A review of recent advances in the operations research literature on the green routing problem and its variants

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Abstract: Since early 2010s, the Green Routing Problem (GRP) has dominated the literature of logistics and transportation. The problem itself consists of finding a set of vehicle routes for a set of customers while minimizing the detrimental effects of transportation activities. These negative externalities have been intensively tackled in the last decade. Operations research studies have particularly focused on minimizing the energy consumption and emissions. As a result, the rich literature on GRPs has already reached its peak, and several early literature reviews have been conducted on various aspects of related vehicle routing and scheduling problem variants. The major contribution of this paper is that it represents a comprehensive review of the current reviews on GRP studies. In addition to that, it is an up-to-date review based on a new chronological taxonomy of the literature. The detailed analysis provides a useful framework for understanding the research gaps for the future studies and the potential impacts for the academic community.

Keywords: Green routing problem; freight transportation; urban logistics; negative externalities; taxonomic review

1 Introduction

Due to the growth in last mile logistics, the negative externalities (noise, land use, accidents, etc.) of transportation have been widely discussed in the literature. Especially, researchers in the domain of operations research have paid attention to the minimization of global-level emissions, namely greenhouse gases (GHGs). The United States Environmental Protection Agency (EPA) has stated in 2009 that GHGs pose a danger to human health and welfare, including carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) and ozone (O_3). As it is widely known, all these gases can also be measured as CO_2-equivalent (CO_2e) emissions. As a result of increasing attention to environmental problems, the consideration of emission reduction has long been the agenda of modern organizations and academic researchers. Routing problems have been widely discussed since the 1960s and there are two main categories of routing problems.

First, the well-known Vehicle Routing Problem (VRP), which consists of finding the best itinerary visiting all the **nodes** of a network. Since its introduction by Dantzig and Ramser (1959) under the "truck dispatching problem", the primary concern of the VRP was the satisfaction of the demands of a predetermined set of geographically-scattered customers around a central depot by the mean of a homogeneous fleet of vehicles located at that depot. The main and commonly defined objective is to ensure a minimum economic cost through the minimization of the total traveled distance, or the total time spent in a route.

Second, the Arc Routing Problem (ARP), which aims at finding the best routes traversing a predefined set of **edges** (in undirected network)/**arcs** (in directed network) with positive demands. The ARP was firstly introduced by the Chinese mathematician Mei-Ko Kwan in 1962 for the case of a rural postman. The defined

Chinese Postman Problem (CPP) presents the basic problem of the ARP. The first appellation of ARP belongs to Golden and Wong (1981), typical applications of ARP include municipal waste collection, snow removal, mail delivery and collection, salt-grit road spraying to prevent ice formation, etc.

The aim of the classic routing problems is to find a minimum cost in terms of economic evaluation. However, green logistics has highlighted the importance of other pertinent non-economic factors to know, i.e., environmental issues.

One of the early considerations of an environmental objective in routing problems was proposed by Sbihi and Eglese (2007, 2010). Indeed, the authors used the time-dependent VRP as an approach for minimizing vehicle emissions. The idea was to avoid congested periods, which are characterized by high emissions because of the non-optimized driving attitude (multiple stops, gear switch, skating, etc.). This initiative had led to the emergence of a new problem, namely the Green Vehicle Routing Problem (GVRP). Similarly, in 2018, Tirkolaee et al. introduced for the first time, the Green Capacitated Arc Routing Problem (GCARP).

In the latest report presented by the European Environment Agency (EEA-2019), the road transport is in continuous progress since 2014 and responsible for 82% of the transport related and one-fifth of the EU's total GHG emissions, respectively. From this perspective, the Green Routing Problems (GRPs), including the GVRP and the GCARP, have been used as a new research tool against an increasing environmental threat of the road freight transportation while ensuring the harmonization of the economic and ecological costs through an effective routing and scheduling of vehicles. In the last decade, the methodological progress and the development of computer and information technologies (CIT) have led to new variants of the GRP to include more realistic constraints and objectives, stimulated by the complex real-life framework.

There are several literature reviews on this topic. For example, Bektaş et al. (2019) presented a survey dealing with GVRP in different modes of transportation. Park and Chae (2018) focused their efforts in resuming the optimization methods developed for the various extensions of GVRPs. Lin et al. (2014) have classified the GVRP into three main problems: The Pollution-Routing Problem (PRP), the Green-VRP and the VRP in reverse logistics. This classification has been adopted in most of the studies since its introduction.

We concentrate our research on works dealing with the GRPs in the forward logistics only; the PRP, the Green VRP and the GCARP. Moreover, only classical conventional powered engine vehicles ensuring the routing are taken into consideration. The new generation of vehicles relies on alternative fuels such as hydrogen, electricity, biofuels and ammonia. Internal combustion engine vehicles rely on different resources like gasoline, diesel, hydrogen, compressed natural gas, methanol, ammonia, etc. The hybrid vehicles combine both conventional internal combustion engines with an electric propulsion system, leading to a better performance and fuel economy. The electric vehicles (EVs) use only electric motors and include two types: all-electric vehicles (AEVs) running only on electricity, and plug-in hybrid electric vehicles (PHEVs) which run on electricity (for short ranges from 6 to 40 miles) and switch over to an internal combustion engine (using alternative fuels) in case of battery depletion. The electric vehicles offer several advantages like saving money (electricity is cheaper than gasoline), the maintenance is less frequent, not polluting, etc.

This new class of vehicles represents a sustainable transport system due to the lower utilization of fossil fuels and hence lower emissions and environment threats. Environmental impacts include not only emissions and climate change, but also ozone layer depletion, human toxicity, acidification, terrestrial Eco toxicity and etc. Even if the electric vehicles are receiving intensive attention, related sales are of 1% of the current passenger vehicle market. The major reason is the non-availability of enough recharging stations. In fact, the owner of an electric vehicle has to limit its path to the perimeter of available charging station, which restricts its daily life. Another claim with the electric vehicles, even if they are considered as non-pollutant mean of transportation, is the non-ecofriendly process of manufacturing. The energy required by electric vehicles is stored in large batteries made of rare earth elements like nickel, lithium, graphite, etc., needing mining activities known to be very polluting.

According to the International Council on Clean Transportation (ICCT), 99% of the batteries running in fossil fuel powered vehicles are recycled in the US. The collection of lithium batteries was about 5% in the

European Union in 2011. The common attitude with cushioned batteries needed for EVs is the incineration or the throw in landfills. Such batteries are composed of chemical components that are not biodegradable and harmful to the environment. The ICCT stated also that, in 2019, the share of diesel cars in the EU dropped from 44% in 2017 to 31%, while the nearly 60% of all new vehicles manufactured by Toyota are hybrid electric.

The paradox of electric vehicles designed to be ecofriendly and to be the new generation of vehicles to promote, and the non-ecofriendly process of manufacturing and end-of-life batteries, is out of the scope of this research. Many authors tackled this issue from an analysis of the whole life cycle of the vehicles starting from the extraction of raw materials to the vehicle disposal. This approach of analysis from cradle to grave is known as life cycle assessment (LCA). Bicer & Dincer (2018) proposed a comparative LCA of internal combustion engine based vehicles (using gasoline, diesel, liquefied petroleum gas, methanol, compressed natural gas, hydrogen and ammonia), hybrid electric vehicles using 50% electricity and 50% gasoline, and all-electric vehicles. Different environmental impacts were considered: abiotic depletion, acidification, eutrophication, global warming, human toxicity, ozone layer depletion and terrestrial Eco toxicity. Pertinent results were concluded as classifying the hydrogen vehicles as the most Eco friendly benign option. In contrast, even if the electric vehicles produce zero CO_2 emissions, their related production and disposal of batteries cause acidification, eutrophication and human toxicity. De Souza et al. (2018) concluded that the EVs, followed by the vehicles using ethanol are the most environment friendly types. They also stated that vehicles with lithium ions batteries cause high human toxicity, while gasoline based-fuel vehicles increase the abiotic depletion and global warming potential. Ashtineh & Pishvaee (2019) considered the transmission gear ratio and fuel type as major factors of emissions and fuel consumption. The study of the life cycle assessment of fuels on environment shows that by, when considering the entire fuel chain production, 37% of GHG emissions may be saved when using biodiesel.

We may refer interested readers in electric and hybrid vehicles to the literature reviews of Dascioglu & Tuzkaya (2019) and Schiffer et al. (2019). Other relevant papers are studied by Bicer & Dincer (2018) and Dolganova et al. (2020).

Incorporating new generations of vehicles (hybrid and electric) in classic routing problems is one of different weapons used in recent research on GRPs aiming at reaching environmental sustainability. However, environmental sustainability is a part of the global concept: corporate social responsibility (CSR). In fact, when a corporation engages in CSR, this means that it is being conscious of all threats and effects on social, economic, environmental and all society's aspects. The subjective nature of such aspects proves the lack of studies considering CSR in green routing context. When checking the available literature, only one paper has been found. Govindan et al. (2019) proposed a distribution model considering the three pillars of sustainability capturing the impacts on all stakeholders. The model takes into account the multi-product context with time windows constraints. Hybrid swarm intelligence techniques are used to solve it and various comparisons based on different metrics are conducted. The paper is an entry key to a new research shutter.

The main objective of this survey is not only to give a structured review on the GRPs but, we hope that it will serve as a useful starting resource for researchers and practitioners. The remaining of this paper is organized as follows. Section 2 describes the survey methodology. Section 3 provides background information on the GRPs with detailed definition along with the analysis and discussion of the existing surveys dealing with the road freight transport externalities. Reviews coping with fuel consumption are also analyzed and discussed. Section 4 presents the principal contributions to the area by proposing two main classes of characteristics defining the GVRPs. The classification is based on the level of optimization leading to one-level and multi-level optimization problems. We also analyzed the literature according to a new taxonomy. Analyses of the GVRP works' evolution and comments on the trends from 2014 to 2019 are particularly the focus of this research. Section 5 presents a recapitulation of the trends in GVRP based on a comparative study of the future directions proposed by two seminal works in 2014 and the recent extensions and contributions. Useful data is provided in Section 6 with information on relevant benchmark tests to use and some future directions based on a study of the studied variants of the GVRP, and some combinations. General conclusions are summarized in the last section.

2 Survey methodology

This section discusses the survey methodology by stating pertinent research questions for which we try to answer to along the review. The process followed in this survey to find pertinent papers is detailed in the second sub-section.

2.1. Scope of the survey

This literature review deals with the GRPs for urban transportation. Other type of modes including rail, air, and maritime transportation are omitted. We refer interested readers to the surveys of Demir et al. (2015) and Bektaş et al. (2019) for other transportation modes. Green supply chain studies are also not included in this survey. More specifically, we only consider publications related to green routing problems ensured by a fleet of classic diesel-powered engine vehicles. This type of vehicles is still used in the transport market and remains to be dominant in at least the next ten years. In fact, in Europe, the fraction of diesel fuel used in road transport has jumped from 51% in 2000 to 67% in 2016 (EEA -2019) confirming hence the dieselization of Europe's vehicle fleet. Also, the diesel consumption is inelastic for articulated trucks and large goods vehicles, which means that the changes in diesel prices do not change the demand for this category (Wadud 2016). Two states-of-the arts review published in 2014 and still being in the top-cited references are dissected (Lin et al. (2014) and Demir et al. (2014)). Reviews appeared after 2014 are analyzed to show the development of the GVRP research over time. Surveys focusing on Fuel Consumption (FC) models are handled, and different related factors are also included. We focus on the literature dealing with GVRP, as the ARP is a very recent topic dating for 2018 and is in its beginning. From the conducted analysis of reviews, this work aims to answer the following Research Questions (RQs):

RQ1: What are the issues tackled in the existing surveys coping with the GVRP in forward logistics?

RQ2: Is there an added value in the existent studies when going from one year to another?

RQ3: In the previous reviews, the used optimization methods are discussed from a perspective of most applied. Did the recent studies follow the same pattern?

RQ4: Have recent works followed the research directions already proposed by the previous surveys?

RQ5: What is new in this review compared with the available surveys on GRPs?

2.2. Literature search process

To answer to these RQs, we have conducted intensive research of pertinent and recent papers belonging to the time interval between January 2014 and December 2019. We investigated in the first rank Scopus database, and the publications were selected based on their relevance to the topic. Several keywords were used in the search process including 'green arc routing problem', 'arc routing problem+ emissions', 'arc routing problem+ environment', 'green vehicle routing problem', 'green routing', 'vehicle routing problem+ fuel consumption', 'vehicle routing problem+ emissions', 'vehicle routing problem+ environment', 'green vehicle routing problem + survey', 'green vehicle routing problem+ state-of-the-art', 'green vehicle routing problem + review' etc. The first selection was performed according to the lecture of the abstract and keywords followed by the decision on whether including it or not in this study. References of the selected articles were also investigated to reach other pertinent works.

