilities that require the most improvement. The impact of congestion has increased over the last 30 years, with the 101 largest US cities reporting that travel delay had increased from 1.1 billion hours in 1982 to 4.8 billion hours in 2011 (Chang et al., 2015). The key impact congestion has on vehicle planning is that travel times between locations vary as a function of the changing traffic patterns. Failure to account for this in routing decisions leads to drivers running out of hours, additional overtime payments and missed deliveries (Haghani and Jung, 2005, Kok et al., 2012). Although traffic data is available to a certain extent and some vendors claim that the routing under congestion capability is implemented on software, a recent literature review (Gendreau et al., 2015) shows that the theory to provide algorithms for time-dependent VRP variants is still scarce.

Many initiatives have been put in place to provide and maintain relevant data for public, private and freight transport, where policy and cooperation are key drivers. Although many questions remain regarding security and costs, technologies to gather travel time data are available. Additionally, there is a clear statement from policy makers to promote the use of open data, it is recognized as the "raw material" for developments in information products and services that can yield great economic and social benefits. The roadmap in policy is based on adapting the legal framework, mobilizing financing instruments and facilitating coordination and experience (European-Commission, 2011).

To sum up

CVRS is used in the transport industry to improve service level by supporting planners in the complex activity of vehicle scheduling. The literature review shows that a range of technological breakthroughs has been implemented in this type of systems in order to provide representation of road characteristics, on-line delivery status and vehicle location, and traffic information in order to support software capabilities required by the industry. However, it is important to understand the barriers found in real life when compared to technological or theoretical concepts, which is intended in this research in order to provide knowledge to software developers, researchers and stakeholders in order to identify the most relevant issues to contribute to the transport industry.

Congestion is reported as a major concern and sampled companies report that it affects the operation in terms of cost increment and deteriorating service. Furthermore, companies identified route optimisation under congestion as one of the two capabilities that require the most development. The technological elements to improve planning under congestion are traffic patterns and time-dependent models in order to provide reliable schedules and both elements are reported as barriers; gathering information in all the links of the road network is a difficult task where some initiatives have been introduced to provide traffic data and although the VRP has received much attention from researchers, recent literature reviews mention that some variants require further research, including time-dependent variants.

Providing algorithms for routing vehicles is reported as a complex research area that might improve the freight industry by creating routes that minimise the impact of some of the current challenges that the industry is facing (e.g., congestion and regulation). The next chapter introduces a literature review in VRP models and solution algorithms in order to understand the benefits and limits of current theory to solve VRP variants.

Chapter 3

A review of VRP variants and heuristic solution procedures

The Vehicle Routing Problem (VRP) is a generic name for a large set of variants involving the optimisation of routes for a fleet of vehicles to serve a set of customers with a number of constraints that represent the restrictions that are present in logistic operations (Baldacci et al., 2012). It is considered an NP-Hard problem due to the complexity of obtaining optimal solutions, meaning that no algorithm has been developed to solve it by proving optimality in a reasonable time for large instances.

The simplest algorithm that one could propose would be the enumeration and evaluation of each possible solution of visiting all customers (n! possible solutions in the worst case scenario with one vehicle). With current computers, for a problem of 25 delivery points, it would take thousands of years of computational time. Therefore, this problem has been of special interest to workers across a number of disciplines (e.g. mathematics, computer science, engineering, *etc*.). Although algorithms that guarantee optimality have been developed to solve up to 200 customers for some VRP variants (Baldacci et al., 2012), metaheuristic algorithms (based on “intelligent” search strategies rather than mathematical approaches that cannot provide results for large instances in reasonable time) might provide fast and reliable solutions for problems of considerable size.

However, when using metaheuristics, researchers should be careful regarding the accuracy of the results, since metaheuristics do not guarantee optimality, and algorithms should be tested in order to understand their capabilities of solving the studied variant (Toth and Vigo, 2001, Vidal et al., 2013, Cordeau et al., 2002). In the previous chapter it was identified that the industry requires time-dependent VRP models that account for congestion. This chapter examines what the (academic) state of the art actually is, and offers a review of the evolution of heuristic and metaheuristic solution methods for VRP variants.

The capacitated Vehicle Routing Problem and the Vehicle Routing Problem with time windows are NP-hard problems that nonetheless have good solutions using metaheuristics due to research in algorithms based on adequate evaluation with available instances (Toth and Vigo, 2001). The first and second sections of this chapter present a review of Operational Research techniques that have been developed and tested with these variants. The following sections deal with richer variants and proposed instances in the literature, along with algorithm research that presents algorithm evaluation in order to identify variants that require additional research, due to a lack of analysis of the accuracy in solution methods.

3.1. The Vehicle Routing Problem and the Capacitated Vehicle Routing Problem

The first formal definition for the VRP was presented by Dantzig and Ramser (1959) for routing a fleet of petrol delivery lorries, where each customer is represented as a point. Every pair of points, also called arcs, is linked by a distance; every point has a demand and all lorries must depart and finish at a central depot; all lorries have the same characteristics. The objective is to find the set of routes with minimum travelled distance or routing time, satisfying that every customer be served once and the capacities of lorries are not exceeded. It was presented as a generalisation of the Travelling Salesman Problem (TSP: where the shortest route through a set of points has to be found). This basic formulation is called capacitated Vehicle Routing Problem (CVRP) (Toth and Vigo, 2001).

The CVRP is NP-Hard (Toth and Vigo, 2001); no exact algorithm has been developed to provide consistently optimal values for instances in the range of 200 customers, even some instances of 100 customers have not been solved for the CVRP (Baldacci et al., 2011). In practice, heuristic and metaheuristic procedures have been developed to procure relatively fast solutions.

Heuristics are algorithms designed specifically for a given problem and explore a limited search space (Toth and Vigo, 2001), while metaheuristic algorithms are search strategies that allow a robust exploration by local search and specially designed procedures, avoiding local optima, forcing the search to new unexplored regions. These strategies have been used for many combinatorial problems (Glover and Kochenberger, 2003). Although heuristics are generally faster than metaheuristic algorithms for the VRP, the solutions are poorer.

Cordeau et al. (2002) presented an evaluation of heuristics and metaheuristic algorithms for the CVRP in terms of accuracy and speed. Accuracy is the difference between the obtained results of the procedure and the optimal value or the best-known value for a certain instance, while speed is the time required to obtain the reported solution. These values can be found in the literature or web pages. Simplicity (i.e. the grade of the algorithm to be replicated obtaining reported solutions) and flexibility (i.e. the grade of the algorithm to accommodate different constraints without decreasing solution accuracy) are attributes introduced in the evaluation. Cordeau et al. (2002) reported that several procedures are not implemented in the routing software due to their complexity and lack of information provided in the literature.

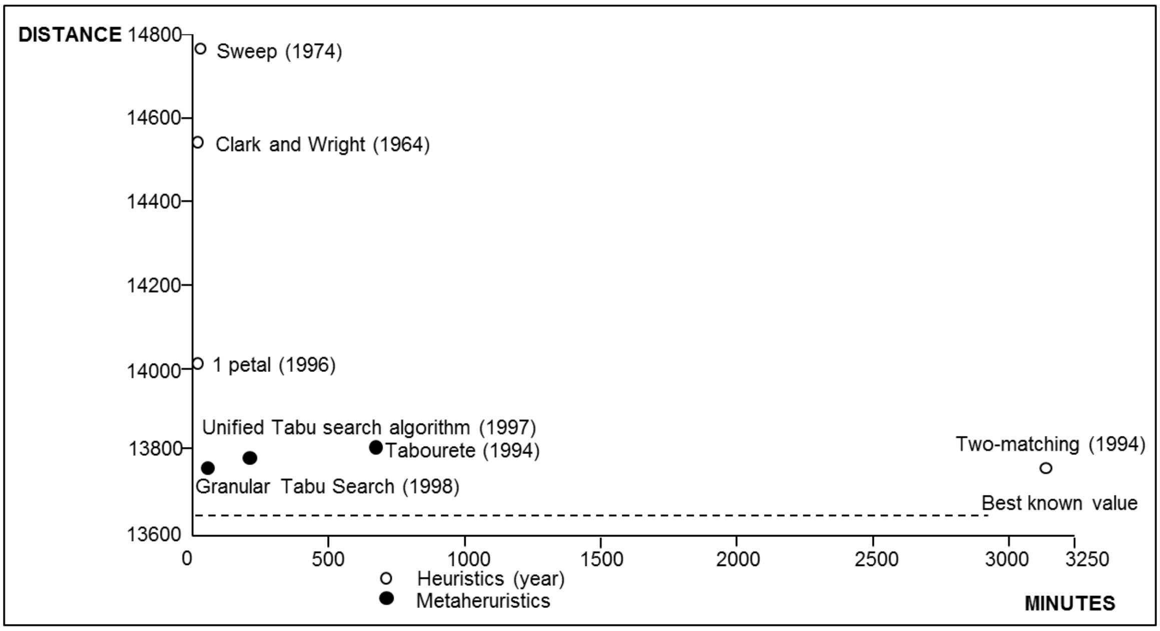


Figure 8. Evaluation for CVRP procedures, 14 instances between 50 and 199 customers. Source: Cordeau et al. (2002)

A comparison of results of different procedures reported in the literature for the CVRP is shown in Figure 8 based on 14 instances, between 50 and 199 customers, where the parameters of evaluation are the sum of travel distance (accuracy) and computational time to obtain the solution (speed). Although accuracy is a very straightforward comparison, speed is more complex due to the fact that hardware (processor, RAM), compiling software and code efficiency have an impact on it (Figliozzi, 2012). Dongarra (2007) presented detailed information to compare relative computer power. Nevertheless, Figure 8 is an example of solution technique evolution for the CVRP due to research in search strategies and computational processor capacity increment.

Metaheuristic algorithms are capable of obtaining greater accuracy than heuristics, for example the Clarke and Wright (1964) heuristic, also called the savings algorithm, is a very well-known algorithm that yields results of 6% average from the best-known values in seconds (Cordeau et al., 2002). The Granular Tabu Search metaheuristic algorithm proposed by Toth and Vigo (1998) is capable of obtaining results within 1% from best-known values.

The savings algorithm is based on the concept of merging routes that offers the highest saving, the pseudo code of the parallel version of the algorithm is presented as follows:

Algorithm 1: Clark and Wright heuristic for the CVRP

Input Data: Let $G = (V, A)$ be a graph where vertex $V = (v_0, v_1, \dots, v_n)$ being v_0 the depot and $v_1, \dots, v_n$ the set of customers, and d_{ij} distances between customers

Start

1. Calculate savings for each pair of customers: $S_{ij} \leftarrow d_{oi} + d_{jo} - d_{ij}$
2. $Create\ n\ routes\ (vehicles)$: $R_k = \{v_0, v_k, v_0\}$
3. $Sort$ S_{ij} in descending order
4. **Repeat**
5. Select highest Saving S_{ij}
6. Check feasibility of merging routes that contains customers v_i and v_j //only routes with edges v_i and v_j may be merged//
7. **If** (merge is feasible) **then**
8. merge routes
9. **EndIf**
10. Disregard selected S_{ij}
11. **Until** all S_{ij} are disregarded

End

Although other heuristics have been developed, metaheuristic algorithms have offered greater accuracy for the CVRP, where some implementations based on Tabu Search (TS) have achieved results on average within one per cent from best-known solutions (Cordeau et al., 2002). Unified Tabu Search (Cordeau et al., 1997), Taburoute (Gendreau et al., 1994) and Granular Tabu Search (Toth and Vigo, 1998) are implementations of TS with high accuracy where researchers have provided execution time to compare algorithms (Cordeau et al., 2002).

TS is based on the concept of exploring the search space by hill climbing and allowing non-improvement movements to avoid local optima. Cycles are forbidden with a Tabu list that impedes visiting an explored neighbourhood (Glover, 1989). The basic elements of TS are presented below; for a detailed description see Gendreau (2003).

- **Search Space and Neighbourhood Structure:** Search Space is the definition of all possible solutions that can be visited; Neighbourhood Structure is the local transformation of the actual solution to construct the neighbourhood at each iteration or move.

- **Tabu List:** This is a list containing information to avoid cycles; although it might contain a full description of the visited solutions, it is rarely implemented due to the required computational effort. Instead, actions in recent transformations or characteristics of visited solutions are recorded.

- **Aspiration Criteria:** Tabu List can impede certain movements that could achieve better values; therefore, evaluation to allow movements that are considered Tabu might be implemented.

- **Termination Criteria:** Because TS do not guarantee optimality, there is not a finalisation per se. Usually, three criteria can be implemented: i) stop at a certain number of iterations or CPU time, ii) stop after a number of iterations without improvement, and iii) stop after achieving a certain estimated value.

- **Intensification:** The concept relies on exploring more thoroughly some promising portions of the Search Space, which might take place by modifying the neighbourhood structure or forcing the utilisation of some values in the solution.

- **Diversification:** This is a procedure to force the search into unexplored areas of the Search Space.

Unified Tabu Search, Taburoute and Granular Tabu Search start with fast heuristics such as the savings algorithm to produce initial solutions and use well-known neighbourhood structures as search space; see Figure 9. The search space may include non-feasible solutions that are penalised in the objective function. A key element to improving the speed is to reduce the neighbourhood size by selecting arcs with a higher likelihood of producing a better move (Cordeau et al., 2002). An example is presented by Toth and Vigo (1998) by not considering in the search process arcs with small “likelihood” of producing a good solution. “Likelihood” is evaluated with the following function, $\vartheta = \beta \times \hat{c}$, where β is a sparsification parameter and $\hat{c}$ is the average cost of the arcs in the initial solution generated with the savings algorithm. With β values between 1–2.5, approximately 10–20% of arcs are used in the neighbourhood construction; intensification and diversification are achieved by modifying the parameter β.

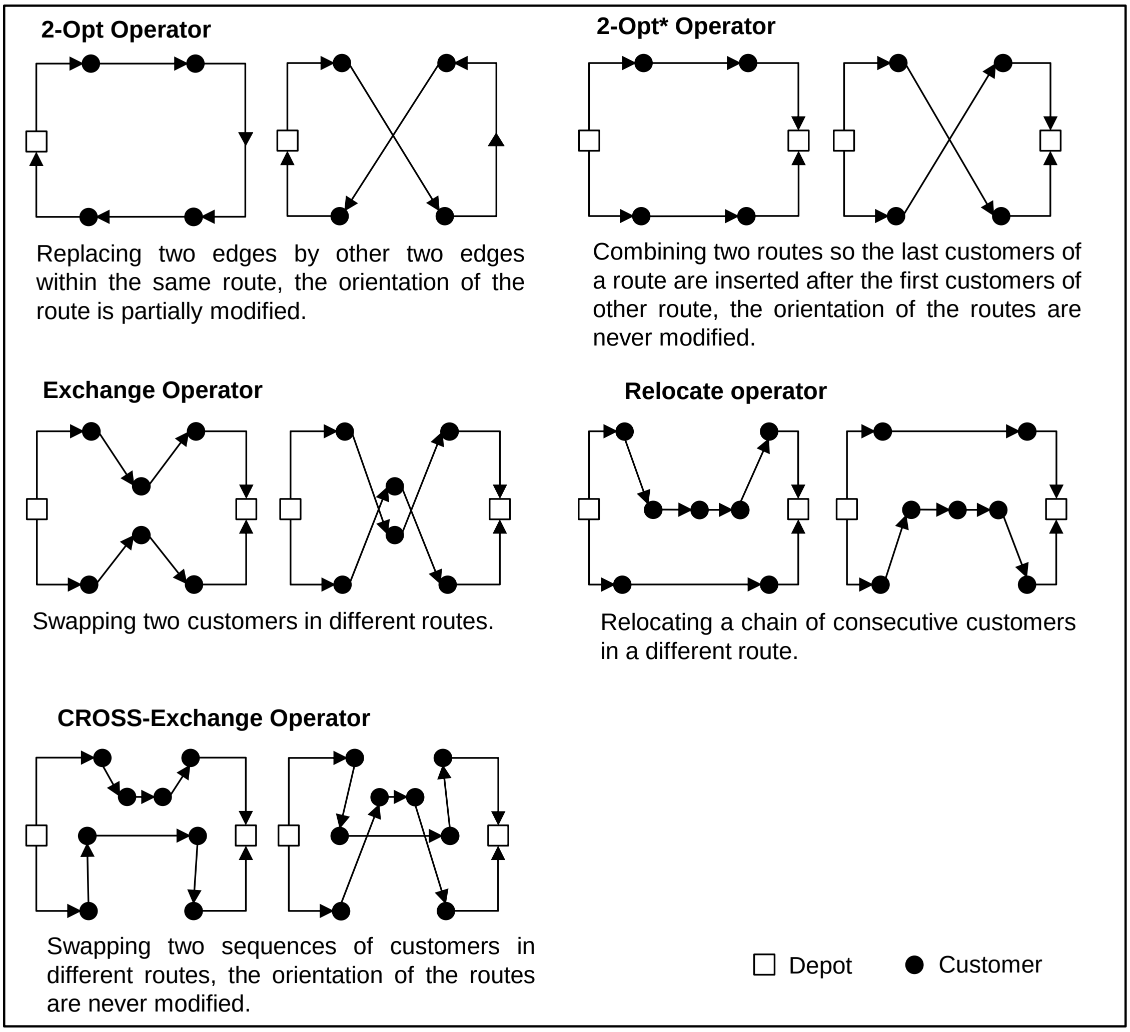


Figure 9. Common neighbourhood structures for the VRP search space.
Source: Bräysy and Gendreau (2005a)

Although the CVRP is an NP-Hard problem, the solution methods have evolved to provide highly accurate solutions for large instances due to increment in computational capacity and the development of search strategies that take advantage of heuristics and well-known neighbourhood structures. In this section, the evolution of algorithm research for a VRP variant has been shown. Although TS is recognised as one of the available solutions, many different concepts might be employed in state-of-the-art algorithms to solve the CVRP and richer variants; the following sections will show some of these search strategies.

3.2. The Vehicle Routing Problem with Time Windows

The Vehicle Routing Problem with time windows (VRPTW) is a VRP variant where each customer has a demand, a time window to be served and each visit has duration. In the hard VRPTW, the service has to start strictly in the time window interval; if the vehicle arrives early it has to wait until the time window allows the service and no customer can be served after the time window is closed, whereas in the soft version, a penalty is associated with every violation of the time window restriction. Commonly the VRPTW has two objectives: first, minimisation of number of vehicles; secondly minimisation of travel distance (Bräysy and Gendreau, 2005a, Bräysy and Gendreau, 2005b, Toth and Vigo, 2003).

The VRPTW is more complex than the CVRP: due to the time window restriction, finding feasible solutions is computationally expensive and minimising the number of vehicles requires additional modifications in the search process (Bräysy and Gendreau, 2005a, Bräysy and Gendreau, 2005b, Vidal et al., 2013). The VRPTW has been the subject of intense research (Bräysy and Gendreau, 2005a, Bräysy and Gendreau, 2005b, Toth and Vigo, 2001, Vidal et al., 2013), and evaluation of procedures is commonly performed with 56 instances of 100 customers created by Solomon (1987); instances of up to 1000 customers were introduced by Gehring and Homberger (1999) following Solomon's methodology. See Table 6 for the description of Solomon's instances. A range of heuristics and metaheuristic algorithms has been developed to solve the VRPTW. Figure 10 shows the evolution in solution accuracy and speed due to research in search strategies and increment in computational processing capacity.

Table 6. Description of Solomon's instances – 100 customers.

Problem class	Number of problems	Description		Best-known values	
		Customer location	Time Window /planning horizon	Cumulative Number of Vehicles	Cumulative Distance
R1	12	Random	Tight	143	14,524.08
R2	11	Random	Lax	30	10,461.33
C1	9	Cluster	Tight	90	7,455.42
C2	8	Cluster	Lax	24	4,718.88
RC1	8	Random-Cluster	Tight	92	11,073.28
RC2	8	Random-Cluster	Lax	26	8,953.92
Total				405	57,186.91

Tight: Short time windows that allows a few number of customer per vehicle and short planning horizon
Lax: Long time window that allows a large number of customers per vehicle and long planning horizon

Source: Solomon (1987) and Vidal et al. (2013)

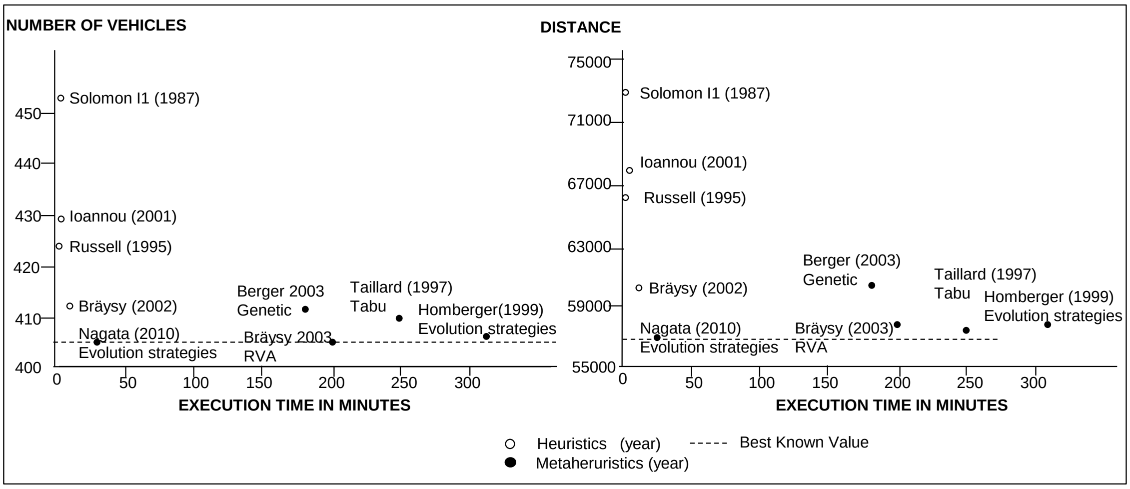


Figure 10. Evaluation for VRPTW procedures, Solomon's 56 instances of 100 customers
Source: Bräysy and Gendreau (2005a), Bräysy and Gendreau (2005b) and Vidal et al. (2013).

A very well-known heuristic is the insertion heuristic I1 proposed by Solomon (1987). With results around 11% from best-known values of number of vehicles and 28% for travel distance, it is considered a fast procedure, easy to implement, but with low accuracy. However, the concept of sorting customers into routes according to time savings by reducing the waiting time is applied in a number of procedures to provide initial solutions for further improvement (Bräysy and Gendreau, 2005b). The pseudo-code is presented as follows; for a full description, see Solomon (1987):

Algorithm 2: Solomon's heuristic I1 for the VRPTW

Input Data: Let $G=(V, A)$ be a graph where vertex $V = (v_0, v_1, \ldots, v_n)$ being v_0 the depot and $v_1, \ldots, v_n$ the set of customers, and d_{ij} distances between customers
μ, α_1, λ : parameters to control weight of distance
α_2 : parameter to control weight of time insertion
$\alpha_1 + \alpha_2 = 1$; $\alpha_1 \geq 0$; $\alpha_2 \geq 0$; $\lambda \geq 0$;

Start
1. **Repeat**
2. Select customer seed v_{seed} //method 1: The farthest unrouted customer
   method 2: The unrouted customer with the earliest deadline//
3. Create route $\{ v_0, v_{seed}, v_0 \}$
4. **Repeat**
5. $C_{11(i,u,j)} \leftarrow d_{iu} + d_{uj} - (\mu * d_{ij})$
6. $C_{12(i,u,j)} \leftarrow b_{ju} - b_j$ // b_j is the starting time of service for customer v_j
   b_{ju} is the new starting time of service at v_j if v_u is inserted//
7. $C_{1(i,u,j)} \leftarrow \alpha_1 * C_{11(i,u,j)} + \alpha_2 * C_{12(i,u,j)}$
8. $C_{2(i,u,j)} \leftarrow \lambda * d_{0u} - \alpha_1 * C_{1(i,u,j)}$
9. **Until** all unrouted customers have been evaluated at all positions in current route
10. Select v_u with lower $C_{2(i,u,j)}$ and insert in current route between v_i and v_j
    //Note that only feasible insertions are allowed//
11. **Until** all customer are in solution

End

State-of-the-art exact methods for the VRPTW are capable of solving instances in the range of 100 customers based on set partitioning formulation and branch-and-price or branch-and-cut algorithms (Baldacci et al., 2012). However, computational time is considerably higher than metaheuristic approaches and some instances still are difficult to solve, e.g. problems with 100 customers can take up to 7.9 hours to solve when a solution can be obtained. Table 7 shows computational time for three exact algorithm approaches using Solomon's instances for 100 customers.

Table 7. Benchmark for exact algorithms for the VRPTW – Solomon's instances 100 customers.

