Sustainable Vehicle Routing Models with Mixed Fleet Vehicles

by

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Abstract

In recent years, decarbonization of transportation has aroused great attention in the world. The transportation sector generates approximately one-fourth of global CO_2 emission yearly and the amount is predicted to be double in 2050. To deal with this issue, sustainable development is forcing transportation sectors to minimize carbon emission produced by the cargo fleets. This thesis introduces vehicle routing models with a mixed fleet to deal with the sustainable development effort of the transportation industry. The mixed fleet in VRP models consists of heterogeneous hydrogen vehicles and conventional vehicles for the distribution system. The hydrogen vehicle has been introduced as an alternative fuel vehicle (AFV) in vehicle routing models for the first time in this work. The fuel consumption of the vehicles is realistically considered as a function of traveled distance, speed, and on-board cargo load. The problems include constraints of vehicle capacity, backhaul, time windows, and maximum tour length for the routes. In addition, the composition of fleets should respect the CO_2 emission cap imposed by the government for the distribution system.

The thesis studies three VRP models. A new hybrid metaheuristic, combining the particle swarm optimization (PSO) and problem specific variable neighborhood search (VNS), is proposed to solve each of the investigating problems in this work. Firstly, it considers a clustered vehicle routing problem (CluVRP). In CluVRP, customers are grouped into different clusters. A vehicle visiting a cluster cannot leave the cluster until all customers in the same cluster have been served. Each cluster and customer has to be served only once. The proposed hybrid PSO algorithm is tested on numerous benchmark instances with various sizes obtained from the CluVRP literature. The thesis then considers the mixed fleet green vehicle routing problem with backhaul and time windows (MFGVRPTW). Extensive computational experiments have been performed on newly generated instances and numerous benchmark instances with various sizes obtained from the literature of VRPB, VRPTW, and VRPBTW. The obtained results of the proposed algorithm are compared with the results found in the literature. Finally, a comprehensive VRP model called GCluVRPBTW is developed for the first time in this thesis. The performance of the proposed hybrid algorithm is evaluated by testing on newly generated GCluVRPBTW instances. The proposed hybrid PSO algorithm for GCluVRPBTW is also tested on newly generated instances of CluVRPB, CluVRPTW, and CluVRPBTW. The proposed algorithm proved to be superior to the state-of-the-art algorithms on the CluVRP, VRPB, VRPTW, and VRPBTW.

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List of Abbreviations

CO_2	Carbon dioxide
AFVs	Alternative fuel vehicles
CVRP	Capacitated vehicle routing problem
VRP	Vehicle routing problem
GVRP	Green vehicle routing problem
VRPB	Vehicle routing problem with backhaul
VRPTW	Vehicle routing problem with time windows
VRPBTW	Vehicle routing problem with backhaul and time windows
CluVRP	Clustered vehicle routing problem
CVs	Conventional vehicles
HVs	Fuel cell hydrogen vehicles
PSO	Particle swarm optimization
Hybrid PSO	Hybrid particle swarm optimization
BC	Branch and cut
UHGS	Unified hybrid genetic search
LMNS	Large multiple neighborhood search
VNS	Variable neighborhood search
EMVRP	Energy minimizing vehicle routing problem
FCVRP	Fuel consumption vehicle routing problem
PRP	Pollution-routing problem
MFGVRPBTW	Mixed fleet green vehicle routing problem with backhaul and time windows
CluVRPB	Clustered vehicle routing problem with backhaul
CluVRPBTW	Clustered vehicle routing problem with backhaul and time windows
GCluVRPBTW	Green clustered vehicle routing problem with backhaul and time windows

CHAPTER ONE

Introduction

1.1 Background

Decarbonization of transportation is no longer a passion; it is an obligation and a mostly unquestioned vital issue for one and all worldwide. In this view, world organizations, such as the conference of parties (COP), European Commission, are on the pathway to put CO_2 emission limit cap for the countries and businesses, and penalty cost otherwise (Yang et al. 2015; Figliozzi 2010). The International Energy Agency (IEA) states the transport sector consumes more than a quarter of global energy and generates the second-highest CO_2 emission (Chen et al. 2019; Bahramara and Golpîra 2018). The emissions from vehicles are more harmful to human health as vehicle releases CO_2 in very proximity to human receptors giving less opportunity for the environment to dilute the emission. Besides, in most shopping malls and warehouses areas, all roads locate nearby the buildings making emission concentration more intensified by reducing the wind speed at emission sources than an open road. Eventually, vehicle transports become a distinguished source of CO_2 than other sources (Colvile et al. 2001). Transportation systems are the essential pillar of countries' economic development (Corlu et al. 2020). Transportation activities contributed to the GDP of the USA and Europe by 5.6% and 5.00% respectively in 2016 (the U.S. Bureau of transportation statistics, 2018). In such, transportation system can be called as "obvious foe" for the world.

Of the transportation services, road transport, the main mode of inland transporting goods on the supply chain, is the major emitter of CO_2 emission (Bektas et al. 2019; Kabadurmuş et al. 2019). The transport activities in terms of tonne-km have increased gradually (on average 2.8% each year) from 1995 to 2005. This radical growth can principally be attributed to escalates in road transportation (on average 3.5% per year), which is still the leading transport mode in this region. Low costs in freight transport, strategic policies of business such as global sourcing, and Just-in-time (JIT) are found as reasons for road transportation to make them famous mode (Aronsson and Huge-Brodin 2006; Golicic et al. 2010). Currently, road transportation carries about 47% of total freight transport activities in the EU (Mahieu 2009). In this way, companies' transportation logistics are greatly contributing to its overall CO_2 emission also (Zhang et al. 2018; Jimenez and Flores 2015), which eventually makes transportation logistics in businesses as an ultimate contributor toward global warming of the earth. Therefore, it is the area where organizations and industry can contribute significantly to both economic and social development, and CO_2 emission reduction (Fares et al. 2015; Lin et al. 2014; Treitl et al. 2014; Offer et al. 2010; Piecyk and McKinnon 2010).

Globally the transportation sector needs to be transformed into a safer scheme by reducing greenhouse gas emissions, air pollution, and its dependency on unsafe fossil fuels (Egbue and Long 2012). In this context, many efforts around the world have been through over long decades such as; motivating travelers to use public transit rather than personal automobiles and use freight rail rather than a truck, increasing public awareness about running down of global oil reserves and energy security concerns, attracting businesses to introduce cleaner fuel energies and efficient vehicle technologies cause to decreased emissions amount for the same miles journeyed and larger mileage per unit of fuel or energy used. Such individual effort is mainly aimed at reducing vehicle miles traveled on roads and reducing fossil-fuel usage. Rather a comprehensive approach in place of adopting individual effort is approvingly recommended (Montoya et al. 2015; Erdogan and Miller-Hooks 2012). Such a comprehensive approach is to explore alternative greener sources of fuel, i.e., electricity, hydrogen, biodiesel, ethanol, natural gas (liquid-LNG or compressed-CNG), methanol, and propane (US DOE 2010).

Evidence also shows that European transport systems are still increasing their greenhouse gas emissions, which consist mainly of CO_2 emissions (Taefi, et al. 2016; Eurostat 2013). The scenarios are almost the same throughout the globe, which necessitates significant efforts to be instrumented to reduce emissions at the national level and organization level around the world (Sarkis and Cordeiro 2012; Vazquez-Brust and Sarkis 2012). Such as the European regulation no. 443/2009 and 333/2014 have been introduced by the European Commission on emission standards for light-duty vehicles to reduce CO_2 emissions in road passenger transport. It also defines, for vehicle manufacturers, an ambitious target of 95 gram CO_2 emissions per km for the whole new vehicle fleet of passenger vehicles (M1 vehicle segment) in 2025. Instead, transport expert viewed target in 2030 should be about 70 gram CO_2 per km to meet GHG emission reduction target in this sector in 2050 of at least 60% compared to 1990 values. Under another EU regulation, 510/2011, a penalty of 95€ is imposed on vehicle manufacturers for every exceeding gram of CO_2 emission above 147 gram CO_2/km of manufacturers' average emission for each vehicle started in 2019 and onwards (Climate action, 2016). In addition, some governments around the world offer incentives for the adaptation of low-carbon alternative fuel vehicles (AFVs) (Pollet et al. 2012). These imply environmental (ecological) and social effects must be taken into consideration when designing transportation logistics policies in the businesses, in addition to the conventional costs solely.