3 The Green Routing Problems

3.1. The Green Arc Routing Problem

As mentioned above, the first appellation of ARP belongs to Golden & Wong (1981). The authors defined the Capacitated Arc Routing Problem (CARP) as follows: given an undirected network, with positive arc demands for each arc which must be satisfied by one of a fleet of vehicles of limited capacity, the CARP aims at finding a number of cycles each of which passes through the domicile (depot) while satisfying all demands at minimal total cost.

The ARP aims at determining optimal routes traversing required edges with positive demands, contrary to the VRP which finds optimal routes traversing all the nodes of the network. Since its introduction, the ARP has been intensively studied. However, when combining green objectives with classic economic targets, the number of publications is very limited.

In Tirkolaee et al. (2018), the authors explicitly stated the remarkable absence of works dealing with ARP and environmental issues. They proposed, to the best of our knowledge, the first appellation Green Arc Routing Problem. They studied the multi-trip extension of the Green Capacitated Arc Routing Problem (G-CARP), aiming at "determining the optimal number of vehicles and optimal routes for each vehicle to minimize an overall objective function involving the cost of using the vehicles and the cost of total CO_2 emissions throughout the network which has a direct relation with total traveled distance".

The Green Arc Routing Problem (GARP) is a recent concept. The first GARP proposed by Tirkolaee et al. (2018) is known under the multi-trip Green Capacitated Arc Routing Problem (G-CARP), minimizing CO_2 emissions and transportation costs. A hybrid genetic algorithm combining a simulated annealing heuristic with a genetic algorithm is developed and resulted good solutions in terms of quality (average gap). Later, Cao et al. (2019) present a modified memetic algorithm for the multi-depot (MMAMD) green capacitated arc routing problem. The proposed algorithm combines ant colony local search strategy with extended neighborhood search. The authors proposed a MILP model minimizing economic costs, make span and carbon emission costs. The model is tested on an instance available in the literature describing real data of road network in Chicago city. The results of the algorithm are of good quality in terms of convergence and diversity.

The GARP is a newly born concept and the research on this topic is in its first steps. Opportunities to explore this topic are wide and could be based on the abundant literature on ARPs.

3.2. The Green Vehicle Routing Problem

We now present the required background information on GVRPs. Concerning the definition of the GVRP; the majority of the authors restricted it to be an extension of the VRP with an environmental concern. As the first appellation GVRP belongs to Erdogan and Miller-Hooks (2012), they considered that the proposed GVRP "seeks a set of vehicle tours with minimum distance each of which starts at the depot, visits a set of customers within a pre-specified time limit, and returns to the depot without exceeding the vehicle's driving range that depends on fuel tank capacity", as they studied a fleet of alternative fuel vehicles. For the general case of engine-powered vehicles, Lin et al. (2014) proposed the following definition, where the GVRP is "characterized by the objective of harmonizing the environmental and economic costs by implementing effective routes to meet the environmental concerns and financial indexes".

Since its introduction, the GVRP had attracted intensive attention. We expose the chronological progress of the studies on GVRP. The most hazardous impacts of freight transportation are detailed in the second sub-section. Several models of fuel consumption are examined in the third sub-section. Next, we propose in this section a chronological up-to-date review of the recent works dealing with the GVRP.

3.2.1. A brief history

The GVRP is concerned with the minimization of emissions of transportation activities and is an extension to the well-known VRP. The VRP is the basic operational-level transportation problem for logistics companies who are looking for finding optimal routes and schedules for a set of vehicle fleets to satisfy the demands of geographically-scattered customers.

The GVRP extends the classical definition of the VRP by considering the environmental impacts of transportation. Since 2007, the concept of GVRP has emerged and received a great deal of attention from academia. Based on these seminal works proposed by Sbihi and Eglese (2007, 2010), academics and researchers have been working on the development of new variants for the VRP concerned with emissions (or FC) minimization.

Kara et al. (2007) proposed the first model that minimizes a weighted distance function as an approach to reduce the FC. The authors defined the first version of the EMVRP. The proposed model is an extension of the capacitated VRP (CVRP). The considered objective is cost minimization defined by the product of the length of the arc multiplied by the total load, based on the rule stipulating that the work equals force times distance, on a flat plan. Later, Figliozzi (2010) considered a similar Energy Minimizing Vehicle Routing Problem (EVRP) model by adding time dependency constraint showing the impact of congestion on vehicle speed. Maden et al. (2010) studied a similar idea on congestion by working on time dependent VRP. They have shown that a 7% reduction in emissions is achievable by considering the time-varying speeds. Their model minimizes the total travel time instead of FC (or emissions). In 2012, Xiao et al. (2012) developed a fuel consumption rate (FCR) model through a regression model based on the load, considered as a significant factor of FC. As fuel consumption is directly related to the emissions, several models had been developed to estimate the amount of FC. In Demir et al. (2011, 2014) an exhaustive review of such models is provided.

Until 2011, only a few studies had been proposed where the environmental concerns are implicitly formulated. The work of Bektaş and Laporte (2011) could be considered as the first seminal work in the green transportation problem. The authors proposed a new variant of the VRPTW, namely the Pollution Routing Problem (PRP). In PRP, vehicle speed on each arc is optimized to minimize the fuel, emissions, and driver costs. The specific characteristic of the proposed PRP is that the load and speed may change from one arc to another, while other parameters remain constant. Since that seminal work, efforts have been made to incorporate more restrictions reflecting the complex real-life situations and studies on GVRP took off. Different variants had been developed by combining various constraints such as: the time windows constraints (GVRPTW/ PRPTW), simultaneous pickups and deliveries (GVRP(S)PD/ PRP(S)PD), consideration of the congested periods (known under the TDPRP), the uncertainty of some parameters (stochasticity), multiple trips where the vehicles can travel more than one time (surveyed recently by Cattaruzza et al. (2018)), and etc.

To the best of our knowledge, the appellation “Green Vehicle Routing Problem” has not been used until 2012. The first paper bearing this appellation in its title is attributed to Erdogan and Miller-Hooks (2012), who used it for the first time to solve a VRP with an alternative fuel-powered vehicle fleet. Such vehicles belong to a recent class of new technologies using greener energy sources. However, this class has a major difficulty of limited driving range aligned with limited refueling infrastructures. Since 2012, the literature has been developed to tackle different extensions of the GVRP. The GVRP term has been used since its introduction and covers all types of vehicles: diesel powered engine vehicles, electric vehicles, hybrid vehicles, etc.

The term “Green” had been used differently since its introduction. It generally covers the incorporation of environmental concerns (emissions and/or fuel consumption minimization) into standard transportation problems. In their book chapter, Bektaş et al. (2016) reviewed several models of fuel consumption. Pertinent variants of the GVRP were also surveyed with a focus on the PRP, with relevant extensions and optimization models.

A seminal survey of Lin et al. (2014) has been concluding relevant works on VRP and GVRP. The literature has been covered from the introduction of the GVRP from 2007 till 2014. Another seminal work is the paper of Demir et al. (2014) presenting an exhaustive list of FC models. Bektaş et al. (2019) proposed the latest survey on GVRP focusing on intermodal transportation. The literature had been covered until 2017. We extend these surveys by presenting an up-to-date state-of-the-art of works dealing with GVRP in forward logistics for road transportation mode.

3.2.2. Negative externalities of road transportation

The extensive use of transportation means and modes in response to the growing globalization has caused negative externalities on different levels. In the Oxford Dictionary, the definition of “Externality” in economics is a consequence of an industrial or commercial activity which affects other parties without this being reflected in market prices. In the transportation field, externalities concern the impact of freight transportation on environment and socio-economic actors. These negative externalities have been handled in the literature and defined differently. Based on the seminal work proposed by Demir et al. (2015) and the latest review paper appearing in 2018 belonging to Ranieri et al. (2018), we group the most relevant externalities in **Fig.1** below.

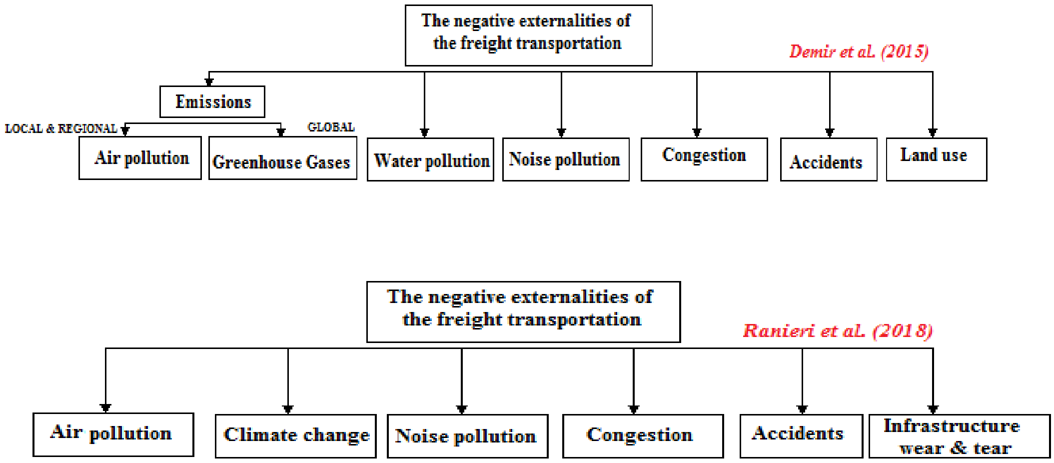

Fig.1 The negative externalities of freight transportation according to the literature

As seen in **Fig.2**, both papers presented six major externalities, where four of them are common: noise pollution, congestion, accidents and land use (infrastructure and wear and tear). While Demir et al. (2015) differentiate between the local & regional scale (air pollution) and global scale (GHGs) when defining the emissions; Ranieri et al. (2018) consider the "Climate change" as an externality coming from the GHGs emissions. "Water pollution" was also defined as an important externality by Demir et al. (2015) while Ranieri et al. (2018) exclude it

Demir et al. (2015) presented a selective review of papers dealing with the modeling of the negative externalities in road, rail, maritime, and air transportation. For each mode of transportation, a mathematical formulation for each type of externalities was provided. The authors proposed five future areas of research. (*i*) The quantification of the amount of the freight transportation can be saved when road mode is shifted to more environmentally friendly modes. (*ii*) Increasing the awareness of individuals about the negative externalities. (*iii*) The modeling of external costs needs to be enhanced. (*iv*) Some aggregates need to be considered when modeling and pricing the externalities. (*v*) More efforts are to be made to emphasize the benefits of reducing the externalities not only to the environment but also to companies. Ranieri et al. (2018) presented externalities differently. A focus is addressed to innovative strategies developed during the last five years (attention on papers appearing after 2013) leading to cost reduction of such negative impacts of urban logistics. Only road transportation is handled in this paper.

As a global remark, it is obvious from the available literature on the different modes of transportation that road is on the top interest, as shown in **Table 1**. This interest is justified by the 76% of inland movements which are operated via roads all over the 28 states of European Unions (EC-2010).

Table 1 Relevance of the negative externalities per transportation mode by *Demir et al.* (2015)

Negative externalities	Road transportation	Rail transportation	Maritime transportation	Air transportation	Pipeline transportation
Air pollution	***	**	**	**	*
Greenhouse Gases	***	**	**	**	*
Noise pollution	***	**	**	**	*
Water pollution	*	*	***	*	*

Congestion	***	*	*	*	*
Accidents	**	*	*	*	*
Land use	**	**	*	*	*

*: Low ** Medium *** High

From **Table 1**, air pollution and GHGs are at the top of the most harmful impacts of road transportation. This fact justifies the growing intension addressed to the GVRP with different extensions trying to minimize the environmental externalities. To this end, many models have been developed to estimate these emissions. Fuel consumption is considered as the direct factor of emissions. As a result, considerable efforts have been made to quantify the FC and thus the emissions incurred.

The next section is dedicated to present an overview of FC models and to some seminal references on this topic.