Problem class	Number of unsolved problems			Average computational time per problem (sec)		
Approach	**1**	**2**	**3**	**1**	**2**	**3**
R1	0	0	0	251	27,412	2,327
R2	1	7	3	28,680	35,292	63,068
C1	0	0	0	25	468	18
C2	0	1	0	40	2,795	2,093
RC1	0	0	0	276	11,004	2,150
RC2	0	3	2	3,767	3,204	15,394

1: Baldacci et al. (2011) Intel Xeon X7350 2.93 GHz 16 GB RAM **2**: Jepsen et al. (2008) Pentium IV 3.0 GHz
3: Desaulniers et al. (2008) Dual Core AMD Opteron 2.6 GHz
Source: Baldacci et al. (2011)

Different metaheuristic algorithms have been developed for combinatorial problems and have been tested with the VRPTW, where high accuracy in reasonable time has been achieved with different search strategies (Vidal et al., 2013). However, they commonly share elements; some of the concepts are listed below with examples of implementations of search strategies that make use of them:

- Creation of initial solution with fast heuristics: Different metaheuristic algorithms create an initial solution with a fast heuristic and then try to improve the initial solution e.g. Tabu Search (Bräysy and Gendreau, 2005b), Variable Neighbourhood Search, and Large Neighbourhood Search (Ropke and Pisinger, 2006).

- Evolutionary algorithms: Genetic algorithms and evolution strategies use simulated evolution based on selection, recombination and mutation in order to solve complex problems, where stochastic elements are commonly present at some stage (Whitley, 2001), state-of-the-art evolutionary algorithms for the VRPTW are Vidal et al. (2013) and Nagata et al. (2010).

- Local search operators: Neighbourhood structures based on arc-and-node exchange are used to explore the search space, see Figure 3, e.g. Tabu Search (Bräysy and Gendreau, 2005b, Cordeau and Maischberger, 2012), Variable Neighbourhood Search and Evolutionary algorithms (Nagata et al., 2010, Vidal et al., 2013).

- Ruin and recreate / Large Neighbourhood Search (LNS): The basic element of these search strategies is the iterative partial destruction of solutions (i.e. the removal of customers from the original routes) and rebuilding them by fast heuristics (insertion of removed customers in the current solution in a smart way: Schrimpf et al., 2000), e.g. Tabu Search (Cordeau and Maischberger, 2012) and Large Neighbourhood Search (Ropke and Pisinger, 2006).

- Guidance and memories: It operates by penalising particular solution features that are considered not to be in “good solutions”, such as long arcs. The algorithm might remember how many times each penalised feature appears in the search process and update the value of the penalty, e.g. Evolutionary algorithms (Mester and Bräysy, 2005, Vidal et al., 2013).

- Ejection chains: Changes in selected elements cause other elements to be ejected from their initial state or position, in the VRP consist of removing a customer from its initial route and trying to insert it in another route by “making room” through consecutive iterations of insertions and removals (Bräysy and Gendreau, 2005a, Glover, 1992) e.g. Tabu Search (Rego, 2001) and Evolutionary algorithms (Nagata et al., 2010).

- Parallel computing: The presence of multiple cores in computers has given workers the opportunity to work with multiple threads in order to speed up the search process (Le Bouthillier et al., 2005), e.g. Tabu Search (Cordeau and Maischberger, 2012) and Evolutionary algorithms (Gehring and Homberger, 2002).

- Mathematical programing hybrids: Although exact algorithms are computationally expensive. the search process can be sped up by its integration with metaheuristic e.g. Branch-and-Price and Large Neighbourhood Search (Prescott-Gagnon et al., 2009) and Evolutionary algorithms and set partitioning formulation (Alvarenga et al., 2007).

In order to speed up execution time, some strategies have been proposed to reduce the search space (Bräysy and Gendreau, 2005b). In the case of local search operators, two acceptance strategies are common: best-accept and first-accept. The best-accept strategy examines the complete neighbourhood and selects the best solution, whereas the first-accept strategy selects the first neighbour that provides an improvement (Bräysy and Gendreau, 2005b). Additional strategies are available, such as allowing only moves between close-distance customers (Garcia et al., 1994) and identifying “promising candidates” in terms of distance, time proximity and asymmetry issues (Vidal et al., 2013). An example is provided by Vidal et al. (2013), where it is proposed to evaluate neighbourhood movements only between the most correlated pair of customers, defined by $\gamma_{(v_i,v_j)}$, which is defined as the weighted sum of distance, the minimum waiting time and the minimum penalty between any pair of customers v_i and v_j.

$$\gamma_{(v_i,v_j)} = d_{ij} + \gamma^{WT}\max\{\mathrm{e}_j + \mathrm{g}_i + \mathrm{t}_{ij} - \mathrm{l}_i, 0\} + \gamma^{TW}\max\{\mathrm{e}_i + \mathrm{g}_i + \mathrm{t}_{ij} - \mathrm{l}_j, 0\}$$

where d_{ij} is the distance between customers v_i and v_j, t_{ij} is the travel time, e_i is the lower time window of customer v_i, l_i upper time window,g_i service duration, γ^{WT} and γ^{TW} are parameters that balance the role of geometrical and temporal parameters and have to be calibrated according to spatial characteristics, distribution and tightness of time windows of the problem at hand. Another technique to speed up the search process is the use of “macronodes”, where a sequence of customers is treated as a node in order to evaluate neighbourhoods (Bräysy and Gendreau, 2005a, Cordone and Wolfler-Calvo, 1997).

A number of techniques have been developed to deal with the different decisions and issues that come up in the implementation of algorithms to solve the VRPTW; perhaps one of the most complete literature reviews that deals with this topic is presented by Bräysy and Gendreau (2005a, 2005b). An important factor in the increased complexity of the VRPTW versus the CVRP is minimising the number of vehicles in the presence of time windows, where a number of approaches have been implemented; see Bräysy and Gendreau (2005a, 2005b). Two-stage algorithms that focus the search firstly by reducing routes and secondly by minimising travel time are more likely to obtain the optimal minimum number of vehicles (Bent and Van Hentenryck, 2004), therefore requiring specific tailoring for each stage.

A successful example of explicit strategies for route minimisation is introduced by Bent and Van Hentenryck (2004). They make use of the metaheuristic algorithm Simulated Annealing for minimisation of vehicles and LNS for distance minimisation due to the fact that initial testing of LNS yielded low accuracy in Solomon instances with lax time windows (i.e. instances with a large number of vehicles per route). In the first stage, routes with a large number of customers and a low number of customers are maintained throughout the search process with the implementation of an objective function that maximises the sum of the squares of route sizes in order to try to insert customers from small routes into large routes, where simulated annealing is used to guide the search. The result of this implementation achieved the best-known values for the number of vehicles (improving the best-known values at the time of publication).

Research on metaheuristics has provided highly efficient algorithms to deal with the VRPTW. Table 8 shows some approaches capable of coping with instances of up to 1000 customers with a high accuracy in a reasonable time, such as the mathematical programming hybrid branch-and-cut and the LNS proposed by Prescott-Gagnon et al. (2009) and evolutionary algorithms (Nagata et al., 2010, Repoussis et al., 2009, Vidal et al., 2013).

Table 8. Benchmark for metaheuristic algorithms for the VRPTW.

Approach		Best-known values	**1**	**2**	**3**	**4**	**5**
	Number of runs		5	3	1	5	5
Number of customers							
100	CNV	405	405	405	405	**405**	405
	CTD	57187	51240	57216	57205	**57187**	57196
	Time (min)		5x30	3x17.9	3.2	**5x5.0**	5x2.68
200	CNV	694	694	694	694	**694**	694
	CTD	168067	168556	169163	168143	**168067**	168092
	Time (min)		5x53	90	4.7	**5x4.1**	5x8.4
400	CNV	1381	1381	1381	1381	1381	1382
	CTD	388013	389011	395936	388548	388466	388697
	Time (min)		5x89	180	34	5x16.2	34.1
600	CNV	2066	2071	**2066**	2067	2067	2068
	CTD	816326	800797	**816326**	789420	789592	786373
	Time (min)		5x105	**270**	80.4	5x25.3	5x99.4
800	CNV	2738	2745	2739	2739	**2738**	2739
	CTD	1357695	1391344	1424321	1352478	**1357695**	1334963
	Time (min)		5x129	360	126.8	**5x27.6**	5x215
1000	CNV	3420	3432	3428	3424	3424	**3420**
	CTD	2036700	2096823	2144830	2040661	2045720	**2036700**
	Time (min)		5x162	450	186.4	5x35.3	**5x349**
Processor			P4-2.8G	Opt-2.3	P4-3	Opt -2.4	Xe-2.93

1. Branch-and-Price and Large Neighbourhood Search Prescott - Gagnon et al. (2009) **2. Evolutionary Algorithm** Repoussis et al. (2009) **3. – 4. Evolutionary Algorithm** Nagata et al. (2010) **5**. **Evolutionary Algorithm** Vidal et al. (2013) Evolutionary Algorithm.
Best known results are in bold CNV: Cumulative number of vehicles CTD: Cumulative travel distance

3.3. Rich models

The CVRP and the VRPTW are frequently not applicable in logistic operations and therefore over the years many variations have been proposed, including, for example, Vehicle Routing Problems with heterogeneous fleets, pickup and delivery, multiple depots, etc. Although algorithms have been developed to provide high accuracy for some theoretical VRP variants, richer variants may require additional algorithm tailoring. In this subsection the literature review is focused on research that performs adequate algorithm evaluation (using benchmark instances) for relevant VRP variants in the industry such as heterogeneous fleets (a must-have feature in CVRS according to Drexl (2012)) or time-dependent Vehicle Routing Problems (in order to provide reliable schedules when congestion is present). It is in the interest of the industry and researchers to understand the capabilities of state-of-the-art algorithms reported in the literature to provide highly accurate solutions in a reasonable time for variants that consider the necessities of the freight industry.

3.3.1. Fleets with heterogeneous vehicles and the Vehicle Routing Problem

Vehicle fleets in real life are rarely homogeneous; fleets are acquired over long periods of time and vehicles will have different characteristics due to technological developments and market conditions, where versatility is a desired fleet characteristic in order to cope with operational constraints (urban environment, access restriction, economies of scale, *etc.*); vehicles may differ in dimensions, weight, capacity, speed, equipment, fuel consumption and cost structure (Bräysy et al., 2008; Hoff et al., 2010). The heterogeneous fleet VRP (HVRP) and the fleet size and mix VRP (FSM) are sets of variants of the VRP that consider vehicles with different characteristics e.g., capacities, travel costs, capital costs, *etc.* (Baldacci et al., 2008). In the HVRP the number of vehicles available per each type of vehicle is restricted, e.g. there are limited vehicles available at the depot, whereas in the FSM there is an unlimited number of vehicles, e.g. a decision is needed about what types of vehicles are required.

The first formal formulation for a heterogeneous fleet was presented by Golden et al. (1984) as the fleet size and mix Vehicle Routing Problem. Over the years, theoretical variants have been proposed, but the notation in the literature is not consistent (Baldacci et al., 2008; Paraskevopoulos et al., 2008). The notation introduced by Baldacci et al. (2008) for the capacitated HVRP and FSM will be used and extended for variants with time windows as follows: HVRP (Heterogeneous VRP), FSM (Fleet Size and Mix VRP), F (Dependent Fixed Costs), D (Dependent Running costs) and TW (Time Windows); see Table 9.

Table 9. Variants for Heterogeneous Fleets.

Problem Name [1]	Unlimited Fleet Size	Dependent Fixed Cost	Dependent Running Costs
HVRP-F-TW		✓	
HVRP-D-TW			✓
HVRP-FD-TW		✓	✓
FSM-F-TW	✓	✓	
FSM-D-TW	✓		✓
FSM-FD-TW	✓	✓	✓

[1] **Notation**: **HVRP** Heterogeneous VRP **FSM** Fleet Size and Mix VRP **F** Dependent Fixed Cost **D** Dependent Routing Cost **TW** Time Windows

Table 10. Publications for VRP models with Heterogeneous Vehicles and Time Windows

Author	HVRPFTW	HVRPDTW	HVRPFDTW	FSMFTW	FSMDTW	FSMFDTW	Method	Benchmark instances	Observations
Jiang 2014			x	x			TS	Liu and Shen 1999 Introduction of instances for the HVRPFDTW	Introduction of benchmark for the HVRPFDTW based on costs and dependent returning time to the depot
Koç 2014	x			x			Hybrid Evolutionary algorithm	Liu and Shen 1999	
Repoussis 2010				x			TS	Liu and Shen 1999	
Braysy 2008				x			Deterministic annealing	Liu and Shen 1999	
Paraskevopoulos 2008	x			x			VNS	Liu and Shen 1999 Introduction of instances for the HVRPFTW	
Dell'Amico 2007				x			Ruin and recreate	Liu and Shen 1999	
Dullaert 2002				x			Heuristics	Liu and Shen 1999	Discussion about dependent cost by distance and time in real life
Liu and Shen 1999				x			Heuristics	Introduction of instances for the FSMFTW	

VRP variants with heterogeneous vehicles with time windows have been studied far less by the scientific community than their counterparts the VRPTW (Koç et al., 2014a) or simpler VRP variants with heterogeneous vehicles without time windows (Hoff et al., 2010). The review of literature in this research will focus on variants with time windows. For a review of simpler variants, refer to Baldacci et al. (2008). Table 10 shows some of the publications focused on heterogeneous vehicles and time windows, the fleet size and mix VRP with dependent fixed costs. FSM-F-TW, where fixed costs include vehicle excise duty (VED), insurance and depreciation of vehicle value, has received the most attention from the theoretical perspective, commonly using instances proposed by Liu and Shen (1999a), based on Solomon's (1987) instances for algorithm performance analysis. For the heterogeneous VRP with dependent fixed costs (HVRP-F-TW), Paraskevopoulos et al. (2008) introduced an extension of instances of Liu and Shen. The available number of vehicles is the best number of vehicles obtained by Liu and Shen (1999b) for FSM-F-TW instances. Recently, instances for the heterogeneous VRP with dependent fixed costs and dependent routing costs (HVRP-FD-TW) were proposed by Jiang et al. (2014). Solution analysis with formally proposed instances was not found in the literature review for the heterogeneous VRP with dependent running costs and time windows (HVRP-D-TW), fleet size and mix VRP with dependent running costs and time windows (FSM-D-TW), or fleet size and mix VRP with fixed costs dependent running costs and time windows (FSMF-DT-TW).

Liu and Shen (1999a) solved the FSM-F-TW with a number of heuristics and an improvement phase based on perturbation and local search, with the objective of minimising the sum of the fixed costs and travel time. The proposed instances are an extension of Solomon’s instances, and three different sets of vehicle costs are considered for each of Solomon’s problems (for a total of 168 problems) with dependent capacities and fixed costs for each type of vehicle (see Table 11).

Table 11. Benchmark instances for the FSMFTW (100 customers) - Liu and Shen (1999a)

Problem	Vehicle type	Capacity	Fixed cost per vehicle		
			a	b	c
R1	A	30	50	10	5
	B	50	80	16	8
	C	80	140	28	14
	D	120	250	50	25
	E	200	500	100	50
R2	A	300	450	90	45
	B	400	700	140	70
	C	600	1200	240	120
	D	1000	2500	500	250
C1	A	100	300	60	30
	B	200	800	160	80
	C	300	1350	270	135
C2	A	400	1000	200	100
	B	500	1400	280	140
	C	600	2000	400	200
	D	700	2700	540	270
RC1	A	40	60	12	6
	B	80	150	30	15
	C	150	300	60	30
	D	200	450	90	45

a, b, c are different cost structures
Source: Liu and Shen (1999a)

Dell'Amico et al. (2007) proposed a Ruin and Recreate metaheuristic approach for the FSM-F-TW, and their solution took advantage of the similarity to the bin-packing problem, where objects of different volumes must be packed into bins, in order to propose new movements. Selected routes are targeted to be served by a smaller vehicle if a number of customers are removed, and a parallel recreate heuristic tries to recreate a new feasible solution. Evaluation of the algorithm's performance showed improved results (6%) when compared to Liu and Shen (1999a). Figure 11 shows the performance of the algorithm when more execution time is allowed.

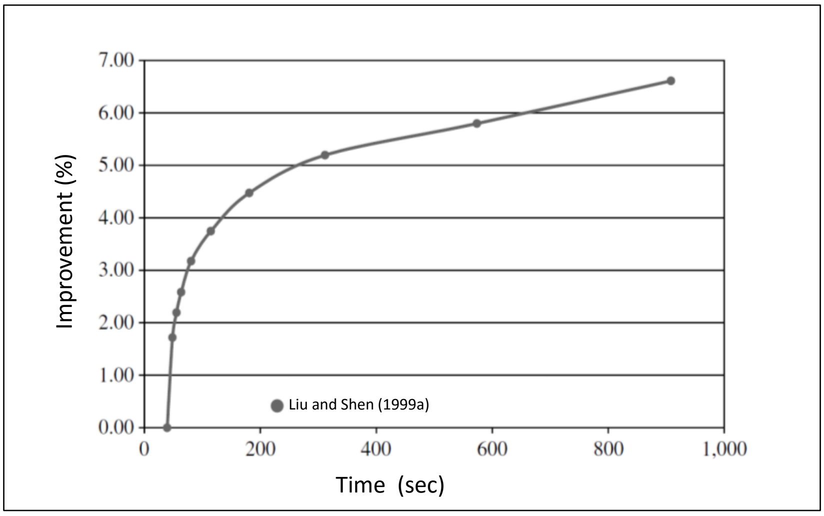


Figure 11. Performance of the Ruin and Recreate algorithm proposed by Dell'Amico et al. (2007) for the fleet size and mix VRP with dependent fixed costs at different execution times. Source: Dell'Amico et al. (2007)

Paraskevopoulos et al. (2008) present a Variable Neighbourhood Search metaheuristic (VNS) using Tabu search for local search for the FSM-F-TW and the heterogeneous VRP with dependent fixed costs with time windows (HVRP-F-TW), proposing benchmark instances, where an algorithm with two stages is tailored: i) the method for construction of an initial solution and minimisation of the number of vehicles describes a construction heuristic with multiple metrics specially designed for heterogeneous fleets and subsequently ejection chains are used to reduce the number of vehicles required where an infeasible search space is temporarily allowed; ii) a Tabu search embedded in a VNS makes use of local search neighbourhoods to improve the solutions. The algorithm improved the resulting values for the FSM-F-TW by an additional 2% when compared to Dell'Amico et al. (2007).

Bräysy et al. (2008) studied the FSM-F-TW with the objective function proposed by Liu and Shen (1999a), and an additional objective function based on route duration. The proposed solution method is based on the construction of an initial solution, minimisation of routes by selecting a complete route for elimination and attempts to insert its customers in the remaining routes, with simple insertion heuristics trying to improve the total cost reduction, and local search with a deterministic annealing framework to guide the search. The algorithm obtained an additional 1.6% reduction when compared to Paraskevopoulos et al. (2008). Bräysy et al. (2009) introduced new instances based on Gehring and Homberger (1999) for instances up to 1000 customers, and their search procedure made use of a threshold acceptance value (where solution deterioration is accepted until a certain threshold value in order to escape from local optima) and guided local search (introduction of penalisation in the objective function of certain solution features that are not considered in near-optimal solutions).

Koç et al. (2014a) studied the FSM-F-TW and the heterogeneous VRP with dependent fixed costs with time windows (HVRP-F-TW), making use of a hybrid evolutionary algorithm and finding improved results of 0.34% over the work of Paraskevopoulos et al. (2008) for the HVRP-F-TW. Jiang et al. (2014) presented a Tabu search for the FSM-F-TW and introduced instances for the HVRP-FD-TW based on Solomon's instances (dependent capacity, dependent fixed cost, dependent variable cost and dependent returning time to the depot) (see Table 12). The objective function is based on costs and distance.

Table 12. Benchmark instances for the HVRP-FD-TW (100 customers) - Jiang et al. (2014).

	Vehicle characteristics					
Problem class	Vehicle type	Available vehicles	Capacity	Fixed Cost	Variable cost	Last Returning time
R1	A	10	50	80	1.0	180
	B	15	80	140	1.2	200
	C	10	120	250	1.4	230
R2	A	10	300	45	1.0	800
	B	5	400	70	1.2	1000
C1	A	20	100	30	1.0	1000
	B	5	200	80	1.2	1236
C2	A	20	400	100	1.0	3000
	B	5	500	140	1.2	3390
RC1	A	10	40	60	1.0	200
	B	20	80	150	1.2	220
	C	10	150	300	1.4	240
RC2	A	10	100	150	1.0	900
	B	5	200	350	1.2	960

Source: Jiang et al. (2014)

Dullaert et al. (2002) presented a set of sequential heuristics for the FSM-F-TW and introduced a discussion about variable running costs in the industry. According to the authors, distance and time should be considered with their corresponding cost coefficients when scheduling vehicles in the freight industry in order to calculate the routing costs rather than using an objective function distance as in the theoretical VRPTW (see Table 13).

Table 13. Representative routing costs in the industry, values in Euros for 1999.

Vehicle type	Fixed cost	Hour coefficient	Kilometre coefficient
Van 0.5 t	144.27	0.27	0.1
Lorry 5 t	154.26	0.29	0.15
Lorry 8 t	162.54	0.3	0.17
Lorry 20 t	187.92	0.35	0.21
Truck and trailer 28 t	195.75	0.36	0.24

Source: Dullaert et al. (2002)

Recently, Koç et al. (2014b) proposed the fleet size and mix pollution-routing problem with time windows, where a number of vehicle types are available and the main objective is the reduction of vehicle fixed costs (depreciation, repair and maintenance, tyres, *etc.*) and routing cost based on travel time (wages) and fuel cost (distance, optimisation of speed across the links and CO_2 emissions). Fuel consumption is estimated with the model of Barth et al. (2005) and Barth and Boriboonsomsin (2009), vehicle dependent parameters are shown in Table 14, and vehicle constant parameters are shown in Table 15. The instances are an extension of the instances proposed by Demir et al. (2012) for the homogeneous mix polluting problem with time windows for up to 200 nodes. The solution procedure is a hybrid heuristic with the principles of an evolutionary algorithm (Koç et al., 2014a), adaptive large neighbourhood search, the Split algorithm for heterogeneous VRP (Prins, 2009) and a Speed Optimisation Algorithm (SOA) (Hvattum et al., 2013; Norstad et al., 2011).

Table 14. Dependent parameters according to vehicle type for estimation of fuel consumption and other costs.

Notation	Description	Light duty (L)	Medium duty (M)	Heavy duty (H)
w^h	Curb weight (kg)	3500	55000	14000
Q^h	Maximum payload (kg)	4000	12500	26000
f^h	Vehicle fixed cost (£/day)	42	60	95
k^h	Engine friction factor (kj/rev/liter)	0.25	0.2	0.15
N^h	Engine speed (rev/s)	38.34	36.67	30
V^h	Engine displacement (liter)	4.5	6.9	10.5
C_d^h	Coefficient of aerodynamics drag	0.6	0.7	0.9
A^h	Frontal surface area (m^2)	7	8	10

Source: Koç et al. (2014b)

Table 15. Fixed parameters for estimation of fuel consumption and other costs.

Notation	Description	Typical values
ξ*	Fuel-to-air mass ratio	1
g	Gravitational constant (m/s^2)	9.81
ρ	Air density (kg/m^3)	1.2041
C_r	Coefficient of rolling resistance	0.01
η	Efficiency parameter for diesel engines	0.45
f_c	Fuel and CO_2 emissions cost (£/liter)	1.4
f_d	Driver wage (£/s)	0.0022
κ	Heating value of a typical diesel fuel (kj/g)	44
ψ	Conversion factor (g/s to L/s)	737
n_{tf}	Vehicle drive train efficiency	0.45
υ^l	Lower speed limit (m/s)	5.5 (or 20 km/h)
υ^u	Upper speed limit (m/s)	27.8 (or 100 km/h)
θ	Road angle 0	0
τ	Acceleration (m/s^2) 0	0

* Refers to the relative fuel-air ratio of fuel and air that enter into the engine ($FAR_{\text{stoichiometric}}$)

$$FAR_{\text{stoichiometric}} = \frac{fuel\ to\ oxidizer\ ratio}{fuel\ to\ oxidizer\ ratio_{\text{stoichiometric}}} = \frac{n_{fuel}/n_{ox}}{(n_{fuel}/n_{ox})_{\text{stoichiometric}}}$$
$$n = number\ of\ moles$$

See El-Mahallawy & Habik (2002)

Source: Koç et al. (2014b)

The conclusions drawn by Koç et al. (2014b) from analysing the results for 100 nodes suggested that the main reduction might be achieved with vehicle type selection by finding the most appropriate fleet composition. By selecting only light duty vehicles the average cost in the test instances increased by 19.88% on average, and 24.9% when only heavy duty vehicles were used. Regarding the optimisation of the vehicle travel speed, by allowing vehicles to travel at maximum speed (100 km/h), there is a small cost increment when compared to optimising the travel speed in each arc, and the authors concluded that in real life operations it might be easier to allow vehicles to travel at the maximum speed due to the small benefit of travel speed optimisation. Figure 12 shows the relation between fuel consumption and average speed using a simplified model to estimate fuel consumption provided by the UK Department of Transport (DFT, 2014), which uses as parameters the type of vehicle and average travel speed.