1.2 Green vehicle routing problem (GVRP)

The vehicle routing problem (VRP) is designated as a core problem in the road transportation optimization strategy (Solomon 1987; Kim et al. 2015). The VRP was first introduced by Dantzig and Ramser (1959) as a linear programming formulation. The VRP aims to obtain a list of least-cost vehicle routes serving several geographically scattered customers under various supply and demand constraints, such as vehicle capacity, fleet size, time windows, route length, and precedence relations between customers, etc. It is commonly studied as a combinatorial optimization model in network design problems and it is an NP-hard problem (Lenstra and Kan 1981). Numerous variants of VRP have been discussed in the literature for around six decades since it was introduced. The most common VRP variant is the capacitated vehicle routing problem (CVRP). The other variants of VRP are arose focusing different aspects of real-world and business situations and their subsequent constraints on route design, such as clustered VRP, heterogeneous VRP, VRP with multiple driving ranges, VRP with time windows, stochastic VRP, VRP with backhauls (VRPB), Open VRP, multi-trip VRP, multi-depot

VRP, green VRP (GVRP), VRP with pickup and delivery, waste collection VRP, multi-period horizons VRP, split delivery VRP, multi-compartment VRP, VRP in Omni-channel, and VRP for a mid-day meal delivery system (Sevaux and Sörensen 2008; Gajpal and Abed 2009a; Gajpal and Abed 2010; Letchford and Salazar-Gonzalez 2019; Madankumar and Rajendran 2019; Soleimani et al. 2018; Vornhusen and Kopfer 2015; Xiao and Konak 2015; Abdulkader et al. 2015; Crainic et al. 2015; Abdulkader et al. 2018; Zhang et al. 2019; Gajpal et al. 2017; Gajpal et al. 2019).

It is assumed in classical VRPs that a number of fixed fleet of vehicles with homogeneous capacity held in a single depot. Implementing green logistic ideas in VRPs and the use of AFVs in fleet vehicle give rise to the new optimization problems named as green vehicle routing problems (GVRPs). The GVRP, first proposed by Erdogan and Miller-Hooks (2012), intends not only at the lowest monetary cost routes but also an environmentally sustainable logistics (Bektas et al. 2016; Sbihi and Eglese 2010). The GVRP models create numerous opportunities for CO_2 emission reduction in the companies by integrating wider environmental and economic goals on their objective functions (Bektas and Laporte 2011). One opportunity is to incorporate emission costs beyond fuel utilization into the VRP objective functions, hence environmental and economic goals can be traded off (Figliozzi 2010). Another opportunity is the deployment of low or zero emission alternative fuel vehicles (AFVs) such as electric vehicles (EVs) or fuel cell hydrogen vehicles (HVs) in routing operation (Schneider et al. 2014). Using heterogeneous and mix fleet vehicles are another recommended approach in green vehicle routing models because mixed heterogeneous fleet offers various driving range, total cost, and vehicle utilization flexibility as accordance with the requirement in the routing operation (Maden et al. 2010; Goeke and Schneider 2015; Kopfer et al. 2014; Juan et al. 2014; Kopfer and Kopfer 2013). Thus, the GVRPs have received great attention from governments, environmentalists, and business organizations nowadays (Ball and Weeda 2015; Lin et al. 2014). For example, the Chinese government is promoting electric vehicles and environmentally friendly transportation policies in China (Zhang et al. 2017). Moreover, expansion of green transportations is more triggered nowadays by strict environmental laws, fluctuation of energy costs, social concerns, increased transportation activities, and green practices in organizations in order to keep the global average temperature rise below 2^{0}C (Santos 2017; Dhar et al. 2017).

The VRP with backhauls (VRPB), first introduced by Deif and Bodin (1984), is another important variant of VRP that aims at the efficient utilization of vehicles for sustainable development. The VRPB delivers cargo in outbound trips and picks up cargo in the inbound trips. Combining the pickup and delivery operations in VRPB improves the efficiencies in the routes (Bergmann et al. 2020). In practice, VRPB is seen when outbound customers are needed priority than inbound customers to avoid rearranging the load inside the vehicles. As the capacitated VRP is proven to be an NP-hard problem, the VRPB is also NP-hard (Thangiah et al. 1996; Kücükoglu and Öztürk 2015).

In the view of green logistics, several companies have already employed AFVs instead of using conventional vehicles (CVs) in their last-mile delivery operations, e.g., in the field of small-package shipping, like UPS, DHL, and DPD particularly in their Urban areas (Kleindorfer et al. 2012; IPC 2011) or the distribution of food (National Renewable

Energy Laboratory 2014) and beverages, like Coca-Cola in the USA, (Heineken International, 2014; Priselac, 2013) as AFVs have no local tailpipe (tank-to-wheels, TtW) greenhouse gas emission, emit only water as a by-product. Fuel cell hydrogen vehicles (HVs), one of the AFVs, are the hydrogen vehicles in which hydrogen fuel is converted into the electricity to power on-board electric motors for vehicle momentum. The advantages of HVs are as follows: compared to EVs, the driving range of HVs are almost double with their longer operating time despite of further cost, effort, or stress. In addition, HVs do not require any battery replacement and can be refueled very fast and easily in less than 5 minutes. These benefits increase the productivity of operators and lower operational expenses. Like EVs, HVs emit zero (tank-to-wheels, TtW) tailpipe emission and only water as a bi-product. The well-to-wheels (WtW) CO_2 emissions of HVs (0.20 kg CO_2 eq/mile) are slightly less than EVs (0.22 kg CO_2 eq/mile). Hydrogen fuel cells do not require any centralized distribution grid. This grid-independence, in turn, implies that as soon as the source of power and water is available, the driving fuel for vehicles by the hydrogen fuel cell can be despatched. Compared to CVs, in a well-to-wheel analysis (WtW), the US department of energy (DOE) approximated 55% less CO_2 (kg/mile) emission and 25% less emission than a hybrid vehicle.

Furthermore, HVs have been treated a successful alternative to CVs due to their less messy and minimal noise fuel cell operation because of their identical driving range with CVs. Thus, decarbonising of road transportation is significantly achieved from the deployment of HVs by reducing transport dependencies on fossil fuel (oil and gas) around the globe. HVs in the road have approximately 40% more fuel economy than diesel or gasoline transports. In total cost of ownership (TCO) analysis for useful vehicle life, HVs are more economical than EVs because of the higher acquisition cost of batteries in EVs, and HVs are expensive than CVs. But in regards to CO_2 emissions and their adverse health costs consideration, HVs and EVs are far away preferable than CVs. HVs are also invincibly favourite than EVs for larger daily distances (Jimenez and Flores 2015). Overall, business distribution logistics are tremendously offered to be more competitive by the distinguishing features of hydrogen fuel cell vehicles (HVs) (Koc and Karaoglan 2016).

Hydrogen fuel cell vehicles (HVs) have not been studied so far in the VRP field, in our best knowledge. HV has been studied for the first time in GVRP in this work, which makes a novelty of this research study. HVs with their many distinguishing features associate with the green economic aspect of routing planning problems make a substantial area in VRP field, especially in its variant GVRP.