3.2.3. Fuel consumption models

Demir et al. (2011) have conducted the first state-of-the-art review on FC models for the VRPs. The authors enumerated some related factors including the **vehicle characteristics** (e.g., the vehicle type, load, air resistance), the **driver** (e.g., acceleration, deceleration), and the **environmental** and **traffic** conditions. Four instantaneous emission models, named *microscopic* models that are necessary to predict traffic emissions more accurately: the Instantaneous FC Model (IFCM), the Four Mode Elemental FC model (FMEFCM), the Running speed FC model (RSFCM) and the Comprehensive Modal Emissions Model (CMEM). The latter has been used intensively since its introduction by Barth et al. (2005) and Barth and Boriboonsomsin (2008), until 2017 when Turkensteen (2017) shows that the assumption of the fixed average speed, adopted in the CMEM and being used without any demonstration compared to fluctuating speed. Two other FC models, the Methodology for calculating Transportation Emissions and Energy consumption (MEET) and the Computer Program to calculate Emissions from Road Transportation (COPERT), were presented as macroscopic models. This class of FC models can be used to calculate national and regional emission inventory.

Later, Demir et al. (2014) have proposed an enhanced version of the proposed one in 2011. They have widened the list of the existing models of FC to group 13 macroscopic and 12 microscopic models. The list of the factors influencing the FC was also more developed. The overall 25 models were analyzed based on eight important dimensions: the robustness, reliability, application in optimization, responsiveness to other air pollutants, the level of awareness, the level of data requirement, the level of technical support and the level of continuous improvement. The main deductions of this analysis are that the microscopic models are more robust, reliable, and more applicable in the optimization area. However, the macroscopic models are more capable of estimating other air pollutants, provide continuous improvement and have more technical support. Finally, the authors have detailed some applications of the proposed FC models at different levels of planning for road freight transportation.

In another study, Zhou et al. (2016) proposed the latest review of the FC models. In this paper, the authors cited the different ways leading to vehicle fuel economy, to know: new engine with potential efficiency improvements of 4–10%, technologies new vehicle technologies with potential efficiency improvements of 2–8%, eco-driving with potential efficiency improvements of 15–25% and eco-routing with possible efficiency improvements of 12–33%. Eco-driving and eco-routing, as new control technologies, represent the most effective ways of fuel economy. For this reason, the authors deducted the need for grouping and discussing the appropriate and best suited instantaneous FC models. The first step was the enumeration of FC factors. As shown in **Table 2**, the elements defined by Zhou et al. (2016) differ from those introduced by Demir et al. (2011, 2014). The authors proposed six classes of factors and defined new ones compared to the five categories of Demir et al. (2014). Based on these six classes of FC factors, the authors proposed a classification of the instantaneous FC models according to their transparency. Three major classes are defined. (*i*) ***White- box FC models***: this class concerns mathematical models of the engine's physical or chemical processes: engine intake, combustion, and exhaust. (*ii*) ***Black- box FC models***: either the entire vehicle or the engine alone is in the scope of such models. (*iii*) G***rey- box FC models***: this class lies between the white-box and black-box models.

To determine the best suited models to be adopted for efficient eco-driving and eco-routing, the authors compared the models based on their advantages, inconvenient, accuracy and factors. The imminent conclusion is that no model could have a high level of accuracy coupled with a simple structure. The white-box models justify well this observation: this class of models does not need intensive experimental data (low accuracy) while its structure is of extreme complexity, which leads to inefficient eco-routing and eco-driving in terms of computation time. Discussion of the data and comparisons of the three classes of models lead to the conclusion that the grey-box FC models are the most recommended for use to obtain efficient eco-routing and eco-driving systems. Concerning the factors influencing the FC (**Table 3**), the surveys differ in this point: similar factors were used in both versions of Demir et al. (2011, 2014) while in the latest version of Zhou et al. (2016), different characteristics were defined, as the research evolves and new factors are being considered.

Table 2 Different FC factors defined in the literature

	FC factors	**Demir et al. (2011)**	**Demir et al. (2014)**	**Zhou et al. (2016)**
Vehicle	Vehicle curb weight	√	√	
	Engine size	√	√	√
	Engine Temperature	√	√	
	Oil viscosity	√	√	
	Gasoline type	√	√	
	Vehicle shape	√	√	
	%of use of electric devices	√		
	Fuel type/ Composition		√	
	Others (e.g., maintenance, age)		√	√
	Loading			√
	Transmission			√
	Speed & acceleration			√
Environment/ Weather	Roadway gradient	√	√	
	Wind conditions	√	√	√
	Ambient temperature	√	√	√
	Altitude	√	√	
	Pavement type	√	√	
	Surface conditions	√	√	
	Others (humidity…)		√	√
Traffic	Speed	√	√	
	Acceleration	√	√	
	Deceleration		√	
	Congestion		√	
	Vehicle-to-vehicle interaction			√
	Traffic signal			√
Driver	Driver behavior			√
	Aggressiveness		√	√
	Gear selection		√	
	Idle time		√	
Travel	Distance	√	√	√
	Time			√
Roadway	Grade			√
	Curvature			√
	Type & roughness			√
Operations	Fleet size & mix		√	
	Payload		√	
	Empty kilometers		√	
	Number of stops		√	

3.2.4. A review of previous review studies

The definition of the GVRP concept belongs to Kara et al. (2007), Sbihi and Eglese (2007, 2010) and later to Bektaş & Laporte (2011). Lin et al. (2014) surveyed the related works to VRP with green issues. The authors proposed a new classification for the GVRP englobing three major problems, namely: the PRP, the G-VRP and the VRPRL. While the G-VRP is concerned with the optimization of the energy consumption through the minimization of the FC, the PRP looks at the conversion of energy to equivalent emissions and speed optimization. Consequently, the PRP is characterized by an objective minimizing the total amount of GHGs caused by speed variations and load. These emissions can be directly measured through commercial solvers or computed as FC rate multiplied by certain factors leading to equivalent CO_2.

In Lin et al. (2014), eighteen variants of the VRP have been enumerated with their dates of appearance and analyzed in deep with the applied optimization methods. Exact algorithms and approximate algorithms have also been considered in the analysis. Saving algorithms, sequential improvement algorithms, sweep algorithms, petal algorithms, and Fisher& Jaikumar two-phase algorithms are the lists of heuristics found in the treated VRP literature. Metaheuristics for the VRP have been classified in two sub-classes. The local search with Tabu Search (TS), Simulated Annealing (SA), Greedy Randomized Adaptive Search Procedure (GRASP), Variable Neighborhood Search (VNS) and Large Neighborhood Search (LNS) form the first class. Population search with Genetic Algorithms (GA) and Ant Colony Optimization (ACO) constitute the main developed metaheuristics. For the GVRP, each class has been defined, and all the related papers have been assigned to and analyzed. The current studies on the G- VRP and the PRP include published works appearing in the period from 2007 to 2012. In total, nineteen (19) works were cited: nine papers for the G-VRP (from which only five were analyzed) and ten for the PRP (from which only six were analyzed). Optimization methods dedicated to both classes of the GVRP in forward logistics were out of interest of the authors. As a cherry on the cake, the authors have defined four principal axes for future researches in the GVRP, based on which next works on GVRP have being guided.

In the same year, Park and Chae (2014) have proposed a different classification for the VRP and GVRP variants from the version of Lin et al. (2014). A brief description of the proposed models of FC, described by Demir et al. (2014), has been introduced. The contribution of this state-of-the-art lies in the classification of the treated papers based on their methods of optimization. Articles were assigned based on the optimization method: either exact or approximate method (including heuristics and metaheuristics). Two types of heuristics have been depicted: constructive route heuristic and the neighborhoods heuristics. Five metaheuristics to know the TS, SA, GA, Scatter Search (SS) algorithm and Artificial Bee Colony have been depicted. In total 40 papers have been analyzed based on the optimization method. Twenty-one of these papers developed metaheuristics (52.5%), followed by exact methods (25%) and heuristics with 22.5%. In term of the number of papers, the first rank is devoted to branch and bound exact method with a percentage of 22.5 (9 papers among 40), followed by the metaheuristics GA and TS (with 20% and 15% respectively).

From 2009, the development of methods of optimization for the GVRP and related variants reached its peak in 2012, with great interest to metaheuristics, in detriment of the exact algorithms. The focus on approximate methods is justified by the NP-hardness of the GVRP which make the exact methods effective for small size instances only. From 2014, the research on GVRP and its extensions have been continued. In the review of Bektaş et al. (2019), and as a key element of GVRP, the authors defined three FC factors related to vehicle, environment, and driving. To reach fuel economy three levels of decision making were determined. (*i*) Strategic and systemic decisions concerning the design, redesign or expansion of the transportation network, (*ii*) tactical decisions concerning the choice of the fleet of vehicles to be used and (*iii*) operational decisions. The road and maritime transportation had been receiving more attention in terms of the number of references covered compared to other means. Road transportation was considered in more than 41 papers (among which 14 works are devoted for electric vehicles) and 29 papers for maritime transportation. Other modes were covered briefly (**Response to RQ1**).

This survey tried to recapitulate the role of operations research in green freight transportation by focusing on the developed optimization methods in each paper analyzed. However, we notice that a few articles were not considered, even if they present valuable contributions. In the next part of this survey, other studies are handled for the first time in a review and an in-deep analysis of related constraints, objectives, and optimization methods are conducted. Similarly to previous surveys, Bektaş et al. (2019) justify the increasing interest to the GVRP through the growing number of papers appearing from 2010 till 2017. The repartition of the used methods of optimization is different from one year to another, as seen in **Fig.2**, but the focus is being given to approximate methods. In **Fig.2,** the methods of optimization covered by Park and Chae (2014) and Bektaş et al. (2019) are merged to demonstrate the chronological evolution. This progress is shown in the right histogram. The left side of the figure shows the evolution of the GVRP studies, as highlighted in both surveys.

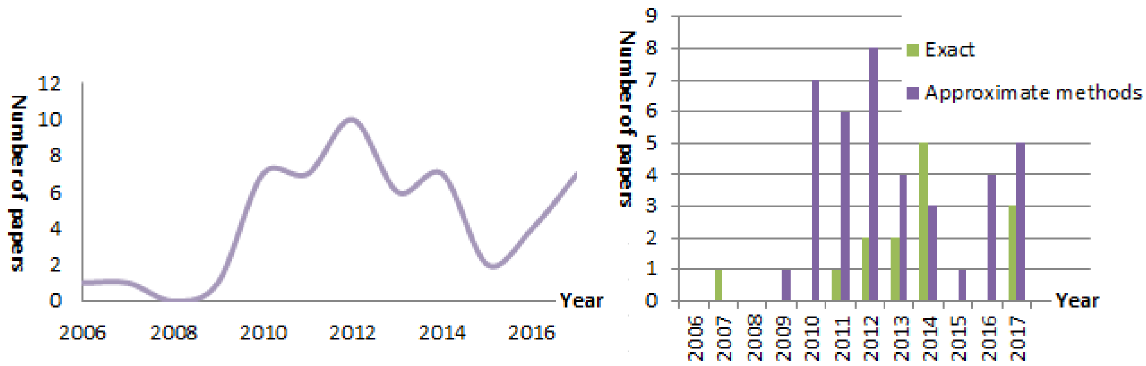

Fig. 2 Chronological evolution of the GVRP with optimization methods until 2017

Based on the provided analysis of the available surveys on GVRP with optimization, we noticed that the research on this topic is in continuous growth, with a pick on 2012 justified by the explosion of the research since the seminal PRP proposed by Bektaş and Laporte (2011).

The literature has been covered until 2017. Based on the research that we have conducted, we were convinced that there exist more works on this topic that were not covered by these surveys, especially with the unexpected decreasing pace of the curve between 2014 and 2015, as illustrated in **Fig.2**. According to Van Wee and Banister (2016) who stated: "(…) in many cases there might still be potential for an additional review, (…) if an existing review needs updating". For this we try in this work to present an up-to-date survey covering the period starting from 2014 and describing the new methods of optimization and the studied GVRP variants in these last years.

4 A detailed analysis of the covered period

The globalization nowadays is bringing more comfort and luxury to the customers' life, but on the detriment of the environment. The worldwide movement of goods and the development of e-commerce are causing harmful effects on the whole ecosystem by emitting dangerous gases. To fight these negative externalities, researchers are working on the development of environmentally friendly systems for the routing and scheduling of transported goods. To optimize such problems, operations research (OR) tools are essential keys to fight its NP-hardness. From fiddly research on the GVRP and developed optimization methods, we notice that the proposed extensions of the GVRP may be classified according to the level of optimization. Based on this criterion, we distinguish two classes of problems: one-level optimization problems and multi-level optimization problems.

4.1. One- level optimization problem

The common classification of the GVRP in the one-level system is the division of Lin et al. (2014) of GVRP in: G-VRP and PRP. When investigating the existent related works (after 2014), we find that there is lot of interesting publications on GVRP proposing new tools of optimization and new formulations. For this reason, we propose a new classification of the existent works dealing with the GVRP in forward logistics, for the fleet of the diesel-powered engine.