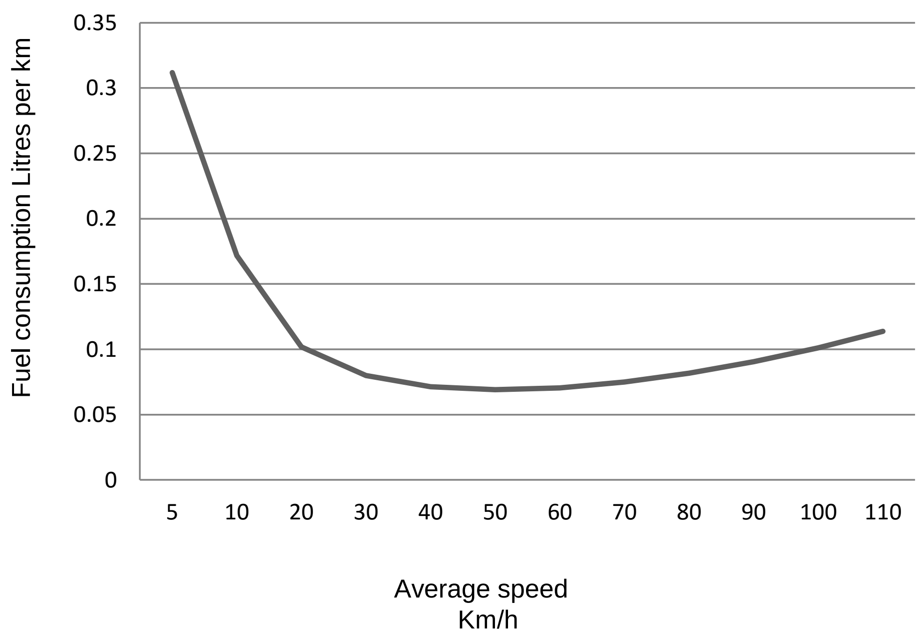


Figure 12. Typical Fuel consumption for a Diesel LGV vs. average speed with constant weight. Source: DFT (2014)

An industry application for VRP variants with heterogeneous fleets and time windows with only dependent physical characteristics (capacity, weigh, access restriction) is presented by Rochat and Semet (1994) and Brandão and Mercer (1997), where the analysis of the solution is based on comparison of manual schedules versus the results of the proposed algorithm. Although the new solutions do not always represent a reduction in the required number of vehicles or costs, which may be up to 24% in certain scenarios, the software is capable of dealing with multiple restrictions in a better way than manual scheduling by offering solutions that comply with weight restrictions, access restrictions and rules on drivers' hours.

Routing vehicles with multiple restrictions is a complex activity that can be improved by software. Companies commonly have heterogeneous fleets to cope with multiple restrictions in real life so VRP models for fleets with heterogeneous vehicles with time windows have attracted attention recently from researchers. Although the metaheuristics are available, it is required to propose more research with adequate benchmark instances for richer instances that consider the multiple restraints found in logistic operations (Hoff et al., 2010).

3.3.2. Rules on Drivers' hours

New restrictions dealing with Rules on Drivers' hours in the VRP have attracted attention in order to mitigate their economic cost in transport operations (Kok et al., 2010a; Kok et al., 2010c; Xu et al., 2003). Driver schedules must be considered and modelling the complete set of restrictions into solution algorithms has imposed new challenges for modellers (Kok et al., 2010c).

Goel (2009) proposed an algorithm to accommodate regulation (EC) 561/2006 (Rules on Drivers' hours for member states of the European Union for vehicles over 3.5 ton) that considers a sub-set of rules that are strict enough to ensure the feasibility of the routes when all regulations are taken into account in long-haul operations (Prescott-Gagnon et al., 2010). A set of benchmarking instances based on Solomon (1987) were introduced. The primary objective is the minimisation of vehicles and the secondary objective is the minimisation of travel distance. The algorithm is based on LNS with a ruin procedure based on random removals and an auction method (Antes and Derigs, 1995) for recreation that involves random elements in the insertion procedure.

Kok et al. (2010c) designed an algorithm for the VRP variant proposed by Goel (2009), and the solution algorithm was based on a restricted Dynamic Programming (DP) algorithm (Gromicho et al., 2008) with a giant tour representation. DP provided improved results (17% fewer vehicles and a travel distance reduction of 5%). Prescott-Gagnon et al. (2010) also studied this variant and obtained a further improvement (an additional reduction in the number of vehicles by 17% and travel distance by 12%) with an LNS tailoring that made use of a column generation heuristic for neighbourhood exploration. The work of Goel and Vidal (2014) has showed promising results by providing a hybrid genetic search capable of coping with driving time regulation for different countries (e.g., United States, Canada, the European Union and Australia) and outperform previous implementations for constant-speed VRP variants.

Although urban and regional freight operations should also comply with regulation (EC) 561/2006, accommodating the restrictions specially designed for long-haul operation such as daily and weekly rest periods may be easily introduced in the planning horizons of one day (routing for the next day), as opposed to long-haul operations, where overnight parking and journeys of more than one day may be considered. However, urban environments are subject to congestion (speed varies according to the time of the day), and providing reliable schedules that comply with the regulations is in the interest of the industry in order to accommodate the regulations at the minimum possible cost. Therefore Kok et al. (2010b) proposed a rich VRP variant that considers time-dependent travel times and a sub-set of rules of the regulation (EC) 561/2006 applicable in urban or regional operations. No other research was found in the literature studying this variant.

3.3.3. Time-Dependent travel times in the Vehicle Routing Problem

VRP variants have assumed constant speed throughout the day; the time-dependent Vehicle Routing Problem (TDVRP) addresses travel time variations during periods of delivery in order to represent congestion (Kok et al., 2012; Malandraki and Daskin, 1992). Congestion is present due to the growing amount of traffic and limited capacity of the road infrastructure, and delays have impacted the logistic sector, so that models that avoid traffic have a large potential to mitigate the impact of congestion (Kok et al., 2012). Analysis of VRP models with time-dependent travel times versus models with constant speed depicts the impact of not considering congestion on routing decisions when speed varies during deliveries. Solution of constant speed models might underestimate the actual travel time, provide infeasible solutions and fail to comply with delivery times (Donati et al., 2008; Fleischmann et al., 2004; Ichoua et al., 2003). The instances proposed by Solomon (1987) are commonly used to evaluate solution algorithms for the VRPTW and a vast range of approaches is available with results near to optimality in little computational time (Bräysy and Gendreau, 2005a; Bräysy and Gendreau, 2005b; Toth and Vigo, 2001; Vidal et al., 2013). Although Donati et al. (2008) and Fleischmann et al. (2004) used variations of this set of instances to evaluate algorithms for the TDVRPTW, only Figliozzi (2012) provides the complete information to fully reproduce instances when speed variation is present. These instances consist of an extension of Solomon's instances with 12 different congestion patterns. Figliozzi (2012) proposed an insertion heuristic to construct an initial feasible solution and a Ruin and Recreate heuristic algorithm to improve the results. Benchmarking for accuracy is performed with the available best-known values for the VRPTW and executing the proposed algorithm for the TDVRP with constant speed data. The VRPTW commonly has two objective functions: firstly the number of vehicles is minimised, secondly the distance is reduced. The results of Figliozzi's (2012) approach provide 4.2% more vehicles and an 8.61% greater distance than the best-known values. Additional speed profiles are provided in order to analyse the impact of congestion patterns on the results. Evaluation of Figliozzi's (2012) approach with constant speed shows that there is still room for improvement and an algorithm capable of improving this special case of the TDVRPTW might provide better solutions in all the proposed instances. Kok et al. (2010b) introduced a variant with time-dependent travel times and a subset of the European driving time regulation applicable in urban or regional operations that might consider planning only one day ahead, where the proposed benchmark instances are an extension of Figliozzi (2008).

The relations between time-dependent travel times, fuel consumption and CO_2 emissions have recently been of interest to researchers. Maden et al. (2010) compared the scheduling of vehicles with and without considering time-dependent travel times for a sample fleet in the south of the UK, obtaining a reduction of 7% of CO_2 emissions by considering travel time dependency. Jabali et al. (2012) considered the fuel consumption, driver and CO_2 costs as well as CO_2 emissions for modified theoretical instances for the VRP without time windows in different scenarios. Speed was restricted in order to save fuel for lorries of 32-42 tons, and it was found that restraining the speed in free flow from 90 to 85 km/h might reduce the fuel consumption without significantly compromising the driver cost.

Franceschetti et al. (2013) proposed the time-dependent pollution-routing problem with time windows with an integer programming solution method. Fuel consumption is estimated with the model of Barth et al. (2005) and Barth and Boriboonsomsin (2009). In this variant, the departure times from the depot and from customers are optimised as well as speeds across the arcs that make-up the route. The test instances are an extension of the instances proposed by Demir et al. (2012) in the cases of 10, 15 and 20 nodes, where the speed intervals are restricted to two periods (congested and free flow). The authors identify a number of conditions in which it is optimal to wait at the end of the service according to different driver wage policies: (i) the driver of each vehicle is paid from the beginning of the time horizon until returning to the depot, or (ii) the driver is paid only for the time spent away from the depot, excluding waiting times at customers (either en-route or performing the delivery). Although the proposed method outperforms previous mathematical solutions, this research only considers two time intervals and further research is required to handle larger problems with more time intervals, due to the restrictions of the proposed mathematical solution approach.

A comprehensive recent review of VRP variants that consider fuel optimisations with constant and variable speeds is presented by Eglese and Bektas (2014). The work of Qian (2012) is mentioned, where a time-dependent VRP variant aims to minimise fuel consumption by optimising speeds in each segment of fixed sequences that conform the schedules but the proposed algorithm (dynamic programming algorithm and heuristics solutions) establish the route between customers. Results in a data set of Bristol suggest that average emissions savings might be 6-7% but at the expense of increasing trip time by 9-10%.

The model reliability might be improved if time dependency is included when congestion is present (Kok et al., 2010b). It is worth mentioning the work of Maden et al. (2010), in which an algorithm was designed for a distribution system of electronic goods that considered time-dependent travel times, a sub-set of Rules on Drivers' hours, and time windows (though the company did not offer time windows). Analysis of routing strategies revealed that planning without considering congestion led to an additional 57 min per vehicle when evaluating the initial constant-speed schedules in a congested environment, and model restrictions were violated. A managerial solution to tackle congestion could be to reduce by 20% the speed when planning the routes in order to produce routes that do not violate restrictions. However, by using the proposed algorithm with the available traffic data, vehicle schedules had 6% less route duration and 7% less CO_2 than when routing with a reduced constant speed.

3.3.4. Unified algorithms

Unified algorithms to solve multiple VRP variants have been proposed (Pisinger and Ropke, 2007, Vidal et al., 2014), and a successful approach is shown by Pisinger and Ropke (2007) for the capacitated VRP, VRP with time windows, multi-depot VRP, site-dependent VRP and open VRP. Each variation is transformed into a rich pickup and delivery model with time windows and the solution algorithm applies an Adaptive Large Neighbourhood Search heuristic (ALNS). The authors reported improved results for some variants when compared to best-known values provided by state-of-the-art algorithms, see Table 16.

ALNS is an extension of the Large Neighbourhood Search, where the procedures used to remove and reconstruct solutions in the search process are chosen from an adaptive mechanism that evaluates performance procedures and favours those that have achieved higher improvements (Ropke and Pisinger, 2006). Heuristics based on LNS have shown outstanding results in solving a number of transportation and scheduling problems of a tightly constrained nature (such as the problem imposed by the use of time windows) (Pisinger and Ropke, 2010). Additionally, LNS stands out in terms of simplicity and wider applicability for complex VRP variants (Vidal et al., 2013).

A very promising approach to solve a number of VRP variants for a large range of logistic configurations is shown by Vidal et al. (2014). In 1045 out of 1099 tested instances the best-known value was retrieved or improved, with a hybrid genetic search addressing attributes by means of assignment (e.g., customers to depots or days), sequencing (neighbourhood structures) and route-evaluation (e.g., time-dependent travel times, driving time regulation).

Table 16. Benchmark of results for a unified LNS algorithm to solve multiple VRP variants (Pisinger and Ropke, 2007)

Variant	Instance (Customers)		Primary Objective		Secondary Objective	Primary Objective	Δ	Secondary Objective	Δ
	Solomon 1987 (100)		405		57,187	405	0.00%	57,192	0.01%
VRP with Time Windows	Gehring and Homberger 1999 (400)	Number of Vehicles:	1,389	Travel Distance:	390,386	1,385	-0.29%	393,210	0.72%
	Gehring and Homberger 1999 (1000)		3,446		2,078,110	3,438	-0.23%	2,110,925	1.58%
Multi-depot VRP	Cordeau 1997 (48-288)	Cost	80,394			80,448	0.07%		
Site-dependent VRP	Cordeau and Laporte 2001 (48-1008)	Cost	90,274			88,810	-1.62%		
Open Vehicle Routing Problem	Used by Brandao 2004 (50-199)	Cost	156		10,340	156	0.00%	10,194	-1.41%

3.4. Discussion of the chapter

Research in metaheuristic algorithms has proved to offer efficient solutions for some VRP variants, and state-of-the-art algorithms make use of different approaches to provide high accuracy in a reasonable time. However, although replicability is considered a requirement in scientific literature, much of the research conducted in VRP variants lacks enough replicability and adequate solution evaluation with the available instances in order to provide solutions for the industry (Cordeau et al., 2002; Drexl, 2012; Figliozzi, 2012).

New elements may be considered if truly innovative solutions need to be designed for the industry. Analysis of vehicle scheduling that considers fleets with heterogeneous vehicles shows some of these new elements, such as Rules on Drivers' hours (vehicles over 3.5 ton have to consider the regulation) and fuel consumption according to the type of vehicle and speed on the road. This last item not only affects the cost structure but also has an environmental impact. Vehicle planning may mitigate the financial cost of accommodating the regulation and the environmental repercussions of the freight transport. Additionally, when working in congested environments (e.g., cities), not considering congestion leads to inaccurate schedules due to underestimation of the travel time, and consequently vehicles will require more time than planned. All the effort to optimise the problem may be lost and solutions may not comply with the promise of service (time windows), regulation and other specific restraints of the business model (e.g., drivers' working day, latest time to return to the depot, *etc*.).

An example of the importance of adequate algorithm research based on the analysis of results with the available test instances is the VRP variant that considers Rules on Drivers' hours. After its first formal formulation along with benchmark instances, improved algorithms in the following year obtained reductions in the number of vehicles of 34% and reduction in travel distance of 17%. Some implementations may be highly inaccurate when dealing with rich variants, therefore two issues must be considered: i) tailoring solution methods for VRP variants is a complex activity that may yield low accuracy when using non-exact algorithms (heuristics and metaheuristics); ii) research in algorithms that do not provide benchmark instances or make use of them to test results cannot guarantee accuracy and the industry must be careful about their implementation.

From the review on industry needs and the state-of-the-art in solution techniques, it is clear that improvements in current algorithms are needed to account for (1) time-dependent travel times to provide accurate schedules in congested environments and (2) Rules on Drivers' hours to provide vehicle schedules that comply with the regulation (most goods vehicles over 3.5 ton in the European Union are subject to this regulation). In the case of the TDVRPTW, Figliozzi (2012) proposed the first set of replicable instances; however, its solution approach still leaves room for improvement when comparing best-known values versus the reported solution in the constant speed case. Furthermore, research in time-dependent travel time and Rules on Drivers' hours in the planning horizons of one day (e.g., the urban case) with benchmark instances has been proposed by Kok et al. (2010b), but the accuracy of the solution has not been analysed. Research on this topic may help the industry to mitigate the impact of congestion and regulation.

There is a range of solution methods from the Operational Research discipline, where some concepts have been identified as promising due to their simplicity and capability to accommodate multiple restraints such as Large Neighbourhood Search. In the following chapters some of these methods will be tailored and tested with the available benchmark instances for some of the most relevant variants identified in this research. The remaining parts of this research will therefore develop improved algorithms for rich models based on industry requirements for i) the TDVRPTW, and ii) the TDVRPTW and Rules on Drivers' hours.

To sum up

Although the main CVRS vendors offer the capability of routing that considers congestion, the surveyed companies stated that further development was required. The literature review shows that exact algorithms for VRP variants are not viable in rich industry applications and metaheuristic algorithms are capable of providing solutions for the industry. However, metaheuristics do not guarantee the optimality and accuracy of new algorithms that deal with rich variants and therefore have to be tested with the available benchmark instances. Only recently have benchmark instances been proposed for the Vehicle Routing Problem with time windows and time-dependent travel times, and a more complex variant that also considers Rules on Drivers' hours.

A reported issue in metaheuristic implementations is the flexibility of the algorithm (the grade of the algorithm to accommodate different constraints without decreasing solution accuracy). Although in chapter 2 surveyed companies stated that transportation costs have increased at a certain extent due to regulation, and to a lesser extent due to Rules on Drivers' hours (see figure 6), there is the need of providing reliable schedules that consider travel time variability originated by congestion along with complying with regulation. Available algorithms might decrease accuracy and produce poor solutions when considering these restrictions; therefore, the importance of understanding the capability of current theory to solve the related variants and to provide efficient algorithms if necessary.

Although there is a range of innovative approaches such as variants that reduce emissions to make transport operations more environmentally friendly, the industry is interested in accurate models that consider time-dependent travel times, comply with regulation and are capable to reduce transport costs. The literature review shows that literature that provides high accuracy for time-dependent variants is still scarce; therefore this research will focus in these issues, where future research might incorporate additional complexities.

Chapter 4

A metaheuristic approach for the Time-Dependent Vehicle Routing Problem with Time Windows

The time-dependent Vehicle Routing Problem with hard time windows (TDVRPTW) is the variant where travel time between locations depends on the time of the day with a strict (non-negotiable) time window for the delivery being initially established by the customer (Figliozzi, 2012, Malandraki and Daskin, 1992). The primary objective is to reduce the number of vehicles required to complete the schedule whilst minimising travel distance and travel time (Figliozzi, 2012).

Variants of the Vehicle Routing Problem (VRP) are NP-Hard and metaheuristic algorithms have been developed to solve the problem with trials suggesting significant improvement in performance over current schedules. Some implementations have achieved high accuracy (difference between best-known values and results of the particular algorithm for available test instances) with execution times that allow logistics planners to realistically use the approach as part of their everyday operations (Cordeau et al., 2002, Drexl, 2012).

In an industry where the profit margin can be as low as 3% (FTA, 2015), logistics companies have recognized the importance of utilising time-dependent VRP variants to support planning and there is a need to further investigate the capabilities of current time-dependent algorithms to deliver improved performance across a variety of operational and traffic settings.

Time-dependent models create new complexities for algorithm design related to tailoring existing search strategies designed specifically for constant-speed models. Common local search procedures require significant modification as alterations within a route as part of the search process could potentially affect the feasibility of the rest of the route. This might alter the departure times of subsequent visits to customers and consequently modify travel times. Route evaluation is considerably more computationally expensive with time-dependent travel times (Harwood et al, 2013) and accommodating hard time constraints for time windows also requires more computational resources than soft constraints where solutions with violations of time windows are allowed (Figliozzi, 2012). Recent work has been done to reduce the computational processing cost of the evaluation of the well-known operator 2 opt for a variation of the Time-dependent travelling salesman problem with no time windows (a schedule with one vehicle). By producing quick estimations of movement evaluation, computational time was reduced up to 80%. However, it requires further development to cope with the large number of search procedures that require the optimization of a TDVRPTW (Harwood et al, 2013).

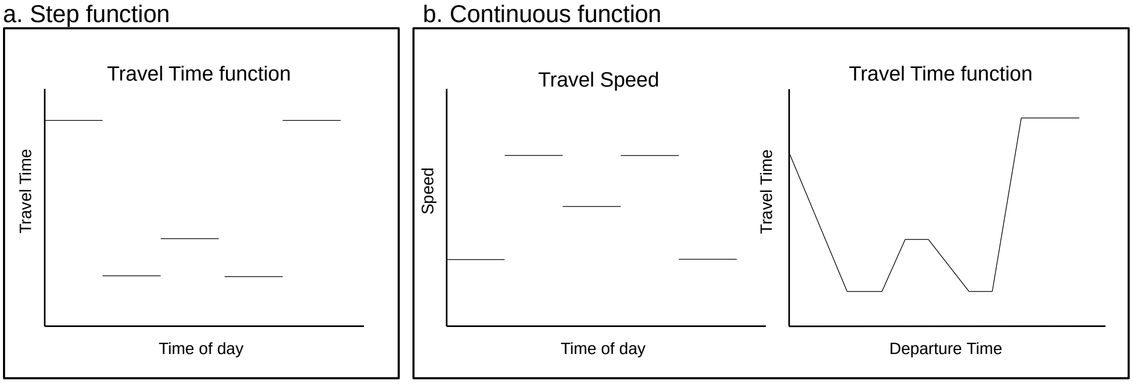
Large Neighborhood Search (LNS) is a search strategy that stands out in the range of concepts among state-of-the-art algorithms to solve vehicle routing models due to its simplicity and wider applicability and it has been extended to successfully address various variants (Vidal et al., 2013). In this chapter, a LNS algorithm is tailored to solve the complexities involved in the TDVRPTW with results compared against available test instances in order to understand its capabilities.

4.1. Previous work

Recent research in time-dependent VRP variants including introduction of benchmark instances is mentioned in the previous chapter. However, in this subsection solution techniques and issues regarding modelling traffic patterns are reviewed.

The first formal formulation of the Time-Dependent VRP was presented by Malandraki (1989) and Malandraki and Daskin (1992), a fleet of vehicles with limited capacity has to visit a number of customers with fixed demands and total travelled time has to be minimised, travel time between customers depends on distance and time of day, a single depot exists, vehicles must depart and return to the depot after finishing the delivery tour, no split deliveries are allowed and service time windows might be present. Two different solution approaches were proposed for instances up to 25 customers generated randomly without time windows, a set of greedy heuristic algorithms and a cutting-plane algorithm. Although the cutting-plane algorithm was more expensive computationally and was able to solve to optimality only small instances, it showed incumbent solutions with lower travelled time in 2/3 of the tested problems with 10 or more customers than the heuristic approach.

The TDVRP formulation of Malandraki and Daskin (1992) was based on a travel time step function where each period of time has a specific travel time between nodes, which leads to an unrealistic assumption, a vehicle with a later departure time might arrive earlier than a vehicle with an earlier departure time across the same link, as it is point out by Ichoua et al. (2003). Later work on the TDVRP has implemented travel time functions that respect the FIFO property “first-in-first-out” based on a continuous function (Figliozzi, 2012, Donati et al., 2008, Fleischmann et al., 2004). Figure 13 shows the difference between Malandraki’s step travel time function and Figliozzi’s continuous travel time function for 5 periods of time in a day (Figliozzi, 2012).



a. (Malandraki and Daskin, 1992)
b. (Figliozzi, 2012)

Figure 13. Different Travel Time functions for constant distance with variable speed.

Work on different TDVRP models has been carried out, Ichoua et al. (2003) studied the TDVRP with soft time windows, where violation of the required service time was permitted but with a resulting penalty in the objective function. The number of routes was fixed and vehicle capacity was not taken into consideration. The objective function was to minimise travel time and penalties incurred due to service time window violations. The solution approach was based on a Tabu Search metaheuristic algorithm, when the schedules created with constant-speed models are analysed under an scenario with time-dependent travel times (variable speed due to congestion), actual travel times are greater than planned travel times and it generates violation of time windows. Fleischmann et al. (2004) presented the TDVRP with and without time windows using scenarios based on real congestion patterns from a traffic information system in Berlin. The solution approach used different heuristic algorithms and local search techniques with the results suggesting that using constant-speed models might generate underestimates of travel time of 10%.

Donati et al. (2008) implemented an ant colony metaheuristic algorithm for TDVRP variants on two sets of instances, the first set is the time-dependent Vehicle Routing Problem with time windows (TDVRPTW) with Solomon's instances using two different speed profiles: a) constant speed in order to compare the special case of the TDVRPTW that is equal to the VRPTW b) speeds assigned randomly. A second set of instances for the TDVRP without time windows using the road network of Padua with data from a traffic information system is used in order to compare the results of using constant speed models in congested roads, travel time underestimation ranges from 5.23% up to 11.98%.

An exact algorithm for the TDVRPTW is presented by (Dabia et al., 2013) using a modified set of the commonly known instances of Solomon (1987) for the VRPTW for up to 100 customers, links between nodes get different speed profiles which were assigned randomly, solution approach is based on a pricing algorithm with column generation and a labelling algorithm, 63% of the 25 customer instances were solved, 38% of the 50 customer and 15% of the 100 customer. However, details about the categorization of links are not provided in order to be able to reproduce the instances.

For the TDVRPTW Figliozzi (2012) proposed an insertion heuristic (*IRCI*) to construct an initial feasible solution and a 'ruin-and-recreate' heuristic algorithm to improve the results (*IRCI-R&R*). Benchmarking for accuracy was performed with available best-known values for the VRPTW and executing the proposed algorithm for the TDVRPTW with constant-speed profiles. The VRPTW commonly has 2 objective functions, to minimise the number of vehicles and their travel distance. Results of Figliozzi (2012) approach suggested a 4.2% increase in vehicles required leading to an 8.6% increase in overall travel distance compared to the best-known values returned by the constant-speed case. Additional speed profiles are provided in order to analyse the impact of congestion patterns in results.