Overall, the VRP with backhaul and time windows (VRPBTW) provides a great perspective for reducing environmental impact and cost of transportation, as it reduces running of empty vehicles and fuel consumptions from better utilization of vehicle capacity combining two different services in the distribution services (Corlu et al. 2020; Santos et al. 2019; Pradenas et al. 2013). Moreover, as the VRPs of transportation distribution logistic contribute to the country's both GDP and CO_2 emission worldwide, it can be concluded that even a small improvement in routing problems and their solutions can bring in large cost reductions and environmental sustainability (Küçükoglu and Öztürk 2015). The heterogeneous fleet vehicles provide additional opportunities to reduce carbon emissions in the routes (Yu et al. 2019). In this view, the mixed fleet based green vehicle routing problems with backhaul and time windows are studied in the thesis work. The consideration of backhaul customers, mixed fleet vehicles, CO_2 emission cap, and hydrogen AFV in the routing problem brings sustainability concerns in the studied works.

1.3 Motivation of the study

The entire study is motivated by the fact that transportation logistics are reportedly viewed as a significant contributor to the CO_2 emission globally which has a substantial effect on the environment, society (public health), and economy. In the future, the CO_2 emission cap is expected to be enforced strictly due to growing environmental concerns worldwide to keep the global average temperature rise below 2^0C. The CO_2 emission is mainly generated from burning fossil fuels such as gasoline and diesel (Koc et al. 2014). This will enforce organizations to use alternative fuel vehicles (AFVs) such as hydrogen vehicles to protect the environment. However, conventional vehicles cannot be eliminated completely because of their lower operational cost. Thus, a mixed fleet with different types of vehicles is becoming common for most of the company's logistics in real-life. A mixed fleet helps to prevent environmental pollution, improve customer satisfaction, and provide opportunities for vehicles choice in the distribution logistics. Moreover, the mixed fleet operation provides the privilege of meeting non-equal customer demands with preferred time windows efficiency from various vehicles having different speed limits, driving range, carrying load capacity, and notably distinct environmental pollutant emission level. Consequently, mixed fleet vehicles reduce CO_2 emission in distribution logistics from a competent combination of multiple vehicles. These observations inspired us to consider the mixed fleet of hydrogen and conventional vehicles and keep the composition of fleets in such a way that it adheres to the government regulation regarding CO_2 emission. Overall, the entire study is motivated by many facts such as worldwide commitment to decarbonize the transportation, CO_2 emission cap for the logistics, employment of AFVs in the distribution logistics. In addition, the VRP with backhaul and heterogeneous fleet provides more opportunities to reduce the CO_2 emission in the routes. This thesis provides a comprehensive VRP model considering many aspects of the existing VRP model such as a realistic model for fuel consumption, CO_2 emission cap, clustered customers, backhaul customers, time windows restrictions, and a mixed fleet vehicle.

1.4 Contributions of the study

In this work, different problems in the logistic distribution network are investigated. The thesis first starts with the clustered vehicle routing problem (CluVRP) followed by the mixed fleet green VRP with backhaul and time windows (MFGVRPBTW) model and finally the green clustered VRPBTW (GCluVRPBTW) model. Each of the investigated models denotes a variant of the VRP. Two of the studied problems are represented as new variants of VRP. The problem formulation and mathematical model for each variant are provided in this research. A solution approach for each problem is developed to solve the problems. The proposed metaheuristic is based on the combination of the particle swarm optimization (PSO) and problem specific variable neighborhood search (VNS). We include new features in the PSO algorithm such as the use of two types of particle and improvement scheme for the personal best solutions. This hybrid PSO is targeted to achieve a better quality solution for the studied problems. Extensive computational experiments have been performed on problem instances. Several benchmark solutions and new best-known solutions have been generated in this work. The proposed algorithm can solve many variants of the VRP problem and can produce better solution than existing algorithms. The main contributions of this research work can be summarized as follows:

- **Clustered vehicle routing problem**

We study the clustered vehicle routing problem (CluVRP) as a variant of the classical capacitated vehicle routing problem. Our proposed hybrid PSO metaheuristic solution method solves the problem and it is evaluated on the benchmark instances found in CluVRP literature. Many new best-known solutions for the CluVRP benchmark instances within competitive CPU time are found in the work.

- **Mixed fleet green vehicle routing problem with backhaul and time windows**

We introduce a mixed fleet green vehicle routing problem with backhaul and time windows (MFGVRPBTW). In the work, a comprehensive green VRPB model comprising different variants of VRPB is presented. To the best of our knowledge, this is the first work to introduce such a comprehensive VRPB model. This research also contributes in terms of the solution method, which can be testified with the scalability of the proposed algorithm in the numerical experiment section. The proposed hybrid PSO metaheuristic is tested on the newly generated MFGVRPBTW instances. It generates many new best-known solutions out of benchmark instances while tested on VRPTW, VRPB, and VRPBTW instances obtained in the literature.

- **Green clustered vehicle routing problem with backhaul and time windows**

We introduce a new green clustered vehicle routing problem with backhaul and time windows (GCluVRPBTW). A mathematical model of the problem is formulated and a new hybrid PSO algorithm based solution approach is designed in the work. The new instances for GCluVRPBTW, CluVRPB, CluVRPTW, and CluVRPBTW are generated, and solutions for each of the problems are obtained. Overall, the GCluVRPBTW is believed to be an important contribution in the field of green VRP, clustered VRP, and also in VRP with backhaul areas.

1.5 Thesis organization

The thesis work is intended to study many VRP models with mixed fleet of hydrogen and conventional vehicles. The work includes three variants of VRP. Overall, the thesis is structured as herein described. The literature of GVRP is reviewed in chapter two, where detailed literature on energy minimizing VRP, fuel consumption VRP, pollution-routing problem, PSO, and VNS are highlighted. In chapter three, the clustered vehicle routing problem is studied. The hybrid particle swarm optimization algorithm is designed to solve the problem, and many new best-known solutions were generated for benchmark instances in the chapter. Chapter four introduces the hydrogen and mixed fleet based green vehicle routing problem with backhaul and time windows (MFGVRPBTW) in the view of dealing with the sustainable development effort of the transportation industry. In this chapter, our designed hybrid PSO algorithm is used to solve the MFGVRPBTW. The proposed metaheuristic efficiently capable of solving the newly generated MFGVRPBTW instances. It is also tested on the benchmark instances of VRPB, VRPTW, and VRPBTW available in the literature. In chapter five, we introduce a new variant of VRP called the green clustered vehicle routing problem with backhaul and time windows (GCluVRPBTW). Our proposed solution method is tested on the new instances for GCluVRPBTW, CluVRPB, CluVRPTW in the chapter. Finally, the conclusion of the work, limitation of the research, and future research directions have been provided in chapter six.

CHAPTER TWO

Literature review of GVRP

The literature related to the GVRP problem is reviewed in this chapter. The literature is divided into three chunks: firstly, energy minimizing vehicle routing problem (EMVRP), and fuel consumption vehicle routing problem (FCVRP). Secondly, pollution-routing problem (PRP) with time window and finally, alternative fuel vehicles (AFVs) based GVRP with time window and recharging station. There is no literature study found on fuel cell hydrogen vehicles (HVs) in the fields of overall VRP or GVRP because the HV has been proposed in this research for the first time in the areas of overall routing problems.

A comprehensive study on GVRP was studied in Bektas et al. (2016), where the areas of EMVRP, FCVRP, and PRP were explained concisely. The two GVRP variants, EMVRP and FCVRP, were viewed generally as the simpler form of PRP. In PRP, time window constraints and decisions on speeds were included. In EMVRP and FCVRP, distance and weighted load function (product of load and distance) were taken into account.

2.1 Energy minimizing vehicle routing problem (EMVRP) and fuel consumption vehicle routing problem (FCVRP)

The sustainability in conventional VRP is imperative in the present time, which includes the environmental cost and social cost on top of the conventional economic efficiency of VRP model (Sbihi and Eglese 2010). A survey study on environmental sustainable VRP was obtained in Eglese and Bektas (2014). The environmental issue, amount of CO_2 emission model, in vehicle routing was affected by vehicle traveled distance, cycle duration of the vehicle route, vehicle carry load, speed, road gradient, vehicle type, engine type, vehicle design environment, traffic congestion, driver's attitude, and operations factors, and many other factors (Demir et al. 2011; Demir et al. 2014). Several methods considering different factors were compared in a study carried out by Frey et al. (2010) and Demir et al. (2011). The CO_2 emission methods were mainly based on analytical emission models. The inclusion of green aspects for CO_2 emission in VRP affects the VRP optimization models in different ways.