The abundance of the contributions depicted from 2014 till 2020 create the need to build a structured classification of the papers. We propose a new taxonomy of the existent works dealing with the GVRP in forward logistics, for the fleet of the diesel-powered engine. This taxonomy aims at drawing a panoramic view of existent research on GVRP and depicting further research horizons. We build this taxonomy according to the main characteristics of a routing problem. We also follow a chronological classification to depict tendencies in the research focus year by year. To the best of our knowledge, this survey is the first one to present a chronological classification of the GVRP studies. To treat the papers, the following taxonomy is defined, based on the characteristics of different GVRP related features, as follows:

- *Type of Problem (TP)*: Two natures of the used data in each paper are distinguished: deterministic data (DET) that is time-independent and constant over the time horizon and stochastic data (STO). Stochastic data is a newly adopted attribute in GVRP that handles the unexpected variations in model parameters such as vehicle speed or traveling time.
- *Type of GVRP's Operation (TO)*: The standard GVRP deals with only delivery (or pickup) (P/D) of goods from depot to customers. In some cases, some customers have loads to be picked up, and others have demands to be delivered. This case is represented under the variant GVRP with simultaneous PD.
- *The Objective Function (OF)*: The GVRP requires not only the optimization of economic objectives, but also the consideration of environmental issues. The majority of the papers merge both objectives (expressed in monetary unit) by considering the fuel consumption cost, to simplify the resolution by the mean of mono-objective (MO) models. Even if their resolution is complicated, other authors developed models that consider multi-objective functions (MU), generally considering several conflictual objectives, reflecting complex real situations.
- *Vehicle (V)*: As a vital element of any routing problem, the vehicle has been being in the top interest of recent studies. Characteristics of the vehicles used in the routing have an impact on the FC and emissions. Using a heterogeneous fleet (HE) of vehicles is preferable, in term of FC and emissions, to the use of a homogeneous fleet (HO).
- *Constraints (C)*: The most modeled constraints are the Time Windows (TW), fixed by customers and during which they expect to be delivered. The constraints of Time Dependency (TD), enabling the consideration of congestion, have important role in GVRP: the emissions during the time period in which the vehicle runs differs from congested period to free-flow period. The driver wages (DRI) are considered as a direct factor of the overall cost.
- *Decision variables (DV)*: When defining the decision variables, all the publications used binary variables indicating if the arc between any two nodes is visited or not. In 2011 when the PRP has been introduced, the speed (SP) was considered as effective factor affecting the final solution. Since that time, many papers consider the speed as decision variable (SP-DV), while others used it as an inherent parameter in FC and emissions modeling (SP). As an important factor of FC efficiency, the load becomes in the top interest of studies in GVRP. It may be considered as a factor of emissions (LO) or as a decision variable (LO-DV).

Our taxonomy is build following an arborescent schema as demonstrated **Fig 3**. Each branching level may be divided into three sub-levels, at most. This division aims at keeping coherence, comprehensiveness, and clarity.

The classifications from the first to the fourth levels are mandatory: these are the essential elements of any routing problem. We could not deal with a routing problem without specifying the type of the operations (pickup and delivery, pickup or delivery), the nature of the data (stochastic or deterministic), the objective of the problem (if it considers a single objective or multi-objectives) and the nature of the fleet of the vehicles. For these categories, each paper must address one attribute of each sub-category. For the constraints, each paper may address one or all the sub-categories. This category may be also ignored by some papers (in this case, it may be a classical capacitated routing problem). The same remark may be conducted for both last nodes of the schema: the load and the speed. These attributes are of great importance in optimizing a GVRP, but some authors ignore them.

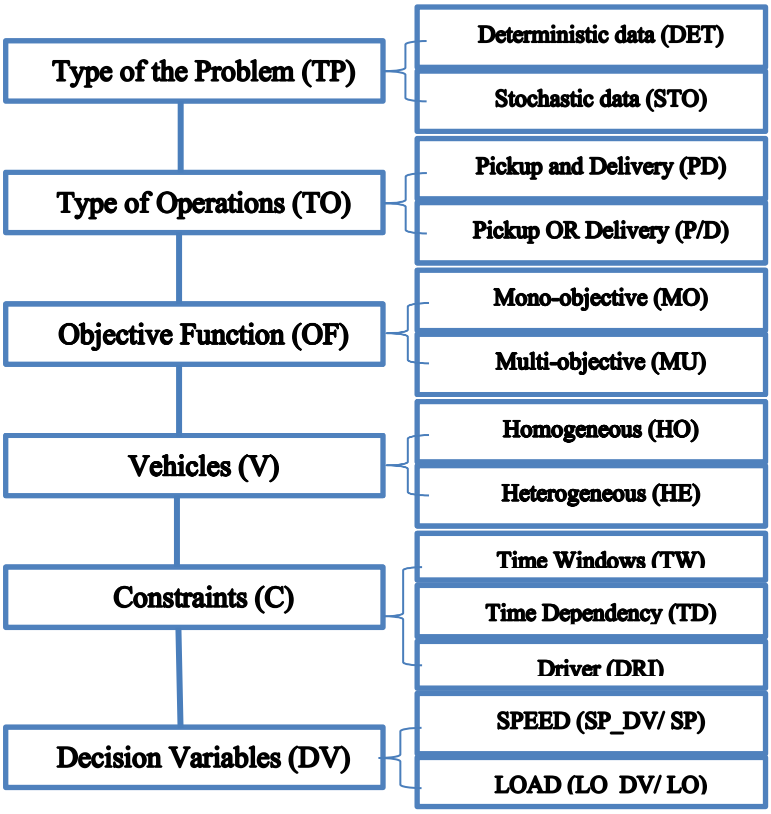

Fig.3 The arborescent schema of the proposed taxonomy

When investigating the literature on GRP in one-level optimization network, we notice the presence of two main classes of problems: The shortest path problem and the GVRP.

4.1.1. Minimum emissions path problem

An extension of the GVRP is the Minimum Emissions Path Problem (MEPP) also called shortest path problem. This problem consists of finding the minimum cost of a path linking an origin to a destination (two customers in the network). For the context of VRP, this problem has been well studied. The well-known Dijkstra's algorithm for the finding of the shortest path has been adopted. A commonly used assumption in this class of problems is the First In-First-Out (FIFO) method. In Ehmke et al. (2016), the authors pointed out that the time-dependent shortest path emissions problem (or TD-MEPP) has been well studied. They also proposed a TD-MEPP and presented two data-driven approaches for the construction of the problem, and an application to a German real case study has been conducted and the results were of high quality. Except for this work, other analyzed papers do not consider TD constraints, but the attentions were directed to the heterogeneous fleet and especially to real applications (cf. **Table3**).

Table 3 Literature on minimum emissions path problem

References	TP		TO		OF		V		C			SP	SP-DV	LO	LO-DV
	DET	STO	P/D	PD	Mo	Mu	HO	HE	TW	TD	DRI				
Qian & Eglese (2014)	√		√		√		√		√				√		
Ehmke et al. (2016)	√		√		√		√			√		√			
Koc et al. (2016)	√		√		√			√				√			√
Qian & Eglese (2016)	√		√		√		√		√				√		
Hosseini-Nassab & Lotfalian (2017)	√		√			√	√					√			√
Liu et al. (2017)	√		√		√			√	√		√	√			√

4.1.2. Evolution of the GVRP studies over the years

The main conclusion regarding the studies conducted on GVRP in 2014 was the focus on the development of models that lie on the load (LO-DV) as a decision variable (**Table 4**). The speed has been considered as an important factor of FC and emissions since the first works dealing with PRP. Research on the factors influencing the FC and emissions has no end. After the speed, many authors stated that the load (LO) is also a crucial factor in the minimization of the FC cost (Bektaş and Laporte 2011). In fact, from the papers depicted in 2014, 86% of them consider the load as a decision variable. Another remarkable use of multi-objective model is depicted during this period: considering other targets when modeling GVRPs models attracted many authors. Demir et al. (2014) defined a bi-objective model for the PRP minimizing both FC and driving time. Elbouzekri & El Hilali (2014) proposed a bi-objective GVRP minimizing the total transportation cost and the total level of emissions. This approach is stipulated by the nature of the GVRP and its extensions, requiring sometimes the optimization of different conflictual objectives simultaneously.

Table 4 GVRP studies in 2014

References	TP		TO		OF		V		C			SP	SP-DV	LO	LO-DV
	DET	STO	P/D	PD	Mo	Mu	HO	HE	TW	TD	DRI				
Ayadi et al. (2014)	√		√			√	√								√
Demir et al. (2014)	√		√			√	√		√		√		√		√
Elbouzekri & El Hilali (2014)	√		√			√	√		√			√			√
Koc et al. (2014)	√		√		√			√	√		√		√		√
Molina et al. (2014)	√		√			√		√	√		√				√
Tajik et al. (2014)	√	√		√	√		√		√		√	√			√
Zhang et al. (2014)	√		√			√	√							√	

From 2014 to 2015, the tendency of considering the LOAD as a decision variable has been changed. The focus has been addressed to the consideration of the congestion (**Table 5**). Time dependency stipulates that the vehicle routing depends on the time of the day it travels on. In peak hours, for example, the speed fluctuates, the FC is important, and the emissions are high. TD is considered as one of the major contributors to emissions increasing in road transportation. It is generally coupled in this period with the use of the homogeneous fleet, time windows and delivery operation. Speed and load are considered in this period as parameters involved in the computing of the FC.

Table 5 GVRP studies in 2015

References	TP		TO		OF		V		C			SP	SP-DV	LO	LO-DV
	DET	STO	P/D	PD	Mo	Mu	HO	HE	TW	TD	DRI				
Jabir et al. (2015)	√		√			√	√								
Koster et al. (2015)		√	√		√		√			√					
Kramer et al. (2015a)	√		√		√		√		√		√		√		√
Kramer et al. (2015b)	√		√		√		√		√		√		√		√
Tiwari & Chang (2015)	√		√		√		√							√	
Vornhusen & Kopfer (2015)	√		√		√			√	√						√
Wen & Eglese (2015)	√		√		√		√		√	√	√	√			
Xiao & Konak (2015a)	√		√			√	√		√	√		√			

Xiao & Konak (2015b)	√	√	√		√	√	√	√	
Zhang J et al. (2015)	√	√	√	√				√	√
Zhang Z et al. (2015)	√	√	√	√					√

The focus on the load as a decision variable is back in 2016. Seventy-three percent (73%) of the publications in this year considered it explicitly. The most pertinent remark in this period is the consideration of heterogeneous fleet. As demonstrated by many authors (Moutaoukil et al. 2016), the use of heterogeneous fleet is more efficient in terms of FC and emissions than the use of the homogeneous fleet. Hsueh (2016) presents a relevant work in 2016 considering heterogeneous fleet with uncertainty affecting the speed. When using a heterogeneous fleet, two types of problems arise. The first one is the Fleet Size and Mix VRP (FSMVRP) introduced by Golden et al. (1984), in which we have an unlimited heterogeneous fleet size. The second one is the Heterogeneous Fixed Fleet Vehicle Routing Problem (H(F)VRP) proposed by Taillard (1999), considering a known fleet size in advance.

The FSM is the most used type of problems regarding its simplicity and feasibility compared to the fixed size fleet. Alinaghian & Zamani (2016) proposed an FSMVRP that minimizes a total cost composed of fixed costs, driver wage, and FC cost. After developing a MILP, the authors propose three heuristics to solve the problem. Moutaoukil et al. (2016) developed a MILP that encompasses the total cost of emissions, fixed and variable costs, in addition to social cost. The model was applied to a real agro-food real supply chain picking up parcels from different manufacturers to a collect center located in Saint-Etienne in France. Pertinent comparisons between the use of homogeneous and heterogeneous fleet were conducted and the evaluation was based on an environmental, economic, and social criterion. Afshar-Bakeshloo et al. (2016) proposed a different problematic under the Satisfactory GVRP considering a heterogeneous fleet in which three pillars of economic, environmental and customer satisfaction are considered. The proposed MILP was tested on real data from the UK.

Ene et al. (2016) developed a Hybrid Metaheuristic Algorithm (HMA) for the heterogeneous fleet VRP (HFVRP) with time windows constraints, to minimize FC and emission. Xiao and Konak (2016) considered the same case of the heterogeneous fleet and TW constraints for their proposed model. They named it, the appellation of Heterogeneous Green Vehicle Routing and Scheduling Problem. When talking about scheduling, the arrival and departure times of each vehicle at each node are considered as decision variables in the model. The proposed MILP was considered partially by solving only a sub-set of the binary variables during the search process. The authors called their mathematical model, Partial MIP (P-MIP). Moreover, they proposed an Iterative Neighborhood Search (INS) metaheuristic. The computational results of the proposed P-MIP-INS on PRPLIB instances provided the best solutions on all the instances.