In some of the time-dependent variants the number of vehicles are fixed and optimisation is only based on travel time reduction across the fleet. However, finding the minimum number of vehicles required in the presence of hard time windows is in itself a complex problem, more computationally expensive with time-dependent travel times. Additionally, most current efficient methods for the VRP variants are intricate and difficult to reproduce (Vidal et al., 2013). Furthermore, some metaheuristic implementations have been tailored to work well in specific test instances by tuning parameters so specifically as considering the best random seed that provides high accuracy (Sörensen, 2015).

There is clearly therefore a need for general and simple methods applicable to practical applications required by the industry (Vidal et al., 2013), such as effective algorithms that consider congestion and provide reliable schedules. However, the capability of current algorithms to provide high accurate solutions for time-dependent VRP variants is still not well understood due to the lack of adequate algorithm evaluation with previously proposed instances.

4.2. Problem definition

- Deliveries are requested by n customers
- let G= (V, A) be a graph where vertex V = (v_0, v_1, … , v_n), v_0 is the depot and v_1, … , v_n the set of customers. Each element of V has an associated demand q_i ≥ 0 (which must be fulfilled), a service time g_i ≥ 0 and a service time window [e_i, l_i]. Note that 0 = q_0 = g_0
- An undetermined number of identical vehicles each with maximum capacity q_{max} are available and stationed at v_0. Vehicles must depart from and return to the depot v_0 at the end of the delivery tour and their maximum capacities cannot be exceeded
- The departure time of any given vehicle from v_i is denoted b_i, its arrival time a_i
- Arrival time to customer v_i must be before l_i. If arrival time is before e_i, the vehicle has to wait until e_i. Each customer can only be visited once

- Let A be the set of arcs between elements of V, having constant distance d_{ij} between v_i and v_j
- For each arc (i,j) ∈ A there exists a travel time $t_{ij}(b_i) \geq 0$ a function of departure time b_i, (e.g. of a form as proposed by Ichoua, Gendreau and Potvin (Ichoua et al., 2003) see Algorithm 3).

The primary objective is to minimise the number of vehicles and the second objective might be either minimisation of travel distance or travel time. In the research proposed by Figliozzi (2012) the second objective is the sum of travel distance and travel time.

Travel time function $t_{ij}(b_i)$ proposed by Ichoua et al. (2003) to account for FIFO restriction, using notation of Figliozzi (2012), is presented as follows, note that travel time depends of departure time from customer v_i :

Algorithm 3: Travel time function

Input Data: b_i ; $T = T_1, T_2, \ldots, T_p$ where each period T_k has an associated constant travel speed $\mathbb{s}_k$, an initial time $t_{\underline{k}}$ and a final time $t_{\overline{k}}$

Start

if $a_i < e_i$ **then**
    $b_i \leftarrow e_i + g_i$
else
    $b_i \leftarrow a_i + g_i$
endif
find k **where** $t_{\underline{k}} \leq b_i \leq t_{\overline{k}}$
$a_i \leftarrow b_i + d_{ij} / \mathbb{s}_k$
$d \leftarrow d_{ij}$, $t \leftarrow b_i$
while $a_j > t_{\overline{k}}$ **do**
    $d \leftarrow d - (t_{\overline{k}} - t)\, \mathbb{s}_k$
    $t \leftarrow t_{\overline{k}}$
    $a_j \leftarrow t + d_{ij} / \mathbb{s}_{k+1}$
    $k \leftarrow k + 1$
end while
Return: a_j

End

---

v_i : customer i a_i: arrival time at v_i b_i: departure time from v_i d_{ij}: distance between v_i and v_j
e_i: greatest lower bound of the time window for v_i g_i: service time (length of the requested service) for v_i
$\mathbb{s}_k$: associated constant travel speed of T_k $t_{\underline{k}}$: greatest lower bound of T_k $t_{\overline{k}}$: lowest upper bound of T_k

4.3. Solution procedure

As previously mentioned in the literature review, there is a range of available operators for neighbourhood exploration and techniques to speed up the search process when solving VRP variants. However, for time-dependent VRP variants, little research is available and analysis of different approaches has not been yet properly addressed. In this research, different techniques were tested to reduce the required number of vehicles and travelled distance/time.

The first approach was to work always in a feasible search space and try to reduce the number of vehicles with ejection chains; however high accuracy was obtained in several minutes. Another approach was to employ elements of genetic algorithms to create a set of parents; this approach was too demanding in terms of computational processing time in order to reconstruct feasible solutions. Additionally, genes that were feasible in certain periods of time became infeasible when inserted in a different time slot due to the characteristics of time-dependent models.

After initial testing, it was decided to use an algorithm that started with a feasible solution created by a fast heuristic that offered some degree of accuracy and employ a metaheuristic approach to improve the solution. The major breakthrough was to use neighbourhood structures present in LNS. Although Figliozzi (2012) proposed an algorithm based on the Ruin and Recreate concept (similar to LNS), exploration is based on a fast heuristic called *IRCI*, rather than the procedures proposed by Schrimpf et al. (2000) Ropke and Pisinger (2006), Pisinger and Ropke (2007), Mattos Ribeiro and Laporte (2012) to solve constant speed VRP variants with LNS.

Further algorithm tailoring to LNS movements was required in order to produce schedules with reduced number of vehicles in reasonable time. The search space is extended to manage violation of time windows where the proposed tailoring identifies particularly difficult customers to accommodate in schedules with reduced number of vehicles, and guide the neighbourhood exploration towards new regions that are able to accommodate those customers.

Additionally, an analysis of neighbourhood structures is presented at the end of this chapter in order to understand the capabilities of LNS versus well-known movements (such as 2-opt and 2-opt*) when exploring the search space in time-dependent VRP variants.

4.3.1. Algorithm Background

Large Neighbourhood Search

LNS is an algorithm for neighbourhood exploration introduced by Shaw (1997) utilising a very similar concept to the ‘ruin-and-recreate’ algorithm introduced by Schrimpf et al. (2000) (Ropke and Pisinger, 2006, Shaw, 1998). A number of partial-destruction procedures are used to remove customers from the solution and a different set of reconstruction procedures are used to create a new solution by inserting removed customers in a smart way, see Figure 14.

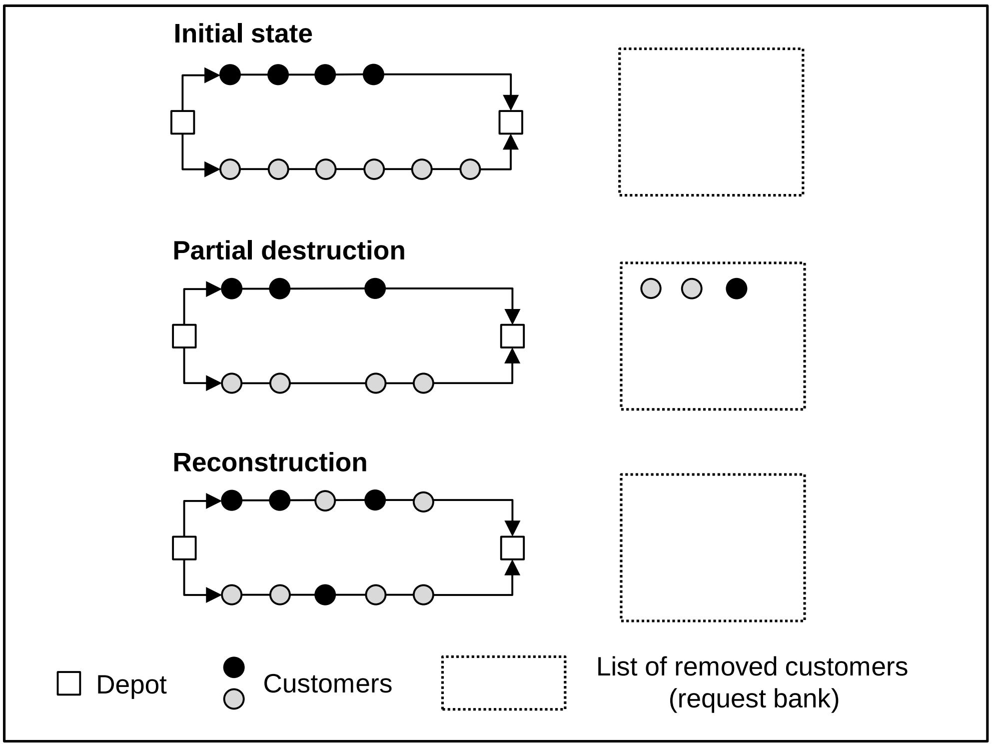


Figure 14. Large Neighbourhood Search movement.

Schrimpf et al. (2000) proposed some basic procedures for the VRPTW that were extended by Ropke and Pisinger (2006), Pisinger and Ropke (2007), and Mattos Ribeiro and Laporte (2012) for VRP variants, some are presented below:

Destruction procedures

- *Random-Ruin*: Randomly select and remove w customers from all customers in the solution.
- *Radial-Ruin*: Randomly select a customer v_i. Remove v_i and w -1 closest customers to v_i.
- *Sequential-Ruin*: Select a random route k (vehicle k) and select a random customer v_i in k. Remove a chain of consecutive customers of length w in k starting with v_i.
- *Worst-removal*: Remove the customers that have the most negative impact according to a function *removal-cost*(v_i).

Recreation procedure

- *Basic-greedy heuristic*: Given the list of removed customers U, calculate an *insertion-cost*(v_i, k, p) for all $v_i \in U$ in all possible routes and positions when v_i is inserted in route k in position p, and insert v_i with the lowest *insertion-cost*(v_i, k, p) in the solution. Repeat the procedure until all $v_i \in U$ are inserted or no feasible insertion exists.

One characteristic of the LNS for VRP variants is that the request bank is an entity that allows the search process for the exploration of infeasible solutions (Ropke and Pisinger, 2006) without directly calculating the violation of restrictions. In the case of the TDVRPTW, any solution with unscheduled customers is infeasible. Additionally, insertion procedures are quite myopic, in order to avoid stagnating search processes, where destruction and recreation procedures keep performing the same modification to a solution, providing diversification in different levels of the search process might improve accuracy of solutions (Mattos Ribeiro and Laporte, 2012).

Previous LNS implementations have made use of other metaheuristic algorithms at the master level to guide the search to new regions and accept improved solutions such as Simulated Annealing (Mattos Ribeiro and Laporte, 2012, Ropke and Pisinger, 2006). In the neighbourhood exploration, applying noise in recreation procedures also avoids stagnation e.g., by using randomisation in the insertion evaluation function in recreation procedures (Ropke and Pisinger, 2006), or tailoring recreation procedures to ensure diversification (Mattos Ribeiro and Laporte, 2012).

Variable Neighbourhood Search

VNS is a metaheuristic algorithm introduced by Mladenović and Hansen (1997) and Hansen and Mladenović (2001). VNS has been previously implemented in a range of combinatorial problems (Hansen et al., 2010) including VRP models (Bräysy, 2003, Kytöjoki et al., 2007) and the TDVRP with soft time windows (Kritzinger et al., 2011). VNS uses local search neighbourhoods and avoids local optima with specially designed procedures called "*Shaking*" which usually have random elements (Hansen and Mladenović, 2001, Hansen et al., 2010). An additional element of VNS is the concept that a local optima in a neighbourhood is not necessarily a local optima for other neighbourhoods, therefore changing neighbourhoods might avoid local optima. The pseudo code that illustrates the basic concept of VNS is presented as follows:

Algorithm 4: Basic concepts of Variable Neighbourhood Search

Start
Initialization by selecting H neighbourhood structures $H = \{h_1,\dots, h_{max}\}$
Initialize Incumbent solution
Current solution ← Incumbent solution
$h \leftarrow 1$
Repeat
    Current solution ← *Shaking* with h^{th} neighbourhood (Incumbent solution)
    Current solution ← *Local search* (Current solution)
        If (Current solution < Incumbent solution) **then**
            Incumbent solution ← Current solution
            $h \leftarrow 1$
        Else
            $h \leftarrow h+1$
        EndIf
Until $h = h_{max}$
End

A characteristic of the presented basic VNS concept is that it works on an ‘only-descendent’ approach. It changes the search space region when an improvement has been found, (lines 8 to 10). However, it may be easily transformed to a ‘descendent–ascent’ approach by introducing some selection criteria to allow exploration of regions with a deteriorated solution, e.g., randomness (Hansen and Mladenović, 2001) or a threshold acceptance value (Kritzinger et al., 2011).

An additional characteristic of VNS is that it does not follow a trajectory, but it explores increasingly distant regions, the set of procedures for “*Shaking”* is at the core of VNS and provides a balance between obtaining a sufficiently large perturbation of the incumbent solution while still making sure desired attributes of “good” solutions are maintained. In order to guide the search, a metric in the “*Shaking”* procedure is introduced (Hansen and Mladenović, 2001), (lines 1 and 6). Local search, line 7, is a set of procedures that allow the exploration of the local search space.

An example of VNS for the multi-depot VRPTW is presented by Polacek et al. (2004), as initialization of an incumbent solution with a cheap heuristic and fast running times was proposed. The set of procedures for “*Shaking”* is based on the CROSS-exchange operator where orientation of routes is preserved and the iCROSS-exchange operator where orientation of routes is reversed. Figure 9 (page 34) shows some well-known neighbourhood exploration procedures.

The “*Shaking*” metric between solutions was established as the number of depots used to generate the new solution and the maximum length of the removed sequence in the neighbourhood construction. Local search was the 3-opt operator neighbourhood with reverse of route orientation not allowed and the length of the sequences to be exchanged bounded by an upper limit of three. Decision about moving the search to a new region follows the descendent–ascent approach with a threshold acceptance value.

Analysis of results in terms of accuracy and speed showed that the proposed VNS was competitive to other metaheuristic algorithms and it was capable to improve some of the best-known results at that moment. A very similar VNS approach for the TDVRP with soft time windows was proposed by Kritzinger et al. (2011).

4.3.2. A hybrid metaheuristic for the TDVRPTW

Search procedures for the TDVRPTW are computationally expensive, with the proposed algorithm designed to guide the search to highly accurate solutions in a reasonable time. The search process is divided into two stages, the first is where an initial incumbent solution is created using a fast construction heuristic to undertake a reduction of vehicles. In the second stage the objective is the minimisation of the sum of travel distance and travel time in order to compare results with the work of Figliozzi (2012).

Stage 1a: Construction of Initial Solution

IRCI heuristic is an algorithm that constructs routes sequentially, designed initially for the VRPTW (Figliozzi, 2008, Figliozzi, 2010) it can also solve the TDVRPTW (Figliozzi, 2012). Its main components are a *generalized-cost-function* that estimates the minimum cost of appending unrouted customers into an existing route (vehicle) or adding a new route and a "looking ahead" evaluation that assess the impact of the current insertion versus other possible insertions. The *generalized-IRIC-cost-function* adapted to handle only hard windows and time-dependent travel times depends on travel time $t_{ij}(b_i)$ between customers v_i and v_j, the service starting time at v_i in route k denoted y_i^k which is the $\max(a_i, e_i)$, the remaining capacity on vehicle k after serving v_i denoted q_i^k, and a set Δ of parameters, $\Delta = \{\delta_0, \delta_1, \delta_2, \delta_3, \delta_4\}$ where δ_0 is the cost of adding a new vehicle, δ_1 takes into account travel time between customers, δ_2 accounts for the "slack" between departure time from v_i and service starting time at v_j, δ_3 accounts for the "urgency" of servicing v_j and δ_4 takes into consideration the spare capacity of vehicle k after servicing v_j. The modified *generalized-IRCI-cost-function* (C_{IRCI}) proposed in this research for inserting unrouted customer v_j after visiting v_i in vehicle k is presented as follows:

$$C_{IRCI}(v_i, v_j, k) = \delta_1 t_{ij}(b_i) + \delta_2(y_j^k - (y_i^k + g_i)) + \delta_3(l_j - \left(y_i^k + g_i + t_{ij}(y_i^k + g_i)\right) + \delta_4(q_i^k - q_j)$$

If adding v_j in vehicle k is infeasible, the *generalized-IRCI-cost-function* of adding a new vehicle is:

$$C_{IRCI}(v_0, v_j) = \delta_0 + \delta_1 t_{0j}(b_0) + \delta_2(y_j^k - e_0) + \delta_3(l_j - t_{oj}(e_o) + \delta_4(q_{max} - q_j)$$

The pseudo code of *IRCI* is presented as follows:

Algorithm 5: *IRCI*

Start
1. **Repeat**
2. For each unrouted customer in *best sequence* calculate *generalized-IRIC-cost-function*
3. Sort in decreasing order customers according to *generalized-IRIC-cost-function*
4. Select z best customers v_i with less *generalized-IRIC-cost-function*, $V'=\{v_1, \ldots v_z\}$
5. **Repeat** for each $v_i \in V'$ (Creation of z sequences, $S = \{s_1, \ldots, s_z\}$)
6. **Repeat**
7. For each unrouted customer in s_j calculate *generalized-IRIC-cost-function*
8. Select customer with lowest *generalized IRCI cost*
9. Insert customer in s_j
10. **Until** all customers are in s_j
11. **Until** z sequences are created
12. Select sequence s_j with best evaluation that insert best customer v_i
13. Insert best customer v_i in *best sequence*
14. **Until** all customers are in *best sequence*
15. **Return:** *best sequence*

End

IRCI evaluates at each insertion in best sequence the customer v_i with less generalized cost (line 2) that offers the best solution in the overall route that is represented in a sequence (lines 5 to 11), the evaluation of the *best sequence* (line 12) is considered on terms of minimum number of vehicles or distance/travelled time and requires the insertion of all customers in order to assess the best route that can be achieved by inserting the evaluated customer v_i in *best sequence* (line 13). The number of sequences evaluated in each insertion z in best sequence is the "width" of the search (line 4). A special characteristic of IRCI is that it produces feasible routes. Additionally IRCI can be repeated with different sets of parameters Δ in order to obtain a more thorough search space. However, in this research parameters were fixed for all the tested instances, δ_0 is a value sufficiently large to force IRCI to generate as few vehicles in each sequence as possible, $\delta_1 + \delta_2 + \delta_3 = 1$ and δ_4 is bounded by 0 and the ratio of the median distance between customers and the median customer demand (Figliozzi, 2012). Values used in this research are ($\delta_0 = 200,\ \delta_1 = 0,\ \delta_2 = 0.8,\ \delta_3 = 0.2,\ \delta_4 = 0.02$).

Stage 1b: *Route Reduction Procedure*

In previous implementations of the LNS for constant-speed models, minimising the required number of vehicles relied on removing routes from an incumbent solution and placing customers in the request bank until a solution was found without unscheduled customers (some customers still in the request bank) (Pisinger and Ropke, 2007, Ropke and Pisinger, 2006). In the initial test of this approach for the TDVRPTW, lengthy computational time was required in order to get high accuracy due to the complexity in movement evaluation originated by time-dependent travel times.

In order to speed up the search process, a strategy to quickly guide the search towards higher accuracy was designed. Solutions which violated time windows were allowed, and the objective function was minimising the sum of violations of time windows (*penalty*). Due to the myopic behaviour of LNS, the search quickly reached stagnation. Small time window violations were generated by frequent pairs of customers. In order to avoid stagnation, a tabu list of forbidden pairs of customers was introduced to force the recreation procedure to unexplored trajectories.

At the extent of the knowledge of the authors, this is the first implementation of LNS with allowed time window violations that exploits the destruction and recreation procedures and introduces a tabu list of forbidden pairs of customers for VRP variants with time windows. This strategy allows sequences of customers to be identified that are particularly difficult to accommodate in a solution with a reduced number of vehicles, and allows the algorithm to focus on scheduling these customers without incurring time window violations while avoiding stagnation. The local search consists of a modified *Worst-removal* procedure to remove customers that generate penalties along with other destruction procedures before executing a modified *Basic-greedy heuristic* for minimisation of time window penalties (*LNS-Penalty Procedure*). The pseudo code of *Number of vehicles minimisation procedure* is presented as follows:

Algorithm 6: *Number of vehicles minimisation procedure*

Start

1. Incumbent solution ← Construction of Initial Solution with *IRCI*
2. Incumbent-penalty solution ← *Remove one route* (Incumbent solution)
3. Tabu List = { Ø }
4. $h \leftarrow 1$
5. **Repeat**
6.   **Repeat**
7.   Current solution ← *Shaking-Route Reduction Procedure* (h , Tabu List, Incumbent-penalty solution)
8.   Current solution ← *LNS Penalty Reduction Procedure* (Current solution, Tabu List)
9.   **If** *penalty*(Current solution) > 0
10.   Tabu List ← Tabu List ∪ Elements-Generate-Penalty(Current solution)
11.   **If** *penalty*(Current solution) < *penalty* (Incumbent-penalty solution)
12. $h \leftarrow 1$
13.   Incumbent-penalty solution ← Current solution
14.   **else**
15. $h \leftarrow h + 1$
16.   **EndIf**
17.   **Until** $h = h_{max}$ or *penalty* (Current solution) = 0
18.   **If** *penalty* (Current solution) = 0
19.   Incumbent solution ← Current solution
20.   Incumbent-penalty solution ← *Remove one route* (Incumbent solution)
21.   Current solution ← Incumbent-penalty solution
22.   Tabu List = { Ø }
23. $h \leftarrow 1$
24.   **Else**
25.   Incumbent-penalty solution ← Current solution
26. $h \leftarrow 1$
27.   **End if**
28. **Until** stop criteria met

Return Incumbent solution
End

The main steps of *Number of vehicles minimisation* are the following:

i) Creation of an initial incumbent solution with *IRCI* heuristic (line 1).

ii) *Remove one route*: The vehicle with the minimum number of customers is removed and its customers are allocated to the request bank in order to be inserted in the other routes that conform the schedule (line 2) with *Basic-greedy heuristic* with the *insertion-cost*^{vm} that is presented in step iii. A *penalty* might be generated, which is calculated as the sum of the time violations of the upper time windows. Each time that the search process reaches a solution with the *penalty* equal to 0 (line 18), a feasible schedule, the solution is stored (line 19) and another vehicle is removed (line 20).

iii) Minimisation of *penalty* with *LNS Penalty Reduction Procedure* (line 8): The local search consists of minimising the *penalty* with LNS procedures: *Random-Ruin, Radial-Ruin, Sequential-Ruin, Worst-removal* and *Basic-greedy heuristic* with the following *insertion-cost*^{vm}.

$$\textit{insertion-cost}^{vm}(v_i, k, p) = \Delta\ Penalty$$

or in case there is no penalty in the insertion

$$\textit{insertion-cost}^{vm}(v_i, k, p) = \Delta\ Travel\ time + \Delta\ Travel\ distance + \Delta\ Waiting\ time$$

where customers that generate penalty are firstly inserted and secondly customers that do not generate penalty are inserted.

In order to avoid stagnation, each time that LNS procedures reach a local optima, the schedule is modified with *IRCI* in order to diversify the search. All customers in a number of vehicles are removed from the solution and assigned to these vehicles with *IRCI* without violation of the time windows. Customers that could not be inserted in these vehicles are inserted in other vehicles using the *Basic-greedy heuristic.* Subsequently LNS procedures are used again to try to reduce the *penalty*.

A tabu list is introduced in order to avoid stagnation, each time that the search reaches a local optima the pairs of customers that generate the *penalty* are recorded, when they appear a third time they are introduced into the tabu list (line 10). *Basic-greedy heuristic* and *IRCI* make use of the tabu list to avoid creating schedules that contain sequences with the pair of customers that are in the tabu list. Each time that the search reduces one vehicle, the tabu list is emptied (line 22).

iv) Diversification with *Shaking-Route Reduction Procedure* (line 7): The exchange operator is used to modify the position in the schedule of h customers in order to create new solutions. Customers to be exchanged are preferably those that generate penalty.

Stage 2: Travel time and travel distance minimisation

This procedure relies on the identification of promising search regions. In each iteration, a new region is visited and explored with a fast algorithm. It is established if the region is promising for intensification with a fast exploration and an evaluation with a threshold value. Intensification is based on LNS and VNS. The objective function value in the search is the sum of travel time and travel distance in order to compare results with the work of Figliozzi (2012). The proposed *Travel timed and travel distance minimisation procedure* is presented below as follows:

Algorithm 7: *Travel time and travel distance minimisation procedure*

```
Start
 1.  Incumbent solution ← Number of vehicles minimisation procedure
 2.  Current solution ← Incumbent solution
 3.  Repeat
 4.     Current solution ← Shaking procedure (Current solution)
 5.     Current solution ← Educate procedure  (Current solution)
 6.     If objective (Current solution) < Threshold value
 7.         Current solution ← LNS-VNS Intensification procedure (current solution)
 8.         If objective (Current solution) < objective (Incumbent solution)
 9.             Incumbent solution ← Current solution
10.         EndIf
11.     EndIf
12.  Until stop criteria met
End
```

The main steps of *Travel time and travel distance minimisation procedure* are the following:

i) Modification of current solution in order to identify a new region with the *Shaking procedure* (line 4): Firstly, a random $vehicle_k$ is selected and all v_i in $vehicle_k$ are inserted in the remaining vehicles when insertions are feasible (no violation of time windows are allowed). Secondly, vehicles are randomly sorted, $S' = \{ vehicle_1, \dots, vehicle_k, \dots, vehicle_m \}$. Thirdly, each v_i in $vehicle_1$ is exchanged, with the exchange operator, in the first feasible insertion in the subsequent vehicles. The third part of the procedure is repeated in all $vehicle_k \in \mathrm{S}', k \neq \mathrm{m}$ and only feasible solutions are allowed.

ii) Identification of a promising regions with the *Educate procedure* (line 5): The procedure consists of 2-opt operator, 2-opt* operator and relocate operator with the length of the sequences to be exchanged bounded by an upper limit of three. These operators conduct a systematic search by modifying the position of customers within the same route and between routes. Although computationally expensive for a large number of iterations, they are used to identify search regions where a fast reduction in the objective function can be achieved. Educate procedure consists of a limited number of iterations. Identified regions that achieve certain objective function value are selected for intensification (line 6).

iii) Search intensification with *LNS-VNS Intensification procedure* (line 7): This procedure consists of minimisation of the objective value with LNS procedures (e.g., *Random-Ruin, Radial-Ruin, Sequential-Ruin* and *Basic-greedy heuristic set to minimise travel time + travel distance*) in an iterative way by using a "*Shaking*" procedure. When the search reaches a local optima, the exchange operator and relocate operator are used to modify the position in the schedule of h customers in order to create new solutions in a similar way than in *Number of vehicles minimisation procedure*.