A concise study on various issues related to linking the green logistics with combinatorial optimization of vehicle routing and scheduling problem was highlighted in research work (Sbihi and Eglese 2010). The authors in the study focused on many aspects of real-time problems such as time-dependent features, transportation features for hazardous materials, and dynamic optimization feature. Different problems arisen from environmental orientation in VRP were also emphasized in this study. The energy minimizing vehicle routing problem was introduced by study Kara et al. (2007) in which a new weighted load-based (vehicle load multiplied by distance on the arc) cost function was optimized. The polynomial size integer programming formulations were presented for the model. The formulation model did not consider the vehicle speed and emission model. In another study (Scott et al. 2010), the influence of road topology (gradient), and payload of vehicles were investigated to minimize routing CO_2 emission. In the study, fixed vehicle speed and fuel utilization rate were considered on the arcs. The emission minimization models in VR were divided into two prime categories, such as models with time-independence and models considers with time-dependent road traffic congestion (Qian and Eglese 2016). The amount of CO_2 emissions was proportional to the fuel consumption of vehicles in all models. The environmental issues in the VRP field were firstly considered by Palmer (2007), a time-independent model, in which CO_2 emission cost was integrated in vehicle routing model for goods vehicles with time window scenarios under the variation of tour duration and distance due to speed change in congestions conditions. This research work was aimed to develop a software based VPR model to estimate the CO_2 emission matrix considering different speeds level under scenarios of road surface topography (mount, hills, gradient, etc.), time window and vehicle distance traveled. A VRPTW heuristic was used to solve the problem. The solution showed that the amount of CO_2 emission was minimized (approximately 5%) when the environmental cost was valued based on the total traveled distance or total cycle time of the route than typical. Another time-independent routing problem studied by Ubeda et al. (2011) in which authors investigated how green logistics could be affected in VRP model of a Spanish distribution company. Distance-based methods were applied in model formulation. Two heuristics, such as Mole and Jameson (1976) method and the nearest neighbour insertion algorithm, were developed for estimating CO_2 emission based on factors, such as vehicle type and its load, fuel type, and road topology. The emission matrices based on each arc explained by Palmer (2007) were used in this study. Jaramillo (2010) introduced a new variant of conventional VRP offering a new objective function of minimizing Ton-Mile instead of minimizing travel distance. The CO_2 emission was considered as a function of payload. Single vehicle was used for small instances in the problem solved by a local search algorithm. The new problem was named as the green single vehicle routing problem (GSVRP). A similar kind of study was carried out by Peng and Wang (2009) by using a genetic algorithm, ant colony optimization, and PSO algorithm. Xiao et al. (2012) considered the fuel consumption for the vehicle, calculated as a product of load and distance, in CVRP was named as fuel consumption vehicle routing problem (FCVRP). The model was intended to reduce CO_2 emission cost and routing cost in the problem, where FCR was linearly proportional to the vehicle load. A metaheuristic simulated annealing with a hybrid exchange rule was designed as a solution method. The proposed FCVRP model could minimize fuel consumption by around 5% compared to the CVRP model. Fixed vehicle speed was in fuel emission calculation models. A method similar to Xiao et al. (2012) estimating the FCR was used in a study by Harris et al. (2011) where the impact of cost optimization on the CO_2 emission model was also assessed as a bi-objective problem. The author claimed that problem formulation improved the vehicle usage rate that eventually reduced logistic costs and energy consumption. Many other studies such as Apaydin and Gonullu (2008), Fagerholt (1999), Marašs (2008), Nanthavanij et al. (2008), Sambracos et al. (2004), and

Taveares et al. (2008) aimed at minimizing total fuel consumption. Nie and Li (2013) proposed an FCVRP model to minimize the routing cost while meeting the constraint of the emission limit for the network. A more detailed FCR was discussed in a review study by Lin et al. (2014). Maden et al. (2010) studied a case study of vehicle routing and scheduling problem with time window where vehicle speed varied on the hours of a day caused by the road traffic. The amount of CO_2 emission was considered as a linear function of speed. A heuristic solution was proposed to explain the problem saving about 7% of CO_2 emission cost. Similarly, Jabali et al. (2012) studied a VRP and scheduling problem which accounted for travel time between arcs (customers), fuel cost, and CO_2 emission cost. But, the amount of CO_2 emission was estimated as a non-linear function of vehicle speed. Finally, a tabu search algorithm for emission based time-dependent routing problem was proposed to obtain optimum speed as regards to CO_2 emission. Moreover, in a view of reducing CO_2 emission, a mathematic model was offered to calculate fuel consumption where vehicle speed and the travel duration on the arc were dependent on the time of travel in routing. In another study by Kuo (2010), time-dependent speed, and travel time were considered VRP. The vehicle speed, distance, and load were used in the problem formulation to estimate the optimum fuel consumption level. A benchmark dataset from literature (Solomon, 1987) was solved in this study by a simulated annealing algorithm. The same problem was again formulated by a Tabu search in another study (Kuo and Wang 2011). Saberi and Verbas (2012) devised the Solomon problem instances once again in their study, in which a model for time-depended VRP with CO_2 emission was minimized optimally. In a study by Figliozzi (2011), vehicle travel speed was introduced as a decision variable to minimize fleet size, distance traveled and cost of the route in a time-dependent VRP. The CO_2 emission was also estimated by trading-off between soft time windows (or congestion levels), and the company's policy restriction. The algorithm, iterated route construction and improvement (IRCI), was used to solve the problem. Before this, Figliozzi (2010a) introduced the emission vehicle routing problem (EVRP) which was an extension of the time-dependent VRP (TDVRP). The objective of the study was to minimize the emission cost and fuel consumption. The amount of emission and energy consumption in the problem was calculated based on the MEET methodology (Hickman et al. 1999; INFRAS 1995). In the methodology, only speed and distance were considered with standard conditions (zero road gradient, empty vehicle, etc.). The problem considering the Solomon instances was solved by an algorithm, where a TDVRP algorithm was implemented to minimize the number of vehicles; the emission was minimized subject to vehicle capacity. The departure times for each pair of customers were also optimized in the algorithm. Three different conditions for traffic congestion such as no congestion, fair congestion, and full congestion, were considered in conjunction with vehicle speed. In a study by Figliozzi (2010b), the amount of CO_2 was minimized by considering average vehicle speed combined with acceleration rates in the problem formulation.