When considering the number of published papers, from 2015 to 2016, the number of papers has not evolved (from 12 to 11) (cf. **Table 6**). This may be justified by the attention that has jumped to the Electric VRP. In the book-chapter proposed by Dascioglu and Tuzkaya (2019), the number of papers dealing with Hybrid VRP has jumped from15% to 33% in the time interval [2015 – 2016].

Table 6 GVRP studies in 2016

References	TP		TO		OF		V		C			SP	SP-DV	LO	LO-DV
	DET	STO	P/D	PD	Mo	Mu	HO	HE	TW	TD	DRI				
Afshar-Bakeshloo et al. (2016)	√		√		√			√	√		√		√		√
Alinaghian & Zamani (2016)	√		√		√			√			√	√			√
Dabia et al. (2016)	√		√		√		√		√		√	√			
Ene et al. (2016)	√		√		√			√	√	√				√	
Fukasawa et al. (2016)	√		√		√		√		√		√		√		√
Gang et al. (2016)	√			√		√	√		√			√			√
Hsueh (2016)		√	√		√			√				√			√
Kumar et al. (2016)	√		√			√	√		√	√			√		√
Moutaoukil et al. (2016)	√		√		√			√					√		√

Naderipour & Alinaghian (2016)	√	√	√	√			√	√	√	
Xiao & Konak (2016)	√	√	√		√	√	√	√		√

In the same line of 2014 and 2016, the LOAD as a decision variable in the developed models is in the top of interest. This is justified by the fact that this factor is being a key element in optimizing GVRPs. Efforts were conducted towards real cases studies (cf. **Table 7**).

The pertinent element in 2017 is the stochastic version of the data. An interest in such type of data is obvious. Stochasticity concerns different parameters (Shukla et al. 2017), speed (Cimen and Soysal 2017, Feng et al. 2017), demand (Liao et al. 2017), travel times (Huang et al. 2017) and sometimes both demand and travel times (Eshtehadi et al. 2017). Such type of data is very significant as the routing problems in real world cases are uncertain. From that state, real cases applications are noticed for this stochastic version of the GVRP (Liao et al. 2017 and Huang et al. 2017). Regarding the works dealing with stochastic data, we notice that the common considered characteristics are: the LOAD (as a decision variable), the homogeneous fleet, and the simple delivery (or pickup) mode. The other characteristics have been handled differently.

From these combinations, future researches in this orientation may be guided. For example, considering stochastic data with TD constraints, with the heterogeneous fleet, with simultaneous TD, TW and DRI may be investigated. Real applications to all combinations are always welcomed.

Table 7 GVRP studies in 2017

References	TP		TO		OF		V		C			SP	SP-DV	LO	LO-DV
	DET	STO	P/D	PD	Mo	Mu	HO	HE	TW	TD	DRI				
Bravo et al. (2017)	√			√		√		√	√		√		√		√
Cheng et al. (2017)	√		√		√			√		√	√		√		√
Cimen and Soysal (2017)		√	√		√		√			√	√	√			√
Eshtehadi et al. (2017)		√	√		√		√		√				√		√
Feng et al. (2017)		√	√		√		√					√			√
Franceschetti et al. (2017)	√		√		√		√		√	√	√		√		
Huang et al. (2017)	√	√	√		√		√		√	√		√			√
Jabir et al. (2017)	√		√		√		√						√		√
Jemai et al. (2017)	√		√			√	√						√		√
Kaabachi et al. (2017)	√		√			√	√		√			√			√
Liao et al. (2017)		√	√		√		√		√			√			√
Majidi et al. (2017)	√			√	√		√		√				√		√
Mirmohammadi et al. (2017)	√		√		√			√	√	√		√		√	
Nabil et al. (2017)	√		√		√			√	√	√			√		
Norouzi et al. (2017)	√		√			√	√			√		√			√
Oliveira et al. (2017)	√		√		√		√					√		√	
Saka et al. (2017)	√		√		√			√	√		√		√		√
Setak et al. (2017)	√		√		√		√			√	√	√			√
Shukla et al. (2017)		√	√		√		√		√		√	√			√
Xiao and Konak (2017)	√		√		√			√	√	√		√			√
Zhou and Lee (2017)	√		√		√		√						√		√
Ziebuhr et al. (2017)	√		√		√			√							√

In the scholars published in 2018 (cf. **Table 8**), the attention is not focused on one characteristic than others. These papers are considering the already existent variants and related features highlighted above. The heterogeneous fleet is not targeted in this period, while the load as a decision variable and the TW constraints are the most adopted characteristics. For the stochasticity, 33% of the papers treated this version of uncertain data. In Rabbani et al. (2018), the authors developed a multi-objective MIP: (*i*) minimizing the total transportation cost, traffic pollution, customer dissatisfaction, and (*ii*) maximizing the reliability of vehicles. A simulated annealing metaheuristic is applied, and the proposed approach is tested on real data of a food distribution company located in Tehran, Iran. This paper is also the first one in formulating the resiliency and considering the reliability in GVRP with stochastic data. In Li et al. (2018), the problem of cold chain logistics, requiring the maintenance of low temperatures during the distribution to keep the products fresh and safe, is tackled. Such problem is more fuel consuming compared to classic routing problems as the maintaining of low temperatures during the transportation and the unloading, is crucial. A multi-objective model coupled with a Particle Swarm Optimization (PSO) algorithm and a modified PSO algorithm are proposed and tested on real data of a cold chain distribution company based in Chongqing, China. In a similar context, Soysal et al. (2018) proposed a green inventory routing problem for perishable products and studied a case study of two suppliers in Turkey. In Niu et al. (2018), the proposed MILP model and tabu search algorithm for the open GVRP with time windows were tested on real Chinese data. Zhang et al. (2018) tested their green vehicle routing and scheduling problem with time-varying speeds coupled with an adaptive large neighborhood search algorithm on real data of a supermarket chain in Changsha, Zhuzhou and Xiangtan, Hunan province of China.

A pertinent key element in the year 2018 is the focus on real applications. Such fact is justified by the abundance of researches and theoretical results on different variants of GVRP needing experimental support.

Table 8 GVRP studies in 2018

References	TP		TO		OF		V		C			SP	SP-DV	LO	LO-DV
	DET	STO	P/D	PD	Mo	Mu	HO	HE	TW	TD	DRI				
Balamurugan et al. (2018)	√		√		√		√					√			√
Eshtehadi et al. (2018)		√	√		√		√		√		√		√		√
Kancharla & Ramadurai (2018)	√		√		√			√				√			√
Li et al. (2018)	√		√		√		√		√			√			√
Liu et al. (2018)	√		√		√		√		√				√		
Matos et al. (2018)	√		√		√			√	√	√					√
Niu et al. (2018)	√		√		√		√		√		√		√		√
Rabbani et al. (2018)		√	√			√		√	√	√	√				
Soysal et al. (2018)		√		√	√		√			√	√				√
Zhang et al. (2018)	√		√		√		√		√	√	√		√		√

Table 9 GVRP studies in 2019

References	TP		TO		OF		V		C			SP	SP-DV	LO	LO-DV
	DET	STO	P/D	PD	Mo	Mu	HO	HE	TW	TD	DRI				
Ai et al. (2019)	√		√			√		√	√		√				√
Dagne et al. (2019)	√		√		√		√								√
Ghannadpour & Zarrabi (2019)	√		√			√		√	√						√
Li et al. (2019)	√		√			√	√								√
Su et al. (2019)	√		√		√		√		√				√	√	
Wang, R., et al. (2019)	√		√		√		√		√						
Wang, Y., et al. (2019)	√		√		√		√		√	√		√		√	
Xu et al. (2019)	√		√			√	√		√	√		√		√	
Yu et al. (2019)	√		√		√			√	√					√	
Zulvia et al. (2019)	√		√			√	√		√	√				√	

After covering most of the extensions related to the GVRP, the recent researches of year 2019 (cf. **Table 9**) focused on multi-objective models were more than one objective is to be optimized. Such problems are hard to solve. Li et al. (2019) and Wang, Y., et al. (2019) treated multi objective GVRP were also multi depot is considered. Xu et al. (2019) proposed a multi-objective model that simultaneously minimizes the total expected FC and maximizes the customer satisfaction by considering soft time windows constraints, fuel consumption functions, non-linear time-varying vehicle speed, and traffic congestion. The proposed approach shows that significant reduction in carbon emissions can be reached with an insignificant decrease in customer satisfaction. Such results encourage firms to adopt green operations in their strategies. Zulvia et al. (2019) proposed a multi objective model for the GVRP of perishable products. The problem minimizes operational costs, deterioration costs (loss incurred by the deterioration of the product’s quality), and carbon emissions. It also maximizes the customer satisfaction. A many-objective gradient evolution algorithm is developed and tested on real case study of a fruit company located in Indonesia. The results show that the algorithm outperforms the results obtained by MOPSO (multi-objective particle swarm optimization), NSGA II (non-dominated sorting genetic algorithm II) and MODE (multi-objective differential evolution) algorithms in terms of diversity and convergence.

Based on the lecture of the data provided in **Table 9**, a response has been elaborated to **RQ2** and general conclusions may be stated as follows:

(i) From one year to another, the tendencies in research directions change. The peak was reached in 2017, and since that date the attention is being addressed to alternative fuel vehicles.

(ii) It is not easy to publish in this domain because almost everything is covered.

4.2. Multi- level optimization problems

In this class, problems aiming at minimizing the routing in different echelons of the forward logistics are grouped. Two major problems may be assigned to this class:

4.2.1. The two-echelon GVRP (2E-GVRP)

The two-echelon vehicle routing problem (E-VRP) is a typical problem in City Logistics. This concept was first discussed by Taniguchi et al. (1999) under the definition: 'the process for totally optimizing 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'. The express courier and parcel services (CEP) is a prime example of City Logistics dealing with last-mile deliveries. The effective assignment of vehicles to routes concerns the CEP to deliver parcels to exigent customers scattered in cities areas.

The particularity of this class of problems is that the delivery to the final customer may not be direct. The first level routing concerns the movement of goods from depot to “satellites”, while the second level (echelon) concerns the transshipment of goods from satellites to customers. Vehicles dedicated for the first echelon are generally of larger capacity than those (i.e., city vans) insuring the second echelon. This type of problems is known under the appellation two-echelon problems. This class of GVRP has been reviewed by Cuda et al. (2015) and tackled recently by Bektaş et al. (2019).

In **Table 10**, we group related references appearing after the survey of 2015 considering environmental issues (2E-GVRP). In the 2E- VRP, a satellite may be visited by more than one vehicle at the first level, in contrast to the second level where a customer is required to be serviced exactly once by a vehicle. From this state, the split deliveries are allowed at the first level only. A 2E-VRP aims at finding the set of routes for both first and second level, while minimizing also total routing cots and handling fees subject to different constraints. The 2E-GVRP extends this definition by adding environmental objectives.

Table 10 Papers devoted to the 2E-GVRP

References	TP		TO		OF		V		C			SP	SP-DV	LO	LO-DV
	DET	STO	P/D	PD	Mo	Mu	HO	HE	TW	TD	DRI				
Soysal et al. (2015)	√			√	√		√			√	√	√			√
Anderluh et al. (2017)	√			√	√		√		√		√	√			√
Tricoire & Parragh (2017)	√			√		√		√							
Wang et al. (2017)	√			√	√		√				√				√
Marinelli et al. (2018)	√			√	√		√							√	
Wang et al. (2018)	√			√		√	√				√			√	
Babagolzadeh et al. (19)	√			√	√		√		√			√			√

Kancharla & Ramadurai (2019)	√	√	√	√	√	√

From **Table 10**, the number of papers from 2015 to 2019 is obviously growing, but small compared with one-echelon problems. The first paper of Crainic et al. (2012) is among the first ones to address green issues in the 2E-VRP, followed by multiple efforts to consider environmental issues into 2E-VRP. Soysal et al. (2015) tackle for the first time the 2E-Capacitated VRP (2E-CVRP) with time dependency that considers FC explicitly by using the Comprehensive Modal Emissions Model (CMEM). The time-dependent speeds are found only in the second echelon. The developed MILP is tested on real data for a supermarket located in the Netherlands. The authors compared results of single echelon and two echelons: the proposed 2E-CVRP provides a better environment friendly solution than the single echelon, which has a lower total cost solution. Tricoire and Parragh (2017) propose Green City Hub Location Routing Problem (GCHLRP). The developed MILP aims at minimizing simultaneously two objectives: minimizing the cost of strategic investments and emissions. This bi-objectivity aims at studying the trade-off between strategic costs (facility locations and fleet size and mix decisions) and future operational emissions. Marinelli et al. (2018) present a major contribution is their paper: the first paper to evaluate the environmental impact of the final solutions. Kancharla and Ramadurai (2019) extended the 2E-VRP with Multi-Depot by including load-dependent fuel minimization objective and a heterogeneous fleet. The proposed model is a Multi Depot two Echelon Fuel Minimizing Routing Problem (MD2E-FMRP) with a mixed fleet.