4.4. Benchmark instances

Due to the fact that the TDVRPTW is an extension of the VRPTW, Figliozzi (2012) proposed a modification to the well-known instances for the VRPTW of Solomon (1987) to account for congestion by adding speed profiles. Solomon instances consist of 56 problems with 100 customers and a single depot. Problems are divided in six classes namely: R1, R2, C1, C2, RC1 and RC2. R accounts for random locations, C for clustered locations and RC for a mix of random and clustered locations. Type 1 consist of schedules with tight time windows that allow fewer customers per vehicle than type 2.

Figliozzi (2012) proposed 4 types of speed profiles, with 3 cases for each type, for a total of 12 speed cases. The depot working time $[e_0, l_0]$ is divided into five periods of equal duration. An additional instance with constant speed of 1 is also introduced in order to compare the performance of the proposed solution for the TDVRPTW with available best-known values for the largely studied VRPTW. Speed profiles are as following:

CASES TYPE a (Fast periods between depot opening and closing times)

TD1a = [1.00, 1.60, 1.05, 1.60, 1.00]
TD2a = [1.00, 2.00, 1.50, 2.00, 1.00]
TD3a = [1.00, 2.50, 1.75, 2.50, 1.00]

CASES TYPE b (Higher travel times at the extremes of the working day)

TD1b = [1.60, 1.00, 1.05, 1.00, 1.60]
TD2b = [2.00, 1.00, 1.50, 1.00, 2.00]
TD3b = [2.50, 1.00, 1.75, 1.00, 2.50]

CASES TYPE c (Higher travel speeds are found at the beginning of the working day)

TD1c = [1.60, 1.60, 1.05, 1.00, 1.00]
TD2c = [2.00, 2.00, 1.50, 1.00, 1.00]
TD3c = [2.50, 2.50, 1.75, 1.00, 1.00]

CASES TYPE d (Higher travel speeds at the end of the working day)

TD1d = [1.00, 1.00, 1.05, 1.60, 1.60]
TD2d = [1.00, 1.00, 1.50, 2.00, 2.00]
TD3d = [1.00, 1.00, 1.75, 2.50, 2.50]

4.5. Implementation and Experimental Results

Algorithm benchmarking is commonly evaluated in terms of accuracy and speed (Bräysy and Gendreau, 2005a, Bräysy and Gendreau, 2005b, Toth and Vigo, 2001). Accuracy can be easily evaluated when data sets are available. However, different factors have an impact on speed such as hardware (processor, ram), code efficiency and compiler (Figliozzi, 2012). Additionally, it is mentioned in the literature that better results might be obtained by tailoring algorithms accordingly to the test instance. This practice is impractical in industry applications that require fast and reliable solution procedures capable to consistently provide high accurate results (Cordeau et al., 2002, Drexl, 2012, Figliozzi, 2012, Golden et al., 1998).

The proposed LNS approach was coded in Java Eclipse version Juno. It has random elements and results might vary in each run, where multi-core processors offer the possibility to execute multiple threads simultaneously. In this research a computer with processor Intel core i7-2600 3.40GHz and 16 GB of ram was used, three independent threads were run simultaneously and the best result of the three was chosen. The algorithm was run with two different sets of parameters according to termination criteria, which consist of maximum number of iterations, maximum running time, and allowed running time without improvement. The first set of parameters (named F) was set to produce a fast algorithm whereas the second one (named L) produces a more thorough search by allowing a larger number or iterations and/or execution time before terminating the procedures.

Donati et al. (2008) and Figliozzi (2012) have presented results for metaheuristic approaches for the TDVRPTW using Solomon instances with constant speed in order to compare results with best-known values for the VRPTW, Table 17. Best-known values for the minimum number of vehicles for the 56 problems was 405. The result for the proposed algorithm, with set of parameter L, is 408 and best-known values can be achieved by extending running time. However, parameter tuning was set to deal with 672 problems (56 problems x 12 speed cases).

Running the proposed algorithm with sets of parameters F (set to a short execution time with fewer number of iterations) and L (set to long execution time with a higher number of iterations) provide higher accuracy than previous implementations for the TDVRPTW in the primary objective (average number of vehicles) for instances R1, RC1 and RC2 (see tables 18-21).

Analysis of the secondary objective (distance) shows that the proposed LNS obtained higher accuracy than *IRCI-R&R* (Figliozzi, 2012) in all instances, results within 1% of best-known values can be achieved by increasing running time. Ant colony approach (Donati et al., 2008) obtained higher accuracy in the secondary objective. However, reduced distances might be achieved easily when more vehicles are used, e.g.: problem type R1, reduction of 0.93% from best-known values is achieved with 5.88% more vehicles.

Table 17. VRPTW results for Solomon's 56 problems with 100 customers – Constant speed

Method	R1	Δ	R2	Δ	C1	Δ	C2	Δ	RC1	Δ	RC2	Δ
Average NV												
(1) Best known value	**11.9**		**2.7**		**10.0**		**3.0**		**11.5**		**3.3**	
(2) IRCI – R&R	12.6	5.88%	3.0	11.11%	10.0	0.00%	3.0	0.00%	12.1	5.22%	3.4	4.62%
(3) Ant Colony	12.6	5.88%	3.1	14.81%	10.0	0.00%	3.0	0.00%	12.1	5.22%	3.8	16.92%
(4) VNS F Best 3 runs	12.2	2.52%	3.0	11.11%	10.0	0.00%	3.0	0.00%	11.6	1.09%	3.3	0.00%
(5) VNS L Best 3 runs	12.0	0.84%	2.8	4.38%	10.0	0.00%	3.0	0.00%	11.6	1.09%	3.3	0.00%
Average Distance												
(1) Best known value	**1210.3**		**954.0**		**828.4**		**589.9**		**1384.8**		**1119.2**	
(2) IRCI – R&R	1248.0	3.11%	1124.0	17.82%	841.0	1.52%	626.0	6.12%	1466.0	5.86%	1308.0	16.87%
(3) Ant Colony	1199.0	-0.93%	967.0	1.36%	828.0	-0.05%	590.0	0.02%	1374.0	-0.78%	1156.0	3.29%
(4) VNS F Best 3 runs	1222.3	0.99%	961.7	0.81%	834.0	0.68%	590.3	0.07%	1405.9	1.52%	1170.0	4.54%
(5) VNS L Best 3 runs	1232.2	1.81%	969.6	1.64%	828.6	0.02%	590.3	0.07%	1404.1	1.39%	1160.0	3.65%

(1) Nagata et al. (2010) CPU Time 25 min (5x5 min), processor Opt-2.4 GHz. **(2)** Figliozzi (2012) CPU Time 19 min, processor Intel Core Duo 1.2 GHz. **(3)** Donati et al. (2008) CPU Time 168 min, Pentium IV 2.66 GHz. **(4)** VNS F (3 threads of 26 min) Intel Core i7 3.4 GHz. **(5)** VNS L (3 threads of 62 min) Intel Core i7 3.4 GHz.

In the TDVRPTW the proposed primary objective is the minimisation of the number of vehicles, secondary objective might be minimisation of travel distance, travel time or both. Figliozzi (2012) proposed the sum of distance and travel time as secondary objective. Tables 18 to 21 show benchmarking of *IRCI-R&R* and the proposed LNS.

The proposed algorithm is capable of obtaining a reduction in vehicles required of up to 12.96% (cases type b, set of parameter L, instance R2, Table 19) and secondary reduction objective up to 19.60% in travelled time and distance with fewer vehicles (cases type a, set of parameter L, instance RC2, Table 18) in a reasonable computational time. Each instance of 100 customers can be solved on average in 26.78 seconds using 3 threads with set of parameter F and 65.35 seconds with set L. Table 22 shows the overall sum of number of vehicles, total travelled distance and total travelled time required to solve the 56 problems in each speed profile.

Table 18. TDVRPTW average results for 3 instances in Case Type (a) 100 customers.

Method	R1	Δ	R2	Δ	C1	Δ	C2	Δ	RC1	Δ	RC2	Δ
(1) Figliozzy IRCI-R&R												
NV	10.8		2.5		10.0		3.0		10.6		3.0	
Distance	1263.3		1243.0		874.3		669.3		1387.3		1444.0	
Travel Time	923.3		875.0		660.3		514.3		1004.3		1012.3	
Second objective	2197.4		2120.5		1544.7		1186.7		2402.3		2459.3	
(2) VNS F												
NV	10.4	-3.53%	2.5	-1.83%	10.0	0.00%	3.0	0.00%	10.2	-4.02%	2.9	-2.03%
Distance	1164.4	-7.83%	1007.4	-18.95%	841.6	-3.74%	589.9	-11.87%	1309.9	-5.58%	1168.6	-19.07%
Travel Time	833.2	-9.76%	674.2	-22.95%	625.9	-5.21%	447.6	-12.97%	924.8	-7.92%	789.2	-22.04%
Second objective	1997.6	-9.09%	1681.7	-20.69%	1467.5	-5.00%	1037.5	-12.57%	2234.7	-6.98%	1957.7	-20.40%
(3) VNS L												
NV	10.3	-4.66%	2.4	-7.19%	10.0	0.00%	3.0	0.00%	10.0	-5.90%	2.8	-7.09%
Distance	1165.6	-7.74%	1013.9	-18.43%	834.7	-4.53%	589.4	-11.94%	1313.0	-5.36%	1178.7	-18.37%
Travel Time	832.6	-9.82%	685.9	-21.61%	619.6	-6.16%	447.2	-13.05%	922.5	-8.14%	795.9	-21.38%
Second objective	2008.5	-8.60%	1702.2	-19.73%	1464.3	-5.20%	1039.7	-12.39%	2245.6	-6.52%	1977.3	-19.60%

(1) Figliozzi (2012) CPU Time 54.1 min, processor Intel Core Duo 1.2 GHz. **(2)** VNS F (3 threads of 78 min) processor Intel Core i7 3.4 GHz. **(3)** VNS L (3 threads of 183 min) processor Intel Core i7 3.4 GHz.

Table 19. TDVRPTW average results for 3 instances in Case Type (b) 100 customers.

Method	R1	Δ	R2	Δ	C1	Δ	C2	Δ	RC1	Δ	RC2	Δ
(1) Figliozzy IRCI-R&R												
NV	11.8		2.8		10.0		3.0		11.5		3.2	
Distance	1277.7		1225.0		880.3		683.7		1441.7		1439.7	
Travel Time	925.7		917.0		655.3		486.0		1035.3		1078.0	
Second objective	2215.1		2144.8		1545.7		1172.7		2488.5		2520.9	
(2) VNS F												
NV	11.2	-4.92%	2.7	-4.26%	10.0	0.00%	3.0	0.00%	10.9	-4.89%	3.0	-6.54%
Distance	1197.7	-6.26%	1004.7	-17.98%	847.3	-3.75%	590.0	-13.70%	1633.2	13.29%	1202.7	-16.46%
Travel Time	853.9	-7.75%	730.6	-20.33%	602.3	-8.09%	432.0	-11.11%	966.4	-6.66%	896.7	-16.82%
Second objective	2051.6	-7.38%	1735.3	-19.09%	1449.6	-6.22%	1022.0	-12.85%	2332.6	-6.26%	2099.4	-16.72%
(3) VNS L												
NV	11.1	-5.68%	2.5	-12.96%	10.0	0.00%	3.0	0.00%	10.8	-6.20%	2.9	-9.14%
Distance	1204.5	-5.72%	1027.8	-16.10%	837.8	-4.83%	589.9	-13.72%	1373.9	-4.70%	1213.1	-15.74%
Travel Time	859.5	-7.15%	752.6	-17.93%	599.3	-8.54%	432.0	-11.11%	968.1	-6.50%	903.7	-16.17%
Second objective	2075.2	-6.32%	1782.9	-16.88%	1447.2	-6.37%	1024.9	-12.60%	2352.7	-5.46%	2119.7	-15.91%

(1) Figliozzi (2012) CPU Time 57.4 min, processor Intel Core Duo 1.2 GHz. **(2)** VNS F (3 threads of 75 min) processor Intel Core i7 3.4 GHz. **(3)** VNS L (3 threads of 186 min) processor Intel Core i7 3.4 GHz.

Table 20. TDVRPTW average results for 3 instances in Case Type (c) 100 customers.

Method	R1	Δ	R2	Δ	C1	Δ	C2	Δ	RC1	Δ	RC2	Δ
(1) Figliozzy IRCI-R&R												
NV	10.9		2.5		10.0		3.0		10.8		2.9	
Distance	1280.0		1242.0		863.3		668.7		1419.0		1439.0	
Travel Time	916.0		868.7		626.7		502.3		1034.0		1020.0	
Second objective	2206.9		2113.2		1500.0		1174.0		2463.8		2461.9	
(2) VNS F												
NV	10.4	-4.50%	2.5	-1.83%	10.0	0.00%	3.0	0.00%	10.3	-4.57%	2.8	-4.00%
Distance	1171.6	-8.47%	1142.0	-8.05%	836.8	-3.07%	589.3	-11.87%	1335.3	-5.90%	1197.2	-16.80%
Travel Time	826.2	-9.80%	800.0	-7.90%	605.1	-3.44%	445.3	-11.35%	960.9	-7.07%	857.2	-15.96%
Second objective	1997.9	-9.47%	1942.0	-8.10%	1441.9	-3.87%	1034.6	-11.87%	2296.2	-6.80%	2054.3	-16.56%
(3) VNS L												
NV	10.3	-5.37%	2.3	-9.57%	10.0	0.00%	3.0	0.00%	10.1	-6.19%	2.7	-7.14%
Distance	1172.7	-8.39%	1022.4	-17.68%	829.7	-3.90%	589.3	-11.86%	1322.6	-6.79%	1196.3	-16.87%
Travel Time	828.7	-9.53%	710.6	-18.19%	601.2	-4.06%	445.3	-11.35%	954.6	-7.68%	855.9	-16.09%
Second objective	2011.6	-8.85%	1735.3	-17.88%	1440.9	-3.94%	1037.6	-11.61%	2287.3	-7.16%	2054.9	-16.53%

(1) Figliozzi (2012) CPU Time 55.9 min, processor Intel Core Duo 1.2 GHz. **(2)** VNS F (3 threads of 72 min) processor Intel Core i7 3.4 GHz. **(3)** VNS L (3 threads of 174 min) processor Intel Core i7 3.4 GHz.

Table 21. TDVRPTW average results for 3 instances in Case Type (d) 100 customers.

Method	R1	Δ	R2	Δ	C1	Δ	C2	Δ	RC1	Δ	RC2	Δ
(1) Figliozzy IRCI-R&R												
NV	11.6		2.8		10.0		3.0		11.3		3.3	
Distance	1292.0		1216.3		865.0		678.3		1421.7		1410.0	
Travel Time	976.0		935.3		665.0		502.3		1063.7		1073.3	
Second objective	2279.6		2154.5		1540.0		1183.7		2496.7		2486.6	
(2) VNS F												
NV	11.3	-3.32%	2.7	-3.23%	10.0	0.00%	3.0	0.00%	10.7	-5.51%	3.1	-5.87%
Distance	1195.1	-7.50%	1026.5	-15.61%	833.5	-3.64%	590.1	-13.01%	1373.0	-3.42%	1178.2	-16.44%
Travel Time	901.3	-7.65%	782.6	-16.33%	642.9	-3.32%	437.7	-12.87%	1020.8	-4.03%	890.4	-17.04%
Second objective	2096.3	-8.04%	1809.1	-16.03%	1476.4	-4.13%	1030.0	-12.98%	2393.8	-4.12%	2068.6	-16.81%
(3) VNS L												
NV	11.3	-3.32%	2.6	-6.59%	10.0	0.00%	3.0	0.00%	10.7	-5.51%	3.0	-7.64%
Distance	1184.2	-8.34%	1005.2	-17.36%	831.3	-3.90%	591.4	-12.82%	1367.3	-3.83%	1169.6	-17.05%
Travel Time	894.2	-8.38%	764.1	-18.31%	641.5	-3.53%	438.6	-12.68%	1013.0	-4.76%	883.9	-17.65%
Second objective	2089.6	-8.34%	1771.9	-17.76%	1482.8	-3.71%	1033.1	-12.72%	2391.0	-4.23%	2056.5	-17.30%

(1) Figliozzi (2012) CPU Time 56.8 min, processor Intel Core Duo 1.2 GHz. **(2)** VNS F (3 threads of 81 min) processor Intel Core i7 3.4 GHz. **(3)** VNS L (3 threads of 189 min) processor Intel Core i7 3.4 GHz.

Table 22. Total Number of vehicles, distance and travelled time in all 56 problems (100 customers) in each of the 12 speed profiles (case types)

Case Type	(1) Figliozzy IRCI-R&R			(2) VNS L		
	NV	Distance	Travel Time	NV	Distance	Travel Time
TD1a	402	64875.0	53643.0	387	57439.0	46703.4
TD2a	378	64580.0	45847.0	361	57105.5	39505.4
TD3a	360	64667.0	41198.0	348	57358.7	35105.3
TD1b	420	65044.0	54053.0	403	57950.2	47892.0
TD2b	398	64925.0	46773.0	378	59178.5	41878.0
TD3b	393	65781.0	42837.0	370	59018.2	37480.2
TD1c	402	65304.0	53346.0	387	57842.2	47051.2
TD2c	380	64921.0	45583.0	360	57794.1	40599.2
TD3c	365	64791.0	40985.0	350	57317.0	36004.6
TD1d	417	64858.0	54930.0	401	57639.0	48841.1
TD2d	399	64304.0	47905.0	387	57317.9	42465.6
TD3d	388	65084.0	44466.0	375	58368.9	39472.9
TOTAL	**4702**	**779134.0**	**571566.0**	**4507**	**694329.1**	**502998.9**
Δ				**-4.15%**	**-10.88%**	**-12.00%**

(1) Figliozzi (2012) **(2)** VNS L

4.6. Analysis of results

The proposed algorithm consistently provided improved results for the TDVRPTW. As previously mentioned, route evaluation in the search process is computationally expensive in TDVRP variants. Therefore, selection of neighborhood structures and its adequate tailoring is at the most importance in algorithm design.

Analysis of the computational complexity of different neighborhood structures and performance shows the capability of the proposed LNS tailoring to quickly achieve high accuracy over other procedures. Well-known neighborhood structures involve the deletion of (up to) x arcs of the current solution and the generation of x new arcs to create the subsequent solution, the complexity of neighborhood exploration is $O(n^x)$ (Zachariadis and Kiranoudis, 2010). 2-opt and 2-opt* operators are commonly used in VRP variants with time windows (Bräysy and Gendreau, 2005a), the first one relocates customers within the same vehicle and the second one relocates customers in different vehicles and their complexity of exhaustively examining all possible solutions “naive exploration” is $O(n^2)$, more complex operators with more arc removals are consequently more computationally complex (Zachariadis and Kiranoudis, 2010).

The computational complexity of a LNS procedure that makes use of *Basic-greedy heuristic* for recreation depends on the number of elements in the request bank, the number of routes (vehicles) and the number of customers in the modified route in current solution. After the first insertion, the subsequent customer insertions are only evaluated in the previously modified route with *insertion-cost*. Therefore, computational complexity largely varies according to the number of routes in current solution, being the worst case a solution with one route and quickly reducing computational complexity with more routes.

It is important to highlight that the concept of LNS relies on designing a neighborhood exploration using a group of LNS procedures, that might make use of random elements to diversify the search process, and effectively exploration of neighborhood is wider than well-known neighbourhood structures.

In order to understand the computational complexity of the proposed LNS tailoring and its benefits, a simplified algorithm for travel time minimisation is introduced where different neighborhood structures are used for local search, namely LNS procedures and 2-opt along with 2-opt* procedures. The pseudo code is presented as follows:

Algorithm 8: *Travel time minimisation procedure 2*

```
Start
  1. Incumbent solution ← Construction heuristic
  2. Current solution ← Incumbent solution
  3. Repeat
  4.    Current solution ← Local Search procedure (Current solution)
  5.    If objective (Current solution) < objective (Incumbent solution)
  6.        Incumbent solution ← Current solution
  7.    EndIf
  8.    Current solution ← Diversification procedure (Current solution)
  9. Until stop criteria met
End
```

The tested instances are R101 and R201 with speed case TD1a (Solomon (1987) instances, see Table 6 page 35). The termination criterion is allowed execution time and it was executed 50 times in a single thread for different execution times in order to illustrate the impact of parameter variation. Note that 2-opt* is restricted, the “naive exploration” only performs a fraction of iterations obtaining deteriorated results in solutions with few routes, such as R201. The behaviour of different local search procedures in *Travel time minimisation procedure 2* is shown in Figure 15. The numbers of routes as a result of Construction heuristic are respectively 21 in R101 and 5 in R201 (See Table 6 in page 35).

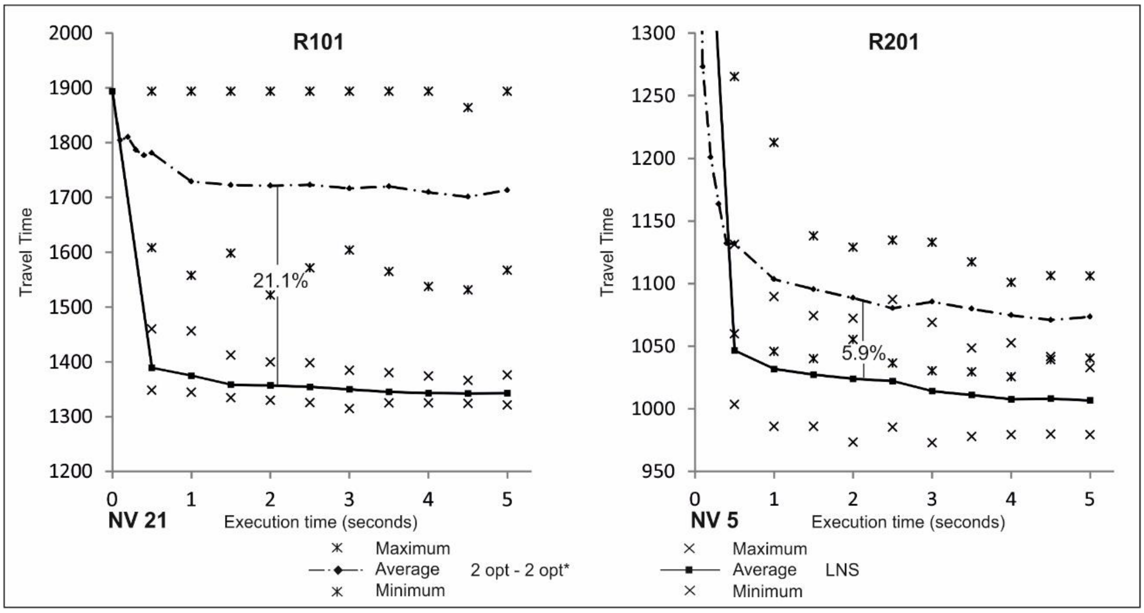


Figure 15. Behaviour of LNS movements vs. 2-opt and 2-opt* in the presence of time-dependent travel times. Solomon instances R101 and R102 (100 customers) – Figliozzi (2012) speed case TD1a.

Results in execution time of 0.5 seconds illustrate the computational complexity and the accuracy of the proposed LNS, see Table 23. 2-opt and 2-opt* were executed a few hundred times whereas LNS complete removals and insertions were executed on average 7,544 times in R101 and 4073 in R102. LNS in instance R101 obtained an average travel time reduction of 22.0% and minimum value reduction of 16.16% over 2-opt and 2opt* local search, in the case of R102 reductions respectively are 7.5% and 5.3%. LNS clearly provides a more accurate local search.

Table 23. Results of executing *travel time minimisation procedure* with different local search procedures at execution time 0.5 s.