2.2 Pollution-routing problem (PRP) with time windows

Bektas and Laporte (2011) presented a new variant of VRP, a time-independent model, called as pollution-routing problem (PRP) model including energy, fuel consumption, and emission of homogenous conventional internal combustion vehicles in the routes. The emission was estimated by speed, load, and soft or hard time windows, using the emissions functions where the instantaneous engine-out emission rate was directly related to the fuel consumption rate suggested by Barth et al. (2005); Scora and Barth (2006); Barth and Boriboonsomsin (2008); Barth et al. (2009). The amount of energy consumed by the vehicle on the arc was directly translated into fuel consumption. The cost of emission (pollution), driver costs, and fuel consumption cost were included in the objective function where vehicle loads, speed of arcs were changed. Vehicle speed was used as one of the decision variables. The PRP model was investigated under three different objective functions, such as distance, weighted load, and energy (fuel) cost minimization. Detailed computational analysis as an integer linear programming problem was carried out to provide the trade-off between three objective functions considering the effect of various speed, load, and time window constraints. The formulation model in that study (Bektas and Laporte 2011) was only valid with a speed level of more than 40 km/h. But in many cases of practical scenarios (traffic congestion), vehicle speed remains lower than 40 km/h. In this view, Demir et al. (2012) extended the single objective PRP model studied in Bektas and Laporte (2011) by taking into account for vehicle speeds 40 km/hr or lower. In the extension, the PRP model with the time windows consisting of a fixed fleet (homogenous) vehicle was proposed by two-stage meta-heuristics. In the first stage, the VRPTW was solved by adoptive large neighbourhood heuristics (which was the extension of the large neighborhood search (LNS) heuristic first proposed by Shaw (1998) and this heuristic can be embedded within the local search heuristics (simulated annealing or tabu search). In the second stage, the initial solution of VRPTW results was used in vehicle speed optimization on arcs using a recursive algorithm, speed optimization algorithm (SOA), in order to minimize the cost of fuel consumption and driver wages. Many data instances consist of a large number of customers (with up to 200) were used in computational analysis. The objective function presented in the previous two studies (Bektas and Laporte 2011; Demir et al. 2012), relating to fuel consumption and driving wage minimizations, were conflicting. Thus, these two objective functions were presented separately to form a new extension of PRP called bi-objective PRP presented in Demir et al. (2014a). The adaptive large neighborhood search algorithm (ALNS), combined with a speed optimization procedure (SOP) was presented to solve this bi-objective PRP. While in PRP (or in any variants of VRP) with time window, the vehicle was allowed to arrive at customers' locations before starting the service at the preferred time window. This phenomenon was called 'idle waiting' emerged to avoid traffic congestion. The idle waiting was first introduced in PRP by Franceschetti et al. (2013) in which the time-dependent PRP was considered by an integer linear programming formulation. Kramer et al. (2015a) dealt with PRP in a view of minimizing fuel consumption cost and operation cost. Fuel consumption level was considered as dependent on travel distance and load. Vehicle speed was considered as a decision variable satisfying the time window constraint in the model. The vehicle departure time delay was not considered in the model. The vehicle department time delay was included in another study by the same authors (Kramer et al. 2015b), which utilized an iterated local search-based metaheuristic to combine the speed, scheduling, and the distance in order to optimize fuel cost and operational costs of the VRP. A single data set from the Demir et al. (2012) and authors' own created data sets were used as benchmark instances in both studies, Kramer et al. (2015a and 2015b). Qian and Eglese (2016) considered a VRP with scheduling problem to minimize CO_2 emission in the problem, where speed was dependent on time. The objective of the model was to obtain optimum routes and the speed of vehicles on the arcs was the decision variable. A tabu search algorithm based on column generation was present to solve the problem. Zhang et al. (2015) studied a VRP problem with constant vehicle speed considering the cost of fuel consumption, CO_2 emission cost, and vehicle usage cost in routes. These three costs were taken into the models in a view of sustainable VRP formulation. Fuel consumption cost includes mainly the oil cost, CO_2 emission cost involved the social and abatement cost for pollution from CO_2 emission, and vehicle usage costs comprised the vehicle depreciation cost, insurance cost, and the drive wages cost, etc. A novel iterated local search algorithm, route splitting tabu search (RS-TS) was proposed to solve the model.

Another important variant of VRP is the VRP with a mixed fleet or heterogeneous vehicle. The research area of VRP with heterogeneous vehicle was introduced by Golden et al. (1984). When different types of vehicles instead of a single type are obtained in routing problems, then VRP with heterogeneous problems arise. Baldacci et al. (2008) stated heterogeneities were obtained from five various conditions, such as limited vehicle numbers, unlimited vehicle numbers, fixed cost of vehicles are included, no fixed costs are included, and variable cost for different vehicle types as regard to heterogeneity in vehicles. Although, vehicles with various carrying capacities, different fuel types, dissimilar CO_2 emission rates were also more common in vehicles heterogeneity. Ubeda et al. (2011) examined the effect of utilizing various degrees vehicles on CO_2 emission by considering distance minimization and CO_2 emission minimization approach. In the view of reducing CO_2 emission in VRP, the study carried out by Jaramilo (2010) was extended by Kopfer and Kopfer (2013) considering various vehicle categories (heterogeneous fleet type) and of fuel consumption in contrast of Jaramilo (2010). Four different categories of vehicle compliance with EC regulation were considered in this study. The amount of CO_2 emission was considered as a function of distance travelled and the amount of carried load on the arcs. The problem in the study was formulated by traditional VRP, EMVRP, and EMVRP-VC concepts. The heterogeneous feature of vehicle fleet was included in the objective function, and emission and fuel consumption varying with vehicle categories were aimed to minimize in the problem model. The computational results were generated on smaller instances (up to 10 customers) by using the exact algorithm, CPLEX. The computational results showed that the EMVRP model reduced the CO_2 emission by 1.5 % (approximately) and increased traveled distance by 1.9% compared to the VRP model. The EMVRP-VC (emission minimization VRP with heterogeneous vehicle) reduced CO_2 emission by 13% compared to the EMVRP and by 14.5% compared to the VRP. The EMVRP-VC increased travel distance by 24.7 % and 22.3% compared to the EMVRP and VRP model due to the added number of vehicles. Kopfer et al. (2014) further studied the EVRP-VC model to reduce the fuel consumption rate and the CO_2 emission amount conjointly in addition to vehicle distance only for heterogeneous vehicle fleets. The heterogeneous vehicles had different payload-dependent fuel consumption features.

Computation results were generated with the CPLEX solver on smaller instances (up to 14 customers). Results showed that using the heterogeneous vehicle in VRP, a significant amount of CO_2 emission could be reduced. Vornhusen and Kopfer (2015) extended the EMVRP-VC problem to EMVRPTWSD-VC by considering more classes of heterogeneous vehicles (from four previously to six), split delivery, and time window features in the problem formulation. The decision variables such as arcs, vehicle types with their corresponding CO_2 emission model for the preferred time window formed this problem as a mixed-integer programming model. The objective of the problem model was to minimize CO_2 emission and travel distance. Computational results showed that permitting split delivery only with the homogeneous fleet (gross weight 12, 20, 26 tons), models generated an overall reduced amount of emission by 1.03%. The overall distance and number of vehicle usages were also decreased by 1.30% and 3.69% respectively. Computational results also highlighted that orientation of more heterogeneous vehicles (from 4 to 6 vehicles having their gross weight between 3.5 to 40 tons), reduced average CO_2 emission furthermore by 16.16%. The overall distance and number of vehicle usages were also reduced by 14.00% and 15.49% respectively. Gusikhin et al. (2010) studied the consumption of fuel of heterogeneous mixed fleet vehicle in a routing problem. The authors emphasized different road types, highways, and city roads, in addition to several vehicle types affecting CO_2 emission. Although the authors did not consider any load as the study focused on only passenger cars. Kwon et al. (2013) measured the CO_2 emission for a vehicle routing problem with the heterogeneous fixed fleet. A fixed type of vehicle diversified with carrying capacity and CO_2 emission level was considered in this study.

The problem formulation was intended to minimize operation costs and carbon emission trading net costs. The vehicle operation cost was directly proportional to the vehicle distance traveled. The cost-benefit related to CO_2 emission trading was calculated from the deviation between the estimated CO_2 emissions in the routing and permitted cap (upper limit) for CO_2 emission. A mixed integer programming model was adopted to denote the problem mathematically. The solutions obtained by the Tabu search algorithm show the CO_2 emission could be decreased without increasing costs because of the benefits of carbon trading. Koc et al. (2014) introduced the fleet size and mix pollution-routing problem (FSMPRP), which as basically an extension of the pollution-routing problem with heterogeneous vehicle fleet with time windows. The problem aimed at minimizing the cost function contained vehicle operation costs, fuel costs, and CO_2 emission costs. Vehicles were considered with a speed function as described by Bektas and Laporte (2011). A hybrid evolutionary metaheuristic was developed having features of a heterogeneous adaptive large neighborhood search procedure and a split algorithm with a speed optimization algorithm. Experimental results highlighted various trade-off options between fuel costs, CO_2 emission costs, distance, vehicle fixed costs, driver wages, and total routing cost. The authors emphasized on using heterogeneous vehicles over homogenous vehicles with a remarkable outcome that heterogeneous fleet with fixed speed offered greater cost benefits compared to the homogenous fleet with optimum speed inclusion.