As a major deduction from **Table 10**, is the focus on the real applications. The 2E-GVRP is closely related to new lifestyle of shopping and consumption, especially the e-commerce. This fact justifies the efforts of real case studies consideration.

4.2.2. Cross-docking problem

In the same line with the 2E-VRP, the cross-docking problem concerns two levels of routing. The major difference is the storage. In fact, in cross-docking, the intermediate distribution center (=cross-dock) is obligatory present, and the storage of goods is prohibited. As a result, inventory costs are reduced, and deliveries are timely. The process consists of unloading goods from an inbound vehicle (that had already visited some suppliers to collect orders) into a cross-dock. In this latter, the products are sorted, and the storage must not exceed 24 hours. Five main activities are obligatory done in a cross-dock: receiving, sorting, storing, retrieving, and shipping. After sorting the goods according to the orders of customers, the reloading process into outbound vehicles is done to the final customer destination. The cross-docking also has the advantage of combining materials from different origins. A representative example of a successful cross-docking system is the FedEx and Home Depot companies. From an operations research view, the paper developed by Yin and Chuang (2016) is the first research work that adds the green discussion for a cross-dock system. The emissions are minimized through optimized management of the dynamic changes. The FC efficiency is considered as an important optimization factor. The authors modeled the VRP in a cross-dock system minimizing the total transportation and operational costs. In the paper proposed by Abad et al. (2018), the authors stated that their work is the second one for considering environmental considerations in the cross-docking system. They proposed a mathematical model minimizing the total system costs and FC. Three metaheuristic algorithms were developed to solve the proposed model: Non-dominated Ranking Genetic Algorithm (NRGA), Non-dominated Sorting Genetic Algorithm (NSGA-II), and Multi-Objective Particle Swarm Optimization (MOPSO). Even if the cross-docking has been widely studied, the environmental considerations are at the beginning of the investigation.

5 Recapitulation of the tendencies in GVRP studies

To evaluate the existent rich data base of works dealing with different extensions of the GVRP, we refer to the seminal papers of 2014 proposed by Lin et al. (2014) and Demir et al. (2014). Then, we will check if the recommended future directions highlighted in these both reviews are considered or no in forthcoming papers.

Through this approach, we aim to shed light on the treated propositions in these two papers, and if there are directions in the GVRP that are still unexplored.

In **Table 11**, future directions (**FD**) proposed by are grouped and responses (**R**) to each one is provided based on the analyzed papers in this survey.

Table 11 The future directions proposed by *Lin et al.* (2014) and *Demir et al.* (2014) and responses

References	Deductions and proposed future directions	Responses from the literature
Lin et al. (2014)	FD1: Although the number of the publications on GVRP is growing, the studies are still limited.	R1: The number of papers has jumped since 2014 till 2019. In this survey, more than 100 papers appearing from 2014 were covered.
	FD2: More realistic experimental data and real-world cases that support the research still need to be provided by government or other official organizations.	R2: Real case studies are conducted since 2014 on different variants and on diverse countries (i.e., Spain, London, France, China, Egypt, Iran, and the Netherlands). Around the quarter of the total number of analyzed papers test their models on real data.
	FD3: Stochastic service time, stochastic traveling time as well as stochastic customer demand are neglected.	R3: Since 2014, stochasticity has been considered in several models. 2017 was characterized by intensive studies on stochastic parameters: demand, speed, travel time and other parameters.
	FD4: Using the fuzzy theory, future studies may explore the trade-off between customer satisfaction, environmental and economic costs.	R4: Afshar-Bakeshloo et al. (2016) have developed a Satisfactory GVRP that, in addition to the traditional objectives of the VRP (economic cost), minimizes the pollution (environmental pillar) and maximizes the satisfaction of customers determined by service level.
	FD5: It is well worth exploring whether a multi-echelon vehicle dispatching system has a significant impact on reducing overall energy consumption and emissions.	R5: Multi echelon and specifically 2-E GVRP have been studied in the last years: e.g., Soysal et al. (2015), Wang et al. (2017), etc.
	FD6: Only TW and capacity constraints are covered (for the G-VRP)	R6: Other constraints have also been considered: time dependency, driver's wage, stochastic data, etc.
	FD7: Heterogeneous fleet is still not explored. To what extent a mixed fleet might contribute to reducing the energy consumption? (for the G-VRP)	R7: Several studies have been developed on heterogeneous fleet. Since 2016, intensive attention has been addressed to the development of models using heterogeneous fleet. Moutaoukil et al. (2016) stated that the use of heterogeneous fleet is more efficient in terms of FC and emissions than the use of the homogeneous fleet.
	FD8: Considering heterogeneous fleet and time dependency (for the PRP)	R8: This future direction was considered later by Koc et al. (2014), Bravo et al. (2017), Saka et al. (2017), etc.
	FD9: Higher variation in customer demand may decrease the energy consumption (for the PRP)	R9: Eshtehadi et al. (2017, 2018) developed a PRP using stochastic demands and travel times. ➔ Tajik et al. (2014) studied both deterministic and stochastic fuel consumption cost, CO_2emissions, travel and service times.
Demir et al. (2014)	FD10: Most of the studies consider speed and load in their formulations.	R10: the speed and load are the most used decision variables since 2014. The load is the most used in almost developed models. Other tendencies have been depicted since 2014: time dependency, stochasticity, heterogeneous fleet, cross-docking, city logistics. However, there is still room for other constraints like the consideration of the split delivery which was considered only by Vornhusen and Kopfer (2015) and Matos et al. (2018).
	FD11: Driver behavior and road gradient are mostly studied in eco-routing studies with the help of GIS software. Driver working hours should be considered in	R11: Many papers had considered the drivers related constraints in modeling: more than the one third of the papers analyzed used such constraints.

	the green logistics studies because of law requirements, as well as the acknowledged health hazards arising from intensive workload of some routing plans. Although some of the available studies could conceivably be modified to reflect these types of real-life requirements, this issue still requires further attention.	
	FD12: Fleet size and mix are attracting increasing attention.	R12: Confirmed. The year 2016 has seen intensive focus on the heterogeneous fleet, with major works on fleet size and mix VRP. Since that time, this kind of problems has attracted much attention.
	FD13: COPERT at a macroscopic level and CMEM at a microscopic level are the most used models.	R13: CMEM is the most used microscopic model, followed by the macroscopic MEET and the FCR, respectively.
	FD14: Heuristics are the mostly used solution approaches.	R14: Metaheuristics coupled with mathematical models are the most used approaches. See Section 5.2.
	FD15: Most studies in the field of green road freight transportation have focused on a limited number of factors, mainly vehicle load and speed	R14: Other factors have been considered, see R10.
	FD16: Besides CO_2e emissions, other traffic externalities could be examined at local and regional levels, such as other pollutants, noise, accidents, and environmental damage.	R16: See externalities' section 3.2.2.
	FD17: Multi-objective optimization may come to play a vital role in green road transportation studies.	R17: Many authors developed multi-objective models to deal with different GVRP extensions: Bravo et al. (2017), Ghannadpour and Zarrabi (2019), Jabir et al. (2015), Jemai et al. (2017), Shukla et al. (2017).
	FD18: Other problems related not only to routing are encouraged like the facility location problem, the depot relocation problem (first attempts in such directions have already appeared in 2011).	R18: We may refer to the City logistics part: Koc et al. (2016).

The comments on each future direction proposed by both Lin et al. (2014) and Demir et al. (2014) are provided in **Table 11** elaborating a **Response to RQ4**. From FD numbers 1-12, the responses were already developed by the previous analysis in the earlier sections. In the following FDs, the answers are provided, in next sections, based on additional data and details of the analyzed papers.

5.1. Used methods in FC calculation

In **Table 12**, the most used models of fuel consumption used in the analyzed literature are grouped. In the first rank, the Comprehensive Modal Emissions Model (CMEM) firstly introduced by Barth et al. (2005) and Barth and Boriboonsomsin (2008) is placed. It takes into account detailed vehicle-specific parameters for the estimations and is composed of three modules: the engine power, the engine speed, and the fuel rate. This microscopic model is very often used regarding its easy application.

The methodology for calculating transportation emissions and energy consumption (MEET) proposed by Hickman et al. (1999) is a well-known macroscopic model. It is often used for the emissions estimations. The Fuel Consumption Rate (FCR) developed by Xiao et al. (2012) and considering a load dependent function was the less used model of estimation. Even if it is a simple model in terms of structure and application, this recent model has not received adequate attention.

Table 12 The used FC models

FC models	References

CMEM	Demir et al. (2014) ; Koc et al. (2014); Kramer et al. (2015a); Soysal et al. (2015); Xiao and Konak (2015); Afshar-Bakeshloo et al. (2016); Alinaghian & Zamani (2016); Dabia et al. (2016); Fukasawa et al. (2016); Gang et al. (2016); Koc et al. (2016); Kumar et al. (2016); Xiao and Konak (2016); Bravo et al. (2017); Cheng et al. (2017); Eshtehadi et al. (2017); Feng et al. (2017);Franceschetti et al. (2017) ; Huang et al. (2017); Kaabachi et al. (2017); Liu et al. (2017); Majidi et al. (2017) ; Saka et al. (2017); Eshtehadi et al. (2018); Kancharla and Ramadurai (2019); Niu et al. (2018); Soysal et al. (2015); Wang Y., et al. (2019);
MEET	Ayadi et al. (2014); Elbouzekri and El Hilali (2014); Xiao and Konak (2015); Vornhusen and Kopfer (2015); Moutaoukil et al. (2016); Naderipour and Alinaghian (2016); Cimen and Soysal (2017); Nabil et al. (2017); Oliveira et al. (2017); Xiao and Konak (2017);
FCR	Zhang et al. (2014); Zhang Z et al. (2015); Jemai et al. (2017);

5.2. Used optimization methods

We summarized all proposed optimization methods to solve different extensions of GVRP in **Table 13**. Different approaches were used: the exact method coupled with or sometimes without a mathematical model is the second more used key of resolution with nearly the quarter of the analyzed papers in this work (**Fig.4**). When developing a mathematical model, authors generally use approximate methods to solve the instances of larger size. Mathematical Model (Math) may be coupled with metaheuristics (M) (nearly half of the papers used this approach), heuristics (H) or sometimes hybridization of both methods. Heuristics and metaheuristics may be used alone without exact methods. We should notice that only a few papers have developed matheuristic (Mh) to deal with GVRP.

A year-by-year evaluation of the methods used in all the covered literature in this review is proposed. From this, we represented a chronological perspective of optimization methods' progress (cf. **Fig.5**). Based on the presented repartition, we elaborated a response to the **FD (14)**. The tendencies in the methods of optimization applied for the GVRPs from 2014 to 2019 have changed. The heuristics are no more the most used approximate methods. The metaheuristics, coupled with mathematical models, are the most applied methods along the covered period, followed by the use of exact methods (**Response to RQ3**). This deduction is available for all the period from January 2014 to December 2019 except the year 2015, in which metaheuristics and heuristics coupled both of them with mathematical models are the most used. The simplicity of metaheuristics' implementation, the satisfactory solutions found, and the NP-hardness of the GVRP may justify this important use of this class of methods.