		Local Search			
Instance		**2-opt & 2-opt***		**LNS**	**Δ**
R101	Best average travel time		1,608.3	1,348.4	16.2%
	Average travel time		1,781.0	1,389.0	22.0%
	Worst travel time		1,893.5	1,460.0	22.9%
	Average Iterations	2-opt	178.9	7,544.2	
		2-opt*	192.7		
R201	Best average travel time		1,059.9	1,003.5	5.3%
	Average travel time		1,132.0	1,046.5	7.5%
	Worst travel time		1,265.3	1,131.2	10.6%
	Average Iterations	2-opt	239.9	4,073.1	
		2-opt*	229.1		

Solomon instances (100 customers) – Figliozzi (2012) speed case TD1a.

Although Figliozzi (2012) implementation for the TDVRPTW was based on the 'ruin-and-recreate' concept, alternative destruction and recreation procedures were proposed rather than LNS procedures. The route improvement procedure consisted of iteratively removing all the customers in selected vehicles in order to rearrange them with a fast heuristic introduced by the author. The criteria to select the vehicles were: a) geographical proximity (distance between any two routes' centre of gravity), b) number of customers in vehicles.

Donati et al. (2008) made use of well-known neighbourhood operators and algorithm tailoring was based on restricting movements taking under consideration customer proximity and the introduction of a variable called “slack time” for each delivery in order to evaluate how long the delivery could be delayed so subsequent visits in the route will not violate time windows in the search process in the presence of time-dependent travel times.

This research consistently provides improved results for the TDVRPTW when compared with previous implementations. It is based on the capabilities of LNS movements to provide a fast and wide exploration of the search space that can quickly reach highly accurate results in the presence of time-dependent travel times and time windows. Furthermore, taking advantage of the capabilities of LNS, additionally tailoring of destruction and recreation procedures also achieved high accuracy in the minimisation of the required number of vehicles.

4.7. Discussion of the chapter

It is clear from the literature that time-dependent algorithms are necessary to substantially improve vehicle planning and scheduling in congested environments, with existing approaches that do not take congestion into consideration leading to extra time and missed deliveries. However, the added complexities of including time-dependent functions in models requires increased computational process capacity to provide as near optimal results as constant-speed models.

Tailoring algorithms to effectively and efficiently solve VRP variants is proven to be a challenging task. In this research, it is shown how two different strategies are used to solve different elements of the time-dependent Vehicle Routing Problem with hard time windows.

For the minimisation of vehicles it was necessary to have a very specific approach of minimisation of time window violations in order to focus the search in scheduling customers that are particularly difficult to accommodate. Large Neighbourhood Search procedures guided with Variable Neighbourhood Search achieved high accuracy with the proposed algorithm tailoring. It provided a reduction of 4.15% vehicles than previous implementations in the 672 test instances.

Travel time or travel distance minimisation strategy was based on the search of distant regions in order to obtain a robust exploration of the search space. When compared to previous implementations, the algorithm was capable to obtain reductions in some test problems up to 19.60% in travel time and distance with fewer vehicles. It consistently provided improved solutions in the 672 test instances.

Although the proposed algorithm makes use of random elements to escape from local optima and can therefore be run on a single processor core if required, parallel computing is also demonstrated here to take advantage of current processor architecture to execute multiple threads and explore different regions of the search space simultaneously without increasing the overall time of the search.

Large Neighborhood Search is a strategy that stands out in Vehicle Routing Problem solution algorithms due to its simplicity and wider applicability to solve different variants. The proposed approach shows its capacity to provide planners and drivers with accurate and reliable schedules when congestion is present using current computer architecture in a reasonable time with adequate algorithm tailoring.

To sum up

From the literature review in Operational Research techniques to solve VRP variants it is clear that metaheuristic algorithms do not guarantee optimality and it is necessary to test their accuracy when studying new variants. This chapter introduces an algorithm based on LNS movements for the time-dependent Vehicle Routing Problem with hard time windows that improves previous implementations, reduction of number of vehicles (4.5%), travel distance (10.8%) and travel time (12%).

In an industry with a low profit margin, these figures are quite relevant to accurately plan vehicles schedules that consider congestion, a required feature identified by companies, where scarce literature is found time-dependent variants. Therefore, in the next chapter the capability of the proposed algorithm will be studied to accommodate a richer VRP variant that considers Rules on Drivers’ hours in order to provide algorithms capable to mitigate the impact of congestion and regulation.

Chapter 5

A metaheuristic approach for the time-dependent Vehicle Routing Problem with Rules on Drivers' hours.

Planners have to consider different restrictions when producing vehicles schedules such as congestion and regulation. Congestion is unlikely to diminish in the near future and stiffer regulations designed to mitigate the negative externalities of freight transport are unavoidable. Among imposed regulation there are the rules on Drivers' hours, which are restrictions that limit driving time and working time according to the vehicle type (VOSA, 2011).

In the case of members of the European Union the regulation (EC) 561/2006 applies to vehicles over 3.5 tons (European Union, 2006) regarding rest periods and breaks for driving time, along with local regulations. In the case of the UK, The Road Transport (Working Time) Regulation 2005 imposes additional restrictions to drivers such as the introduction of mandatory breaks after certain working time (VOSA, 2011). Although regulation for vehicles under 3.5 tons also has been introduced in the UK, it is much less difficult to accommodate (see Table 3 in chapter 2 for the detailed set of restrictions according to vehicle type).

However, the set of regulations for vehicles over 3.5 tons that impose rest periods and maximum working time per week or fortnight can be easily accommodated in logistic operations dedicated to urban or regional distribution in everyday planning, as opposed to long haul operations that should consider resting places and resting times and consequently longer planning horizons. The benefits of solving a relaxed problem that do not consider all the set of restrictions but only a sub set when relaxed constraints are not active is that problem complexity is reduced, algorithm tailoring is less demanding, and highly accurate solutions in reasonable time are more likely to be obtained. In order to cope with time-dependent travel times and driving time regulation for multi-drop operations (schedules with up to 100 deliveries) with restrictions that only consider one planning day, Kok et al. (2010a) formally introduced a VRP variant, the time-dependent Vehicle Routing Problem with time windows and European regulation on driving and working hours (TDVRP-EC), along with benchmarking instances and reported results of a restricted dynamic programing algorithm.

In this chapter an algorithm for the TDVRP-EC is tailored based on the LNS algorithm introduced in chapter 4 and results are compared with the algorithm proposed by Kok et al. (2010a). Additionally, the algorithm is tailored to cope with The Road Transport (Working Time) Regulation 2005 required in the UK and results are reported. At the extent of the knowledge of the author this is the first research that studies the time-dependent Vehicle Routing Problem with time windows and European regulation on driving time and UK working hours (TDVRP-EC-UW) reported in the literature.

A desired attribute that is not considered in the traditional VRPTW is the construction of compact schedules that minimise the time that drivers expend on the street. In the VRPTW resulting routes might impose long waiting times to drivers because the secondary objective is minimising travel distance or travel time. Although waiting time in customer locations might be considered as break time, some companies pay for breaks and therefore it has an economic impact e.g. truck driver hiring costs (Kok et al., 2010a). In the case where companies have the policy of not paying breaks, one can infer that drivers would prefer compact routes where break times are only imposed to comply with regulation or because no other feasible sequence of visits is found with shorter waiting time. In order to produce compact routes it is necessary to specifically tailor the algorithm (Kok et al., 2010a). The TDVRP-EC proposed by Kok et al. (2010a) and the TDVRP-EC-UW consider travel distance or route duration as second objective.

Additionally, Kok et al. (2010a) highlighted the importance of considering congestion and consequently time-dependent travel times in vehicle planning in order to schedule breaks adequately and comply with the rules on Drivers' hours.

The cost structure of transportation depends on different elements such as fixed costs of vehicles, running costs associated to travel distance and duration of route and labour costs per hour (Dell'Amico et al., 2007). In this chapter an analysis of impact on transportation costs according to the accuracy of the algorithm is also introduced.

5.1. Previous work on Rules on Drivers' hours

Kok et al. (2010a) introduced a new VRP variant with time-dependent times, time windows, and a sub-set of rules for regulation (EC) 561/2006 (TDVRP-EC). The sub-set of rules apply for regional or urban environments when schedules only consider daily planning horizons, the decisions supported by the model are: i) assigning customers to vehicles, ii) sequencing customer visits for each vehicle, and iii) selecting departing times for each vehicle from the depot and also at each customer to account for the sub-set of Rules on Drivers' hours where breaks are considered to be taken only at customer locations. Additionally, instances are proposed based on Solomon (1987) and Figliozzi (2008). The algorithm is an extension of Kok et al. (2010c) for regulation (EC) 561/2006 that takes under consideration the insertion of breaks in a Dynamic Programming heuristic. A characteristic of the algorithm is that route duration minimisation as second objective leads to substantial reduction of route duration, but more vehicles and longer travel distance is required (Kok et al., 2010a). In the literature review no other work was found dealing with Rules on Drivers' hours and time-dependent travel times.

5.2. Problem definition

Both the TDVRP-EC and the TDVRP-EC-UW are extensions of the TDVRPTW, therefore the problem description presented in section 4.2. is still applicable for these variants, where the primary objective is minimisation of the number of vehicles but the second objective is either minimisation of travel distance or route duration. Rules on Drivers' hours applicable to vehicles over 3.5 ton in the UK are subject to regulation (EC) 561/2006 and The Road Transport (Working Time) Regulation 2005, therefore common definitions are required to introduce these constraints into the model, the following are proposed:

> Route Duration: Period of time between the vehicle leaves the depot before the first request and the vehicle returns to the depot after servicing the last request.
>
> Accumulated Working Time: Accumulated time during which the driver cannot dispose freely of his free time (driving, loading or unloading, other work). It includes awaiting to service a customer where their foreseeable duration is not known.
>
> Accumulated Driving Time: Accumulated time during which the driver has been driving between a valid break of 45 min, see RD1.
>
> Total Accumulated Driving Time: Accumulated time during which the driver has been driving in the working day.
>
> Accumulated Break EC: Accumulated break that accounts for (EC) 561/2006 following restriction RD1.

Accumulated break UW: Accumulated break that accounts for The Road Transport (Working Time) Regulation 2005.

The additional sets of constraints applicable for planning horizons of one day to account for the Rules on Drivers' hours are as follows:

Relaxed driving time constraints following regulation (EC) 561/2006 as proposed by Kok et al. (2010a)

RD1. A period between two breaks of at least 45 min is called a driving period. The accumulated driving time in a driving period may not exceed 4.5 h. The break that ends a driving period may be reduced to 30 min if an additional break of at least 15 min is taken anywhere during that driving period. The driving hours regulations do not allow service times at customers to be considered as break time.

RD2. The total accumulated driving time may not exceed 9 h for any individual driver.

RD3. The route duration may not exceed 13 h for any individual driver.

The Road Transport (Working Time) Regulation 2005 (VOSA, 2011)

RD4. Mobile workers must not work more than 6 consecutive hours without taking a break.

RD5. If the Accumulated Working Time total between 6 and 9 hours, working time should be interrupted by a break or breaks totalling at least 30 minutes.

RD6. If the Accumulated Working Time total more than 9 hours, working time should be interrupted by a break or breaks totalling at least 45 minutes.

RD7. Breaks should be of at least 15 minutes' duration.

Constraint RD3 is proposed by Kok et al. (2010a) in order to comply with the part of regulation EC (561/2006) that dictates that daily rest period shall be at least 11 hours. Although the original restriction in regulation EC (561/2006) could be handled in different ways, it is considered in this research as proposed by Kok et al. (2010a) in order to be able to compare results of the proposed algorithm.

An example of a valid schedule for regulation (EC) 561/2006 in a single work day for one vehicle (driver) is shown in Figure 16. RD1 is satisfied by taking 2 breaks of total duration of 45 min after an Accumulated Driving Time of 4.5 h, the first break of 15 min and the second one of 30 min.

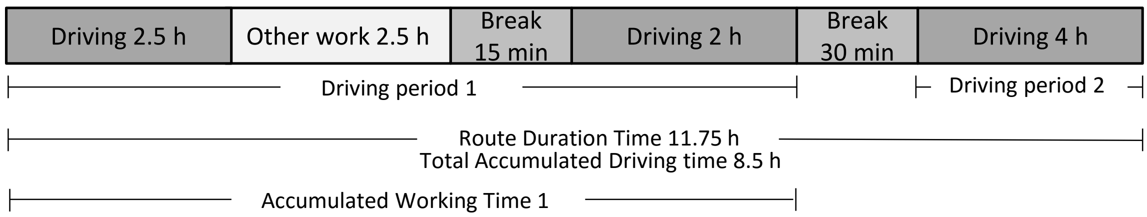


Figure 16. Valid schedule for deliveries with regulation (EC) 561/2006.

However, the schedule presented in Figure 16. is invalid when applying The Road Transport (Working Time) Regulation 2005 because there is only a 15 min break in Accumulated Working Time 1 (7 hours), it should be an Accumulated Break UW of 30 min in an Accumulated Working Time with a duration between 6 and 9 hours, as shown in Figure 17.

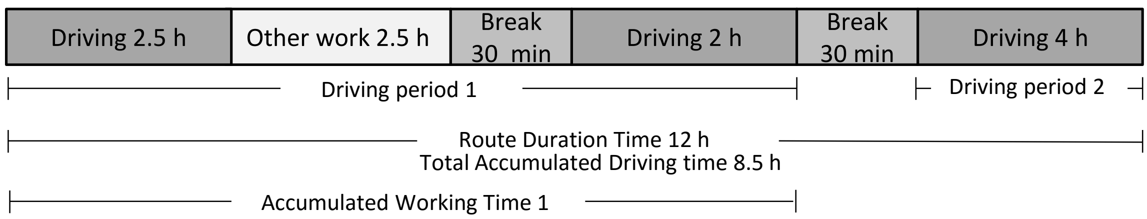


Figure 17. Valid schedule for deliveries with regulation (EC) 561/2006 and The Road Transport (Working Time) Regulation 2005.

5.3. Algorithm description

Inclusion of Rules on Drivers' hours requires a more complicated model that the TDVRPTW, it is necessary to account for accumulated driving time, accumulated working time and designing model constraints that assure the insertion of breaks that satisfy regulation. Due to the fact that LNS movements quickly reached highly accurate solutions in the TDVRPTW, the algorithm is based on the LNS tailoring introduced in chapter 4, initial testing with other Operational Research techniques required long execution time to reach high accuracy (i.e. genetic algorithms and ejection chains). However, the proposed tailoring makes use of fewer elements due to the complexity of accommodating Rules on Drivers' hours in implementation, e.g., a much simpler construction algorithm is introduced based on *Basic-greedy heuristic* instead of *IRCI;* removing the use of well-known neighbourhood structures (which might require longer computational time than LNS movements); and using a much simpler diversification strategy based on Tabu search instead of Variable Neighbourhood Search.

The aim with this algorithm tailoring is to produce a solution with the characteristics proposed by Cordeau et al. (2002) for implementations that can be used in the industry (i.e. accurate, fast, simple and flexible). The proposed algorithm firstly constructs a feasible route, then minimises the number of vehicles in a search space that allows violations of time windows and finally minimises the second objective (distance or route duration).

The centre of the tailoring is the design of an algorithm called "*Scheduler",* that accounts for Rules on Drivers' hours based on object programming in its implementation*. Scheduler* object is called across the algorithms that create LNS movements. As proposed by Kok et al. (2010a) breaks are only taken at customer locations.

***Scheduler* for Drivers' hours Rules**

The purpose of *Scheduler* is to determine where to insert breaks in the current LNS movement (removing or inserting customers in a solution) by calculating the driving time required by the movement and subsequently calculating the Accumulated Driving Time and Accumulated Working Time and establishing if a break is required. In the case of an insertion, it starts in the customer prior to the position of the insertion and determines if in order to make possible the insertion, the insertion of a break is required. It later calculates break requirements in the following customers that are in the route, see Figure 18.

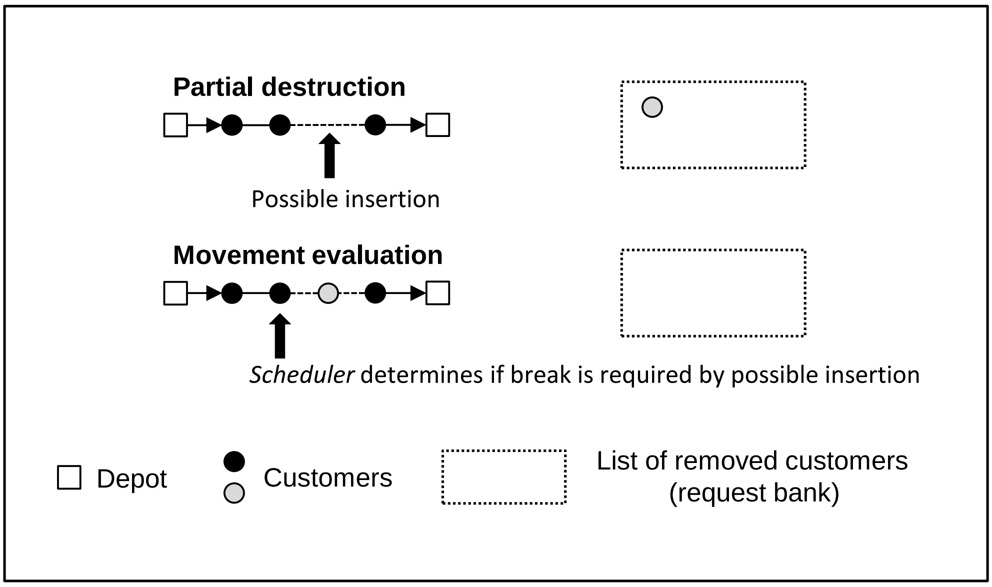


Figure 18. Description of the evaluation performed by *Scheduler* to establish if insertion or break are required.

The time windows in the model might impose drivers to wait at a customer location when the arrival time at a customer is earlier than the lower time of the time window. Waiting time at a customer might be valid as a break or part of a break, the conditions that trigger the scheduling of a break and possibly requiring more time at a customer location are the following:

- By visiting the next customer accumulated driving time is over 4.5 h without a 45 min valid Accumulated Brake EC (Constraint R1).
- By visiting and conducting the service at the next customer accumulated working time is over 6 h and under 9 h and accumulated break UW is under 30 min.
- By visiting and conducting the service at the next customer Accumulated Working Time is over 9 h and Accumulated Break UW is under 45 min.

Additionally, when customer time windows impose waiting time due to early arrival, breaks that count for Rules on Drivers' hours could be taken even if no trigger from Rules on Drivers' hours is activated (not requiring additional time at customer location), therefore taking advantage of waiting times, a model characteristic not implemented by Kok et al. (2010a).

(The conditions implemented in *Scheduler* to comply with the Drivers' hours rules are presented in a textual description in order to make easier the comparison with the problem definition)

- If waiting time is equal or longer than 15 min and shorter than 30 min, a break of 15 min is inserted that accounts for Accumulated Break UW. It might account for Accumulated Brake EC if Accumulated Break EC is equal to 0 min.

- If waiting time is equal or longer than 30 min and shorter than 45 min, a break of 30 min is inserted that accounts for Accumulated Break UW. It might account for Accumulated Break EC in the case that the previous value of Accumulated Break EC is equal to 15 min (insertion of a 30 min break) or in the case that the previous value of Accumulated Break EC is equal to 0 min (insertion of a 15 min break).

- If waiting time is equal or larger than 45 min, a break of 45 min is inserted that accounts for Accumulated Break UW and Accumulated Break EC.

Note that each time that Accumulated Break EC reaches 45 min a new driving period is inserted (Accumulated Break EC takes the value of 0 min).

Note that breaks required by regulation (EC) 561/2006 also count for The Road Transport (Working Time) Regulation 2005.

The conditions to establish if additional time is required at a customer location to satisfy breaks for Rules on Drivers' hours are the following:

- If waiting time is longer than the required break, no extra time at customer location is inserted.

- If waiting time plus the length of the time window is equal or longer than the required break, an additional time at customer location is inserted of duration of the required break minus the waiting time (break start as soon as the vehicle arrives at the customer and service does not start until the break is finished).

- If waiting time plus the length of the time window is shorter than the required break, service starts at the first feasible time and time at customer location is inserted of duration of the required break (break starts after the service).

In order to determine break insertions and additional time at customer locations it is required to calculate different characteristics of the route. Therefore, additional return values of *scheduler* that do not impose extra computational burden are also calculated, returns values of *scheduler* are the following:

- Customer where breaks are scheduled
- Duration of breaks
- Duration of insertion of time at customer
- Sum of time window violations
- Total distance
- Total travel time (driving time)
- Total waiting time
- Route duration
- Feasibility of route or penalty (violation of time windows when service start after the upper time of the time window)
- A random value if insertion is feasible

Different return values of *scheduler* are used according to the objective value in the optimisation stage.

The last item is used to diversify the search process of LNS and avoid stagnation in recreation procedures by using a random order to reinsert customers; this is a new characteristic from the algorithm presented in chapter 4.

Construction procedure

The proposed construction procedure is rather simple and makes use of random elements to generate different solutions that have the characteristic of being feasible, it is presented as follows.

Algorithm 9: Construction procedure

Start
1. Creation-of-route ← true
2. Inserted-Customers ← 0
3. k ← 0
4. **Repeat**
5. **If (**Creation-of-route = true**) then**
6. Randomly select customer v_i'
7. Create route $\{v_0 - v_i' - v_0\}$
8. Creation-of-route ← false
9. Inserted-Customers ← Inserted-Customers + 1
10. **End If**
11. **If (**Creation-of-route = false**) then**
12. **Repeat**
13. For each unrouted customer calculate *insertion-cost*^{cp} (v_i, k, p)
14. Select customer with lowest *insertion-cost*^{cp}
15. Insert customer in route k position p
16. Inserted-Customers ← Inserted-Customers + 1
17. **Until** no feasible insertion in route k
18. **End if**
19. $k \leftarrow k + 1$
20. **Until** Inserted-Customers = Number of customers to schedule

End

The *insertion-cost*^{cp} (line 14) is the following function:

$$\textit{insertion-cost}^{cp}(v_i, k, p) = \delta_1^{cp}\ \Delta\, Total\ Travel\ Time + \delta_2^{cp}\ \Delta\, Total\ Waiting\ Time$$

where $\Delta\, Total\ Travel\ Time$ is the variation in total travel time by inserting customer v_i in route k in position p, $\Delta\, Total\ Waiting\ Time$ is the variation in total waiting time by inserting customer v_i in route k in position p, δ_1 and δ_2 are parameters to weight the impact of travel time and waiting time, $\delta_1^{cp} + \delta_2^{cp} = 1$; δ_1^{cp} and δ_2^{cp} might vary randomly.

This procedure can be repeated a number of times where the solution with minimum number of vehicles is chosen as the initial solution for minimising the number of vehicles.

Minimisation of the number of vehicles procedure

This procedure is very similar to the LNS algorithm for the TDVRPTW presented in chapter 4 for minimisation of number of vehicles, the route (vehicle) with minimum number of customers is removed and customers are reinserted in the solution creating violations of the upper limit of the time windows. The procedure reduces the penalties by using LNS movements, it is presented as follows:

Algorithm 10: *Minimisation of number of vehicles procedure*

```
Start
 1.  Incumbent solution ← Construction of Initial Solution
 2.  Current solution ← Remove one route (Incumbent solution)
 3.  Repeat
 4.       Current solution ← Diversification Penalty Procedure (Current solution)
 5.       Current solution ← LNS Penalty Reduction Procedure (Current solution)
 6.       If penalty(Current solution) = 0
 7.           Incumbent solution ← Current solution
 8.           Current solution ← Remove one route (Incumbent solution)
 9.       End if
 10. Until stop criteria met
Return Incumbent solution
End
```

The main steps of *Minimisation of number of vehicles procedure* are the following:

i) The *LNS Penalty Reduction Procedure* (line 5) makes use of ruin procedures (*Random-Ruin*, *Radial-Ruin*, *Worst-removal*) and *Basic-greedy heuristic* with the following *insertion-cost*^{cp}:

$$\textit{insertion-cost}^{cp}(v_i, k, p) = \Delta\, Penalty$$

or in case there is no penalty in the insertion (in order to avoid stagnation) two *insertion-cost*^{cp} might be used.

$$\textit{insertion-cost}^{cp}(v_i, k, p) = \Delta\, travel\ time + \Delta\, waiting\ time$$

or

$$\textit{insertion-cost}^{cp}(v_i, k, p) = \text{Random value}$$

where customers that generate penalty are firstly inserted and secondly customers that do not generate penalty are inserted.

ii) The *Diversification Penalty Procedure* (line 4) is based on selecting a random number of customers that generate penalty (*Worst-removal*) along with *Random-Ruin* and inserting them in a different route (vehicle) in the solution with *Basic-greedy heuristic* with the previously mentioned *insertion-cost*^{cp}.

Minimising second objective

This procedure can minimise travel distance or route duration by using LNS movements. The search strategy at master level is a simple tabu search that prevents the search to explore previously visited regions instead of the Variable Neighbourhood Search implemented for the TDVRPTW.