2.3 Multi-objective GVRP

Many studies reveal that fuel consumption and CO_2 emission are greatly influenced the vehicle types (Demir et al. 2011, 2014b). In manufacturing businesses, light-duty vehicles are prospective to increase total routing distances and they are also more likely to increase CO_2 emissions, even though heavy-duty vehicles have larger engines consuming more fuel per distance unit than the light-duty vehicles (Campbell 1995a, 1995b). In addition, heavy-duty vehicles are recommended to replace by heterogeneous vehicles for a purpose of minimizing routing CO_2 emission (Kopfer and Kopfer 2013; Kopfer et al. 2014; Vornhusen and Kopfer 2015). Heterogeneity of the vehicles occurs from several engine friction coefficients, engine speed, engine displacement co-efficient, aerodynamic drag force factor, frontal surface area, driven train efficiency factor, curb weight and carrying capacity, payload of the vehicles (Bektas and Laporte 2011). Moreover, in the context of vehicle speed, the characteristics of GVRP are also conflicting. Such as, higher vehicle speeds denote the tendency of shorter routing distance but concurrently higher speeds result in a greater amount of CO_2 emission. Therefore, the reduction of pollution and CO_2 emission is required an optimum vehicle speed to be maintained in the routing instead of minimum speed. Because the same as higher vehicle speed, minimum speed also results in higher CO_2 emission. Even minimum vehicle speed could generate feasible solutions with empty or severely smaller routes. Subsequently, VRP formulation with the optimum vehicle speed (greater than minimum speed) can generate more CO_2 emission with larger routing distance. Accordingly, better integration of vehicle speed and vehicle type possibly with many other factors is highly recommended to be included in routing problem formulation (Kramer et al. 2015a). Overall, the green orientation in the conventional VRP problem leads to GVRP as a bi-objective (or multi-objective) optimization problem that intends to reduce CO_2 emission and distance traveled. Conventionally, the amount of CO_2 and distance traveled are directly related to fuel consumption and operational cost in the routing. The multi-objective optimization attitude offers a set of Pareto optimum solutions that facilitates a systematic trade-off analysis between conflicting objective functions in a problem. The Pareto optimality of the multi-objective problem is evaluated in a manner in which one objective is kept fixed, and the other two objectives are compared and so on. The Pareto front is generated from the best solution of one objective function while other objective functions' coefficients are varied according to the cost and other constraints happen in real-life scenarios (Chaudhari et al. 2010). Jabir et al. (2015) proposed a multi-objective optimization model for GVRP where the objective was to reduce the CO_2 emission while preventing an increase in economic cost. Economic costs included fixed costs, route cost, fuel consumption cost, and other operational costs. CO_2 emission costs (in terms of cost of tons of CO_2 emission) represent the environment impact measured as a function of load, vehicle type, and vehicle engine coefficients. The optimization solution for conflicting objective functions forced to generate Pareto optimal solution. The hybrid metaheuristic was used in solving the problem, in which ant colony optimization (ACO) was utilized to find the economic optimum routes. Then, the low CO_2 emission routes were generated by a variable neighborhood search (VNS). Molina et al. (2014) generated and solved a multi-objective mixed-integer linear programming optimization problem having three goals such as minimizing internal cost, NO_2, and CO_2 emission. The problem was considered for a heterogeneous fleet with time window constraint. The problem consisted of a supermarket problem with 17 delivery points served from a single depot. A multi-objective heuristic algorithm based on a well-known Clark and Wright saving algorithm modified for the heterogeneous vehicle was proposed to solve the optimization problem. NO_2 and CO_2 emission were calculated from fuel consumed by the vehicle types multiplied by the emission factor for each emission type. Another multi-objective green cargo routing problem with cost and emission function was carried out by Siu et al. (2012). The two objectives of this study were to optimize the CO_2 emission and traditional operation cost in the routing. Different transport modes such as scheduled flights and train service were considered in the problem. Each arc connecting the customer has its weight carrying limit (cap) and transportation fee per km. The genetic algorithm was implemented for the problem, then after Martins' label-setting algorithm was used for the multi-objective problem. (Martins' algorithm was a generalization of the famous Dijkstra's shortest path algorithm for a multi-objective problem with multiple decision variables). Martins' algorithm was used to generate the Pareto optimal solution for the problem. The research work, stated previously in this research, carried out by Demir et al. (2014a) was also a bi-objective optimization problem with CO_2 emission and driving time reduction. The original study was proposed by Bektas and Laporte (2011), and then studied by Demir et al. (2012) as single-objective problem to reduce the CO_2 emission and routing cost of the optimization problem. Kumar et al. (2015) studied a multi-objective optimization problem of pollution routing problem with soft time window (with waiting penalty charge). The conflicting objective functions were dealt to reduce operation cost and CO_2 emission that was equivalent to fuel consumption. Various speed levels of homogeneous vehicle and their carrying loads for each arc were considered a decision variable. Vehicle speed and loads were also used to estimate the fuel consumption level on the arc as a basic equation used in Demir et al. (2012, 2014a) but modified for a multi-period time window. This multi-objective optimization problem was solved by generating Pareto optimal solutions. Pareto frontier or non-dominated solution was the optimum solution which cannot be improved further without breaking another optimum solution or any constraint (Melián-Batista et al. 2014). An algorithm called self-learning particle swarm optimization (SLPSO) was proposed to obtain the Pareto fronts in the problem. In the field of VRP, many other multi-objective optimization problems were studied such as Jozefowiez et al. (2009) where distance travelled, and route imbalance were optimized, Tan et al. (2006) optimized two conflicting objective functions such as optimization of the number of vehicles and total route distances. A hybrid multi-objective evolutionary algorithm (HMOEA) was used in the study to solve the benchmark 56 VRPTW Solomon's 100 customer instances. Androutsopoulos and Zografos (2012) studied another bi-objective VRP and scheduling problem with time window and time-dependent feature for hazardous material distribution. Kaiwartya et al. (2015) proposed a multi-objective dynamic VRP with time seed based problem which was solved by Particle swarm optimization. Kovavs et al. (2015) presented a multi-objective optimization problem by extending the generalized consistent VRP. Two exact solution approach and one heuristics algorithm were used to solve the problem. Similarly, Ghoseiri and Ghannadpour (2010) presented a multi-objective VRP with time window. A goal programming approach and an efficient genetic algorithm were aimed to solve the problem. Franceschetti et al. (2013) presented a linear integer programming based VRP.

2.4 GVRP with time windows

When time windows of the customers, preferred service time, are added in VRP then a new variant of CVRP is formed called the VRP with time windows (VRPTW). The chosen time window can either be a hard or soft condition. The hard time windows do not allow the vehicles to serve the customers out of the preferred time window. Vehicles are normally permitted to wait at no cost if they arrive earlier but later arrival is not allowed. On the contrary, the soft time windows allow the vehicles both early and late servicing at customers out of the preferred time window but subject to some penalty cost of customer inconvenience. The VRP with time window was surveyed in studies of Bräysy and Gendreau (2005a, 2005b), and Toth and Vigo (2014). Tas et al. (2014) proposed two exact algorithms, a column generation and a branch-and-price, for a vehicle routing problem with soft time window (VRPSTW), where time-independent travel time was considered as stochastic due to traffic congestion in real life. The model dealt with uncertainly in travel time following known probability distribution. In another study, Tas et al. (2014) focused on VRPSTW with dissimilarity from their study that time-dependent stochastic travel times were utilized. The Factual travel times (arrival times) were converted from time-independent travel time (arrival time). Two meta-heuristics such as a Tabu Search and an Adaptive Large Neighborhood Search were developed in this study to solve the problem. A VRPSTW problem was addressed in a study where two exact algorithms such as standard branch-and-cut-and-price and bi-objective optimization based on the bisection method (Salani et al. 2016). The VRPSTW was also studied in many other studies (Bhusiri et al. 2014; Fu et al. 2008; Liberatore et al. 2011; Qureshi et al. 2009; Chiang and Russell 2004). A benchmark time-dependent VRP with time window (VRPTW) was introduced by Figliozzi (2012). Another VRPTW problem with split delivery was studied by an exact algorithm, branch and price and cut in Archetti et al. (2011). A VRP with hard time windows was proposed in a study by Ehmke et al. (2015) where travel times on the paths were stochastic (probabilistic) rather than fixed. The probabilistic travel time resulted in a probability of violating time window constraints, while the objective of the model was to minimize the routing cost. The Solomon benchmark data sets were used to investigate the problem model by the LANTIME tabu search algorithm. The VRPTW was also investigated in many studies such as Baldacci et al. (2012), Gendreau and Tarantilis (2010), Kallehauge (2008), Vidal et al. (2012) and Hashimoto et al. (2013). Dhahri, et al. (2015) addressed a VRPTW with preventive maintenance activities as a scheduling problem. A variable neighborhood search (VNS) metaheuristic was proposed to solve the problem.