Table13 Literature on GVRPs

Reference	GVRP's extension	Exact Method	Solution Approach	Case Study
1. Ayadi et al. (2014)	GVRPM	√	M	-
2. Demir et al. (2014)	PRP	√	M	-
3. Elbouzekri & El Hilali (2014)	GVRP	√	M	-
4. Koc et al. (2014)	FSMPRP	√	H,M	-
5. Molina et al. (2014)	HVRP	√	H	√
6. Qian and Eglese (2014)	GVRP	√	H	√
7. Tajik et al. (2014)	TWPDPRP	√	-	-
8. Zhang et al. (2014)	EVRP	√	M	-
9. Jabir et al. (2015)	MDVRP	√	M	-
10. Koster et al. (2015)	DVRPSTD-TM	-	H	-
11. Kramer et al. (2015a)	PRP	-	Mh	-
12. Kramer et al. (2015b)	PRP	-	H	-
13. Soysal et al. (2015)	2E-CVRP	√	-	√
14. Tiwari and Chang (2015)	GVRP	√	H	√
15. Vornhusen and Kopfer (2015)	EVRPTWSD-VC	√	-	-
16. Wen and Eglese (2015)	VRPTW	√	H	√
17. Xiao and Konak (2015a)	GVRSP	√	M	-
18. Xiao and Konak (2015b)	GVRSP	√	M	-

19. Zhang J et al. (2015)	LCRP	√	H	-
20. Zhang Z et al. (2015)	3L-FCVRP	-	M	-
21. Afshar-Bakeshloo et al. (2016)	S-GVRP	√	-	-
22. Alinaghian and Zamani (2016)	FSMGVRP	√	H	-
23. Dabia et al. (2016)	PRP	√	-	-
24. Ene et al. (2016)	HFVRP	-	M	-
25. Ehmke et al. (2016)	EMP	-	H	√
26. Fukasawa et al. (2016)	PRP	√	-	-
27. Gang et al. (2016)	GVRSP	√	M	-
28. Hsueh C-F (2016)	GVRP	√	M	-
29. Kumar et al. (2016)	MMPPRP-TW	√	M	-
30. Koc et al. (2016)	GVRP	√	M	-
31. Moutaoukil et al. (2016)	FSMVRP	√	-	-
32. Naderipour and Alinaghian (2016)	OTDVRP	-	M	-
33. Qian & Eglese (2016)	GVRP	-	H	√
34. Xiao and Konak (2016)	HGVRSP	√	M	-
35. Anderluh et al. (2017)	2E-VRP	√	M	√
36. Bravo et al. (2017)	PRP	√	M	-
37. Cheng et al. (2017)	IRP	√	-	-
38. Cimen and Soysal (2017)	GSTDCVRP	-	H	-
39. Eshtehadi et al. (2017)	PRP	√	-	-
40. Feng et al. (2017)	VRPFSV	√	M	-
41. Franceschetti et al. (2017)	TDPRP	-	M	-
42. Hosseini-Nasab and Lotfalian (2017)	GVRP	√	-	√
43. Huang et al. (2017)	TDVRP–PF	√	-	√
44. Jabir et al. (2017)	MDGVRP	√	M	-
45. Jemai et al. (2017)	bi-GVRP	√	M	-
46. Kaabachi et al. (2017)	GMDVRPTW	√	M	-
47. Liao (2017)	On-line VRP	√	M	√
48. Liu et al. (2017)	GVRPTW-PF	√	-	-
49. Majidi et al. (2017)	PRPSPD	√	M	-
50. Mirmohammadi et al. (2017)	PGVRP-TD-TW	√	-	-
51. Nabil et al. (2017)	GVRSP	√	-	√
52. Norouzi et al. (2017)	TDVRP	√	-	-
53. Oliveira et al. (2017)	CVRP	-	M	√
54. Saka et al. (2017)	PRP	√	H,M	-
55. Setak et al. (2017)	TDPRP	√	M	-
56. Shukla et al. (2017)	NF-PRP	√	M	-
57. Tricoire & Parragh (2017)	GCHLRP	√	-	√
58. Wang et al. (2017)	2E-CVRP-E	-	Mh	-
59. Xiao and Konak (2017)	TD-VRSP-CO_2	√	M	-
60. Zhou and Lee (2017)	GVRP	√	H	-
61. Ziebuhr et al. (2017)	EVRP-VC	√	H	-
62. Balamurugan et al. (2018)	IRP	√	M	-
63. Eshtehadi et al. (2018)	PRP	√	H,M	-
64. Kancharla and Ramadurai (2018)	MDCVRP	√	-	-
65. Li et al. (2018)	GVRPCCL	√	M	√
66. Liu et al. (2018)	GVRP	-	H	-
67. Marinelli et al. (2018)	2E-CVRP-E	√	-	-
68. Matos et al. (2018)	GVRSP-SPLIT	√	H	-
69. Niu et al. (2018)	GOVRPTW	√	M	√
70. Rabbani et al. (2018)	STDGCVRSP	√	M	-
71. Soysal et al. (2018)	IRP	√	-	-
72. Wang et al. (2018)	2E-CMCVRP	√	M	√
73. Zhang et al. (2018)	GVRSP	√	M	√
74. Ai et al. (2019)	VRPTW	√	-	√
75. Babagolzadeh et al. (2019)	2E-OVRP-E	√	-	-
76. Dagne et al. (2019)	GVRPMD	√	M	-
77. Ghannadpour and Zarrabi (2019)	VRPTW	√	M	-
78. Kancharla and Ramadurai (2019)	MD2E-FMRP	√	M	-

79.	Li et al. (2019)	MDGVRP	√	M	-
80.	Su et al. (2019)	GVRP	√	-	-
81.	Wang R., et al. (2019)	GFVRP	√	H	-
82.	Wang Y., et al. (2019)	MDGVRP	√	M	-
83.	Xu et al. (2019)	GVRP	√	M	-
84.	Yu et al. (2019)	HFGVRPTW	√	-	-
85.	Zulvia et al. (2019)	GVRP	√	M	√

GVRPM: Green Vehicle Routing Problem with Multiple trips; **GVRSP**: Green Vehicle Routing and Scheduling Problem; **S-GVRP**: Satisfactory GVRP; **FSMGVRP:** Fleet Size & Mix GVRP; **HGVRSP**: Heterogeneous Green Vehicle Routing and Scheduling Problem; **GVRPMD/MDGVRP**: Multi Depot capacitated GVRP; GVRPSPTD: **GVRPCCL**: GVRP for Cold Chain Logistics; **STDGCVRSP**: Stochastic Time-Dependent Green Capacitated Vehicle Routing and Scheduling Problem; **HFGVRPTW**: Heterogeneous Fleet GVRP with Time Windows; **GVRPTW-PF**: GVRP with Time Windows and Path Flexibility**; PGVRP-TD-TW**: Periodic GVRP with Time Dependent and Time Windows; **FSMPRP**: Fleet Size & Mix Pollution Routing Problem; **TWPDPRP**: Time Windows Pickup & Delivery PRP; **MMPPRP-TW**: Multi-objective Multi-vehicle Production and PRP with Time Windows; **TDPRP**: Time Dependent PRP; **PRPSPD**: PRP with Simultaneous Pickup & Delivery; **NF-PRP**: NSGA-II based fuzzy PRP; **EVRP**: Environmental vehicle Routing Problem; **EVRP-VC**: Emissions minimizing VRP with Vehicle Classes; **EVRPTWSD-VC**: Emission VRP with Time Windows, Split Delivery and Vehicle Classes; **EMP**: Emissions Minimizing Paths; **HVRP**: Heterogeneous Vehicle Routing Problem; **HFVRP**: Heterogeneous Fleet Vehicle Routing Problem; **MDVRP**: Multi Depot VRP; **MDCVRP**: Multi Depot Capacitated VRP; **GMDVRPTW**: Green Multi Depot VRP with Time Windows; **VRPTW**: VRP with Time Windows; **VRPFSV**: VRP with Fuel consumption and Stochastic speeds; **OTDVRP**: Open Time Dependent VRP; **TDVRP-PF**: Time Dependent VRP with Path Flexibility; **GOVRPTW**: Green Open VRP with Time Windows; **TD-VRSP-CO_2**: Time Dependent Vehicle Routing & Scheduling Problem with CO_2 consideration; **DVRPSTD-TM**: Dynamic VRP with Stochastic Time-Dependent travel times and Traffic Management control; **GSTDCVRP**: Green Stochastic Time-Dependent Capacitated VRP; **LCRP**: Low Carbon Routing Problem; **IRP**: Inventory Routing Problem; **3L-FCVRP**: 3-Loading constraints Fuel Consumption VRP; **2E-CVRP**: 2E-Capacitated VRP; **GCHLRP**: Green City Hub Location Routing Problem; **2E-CVRP-E**: 2E-CVRP with Environmental considerations; **2E-CMCVRP**: two-echelon collaborative multiple centers vehicle routing problem.; **2E-OVRP-E**: 2E-Open VRP-with Environmental considerations; **MD2E-FMRP**:Multi Depot 2 Echelon Fuel Minimizing Routing Problem;

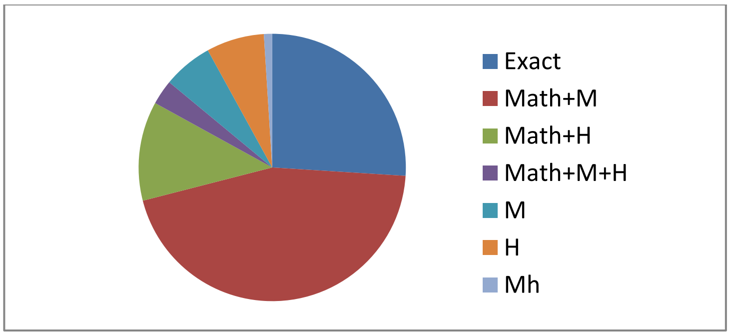

Fig.4 Distribution of the papers according to the optimization method

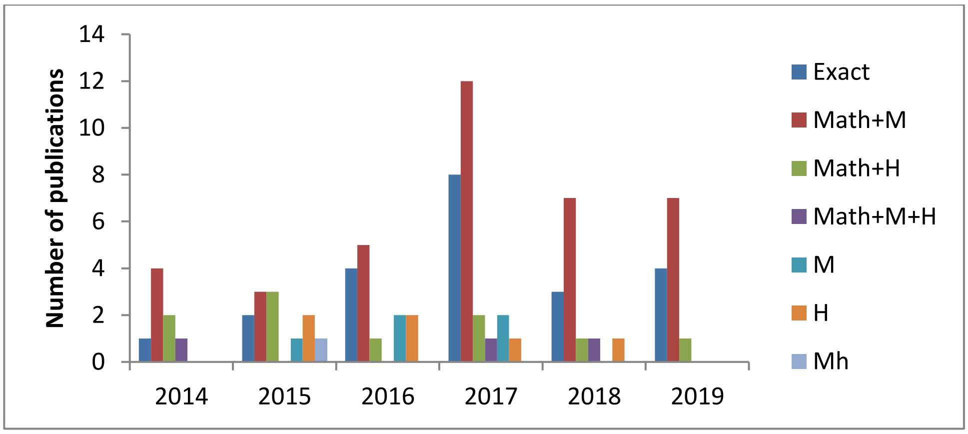

Fig.5 Repartition of the methods of optimization per year

6 Discussion

Based on the collected papers and on the adopted taxonomy, we test the robustness of our approach: do the proposed attributes and classification cover the majority of the papers?

It is evident, from a global observation of tables, that some cells remain empty. This means that the corresponding publications do not cover that attribute. However, these blank cells leave only 6% of the end-nodes (DV) of the tree, representing the consideration of the load and/or speed in the problem definition.

94% of the analyzed publications consider the load and speed as important factors of emissions in their GVRP modeling. For the columns, the less marked column is the attribute STO (stochastic data) with only 14% of the overall number of publications considering this type of operations. This percentage is followed by the attributes PD (pickup and delivery) with 15% and load as a parameter, appearing in 16% of the papers. The stochastic data remains hard task to tackle regarding the lack of efficient methods of optimization and prediction. In contrast to the 16% of the attribute load as parameter affecting the emissions or FC, the definition of the load as a decision variable represents 65% of the overall publications. This shows the importance of this attribute when dealing with GVRPs. Routing with homogeneous fleet is the commonly used type of vehicles, but the attention is being directed also to the heterogeneous fleet appearing in almost the third of the publications. The use of heterogeneous fleet of vehicles shows important savings in terms of emissions. Time windows are the most commonly defined constraints (59% of all the papers), followed by the driver wages and time dependency (appearing in 34% and 31% of the overall number of the publications treating one-level optimization problems, respectively).

All these percentages show the effectiveness of the considered attributes in describing GVRP and its common extensions. The proposed approach classifies more than 85 publications published in refereed journals during the period 2014-2019. We intend that this taxonomy will enable beginners in the GVRP field to have a sufficient and detailed background on the latest contributions. The tests of the taxonomy applied on disparate articles dealing with the GVRP approve the robustness of the defined attributes in describing a GVRP. A general conclusion that may be conducted is that the GVRP has been well covered and therefore, the research in this topic becomes challenging. For this, we propose in the next section some data that may help any researcher in this filed hoping to develop or to deal with uncovered problematics. For this reason, we present the main benchmark tests used in the literature. A representation of the most used factors in the developed extensions of the GVRPs and a combination of these factors are studied and described.