Algorithm 11: *Minimisation of travel distance/route duration procedure*

Start
1. Incumbent solution ← Construction of Initial Solution
2. Current solution ← Minimisation of number of vehicles procedure (Incumbent solution)
3. **Repeat**
4. Current solution ← *Diversification Second Objective* (Current solution)
5. Current solution ← *LNS Multi-objective* (Current solution)
6. **If** *Objective*(Current solution) < *Objective*(Incumbent solution)
7. Incumbent solution ← Current solution
8. **End if**
9. **Until** stop criteria met
10. Current solution ← *Optimisation Departure Time procedure* (Current solution)

Return Incumbent solution
End

The main steps of *Minimisation of travel distance/route duration procedure* are the following:

i) *LNS Multi-objective* (line 5): It makes use of ruin procedures (*Random-Ruin, Radial-Ruin and Sequential-Ruin*) and *Basic-greedy heuristic* for recreation, where *insertion-cost*^{trp} makes use of different returns values of *scheduler* to avoid stagnation.

$$insertion\text{-}cost^{trp} = \delta_1^{trp}\ \Delta\, Total\ Travel\ Time + \delta_2^{trp}\ \Delta\, Total\ Waiting\ Time + \delta_3^{trp}\ \Delta\, Total\ \ Distance$$

where

$$\delta_1^{trp} + \delta_2^{trp} + \delta_3^{trp} = 1;\ \delta_1^{trp}\ ,\delta_2^{trp} \text{ and } \delta_3^{trp} \text{ might vary randomly}$$

or

$$insertion\text{-}cost^{trp} = \ \Delta\, Route\ duration$$

or

$$insertion\text{-}cost^{trp} = \ \text{Random value}$$

ii) *Diversification Second Objective* procedure (line 4): It is based on removing two sequences of customers of random length calling *Sequential-Ruin* and inserting them in the solution with *Basic-greedy heuristic* with *insertion-cost*^{trp} set as a random number when insertion is feasible. A Tabu search maintains records of explored solutions to force the search to new regions, the recorded tabu solution characteristic is the value of the objective function.

In the case of route minimisation as second objective, evaluation to store an improved solution (line 6) makes use of *Optimisation Departure Time procedure* to obtain the minimum possible route duration of the current solution.

Optimisation Departure Time procedure is an algorithm that moves forward the departure time from the depot in an iterative way until the route becomes infeasible and modifies the route if it finds a departure time that reduces the route duration.

Although the proposed tailoring can minimise travel distance or route duration, an optimisation of departure times is always executed in order to minimise route duration when the search is terminated (line 10). In the case of minimisation of travel distance, it doesn't affect the obtained distance and provides solutions with compact routing times.

5.4. Test instances

The well-known test instances for the VRPTW proposed by Solomon (1987) consist of 56 problems of 100 customers. Figliozzi (2008) modified them by adding speed profiles in order to account for congestion. The depot opening time $[e_o, l_o]$ is divided into 5 periods of equal duration, with 3 speed profiles (TD1-TD3). An additional profile (TD0) with constant speed of 1 is also considered in order to offer result comparison for best-known values with constant speed models, the speed profiles are as follows:

TD0 = [1.00, 1.00, 1.00, 1.00, 1.00]
TD1 = [1.00, 1.60, 1.05, 1.60, 1.00]
TD2 = [1.00, 2.00, 1.50, 2.00, 1.00]
TD3 = [1.00, 2.50, 1.75, 2.50, 1.00]

Solomon instances present different depot opening times where units of distance and time are equal. For ease of comparison therefore Kok *et al.* (2010) introduced an additional modification, where required breaks of regulation (EC) 561/2006 are scaled to a working day of 12 hours (from 7 AM until 7 PM) based on the different opening times of the depot in Solomon instances (the length of the break and the maximum time of Accumulated Driving Time without break are scaled). These scaled instances with the Figliozzi (2008) speed profiles collectively provide (56x4=) 224 test instances that are used as the basis of the results in this chapter.

5.5. Experimental results

Rules on Drivers' hours

Analysis of additional logistic resources required to accommodate the Rules on Drivers' hours along with algorithm accuracy is possible by comparing the results of different algorithms when tested with similar VRP variants, namely the VRPTW (no regulation or congestion are considered), EC (European regulation on driving and working hours) and EC-UW (European regulation on driving and working hours and The Road Transport (Working Time) Regulation 2005 required in the UK). The VRPTW has been largely studied and highly accurate result values are available with primary objective minimisation of vehicles and secondary objective minimisation of travel distance (Toth and Vigo, 2001). Table 24 shows the minimum number of required vehicles and travel distance when algorithms are set to minimise travel distance as secondary objective and no congestion is considered for the mentioned variants. While the DP algorithm of Kok et al. (2010a) requires 26.9% more vehicles and 26.7% more travel distance to accommodate regulation (EC) 561/2006 when compared to best-known values for the VRPTW, the algorithm proposed in this research requires only 6.9% more vehicles and 4.7% travel distance. Results also show that in order to accommodate regulation EC-UW it is required 11.6% more vehicles and 6.6% travel distance when compared to the VRPTW.

Table 24. Impact of Rules on Drivers' hours with no congestion (TD0), minimising travel distance as secondary objective, Solomon instances (100 customers).

Variant and algorithm			NV	Δ	Distance	Δ
VRPTW		(1)	405		57187	
EC	DP	(2)	514	26.9%	72464	26.7%
EC	LNS	(3)	433	6.9%	59862	4.7%
EC-UW	LNS	(4)	452	11.6%	60995	6.7%

(1) Best-known values, see Vidal et al. (2013) **(2)** Kok et al. (2010a) Running time 138 min (Core 2 Quad 2.88 GHz, 4 GB Ram) **(3-4)** Running Time 112 min (Core i7 3.4 GHz, 16 Ram)

European regulation on driving and working hours and time-dependent travel times.

The DP algorithm (Kok et al., 2010a) and the proposed LNS can schedule vehicles with time-dependent travel times, regulation (EC) 561/2006 and minimisation of route duration as secondary objective. LNS provides improved solutions with 19.0% less vehicles, reduction of 4.4% in route duration along with routes with 17.7% travel distance, results are shown in Table 25. A characteristic of the DP algorithm is that in order to deal with time-dependent travel times it requires additional execution time Kok et al. (2010a), whereas the proposed LNS was set to maintain the same execution time as that in the constant speed case. Although speed comparison of algorithms is a complex activity due to difference in CPU capacity and language compiler, it is important to highlight that the proposed LNS obtained a large reduction in number of vehicles and travel distance in a fraction of the execution time.

Table 25. Results for regulation (EC) 561/2006 on driving hours in urban or regional environments and different levels of congestion, minimising route duration as second objective, instances based on Solomon (100 customers).

	DP (1)			LNS (2)		
Speed profile	NV	Distance	Route Duration	NV	Distance	Route Duration
TD0	523	73584	272160	433	60183	259603
TD1	494	73808	254240	401	60461	236927
TD2	458	74256	243712	374	61200	235946
TD3	458	74480	236768	358	61826	230304
Total	1933	296128	1006880	1566	243671	962780
Δ				19.0%	17.7%	4.4%

(1) Kok et al. (2010a) Running time 1138 min (Core 2 Quad 2.88 GHz, 4 GB Ram)
(2) Running time 448 min (Core i7 3.4 GHz, 16 Ram)

European regulation on driving and working hours, The Road Transport (Working Time) Regulation 2005 and time-dependent travel times.

In this research results for the VRP variant with time windows, Regulation (EC) 561/2006 on driving and working hours and The Road Transport (Working Time) Regulation 2005 in the UK with time-dependent travel times are introduced, see Table 26.

Table 26. Results for regulation (EC) 561/2006 on driving hours and The Road Transport (Working Time) Regulation 2005 in urban or regional environments and different levels of congestion, minimising route duration as second objective, instances based on Solomon (100 customers).

Speed profile	NV	Distance	Route Duration
TD0	452	62137	275348
TD1	422	62816	262902
TD2	398	63147	252541
TD3	383	63203	246971
Total	1655	251302	1037762

Running time 448 min (Core i7 3.4 GHz, 16 Ram)

Cost Implications in vehicle scheduling of Drivers' hours Rules

Minimising total cost rather than travel distance is actually the core objective of logistics scheduling in reality (Dullaert et al., 2002). It is therefore important to analyse results in relation to overall cost implications rather than mere theoretical objective values. A variation of the instances proposed by Kok et al. (2010a) is introduced to account for logistic costs when the different set of rules of Drivers' hours are introduced in a scenario that does not consider congestion, namely: i) consideration of the industry logistic costs, ii) escalation of distances and break times to represent deliveries in a working day in an urban environment and iii) the use of a speed that represents the conditions of urban roads.

Based on a survey of UK logistics operators conducted by FTA (2014) fixed costs (including vehicle excise duty (VED), insurance and depreciation of vehicle value), variable costs (including fuel consumption, tyre wear and maintenance) and time related costs (including driver wages and National Insurance contributions) can be estimated (a Lorry of 7.5 ton is used as the example here). The following cost coefficients are proposed: Fixed cost per vehicle per day £17.8, coefficient per km £ 0.25 and coefficient per hour £ 9.91.

In instances proposed by Kok et al. (2010a) the parameters to establish breaks (maximum driving time of 4.5 hours, required break 45 min, etc.) are scaled accordingly to the opening time of the depot in Solomon instances, which vary to represent different time windows characteristics, see Table 6 page 35. In the instance variation proposed in this research, distances, time windows and depot opening times are scaled to a working day of 12 hours (7:00 AM – 7:00 PM), while maintaining a maximum driving time without break of 4.5 hours and required break of 45 min.

Additionally, it is necessary to further scale the travel distances in the Solomon instances to be realistic based on a feasible speed (in the original Solomon instances the units of distance and travel time are equal). Therefore travel distance is calculated by multiplying the travel time (which is the same travel distance in the theoretical instances of Solomon) by the average speed in free flow condition in urban areas of 48 km/h.

The economic impact of considering Rules on Drivers' hours in urban conditions is shown in Table 27. With the proposed algorithm in this research, in the theoretical instances, the cost of regulation (EC) 561/2006 is 3.0% and the cost of the full set of rules is 6.9%. An estimation of the cost of regulation (EC) 561/2006 using the DP algorithm is feasible by extrapolating the additional number of vehicles, route duration and travel distance provided by the algorithm when compared to the results of LNS (19.0%, 4.4%, 17.7% respectively). The estimated solution provided by the DP algorithm is £ 94,535, 8.9% more expensive than the results obtained by the proposed LNS.

Table 27. Cost implications of Rules on Drivers' hours.

VRP Variant	NV	Route Duration (Hours)	Distance (Km)	Cost (£)	Δ
VRPTW	416	4053	81261	83994	
EC	433	4226	81882	86862	3.0%
EC-UW	452	4399	82795	89818	6.9%

5.6. Discussion of the chapter

The industry requires models and algorithms capable to cope with a range of restraints found in real life operations that impose extra costs and affect operation, such as Rules on Drivers' hours and time-dependent travel times. Although rich VRP variants are a challenge to researchers and software developers, state-of-the-art search strategies can produce highly accurate solutions that ameliorate the logistic resources required to accommodate new conditions. A characteristic of a previously reported algorithm, which accounted for regulation (EC) 561/2006, was that compact routes were obtained at the expense of providing schedules with higher number of vehicles and longer travel distance. The LNS tailoring presented in this research obtained solutions with shorter route duration (4%), with fewer required vehicles (19%), and less travel distance (17%) in reasonable time when tested with previous implementations reported in the literature when time-dependent travel times are considered.

Although the proposed LNS algorithm makes use of fewer elements than the LNS proposed in chapter 4, analysis of results when comparing best-known results for the VRPTW in terms of number of vehicles and travel distance, shows that the LNS for regulation (EC) 561/2006 presented in this chapter provides schedules with only 6.9% more vehicles and 4.7% longer travel distance than best-known values for the largely studied variant, note that LNS accommodate regulation (EC) 561/2006.

Furthermore, an economic analysis of the impact of the regulation and algorithm accuracy is also introduced. According to the analysis of theoretical instances, in the case of only considering regulation (EC) 561/2006, by using a previously reported algorithm, the estimated extra cost for providing solutions that comply with regulation is 12.45% whereas the LNS algorithm provides solutions with a mere 3.0% of extra cost with an execution time of 2 minutes per instance (100 customers). Accommodating Regulation (EC) 561/2006 and the Road Transport (Working Time) Regulation 2005 required in the UK have a cost of 6.9%

Regarding algorithm tailoring, LNS is considered a simple search strategy capable to provide highly accurate solutions for rich problems, this research is an example of it. As reported in chapter 4, LNS offers a quick and thorough search for the time-dependent VRP with time windows, and it can be tailored to accommodate complex restraints and still offer highly accurate solutions for richer time-dependent VRP variants.

Nevertheless, the tested instances are theoretical and analysis of results has to be taken carefully. There is a range of logistic configurations with different complexities, e.g. length of journey, time window service promise, economies of scale, level of congestion, *etc*. Analysis of the outcome of the proposed algorithm should consider the complexities involved in the studied logistic operation.

To sum up

This chapter introduces an implementation of LNS capable to deal with a rich VRP variant that considers time-dependent travel times and Rules on Drivers' Hours. A characteristic of the proposed algorithm is that it introduces a modification to LNS movements to quickly reduce the number of vehicles, achieving solutions with 19% less vehicles when accounting for Regulation (EC) 561/2006 than previous implementations.

Furthermore, a cost analysis is introduced based on the current structure of the freight industry. Results show the importance of adequate algorithm design and evaluation to mitigate the impact of the challenges that the industry is facing, the proposed algorithm provides routes that accounts for regulation (EC) 561/2006 with a reduced cost (8.9%) when compared to previous algorithms reported in the literature. Additionally, benchmark values are introduced for a VRP variant that considers regulation (EC) 561/2006 and the Road Transport (Working Time) Regulation 2005 required in the UK.

Chapter 6

Application of a rich time-dependent VRP variant in home delivery and the last-mile problem

New challenges have arisen in the transport industry, such as road congestion and regulation imposed by authorities to tackle the negative impacts of transport. This coupled to the ever demanding customer and the move to same-day delivery has meant that logistics providers have had to continually improve their level of service (Ehmke et al., 2012). The continuous growth of e-commerce in the last 16 years and home delivery imposes new conditions on the industry (Visser et al., 2014). In the case of required customer presence or signature, more accurate schedules are needed, and dispatchers and drivers often complain about their inaccuracy due to underestimation of travel times (Eglese et al., 2006, Ehmke et al., 2012). Current retail trends show that online sales represent 14% of all UK brick-and-mortar stores and e-commerce and this is expected to rise up to 35% by 2020 (Javelin-Group, 2011; Visser et al., 2014), where it is estimated that 12% of first deliveries fail (Visser et al., 2014). This situation has drawn attention to certain issues in the final part of the supply chain when the product is delivered to the customer, which is referred to in the literature as the 'last-mile problem' (Gevaers et al., 2011),

The last mile is considered as one of the more expensive, less efficient and polluting sections of the entire logistic chain (Gevaers et al., 2011). Some of the issues involved are the security aspects regarding a safe place to leave the packages, the not-at-home problem when the customer may have to sign, and a lack of critical mass to achieve economies of scale that make the operation profitable (Boyer et al., 2009, Gevaers et al., 2011). Although some successful business examples with delivery to customers are Ocado (groceries delivery), Office Depot (office supply) and package logistic providers such as UPS, there are catastrophic examples, such as Webvan, the online grocery business that was initially valued at over US$ 5 billion and eventually made losses of hundreds of millions until it went bankrupt (Boyer et al., 2009, Ring and Tigert, 2001). Webvan service's promise of time windows of 30 minutes proved to be a huge logistical challenge (Boyer et al., 2009), where some of the biggest mistakes were to not understand customers' expectations, poor marketing, and aiming at a large geographic area, which proved to be too costly (Lunce et al., 2006). Companies need to face the trade-off between satisfying customer expectations to improve sales and the related logistic costs (Yang et al, 2014).

Last-mile costs may account for 13% to 75% of logistic costs (Gevaers et al., 2011; Onghena, 2008), with one of the most substantial issues occurring when delivery requires the presence of the customer. If no specific window of delivery is arranged, the failure rate will be inevitably high and consequently additional visits will be necessary. Failed delivery rates may be reduced by allowing customers to choose the delivery time, but at the expense of increasing logistics costs. Tight time windows require more mileage for the same number of deliveries, a phenomenon referred to as the 'ping-pong effect' due to the graphic visualization of the schedule where vehicles have to revisit geographically close locations at different times to accommodate time windows (Gevaers et al., 2011).

Although in some business models time windows are allowed in the service e.g. online groceries such as Ocado (1-hour time window) and Tesco (2-hours time window[2]) (Boyer et al., 2009), currently most home delivery services do not provide a time window for the delivery (Visser et al., 2014). The identified issues from the customer perspective in home delivery are: i) not on time, not at home, not delivered; ii) delivery charges are too high, delivery time too long; and iii) forced to stay at home (about 50% stay at home (Visser et al., 2014)).

A number of technologies and initiatives are available to support planners in order to satisfy customers' expectations. Such has been the scientific interest in improving logistics operations in cities, the concept of city logistics is defined as 'the process for totally optimising the logistics and transport activities by private companies in urban areas while considering the traffic environment, the traffic congestion and energy consumption within the framework of a market economy' (Taniguchi et al., 2001), where ITS and models are crucial in the optimisation of urban freight systems (Taniguchi & Thompson, 2002).

The importance of improving freight transport in cities relies on the fact that 85% of the EU's GDP is generated in urban areas where 72% of the European population lives (Cattaruzza et al., 2015; European-Commission, 2009). Some of the special characteristics of route planning in urban areas are: congestion and reliability of schedules, high density, accidents, regulation and access restriction (especially in old European cities where streets are narrow, with restricted parking) (Cattaruzza et al., 2015).

[2] http://www.tesco.com/groceries/help/default.aspx?rel=help#my_delivery. Accessed on 04-09-2015.

Boyer et al. (2009) studied the impact of customer density and length of the promise of time windows, taking into consideration logistic conditions in the US for grocery delivery, but without accounting for congestion, finding that costs increased in low-density areas and tight time windows, e.g. by comparing a delivery with no time windows with a service promise of a 3-hour time window, delivery costs increased by 45%. Boyer et al.'s (2009) methodology was based on using commercial software to provide results, with no discussion regarding the accuracy of the algorithm.

The impact of urban congestion has increased over the last 30 years, with the 101 largest US cities reporting that travel delay had increased from 1.1 billion hours in 1982 to 4.8 billion hours in 2011 (Chang et al., 2015). Rising levels of traffic congestion mean that logistics providers face the challenge of maintaining time-critical service levels whilst at the same time minimising the extra costs that congestion and delays impose. However, the research by Boyer et al. (2009) does not consider the impact of congestion.

The algorithm proposed in chapter 5 is capable of coping with time-dependent travel times and Rules on Drivers' hours with high accuracy. Therefore, in this chapter the algorithm is used in instances that account for urban conditions in order to provide knowledge to researchers and the industry regarding the last-mile challenge and to show the implications of using the proposed algorithm in the analysis of the supply chain.

6.1. Previous work

The research presented by Boyer et al. (2009) was based on randomly generating a set of instances in an unmentioned metropolitan area of 5,120 km^2, where the impact of the length of time window and density of customers in vehicle schedules were studied. Addresses of students were used as customer locations and service time was established as 10 min. Each experiment was replicated between 5 and 10 times and solved in a server with the routing software Descartes; small instances (500 customers) required from 1 to 2 hours whereas large instances (4000 customers) required over 24 hours.

One of the main contributions of the paper is proposing a methodology to estimate delivery costs for multi-drop operations, where the independent variables are length of the time window and density of customers, see Table 28. Giving a transport cost structure with vehicle depreciation per year of US$ 8,000, running costs of US$ 0.375 per kilometre, labour costs of US$ 20 per hour and assuming average route duration of 8 hours and that vehicles work 250 days per year, the cost per delivery in US$ is estimated as follows:

$$Cost\ per\ delivery = \ Fixed\ cost + Variable\ cost + Time\ related\ cost\ ; \ \ where$$

$$Fixed\ cost = 8000 * \frac{1}{250 * Stops\ per\ route}$$

$$Variable\ cost = 0.375 * \frac{Kilometres\ per\ route}{Stops\ per\ route}$$

$$Time\ related\ cost = 20 * \frac{8}{Stops\ per\ route}$$

Table 28. Cost per delivery according to customer density and length of time window.

Customer Density	0.097 (500 customers)				0.39 (2000 customers)				0.78 (4000 customers)			
Area 5120 Km2	Stops per route	Kilometres per delivery	Cost per delivery	Δ	Stops per route	Kilometres per delivery	Cost per delivery	Δ	Stops per route	Kilometres per delivery	Cost per delivery	Δ
Time Windows												
No TW	22.3	49.5	9.1		30.9	44.3	7.6		32.8	39.7	7.0	
2 hr	15.0	56.2	13.7	50%	22.1	58.5	11.3	48%	24.0	57.1	10.3	47%
1 hr	13.4	54.8	15.3	67%	18.9	60.5	13.3	75%	21.1	59.4	11.8	69%

Source: Boyer et al. (2009)

Results obtained by Boyer et al. (2009) show the impact of tight time windows: providing a 2-hour time window presents an average transport cost increment of 48%, and a 1-hour time window an increment of 70%. However, transportation costs per delivery decrease in the presence of high customer density. The costliest scenario is low customer density (500 customers) with a time window of 1 hour (US$ 15.3 per delivery), whereas the least expensive scenario is in conditions with high customer density (4000 customers) with no time window (US$ 15.3 per delivery). This shows the impact of market penetration and service promise – in the studied scenarios it may mean a cost overrun of up to 118%.

Low customer density might be the result of low market penetration or actually few people living in the area. However, it is important to consider the density of deliveries in a territory (Boyer et al., 2009). An example is presented by a UPS representative statement: 'It's an important determination because it costs a little less to ship to a commercial address. That's because it's less expensive to deliver to densely clustered commercial addresses than to residences often scattered throughout sprawling suburban neighbourhoods."'[3]

Economies of scale are vital to obtain low logistics costs (Chopra & Meindl, 2007). In the research by Boyer et al. (2009), customers' locations are randomly chosen from a list of students. However, the density pattern that might be found in an actual grocery delivery operation is not addressed nor the consequent road speeds or congestion present in the city or suburban areas. A metropolitan area consists of a densely populated urban area (city) and its less-populated surrounding territories. Take for example New York and its metro area: the

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[3] UPS http://compass.ups.com/article.aspx?id=2147483832 Accessed 05-09-2015.

population of the city is over 8 million people in a land area of 784.76 km^2, the population of the total metropolitan area is over 18 million in a land area of 17,319 km^2.[4] A higher density of customers may be expected in the city than in the rest of the metropolitan area. Additionally, other circumstances that affect the operation may vary in urban or semi-urban areas, such as congestion and speed limits.

Logistics configuration and business strategies also impose different logistic conditions. In the instances proposed by Boyer et al. (2009) for an online grocery company, the depot serviced an area of 5120 km^2 with a maximum of 4000 customers, with a service time of 10 minutes and vehicles with a capacity of up to 33 deliveries. The case of Sainsbury, the giant supermarket in the UK, shows a different logistic configuration, Sainsbury's online operates from almost 200 sites across the UK with a fleet of approximately 1300 vans (specially designed to maximize volume and controlled temperature). It is available to 90 per cent of UK households, with a 6 minutes service time and a total of 120,000 deliveries per week (Commercial-Vehicle-Engineer, 2012).

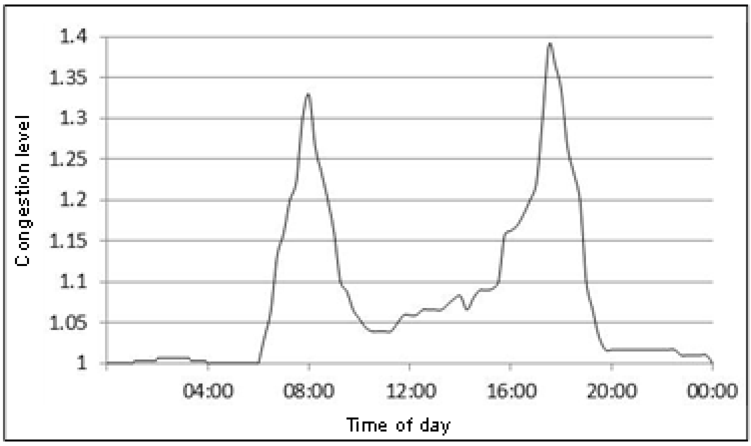
In order to understand the practical implications of the algorithm introduced in this research a number of scenarios are designed to account for the restraints found in urban environments (congestion, density of population) and service conditions of home delivery (length of the time window).

6.2. Scenarios

One of the different logistic conditions in the UK that differs from the United States is that the UK is more densely populated with a reduced area of territory. The proposed scenarios are based on an area of the UK densely populated, 400 km^2 in size (the distance between the depot and the furthest customers is 10 km) and the number of deliveries are 100 and 400 customers. Length of time window varies between no time window to a tight time window of 1 hour. The depot opening time is between 9 a.m. and 7 p.m.

Additionally, different levels of congestion are introduced in the analysis. The average US pattern of congestion in urban environments according to the time of day is presented in Figure 19. Commonly there are two peaks of congestion, morning and evening. TomTom (2015) has introduced the congestion level traffic index (see Table 29 for the level of congestion in selected cities). The congestion level of cities is measured by the calculated increment in overall travel times when compared to a free-flow situation. For example, a congestion level of 20% corresponds to 20% longer travel times compared to free-flow conditions. The indicator weights the number of measurements, therefore busier and more important roads have more influence than quieter roads. Table 29 shows the TomTom traffic index for selected cities.