2.5 Alternative fuel vehicle (AFV) based GVRP with time windows and recharging station

Evidence shows that in the last lustrum companies, governments, and other organizations have been using remarkably increased numbers of AFVs in the transport operation. The orientation of AFV in GVRP forms another important facet of GVRP in which the alternative fuel vehicles (AFVs) in routs. So far, AFVs in GVRP include biodiesel, hydrogen, electricity, methanol, ethanol, liquid-LNG natural gas, and compressed-CNG natural gas. Generally, AFVs have limited tank capacity, so vehicles need to visit alternative fuel stations (AFSs) en-route. The study carried out by Artmeier et al. (2010) was the first that extended the conventional short-path algorithms to address energy-optimal routing considering battery powered-electric vehicles. The study had the objective of finding energy-efficient routes satisfying the energy limit for the road logistics and the remaining charge of the battery was maximal. Energy consumption of the battery was calculated by multiplying distance of the arc with a factor represent the speed conjunction with deceleration and acceleration while running the vehicles. Vehicle routes were considered feasible only if their required energy did not go beyond the charging level of the battery. Authors claimed that the features of EV such as limiting driving range, larger recharging time, and ability to regain energy during deceleration while running require a new routing algorithm. The problem was solved by an energy-optimal routing algorithm. Formally, the use of AFVs in an extended CVRP work to GVRP with time window was introduced in a study by Erdogan and Miller-Hooks (2012). In the problem, each customer (each edge) was related to a travel time where vehicle speed was constant. There were non-uniformly distributed AFSs around the routes. These jagged distributions of AFSs lead to deciding the time for vehicles to visit the refueling stations. The limited driving range of the vehicles corresponded to the fuel tank capacity limitation in the study. The time window constraint forced to choose the required vehicle with a suitable driving range to optimize total tour duration within the given maximum tour duration. AFSs and depot, opted as refueling stations, were permitted to visit multiple times during the tour. The mathematical formula was proposed to minimize the total travelled distance by the AFVs in a given time. The arc, fuel level and the arrival time at the customer were chosen as decision variables. Two heuristics such as the modified Clarke and Wright saving algorithm (Clark and Wright 1964) to take account of AFSs node, and the density based clustering algorithm (DBCA) for spatial clustering properties of the problem were proposed to solve the problem. A local search method was adopted after the feasible routes were obtained from the previous results. A randomly generated dataset and a case study data set from real (consisted of 500 customers and 21 AFSs) world were utilized in this study. Schneider et al. (2014) introduced the electric vehicle in GVRP with time window and recharging stations. The limited driving range due to restricted battery capacities of the vehicles dictated to visit the recharging stations in order to complete the routes. Available researching stations were allowed to visit unlimitedly. The recharging time was not fixed as it depended on the current battery level and battery capacity while it was being charged. For the sake of simplicity, the recharging process was considered as linear with time in this study. Though, the recharging process is not linear in real-life as it requires increased time for the last 10%-20% of the battery capacity (Marra et al. 2012). Vehicle speed was considered as constant and the remaining fuel level, cargo load, and arrival time at the customer were considered as decision variables in the problem. The model was intended to minimize the total travelled distance of the vehicles. A hybrid heuristic combining variable neighborhood search (VNS) and tabu search as a technique for local optimization was presented to solve the problem. The well-known Solomon instances for VRPTW were modified with recharging station and the dataset used in Erdogen and Miller-Hooks (2012) have also been utilized in the study for computation analysis. The proposed approach in the study was also applied to the dataset used for the multi-depot VRP with inter-depot routes (MDVRPI) (Crevier et al. 2007; Tarantilis et al. 2008). The presented approach in the study was capable of improving previous MDVRPI results and new solutions had been obtained for the dataset. Moreover, two sets of benchmark dataset for E-VRPTW were designed in this study, such as asset of small size instances that able of being solved by exact solution with CPLEX to evaluate the performance of proposed VNS/TS, and a set of instances with realistic size set of instances to assess the effectiveness of the proposed hybrid heuristics. Conrad and Figliozzi (2011) presented a new variant of VRP called the recharging vehicle routing problem (RVRP). In RVRP, the electric vehicles with a limited driving range due to restricted battery capacity were permitted to get recharge at certain customers' locations within the route instead of recharging form the dedicated recharging stations. The authors claimed that this feature has more practical applications because of the quick recharging capabilities of electric vehicles. Independent of current recharge level with respect to battery capacity, vehicles can be recharged taking a fixed time. Phenomenon implied that recharging and service at the customer location can happen simultaneously. Every customer has a soft time window constraint to be served. There were three decision variables: conventional binary variable from one node to another, binary variable if a vehicle was recharged at customer or not, and service start time at customers. The objectives of the formulation were to minimize the number of routes and to minimize the cost of distance traveled, service time, and vehicle recharging cost. The Solomon datasets for VRPTW were used to perform the computation results though hard time window the dataset was relaxed for this study. An iterative construction and improvement heuristic algorithm was used in this study. A similar algorithm was also used in another study Figliozzi (2010b). Goeke and Schneider (2015) presented a mixed fleet based VRP with electric vehicle and conventional internal combustion vehicle with hard time window. Rather, considering energy consumption to be linearly related to travel distance (Erdogan and Miller-Hooks 2012; Schneider et al. 2014), a realistic energy consumption model was considered which was dependent of speed, gradient, and carrying load on the arcs. The authors highlighted that the realistic energy consumption model plays an important impact on routing models which considers fuel cost and vehicle emission (Bektas and Laporte 2011; Jabali et al. 2012). Although a mixed fleet of the electric and conventional vehicle was considered but all vehicles had a fixed carrying capacity in the proposed model. Recharging stations were allowed to be visited for electric vehicles but there were no refueling stations for conventional combustion vehicles. Recharging time was dependent on fixed recharging rate and difference between maximum battery capacity and the current charge state of the battery. Arrival time at the customers, remaining cargo load at the customers, and remaining battery capacity were considered as decision variables. The model had the objective function of minimizing vehicle travel distance, cost consisted of vehicle usage cost and driver cost, and cost including battery replacement cost. One interest modification had made in the computational analysis that was the gradient and speed was considered constant on the arcs, where these two variables were considered as a dependency for fuel consumption in the proposed model. Finally, an adaptive large neighborhood search algorithm was proposed to solve the model. Desaulniers et al. (2014) generated an effective branch-price-and-cut exact algorithm for the four variant of EVVRTW problem that originally was introduced by Schneider et al. (2014). The four variants were introduced regarded to recharging the battery. These were: a single and full recharging battery, multiple recharges and full recharging (Schneider et al. 2014), single recharge and partial recharging, and multiple and partial recharging battery per route. The instances consisted of up to 100 customers and 21 battery recharging stations were adopted for computational experiments in this study. Although, computational experiments showed that some instances with 50 customers can result in their optimum results. Felipe et al. (2014) presented a GVRP with multiple technologies and partial recharges (GVRP-MTPR), which was an extension of the GVRP study introduced by Erdogan and Miller-Hooks (2012). Erdogan and Miller-Hooks (2012) was the first study that introduced recharging stations for electric vehicles in VRP. Schneider et al. (2014) extended their work by introducing customer time windows constraint in E-VRP with recharging station, where vehicles were allowed to recharge the battery at the recharging station. Probably in this evolution, Felipe et al. (2014) extended the work carried out by Erdogan and Miller-Hooks (2012) in a new way by considering partial charging at the recharging station. Partial recharging has several positive influences in routing such as cost saving because remaining recharging can be done at the depot at a much lower price, time saving in routing assist making certain for total maximum duration constraint. Besides, battery