6.1.Benchmark instances

The well-known PRPLIB proposed by Demir et al. (2012) are the most used in the literature (cf. **Table 14**). This benchmark contains nine groups. Each one of them is composed of 20 instances. The whole benchmark is based on real data collected from UK cities. Each instance is characterized by the number of customers, the vehicle curb weight, the maximum payload, maximum and minimum speed level, and the distance between nodes. Other benchmarks are used in the literature but with smaller frequencies. Future works may be conducted on developing some instances for the GVRP with heterogeneous fleet and split delivery. Such benchmarks do not exist for GVRPs.

Table 14 Benchmark test instances

Instance	Reference
CVRP (*Christofides, Mingozzi, and Toth 1979*)	*Elbouzekri and El Hilali* (2014)*; Oliveira et al.* (2017) ;
SOLOMON instances (*Solomon 1987*)	*Zhang et al.* (2014); *Vornhusen and Kopfer* (2015); *Dabia et al.* (2016) ; *Ene et al. (2016)* ; *Norouzi et al.* (2017) ; *Ghannadpour and Zarrabi (2019)*; *Yu et al. (2019)* ;
AUGERAT instances (*Augerat et al. 1995*)	*Alinaghian & Zamani* (2016); *Ene et al.* (2016) ; *Naderipour and Alinaghian* (2016) ;
PRPLIB (*Demir et al. 2012*)	*Demir et al.* (2014) ; *Koc et al.* (2014) ; *Kramer et al.* (2015a); *Kramer et al.* (2015b); *Hsueh C-F* (2016) ; *Kumar et al.* (2016) ; *Xiao and Konak* (2016) ; *Fukasawa et al.* (2016); *Eshtehadi et al.* (2017); *Bravo et al.* (2017) ; *Cimen and Soysal* (2017) ; *Feng et al.* (2017) ; *Franceschetti et al.* (20147); *Kaabachi et al.* (2017) ; *Shukla et al.* (2017) ; *Zhou & Lee* (2017) ; *Majidi et al.* (2017) ; *Saka et al.* (2017) ; *Xiao and Konak* (2014) ; *Eshtehadi et al.* (2018) ; *Wang Y., et al. (2019)* ;
ELBOUZEKRI instances (*Elbouzekri et al. 2013*)	*Ayadi et al.* (2014) ;
KOPFER instances (*Kopfer et al. 2014*)	*Ziebuhr et al.* (2017) ;
KRAMER instances (*Kramer et al. 2015a*)	*Kramer et al.* (2015a) ; *Kramer et al.* (2015b) ; *Fukasawa et al.* (2016);
VRPLIB	*Jemai et al.* (2017);
EILON data (*Christofides & Elion 1969*)	*Elbouzekri and El Hilali* (2014); *Zhang et al.* (2014) ; *Zhang J et al.* (2015); *Kancharla and Ramadurai* (2019) ;

VRP instances (*http://www.bernabe.dorronsoro.es/vrp/*)	*Tiwari and Cheng* (2015)*;*

6.2. Combinations

In the same line with the data mentioned above, we try along this review to supply the reader with interesting and useful information concerning the GVRP. Based on this we present a classification of the analyzed papers using a combination of the used constraints, version of the model, nature of the fleet used and defined objective functions. In **Appendix A**, we assign each paper to its corresponding combination. The most studied problems are the most basic formulations: deterministic data for a fleet of homogeneous vehicles to minimize the emissions (or FC). The time windows constraints are the most applied. Also coupling the objective of emissions (or FC) minimization with total transportation cost minimization (TTC) is largely studied. The adopted approach of combination draws a clear idea about the already considered problematics and those needing to be more explored. As previously mentioned the split delivery has not yet received deserved attention. Concerning the stochastic data, efforts are made to implement this version into GVRPs extensions. However this version is focusing on homogeneous fleets more than heterogeneous, which reflect real situations more than the homogeneous vehicles. Different combinations could be extracted from the Appendix leading to further contributions.

7 Conclusions

In this survey, we conducted an up-to-date reviewing of the latest papers dealing with GVRP. Even if the problem dates for 2007, the literature on this topic is rich with several studies and reviews. The summary of the contributions of this review provide a **response to RQ5** and are the followings:

- A review of the recent surveys appearing after 2014 as one of the major contributions of this paper. We also considered and analyzed the reviews published after the two seminal surveys proposed by Demir et al. and Lin et al. in 2014. The major contributions of each reviewed state-of-the-art are highlighted.
- The in-deep analysis of the recent reviews with their main added values in the topic constitutes the basis of this review. In fact, proposed future directions in the last reviews and the studied axes already studied are considered as pillars of the discussion section.
- A new taxonomy of the studied GVRP and related extensions is proposed according to the optimization level. An exhaustive rich list of papers was classified based on these classes.
- Optimization methods were one of the most important pillars of this survey. We show through the chronological enumeration of the used optimization methods that the metaheuristics (coupled with mathematical models) is the most proposed approach to solve the GVRP.
- We provide the reader with some useful information about the benchmarks used in this type of routing problems.

Even if the GVRP seems to be well covered, there is also room for practical research ideas. The field is now open to innovation. Moreover, the GVRP with split delivery seems to be still uncovered. Real-life applications are always needed.

We set a trend for the GVRP and identify the following areas as further research directions.

- Reducing negative externalities create various benefits not only to the environment but also to logistics companies. Although many studies focused on only CO_2 or CO_2 equivalent emissions, further attention to other externalities is required like layer depletion, human toxicity, acidification and, etc.,.
- One interesting area is to look at (semi-)autonomous vehicles in the domain of green routing. New models and applications will be needed to reflect the environmental concerns for the upcoming technologies.
- Many studies consider only deterministic network parameters. As we know, especially congestion leads to uncertain travel times and it affects the amount of fuel consumed. Therefore, there is a need to look at stochastic and dynamic studies to capture the real characteristics of the GVRPs.

- Several variants applied for the classic VRP had been conducted to the GVRP. Nevertheless, some variants were not explored like the site-dependent GVRP. In addition, there is still room for combined constraints, like multi-compartment GVRP with time windows, time-dependent constraints and heterogeneous fleet. Investigation in such combinations is welcomed.
- There are several approximate solution methodologies for the solution of GVRPs. However, due to the complexity of these problems, the efforts on exact methods are still behind and more research should be focused on this class of approaches.
- Even if metaheuristics had been extensively applied, there is a lack in solving GRPs with new techniques like swarm intelligence and hybrid swarm intelligence approaches.
- Environmental concern in routing problems is one of the three pillars of sustainability, which is a part of the corporate social responsibility (CSR). Even if it seems to be hard to model and evaluate such social and environmental aspects (like equity, safety, accidents, risks, etc), CSR is nowadays needed to do well in societies and protect the human being and ecology.

And finally, we also note that green logistics activities can be linked circular economy and supply chain management as the transportation is the core element of both concepts. For example, planning the raw materials or semi-finished goods for the production purpose (i.e., based on the lot sizing) and collection of used goods from customers for remanufacturing or recycling purposes (i.e., with a circular economy) can also be studied together with green logistics. There is an urgent need for more integrated production, circular economy and green logistics studies with the focus on greening vehicle routes.

Appendix A Classification of the papers according to the combination of some related characteristics

Version	Fleet nature	Objective function	Constraints	Reference
Deterministic	Homogeneous	Min (Emissions/FC)		*Tiwari and Chang (2015); Oliveira et al. (2017); Zhou and Lee (2017); Balamurugan et al. (2018);*
Deterministic	Homogeneous	Min (Emissions/FC)	TW	*Majidi et al. (2017); Qian and Eglese (2014); Qian and Eglese (2016);*
Deterministic	Homogeneous	Min (Emissions/FC)	TD	*Naderipour and Alinaghia (2016); Ehmke et al. (2016);*
Deterministic	Homogeneous	Min (TTC+ Emissions/FC)		*Zhang et al. (2014); Jabir et al. (2015); Jabir et al. (2017); Dagne et al. (2019); Zhang J et al. (2015); Zhang Z et al. (2015);*
Deterministic	Homogeneous	Min (TTC+ Emissions/FC)	TW	*Elbouzekri and El Hilali (2014); Gang et al. (2016); Kaabachi et al. (2017); Li et al. (2018);* Liu *et al. (2018);Ai et al. (2019) ;*
Deterministic	Homogeneous	Min (TTC+ Emissions/FC)	TW+TD	*Kumar et al. (2016)*;
Deterministic	Homogeneous	Min (TTC+ Emissions/FC)	TD+ DRI	*Setak et al. (2017); Soysal et al. (2015);*
Deterministic	Homogeneous	Min (TTC+ Emissions/FC)	TW+TD+ DRI	*Wen and Eglese (2015); Zhang et al. (2018);*
Deterministic	Homogeneous	Min (Emissions/FC+ Driver wage)	TW+ TD	*Franceschetti et al. (2017);*
Deterministic	Homogeneous	Min (Emissions/FC+ Driver wage)	TW+ DRI	*Kramer et al. (2015a); Dabia et al. (2016); Fukasawa et al. (2016); Niu et al. (2018);*
Deterministic	Homogeneous	Min (Emissions/FC+ Time)	TD	*Norouzi et al. (2017);*
Deterministic	Homogeneous	Min (Emissions/FC+ Time)	TW+TD	*Xiao et al. (2015a);*
Deterministic	Homogeneous	Min (Emissions/FC+ Time)	TW+ DRI	*Demir et al. (2014);*

Deterministic	Homogeneous	Min (Emissions) Min (Operating costs) Max (Customer satisfaction)	TW TD	*Wang Y., et al. (2019);Xu et al. (2019); Zulvia et al. (2019);Li et al. (2019);*
Stochastic	Homogeneous	Min (Emissions/FC)	TW	*Eshtehadi et al. (2017); Wang et al. (2019);*
Stochastic	Homogeneous	Min (Emissions/FC)	TW+DRI	*Shukla et al. (2017);*
Stochastic	Homogeneous	Min (Emissions/FC+ Driver wage)	TW+ DRI	*Eshtehadi et al. (2018);*
Stochastic	Homogeneous	Min (TTC)	TD+ DRI	*Cimen and Soysal (2017);*
Stochastic	Homogeneous	Min (TTC+ Emissions/FC)		*Feng et al. (2017);*
Stochastic	Homogeneous	Min (TTC+ Emissions/FC)	TW+TD	*Huang et al. (2017);*
Stochastic	Homogeneous	Min (TTC+ Emissions/FC + Driver)	TD+ DRI	*Soysal et al. (2018);*
Stochastic	Homogeneous	Min (Emissions/FC+ Penalty)	TW+ DRI	*Tajik et al. (2014);*
Stochastic	Homogeneous	Min (Emissions/FC+ Penalty+Time)	TW	*Liao et al. (2017);*
Stochastic	Homogeneous	Min (Travel Time)	TD	*Koster et al. (2015);*
Deterministic	Heterogeneous	Min (Emissions/FC)		*Ziebuhr et al. (2017); Kancharla and Ramadurai (2019);*
Deterministic	Heterogeneous	Min (Emissions/FC)	TW	*Ene et al. (2016);Yu et al. (2019);*
Deterministic	Heterogeneous	Min (Emissions/FC)	TW+ SPLIT	*Vornhusen and Kopfer (2015);*
Deterministic	Heterogeneous	Min (Emissions/FC)	TW+TD+SP LIT	*Matos et al. (2018);*
Deterministic	Heterogeneous	Min (Emissions/FC)	TW+TD	*Xiao et al. (2016);*
Deterministic	Heterogeneous	Min (TTC+ Emissions/FC)		*Moutaoukil et al. (2016); Koc et al. (2016);*
Deterministic	Heterogeneous	Min (TTC+ Emissions/FC)	TW	*Ghannadpour and Zarrabi (2019);*
Deterministic	Heterogeneous	Min (TTC+ Emissions/FC)	TD+ DRI	*Alinaghian and Zamani (2016);*
Deterministic	Heterogeneous	Min (TTC+ Emissions/FC + Driver wage)	TW+ DRI	*Koc et al. (2014); Molina et al. (2014); Afshar-Bakeshloo et al. (2014);Ai et al. (2019);*
Deterministic	Heterogeneous	Min (Emissions/FC+ Driver wage)	TW+ DRI	*Liu et al. (2017);*
Deterministic	Heterogeneous	Min (Emissions/FC+ Driver wage+ Speed)	TW+ DRI	*Saka et al. (2017);*
Deterministic	Heterogeneous	Min (Emissions/FC+ Penalty)	TW+TD	*Xiao et al. (2015b); Xiao et al. (2017);*
Stochastic	Heterogeneous	Min (TTC+ Emissions/FC)		*Hsueh C-F (2016);*
Stochastic	Heterogeneous	Min (TTC)+Min (Emissions)+Min (dissatisfaction)+ Max(Reliability)	TW+TD+DR I	*Rabbani et al. (2018);*

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