[4] United States Census Bureau https://www.census.gov/dataviz/visualizations/026/508.php (2010) Accessed 05-09-2015.



Source: US Department of Transport (2003)
Figure 19. Variation in Congestion by time-of-day.

Table 29. TomTom Traffic index for selected cities.

World rank	City	Congestion level	Morning peak (1)	Evening Peak (2)
1	Istanbul (Turkey)	58%	76%	109%
10	Los Angeles (US)	39%	60%	80%
16	London (UK)	37%	65%	67%
90	Birmingham (UK)	24%	46%	50%
-	Southampton (UK)	24%	56%	51%

(1) The busiest one-hour-long period in the morning
(2) The busiest one-hour-long period in the evening
Source: TomTom (2015).

Congestion is introduced in the scenarios following the same pattern presented in figure 19. The four congestion levels are as follow: i) (**S0)** No congestion (constant speed of 48 km/h); ii) (**S1**) the evening peak speed is reduced by a factor of 1.4 compared to a free-flow state (a very similar pattern to that presented in Figure 19); iii) (**S2**) the evening peak speed is reduced by a factor of 1.7 compared to the free-flow state; and the rest of the speeds in each 15 minutes interval are scaled accordingly, based on the pattern shown in Figure 19). Note that free-flow conditions are not present in the analysed period (9:00 AM to 7 PM), iv) (**S3**) the evening-peak speed is reduced by a factor of 2.0 compared to the free-flow state, and the rest of the speeds are scaled accordingly, a similar condition to that in Turkey. See figure 20.

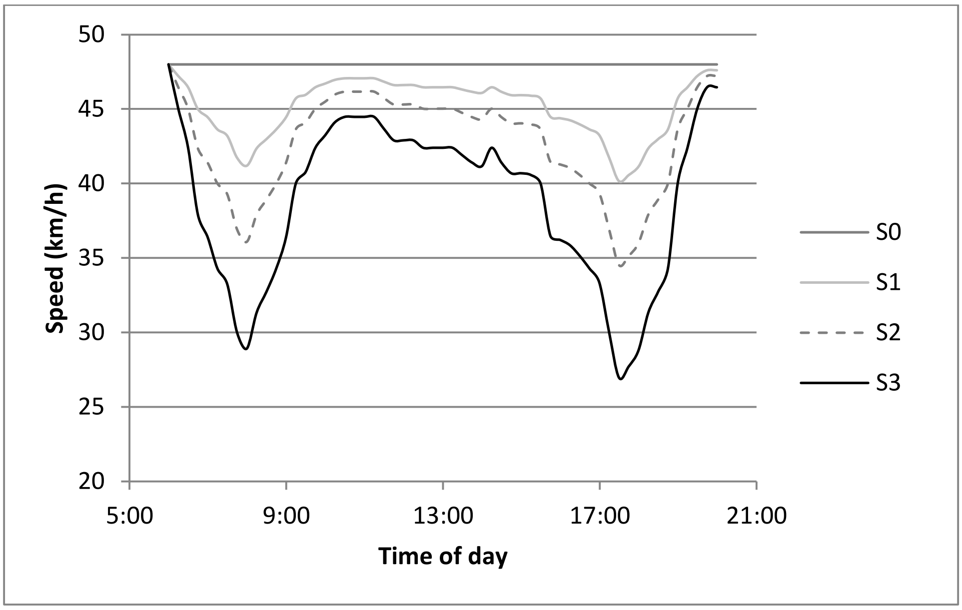


Figure 20. Speeds according to congestion level.

Due to the fact that the aim of this chapter is to show the impact of congestion, regulation and customer density, a simplified experiment is designed where the distances between the nodes are represented as the Cartesian distances between the points. Locations of customers follow the patterns introduced by Solomon (1987) for 100 customers and extended to 400 customers by Gehring and Homberger (1999), namely: random, cluster and random-cluster. Coordinates are scaled to an area of 400 km^2. Figure 21 shows the location of the customers in the different scenarios. Although in the real world many roads are quicker to traverse at some times of day than at others and the algorithm is capable to consider this data (e.g., obtaining data from Google traffic), in the proposed instances congestion varies in an uniform way in all the links of the instances according to the four congestion levels presented in figure 20. Parameters are set to a 3.5 ton diesel van with the following cost coefficients (estimations based on FTA (2014)): fixed cost per vehicle per day £12.51, coefficient per km £ 0.17 and coefficient per hour £ 9.91. Fuel consumption is calculated according to DFT (2014) (see Figure 12 page 49) and emissions according to CarbonTrust (1 Litre of diesel = 2.6676 $KgCO_2e$).

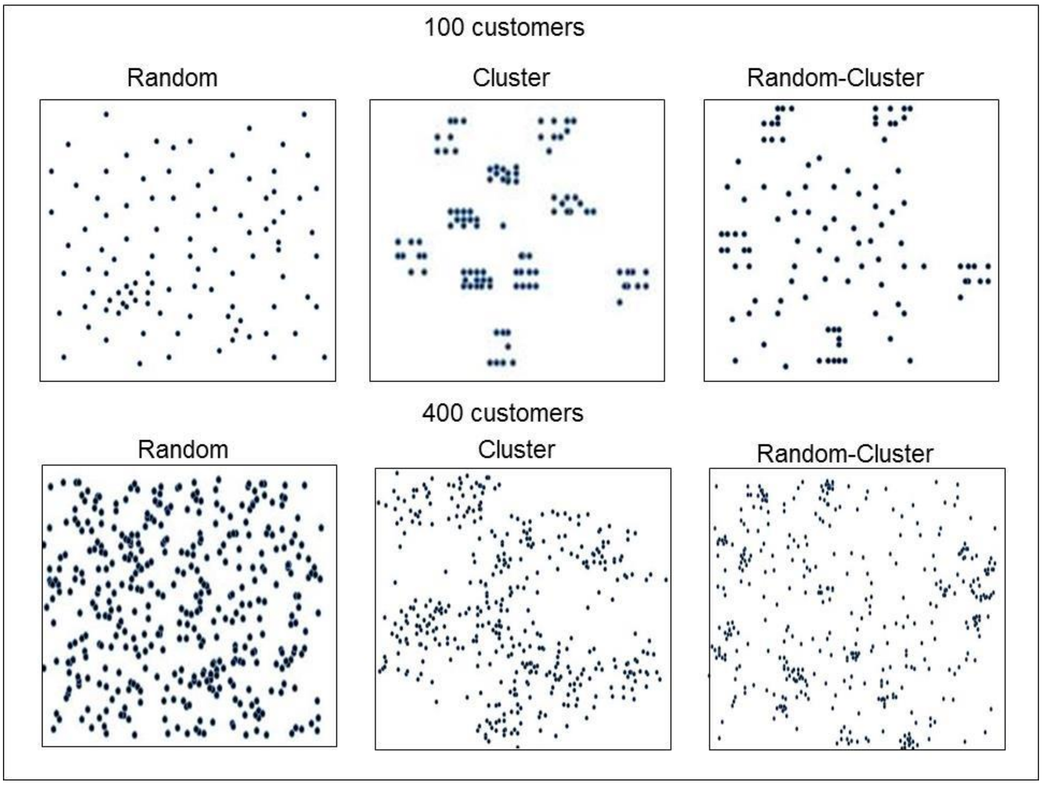


Figure 21. 6 scenarios of customer location (area: 400 km^2).

6.3. Experimental results

Instances were executed in a Corei7 with 16 GB of ram in a single thread with the algorithm introduced in chapter 5; the primary objective was the minimisation of the number of vehicles and the second objective was set to minimize total cost rather than the minimisation of route duration. Execution time for instances of 100 customers was set to 2 minutes and for 400 customers 5 minutes.

Impact of length of time windows and customer density

Routing results of executing three instances (clustered, clustered-randomly, randomly) with 100 customers and 400 customers for different lengths of time windows are shown in Table 30. Tight time windows are more expensive and present a considerable environmental impact (up to 74% more cost and 196% more emissions by comparing No time window vs. 1-Hour time window in instances of 100 customers). However, the impact in cost and emissions can be reduced with higher density (see instances with 400 customers). The studied instances show the importance of promise of service in logistic operations. A 1-Hour time window with low customer density is 111% more expensive than a No time window with high density, where emissions increase by 444%.

Table 30. Analysis of delivery costs with different length of time windows and customer density for a diesel van at a constant speed of 48 km/h (No regulation)

	No Time Window	AM or PM		2 Hour Time Window		1 Hour Time Window	
3 Instances of 100 Customers			Δ		Δ		Δ
NV	6	6		6		9	
Total Route Duration (Hr)	37.1	40.7		49.2		59.6	
Total Distance (Km)	341.3	487.8		759.5		1,012.7	
Total $KgCO_2e$	63.0	90.1		140.2		187.0	
Total Cost (£)	500.8	561.4		691.8		875.4	
$KgCO_2e$ per delivery	0.2	0.3	42.9%	0.5	122.5%	0.6	196.7%
Cost per delivery (£)	1.7	1.9	12.1%	2.3	38.1%	2.9	74.8%
3 Instances of 400 Customers							
NV	15.0	15.0	Δ	18.0	Δ	22.0	Δ
Total Route Duration (Hr)	135.5	139.0		160.0		193.3	
Total Distance (Km)	743.8	910.4		1,723.0		2,313.0	
Total $KgCO_2e$	137.3	168.1		318.2		427.1	
Total Cost (£)	1,657.0	1,720.0		2,103.8		2,584.1	
$KgCO_2e$ per delivery	0.1	0.1	22.4%	0.3	131.6%	0.4	211.0%
Cost per delivery (£)	1.4	1.4	3.8%	1.8	27.0%	2.2	56.0%

Impact of congestion and regulation

Total costs and performance indicators for delivering in the six test instances with different levels of congestion and set of regulations are shown in Table 31. As expected, with higher congestion levels there are increments in costs and fuel consumption (emissions) in any case of regulation (up to 9% cost increment at congestion level S3 in EC-Regulation and up to 6.3% increment in emissions at No regulation). Enforcing the full set of regulations in the UK has an average extra cost of 5.7% at different levels of congestion.

Table 31. Delivery costs with different levels of congestion for a diesel van.

		NV	Route Duration (Hr)	Travel Time (Hr)	Distance (Km)	$KgCO_2e$	Δ	Delivery Cost (£)	Δ		Δ
No regulation	S0	97	814.2	172.7	8,291.6	1,531.0		10,692.3			
	S1	97	829.2	191.6	8,663.3	1,609.9	5.1%	10,904.1	2.0%		
	S2	99	838.8	198.5	8,495.6	1,593.8	4.1%	10,995.8	2.8%		
	S3	103	855.2	218.5	8,456.2	1,627.9	6.3%	11,201.7	4.8%		
								Sum delivery cost (£)		43,793.8	
EC-Regulation	S0	100	838.1	178.6	8,574.7	1,583.3		11,014.8			
	S1	100	850.5	188.9	8,542.7	1,587.4	0.3%	11,132.2	1.1%		
	S2	101	860.1	195.8	8,381.6	1,572.4	-0.7%	11,212.5	1.8%		
	S3	108	930.2	218.0	8,438.9	1,624.4	2.6%	12,004.5	9.0%		
								Sum delivery cost (£)		45,364.1	3.6%
Full Regulation	S0	100	862.9	177.0	8,498.3	1,569.2		11,247.6			
	S1	101	880.8	189.7	8,439.0	1,572.1	0.2%	11,427.4	1.6%		
	S2	103	900.1	199.4	8,537.4	1,601.6	2.1%	11,660.4	3.7%		
	S3	109	921.6	222.6	8,627.9	1,660.1	5.8%	11,964.0	6.4%		
								Sum delivery cost (£)		46,299.4	5.7%

6.4. Discussion of the chapter

This chapter introduces a practical application of using a rich VRP variant to study the last-mile problem found in home delivery. Although extensive analysis could be proposed regarding the impact of decisions related to routing in the supply chain, the aim in this research is to show the possible benefits obtained with algorithm research based on the necessities of the industry. The presented analysis shows the impact of length of time windows at different levels of density of deliveries in a territory of 400 km^2 in terms of delivery costs and emissions (by introducing the estimation of fuel consumption according to average speed and vehicle type proposed by the DFT (2014)), e.g. the cost of imposing a time window of 1 hour with 100 customers is a cost increment of 74% and 196% more CO_2 emissions when compared to a service with no time windows, etc.

A straight comparison of results with the research of Boyer et al. (2009) is difficult due to the fact that cost structure is different in each country as is the size of the studied territories, in Boyer et al. (2009) the studied area is more than 12 times the territory in this research, a characteristic of US when compared to the UK in logistic challenges. Nevertheless, the cost trend of imposing tighter time windows is similar: the tighter the time window the higher the cost. The solution method proposed by Boyer et al. (2009) was based on commercial software, which required execution time of 1 to 2 hours in instances of 500 customers and congestion was not considered. The algorithm proposed in this research requires 2 minutes to produce solutions that improved best-known solutions for time-dependent problems with 100 customers. Execution time for instances with 400 customers was set to 5 minutes.

The impact of congestion in the studied logistic configurations show the relation between the level of congestion and logistic costs: a congestion level of 2 (where speed in the evening peak is reduced by a factor of 1.4 compared to a free-flow state) imposes an extra cost of 9%. Further analysis of results shows the impact of service time on this type of operation. In the proposed scenarios, service time was set at 6 min based on the case of Sainsbury's (Commercial-Vehicle-Engineer, 2012), where the driver would expend a large portion of their day in the doorway of customers, around 75% in the scenario with 400 customers, where the average number of deliveries per vehicle per day is 69 (the total time per route expended in service time is 6.8 hours out of around 9 hours of route duration per vehicle). This shows the importance of the training and experience of drivers to reduce the service time per delivery in multi-drop operations, such as parcel delivery or online groceries.

Continuing with the case of online groceries, in recent years it has been stated in the media that these types of operations are unviable, with logistic costs per delivery of £20[5] where brick-and-mortar customers subsidize online shoppers. However, the analysis of results in this chapter shows the importance of the length of time window and density of deliveries, where costs can be as low of £1.4 with no time window or £1.8 with a 2-hour time window or as high as £2.9 with a 1-hour time window in territories with low customer density. These values are not intended to be representative to the industry, but they are an example of how to use algorithms to calculate delivery costs. The use of rich algorithms with high accuracy may help the industry to support logistics operations and the design of the supply chain to provide better solutions according to the specific characteristics of the business model.

As previously mentioned, additional analysis could be proposed to study other issues in delivery operations with the algorithm introduced in chapter 5, such as: i) delivery cost structure and the relation between length of time windows, congestion and location of customers; ii) impact of the location of the depot, where the fast execution time of the algorithm may be used to run simulations; iii) impact of vehicle selection, etc. However, these analyses are out of the scope of this research and it was only intended to show the relevance of developing such algorithm.

[5] Daily Mail http://www.dailymail.co.uk/news/article-2707071/Supermarket-giants-lose-100million-year-online-delivery-services-Cost-delivery-means-effectively-paying-customers-shop-them.html. Accessed on 04-09-2015.

Chapter 7

Contributions and conclusions

This research takes new approaches, or at least some that are not common in the literature, regarding the Vehicle Routing Problem. It is not only based on taking a variant and improving best-known solutions for a set of instances or showing an industry implementation without algorithm evaluation, but it considers the requirements of the industry and the available data sets brought by ITS development (presenting a literature review of its barriers), where the importance of the variants chosen for study are validated by a literature review and surveying of companies. Algorithms are specifically tailored and their accuracy is evaluated with available benchmark instances. The proposed algorithms in this research consistently improve theoretical results of state-of-the-art implementations to solve the studied variants, and the managerial implications of such algorithms are demonstrated in scenarios that consider the restraints found in real operations.

The literature review shows that not using time-dependent models and congestion data when planning vehicle routes might lead to inaccurate schedules that underestimate actual travel times and violate time windows of deliveries expected by customers, where all the effort of providing optimised routes is lost in congested environments by not using an adequate model and data set. The freight industry is responsible for transporting goods through traditional logistic configurations along with satisfying new customer expectations. Current retail trends show that customer preferences are shifting towards e-commerce and consequently home delivery. The last mile problem is considered one of the major challenges in distribution, where urban conditions have to be considered, congestion has continuously increased and its patterns are available thanks to ITS implementations to a certain extent.

Although main CVRS companies claim that models that consider congestion are implemented, the surveyed companies recognised that the software capabilities that required the most development are: i) route optimisation minimising the impact of congestion, and ii) accuracy of information regarding vehicle restriction to certain zones and times. Gathering, processing and distributing the data required to provide accurate maps and data that satisfy the requirements of the freight industry requires policy and resources to involve a range of stakeholders, where a number of initiatives have been put in place. The scope of this research is restricted to reporting on current technologies and data sets mentioned in the literature along with their barriers, and providing knowledge regarding the core analytic tool, the VRP variants that optimise freight operations and are capable of mitigating the impact of new conditions such as congestion and regulation.

The literature review of techniques to solve the VRP shows that exact algorithms are not viable for rich models, where in some instances in the range of hundreds of customers for the basic VRP with time windows have eluded achieving optimality and metaheuristic algorithms are capable of providing high accuracy in execution times that are sufficient to support the industry with an adequate algorithm design. Issues that must be considered in algorithm design include: i) metaheuristics do not guarantee optimality and their accuracy should be evaluated with benchmark instances. Poor accuracy has been reported in some implementations and a characteristic of the freight industry is low profit margin, therefore solutions should be as effective as possible to reduce costs and mitigate the impact of the operation; ii) although the Operational Research community is interested in developing complicated approaches with high theoretical value, the industry requires easy-to-implement algorithms capable of producing high accuracy bearing in mind the restrictions found in real operations in reasonable time.

Although VRP variants that consider congestion have been previously proposed, research with adequate algorithm evaluations is still scarce. For the time-dependent VRP with time windows (TDVRPTW) a set of instances were previously introduced; the primary goal is the minimisation of the required number of vehicles and the secondary objective is travel time and/or distance minimisation. In this research an algorithm to solve time-dependent VRP variants is tailored using the concept of neighbourhood exploration based on LNS along with algorithm modifications in order to speed up the search process in the presence of time-dependent travel times by allowing penalties for time windows violation in the stage of vehicle minimisation and focusing the search on allocating customers particularly difficult to insert in a reduced number of routes. Previous LNS approaches used different strategies in this stage (utilisation of a request bank to temporarily “store” unrouted customers and try to insert them in a feasible solution).

In the stage of travel time minimisation, neighbourhood exploration only allows feasible solutions. LNS movements prove to be more efficient than well-known neighbourhood structures for providing highly accurate solutions in both stages using the proposed tailoring; the algorithm is capable of obtaining reductions in some test instances for the TDVRPTW of up to 18% in distance with 19% less travel time and 7% fewer vehicles. It consistently provided improved solutions in the 672 test instances (average reduction in number of vehicles of 4.15% and travel time of 12.0%).

A richer time-dependent variant that considers Drivers' hour rules in urban or interurban environments Regulation 561/2006 (EC) (European Union, 2006) and time windows was also previously introduced. In this variant the primary objective is the minimisation of the number of vehicles, while the second objective is the minimisation of route duration. In this research, LNS is also adapted to cope with driving time regulation following a similar approach designed for the TDVRPTW. The LNS tailoring is capable of obtaining an average reduction in the number of vehicles of 19% and route duration of 4.4% whilst also reducing travel distance by 17.7%. Additionally, an extended variant is introduced to also comply with the Road Transport (Working Time) Regulation 2005 (VOSA, 2011) in UK freight regulation.

The economic analysis of results according to the cost structure of the industry is a clear example of the benefits of tailoring algorithms to accommodate the new restrictions that the logistic sector is facing. By using the proposed algorithm in this thesis, routing solutions that comply with Regulation 561/2006 (EC) and time-dependent travel times for vehicles over 3.5 tons are 8.9% less expensive than using a previous implementation reported in the literature for this variant.

From the theoretical perspective, in algorithm design, minimising the number of vehicles in richer variants has been a challenge. Proof of that is the TDVRPTW along with the VRP with time windows and Rules on Drivers' hours (Prescott-Gagnon et al., 2010). The proposed modification of LNS to intensify the search in customers that generate penalties in solutions with a reduced number of vehicles was capable of reducing the number of vehicles in the studied variants. The proposed algorithms are capable of obtaining high accuracy in a matter of a few minutes even in variants as computationally demanding as time-dependent travel times with Rules on Drivers' hours, where it is also required to decide the departure times that minimise the objective. Fast execution times are a desirable characteristic in everyday operations or when analysing different decisions within the configuration of the logistic configuration in its design or planning. With regard to the issues in algorithm design previously mentioned, LNS is considered an easy-to-implement metaheuristic and this research proves its capacity to achieve high accuracy where algorithm modification is proposed and described in order to provide accurate solutions for relevant variants that are important to the industry.

The benefits of using fast and accurate algorithms that consider congestion and regulation are demonstrated in this research by studying the last mile problem. The concept of city logistics relies on optimising transport activities in urban areas while considering the following elements: congestion, energy consumption and the market economy. The algorithms developed in this research take these elements into consideration and provide an example of their utilisation by analysing the impact of length of time window (e.g. the shorter the time window, the more CO_2 emissions per delivery) and different levels of congestion (e.g. with more congestion, more vehicles might be required).

Congestion is present in urban areas and has been consistently increasing. Additionally, the market is shifting towards new trends involving home delivery in congested environments with higher customer expectations. Logistic companies might make use of the algorithms proposed in this research to understand the capabilities of their current infrastructure, identify the impact of changes within their supply chain and plan accurate schedules that account for congestion and Rules on Drivers' hours in order to comply with customer requirements at a minimum cost with the rationalisation of available resources. Nevertheless, recent contributions in VRP variants that try to reduce the environmental impact of transport have been recently introduced; it is worth to propose as future research techniques to reduce CO_2 emissions while maintaining cost reductions with the tailoring of the algorithms proposed in this research.

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APPENDIX A. QUESTIONNAIRE OF SURVEY FOR EVALUATION OF CVRS CAPABILITIES

Q1 Company name?

Q2. What is the main purpose of the vehicle fleet? If required multiple choices can be selected.

- [ ] Provides freight services to other companies (e.g.: Transport providers, 3PL, etc.)
- [ ] Supports private operation (The core of the company is other than logistic services but have own vehicles to support operation)

Q3. What kind of operation is supported by the fleet? If required multiple choices can be selected.

- [ ] Goods and others (e.g.: Post, waste, ancillary, etc.)
- [ ] Services (e.g.: Maintenance and repair, engineering services, etc.)

Q4. What type of journeys does your company specialise in? If required multiple choices can be selected.

- [ ] Urban
- [ ] Regional (480 km)
- [ ] Long Haul (Over 480 km)

Q5. How centralised is the routing of vehicles?

- [ ] Company has only one depot that manages all the vehicles
- [ ] Company operates several depots and scheduling is performed individually at each depot
- [ ] Company operates several depots and scheduling is centralised

Q6. Fleet description

How many vehicles under 3.5 tonnes are operated by your company in the U.K.?

How many vehicles over 3.5 tonnes are operated by your company in the U.K.?

Q7. How would you describe the routing procedure in your depot for scheduling the cargo fleet? If required multiple choices can be selected

- [ ] Fixed schedule
- [ ] Not supported by software and variable
- [ ] Supported by software and variable

If Q7 answer is Fixed schedule

Q8. What are the main reasons for having fixed schedules in your depot for scheduling the cargo fleet?

Q9. Please grade each of the possible impacts that congestion has had on your transport operation.

Using the scale 1 (no impact at all) to 5 (high impact).

Transportation costs have increased	
More vehicles are required to support the operation	
More drivers are required to support the operation	
Service level has decreased	

Q10. If other please state it and grade it

Q11. What type of software supports the scheduling of the cargo fleet?
If not in-house please state the name of the software

- ☐ Off-the-shelf software
- ☐ Provided by a software company with tailor-made functionalities
- ☐ In-house

Q12. Please grade each of the following reasons for having routing software according to your cargo transport operation. Using the scale 1 (not agree at all) to 5 (strongly agree).

Control costs	
Reduce scheduler's time	
Control emissions	
Control fuel consumption	
Improve service level	
Avoid congestion	
Provide road information to drivers	
Provide information about access restriction to certain zones and times	
Balance routes	

Q13. If other please state it and grade it

Q14. Please grade the capabilities of your routing software.
Using the scale 1 (large improvement required) to 5 (excellent functionality).

Allows the modification of the objective function	
Supports different vehicle characteristics	
The road representation is accurate	
Access restriction to certain zones an times is depicted accurately	

Provides support to schedule braking times for drivers	
Optimises routes minimising impact of drivers' hours regulation	
Supports different speeds according to the time of the day	
Optimises routes minimising impact of congestion	
Supports localisation of vehicles to track vehicles and evaluate performance	
It records information of drivers' driving times to comply with drivers' time regulation	
Supports re-routing during delivery	

Q15. Please describe what elements can be improved in routing software to provide higher benefits

Q16. Do you have any other comment that you consider may be relevant?