recharging operation can be performed in various ways with different technologies, such as plugging the battery in elected grid by recharging point that compatible with the conventional petrol pump station. Charging on household plug though it may take longer time, it was cheaper but due to a longer time, it was recommended for night time at the depot and vehicle start the routing with a fully charged battery. Recharging can be done in an hour by the technology called CHAdeMO protocol (Paschero et al. 2013). Moreover, many wireless recharging systems are available that capable of recharging at twice faster than CHAdeMO. Wireless recharging systems are comparatively expensive but also enable recharging while the vehicles are located on a platform. In the study, multiple visits even simultaneous visits to recharging stations are allowed. Therefore, different recharging speeds and recharging costs are considered in the work. Energy consumption was considered as proportional to the distance traveled. There was a maximum duration constraint for each route and there were limited numbers of vehicles in the problem. There are many decision variables considered such as amount energy available when arriving the node and when leaving the node, amount of remaining load when leaving a node, amount of energy recharged at the node using a technology, amount of energy recharged at the depot, departure time at the node, and conventional binary variable. The objective of the study was to minimize the cost consisted of recharging cost at the depot at night time and at recharging station at day time, and fixed cost related to battery cycles. As a new problem, authors in this study created a new dataset for this problem along with some instances from similar literature Schneider et al. (2014) and Erdogan and Miller-Hooks (2012). The overall dataset was solved by several heuristics in this problem. Another GVRP with zero emission vehicles was presented by Montoya et al. (2014), where two-phase heuristic was generated to solve the problem. In another study, Schneider et al. (2015) described the vehicle routing problem with intermediate stops (VRPIS) where the requirements for stopping at intermediate facilities were taken into account. Authors hereby incorporated some practical scenarios in VRP when intermediate stops have to happen such as refill the products, refueling or recharging, and waste disposal, etc. These kinds of stops are different from the regular VRP stops in two aspects for example, intermediate stops are optional and they rely on the state of vehicles' load and fuel or charge level. Optional customers stop were considered in many studies like Archetti et al. 2013; Tarantilis et al. 2008), which were contrasted in Schneider et al. (2015) that intermediate stops were aimed to keep the vehicle operational, not directly related to profit maximization or even customer service. Moreover, Schneider et al. (2014) studied E-VRPTW with recharging station and a heuristic method was used to solve the problem by the VNS algorithm. In the solution, initially, number of the vehicles in the route was minimized then travel distance of the vehicles was minimized. On the contrary, Schneider et al. (2015) considered a constraint of maximum rout duration. The service time required in the intermediate stoppage was incorporated in time window constraints in the VRP model. The aimed to minimize the total cost consists of total travel costs and total fixed costs of the vehicles. The authors generated an adaptive variable neighborhood search (AVNS) for solving the VRPIS. In real-life scenarios, intermediate stops happen when intermediate stops for refueling or recharging, for example, some companies have their dedicated refueling or recharging station which offers cheaper refueling. In addition, battery electric vehicles require recharging during their longer routes due to their limited driving range. The visit for recharging was not fixed in the routes but depends on the current charging level of the battery, in this way VRP with recharging station can be considered as a special case of VRPIS (Schneider et al. 2015). Hiermann et al. (2016) introduced the electric fleet size and mix vehicle routing problem with time window and recharging stations (E-FSMFTW) based on the FSMVRPTW by Braysay et al. (2008) and E-VRPTW by Schneider et al. (2014). It was claimed that the limited battery capacity of the electric vehicles was the main deficiency for their competitiveness in the routing problem. The mixed fleet of electric vehicles was different in terms of their capacity, battery size, and acquisition fees, which was the difference from the study by Geoke and Schneider (2015). The decision variable includes the vehicle types, recharging time, and recharging location in completing the routes. The objectives of the study were to minimize the acquisition costs (fixed cost) of vehicles and total traveling costs for each vehicle. The authors created the new dataset for the problem. The two conditions were considered in the objective function calculation, a researching station did not require to be visited at all in the solution and a recharging station was allowed to visit at most once by a single vehicle. The mathematical formulation was defined as mixed integer programming (MIP). The branch-and-price algorithm was proposed initially in the study for the VRPTW to generate benchmark exact solution results by solving smaller instances. In addition, a metaheuristic algorithm based on adaptive large neighborhood search (ALNS) enhanced was by local search and labeling procedures. Barco et al. (2013) proposed a comprehensive VRP related to a real-life scenario of airport shuttle operation by battery electric vehicles. The case study considered carrying the airport passengers from airport to hotels carried out by plug-in electric battery vehicles. The problem was proposed to minimize the routing cost, operating cost of vehicles with better scheduling for recharging within time window. A differential evolution algorithm was proposed to solve the problem. In the algorithm, at first, the energy consumption of each road was calculated by using longitudinal dynamics equation considering acceleration and speed change on the road (Munoz et al. 2012), then based on the energy consumption, routes were selected satisfying preferred time window. When energy consumption and routes were developed, the schedule for recharging the battery was generated and optimizes the whole model. Preis et al. (2014) studied an energy-optimized electric vehicle routing problem with time window and static recharging time. The study aimed to optimize the energy consumption of the vehicle in the routs. The energy consumption of the vehicle depended on the vehicle carrying load and gradients of the arc. The problem was formulated as mixed-integer programming. The authors generated a number of 160 sets of test instances having a diameter of 10 km as basin shape. Only one depot was assumed to be located at the center and customer numbers varied from 10 to 100 but the number of recharging stations was accepted at fixed three. Electric vehicles were assumed as homogeneous with an unlimited number having an unfilled weight of 2 tons and maximum carry capacity was 200 kg. Vehicle speed assumed as fixed at 15 km/h. An adapted tabu search heuristic was proposed to solve the problem instances. Yang et al. (2015) studied a new variant of VRP problem, named the environmental VRP with soft time window and multiple vehicle types. A multi-objective VRP problem with three different vehicle types such as environmental, sub-environmental, and conventional energy-consumption vehicles was presented in the study which had the conflicting aims of reducing costs, increasing customer satisfaction, and reducing environmental pollution. Five attributes were considered for each vehicle in the heterogeneous fleet such as variable operation (traveling) cost per unit of time, fixed cost, maximum speed, load carrying capacity, and environmental emission factor. Problem formulation was to decide the routes, vehicle type and speed, and carrying load to satisfy the customer with minimum emission pollution. The vehicle traveled distance and vehicle type were the determinants of environmental pollution in the problem model. The authors created a dataset for the computational analysis in this study. A hybrid genetic algorithm was proposed to solve the problem successfully. In addition, Pareto optimality analysis of three-objective optimization models was carried out. Sensitivity analysis showed that operation cost and environmental emission had a strong correlation with vehicle speed and load carrying capacity of vehicles had an impact on operation cost, environment emission, and customer satisfaction. Bruglieri et al. (2015a) proposed a routing and scheduling problem of electric vehicle with time window and partial recharging. It was viewed that partial recharging at recharge station had a positive influence on decreasing total recharging time and vehicle serving the customers in time. Vehicles were assumed to be homogeneous with fixed carrying capacity, speed, battery consumption, and recharging rate. The arrival time, remaining vehicle capacity, and battery level at each customer location were considered as decision variables. The mathematical formulation of the problem was seen as mixed integer linear programming (MILP) to minimize the number of vehicles and the total route duration for the vehicles. Total time was calculated from the sum of recharging time, traveling time, and waiting time of the vehicle. The problem was solved by the proposed metaheuristic algorithm, the variable neighborhood search branching (VNSB). Several benchmark instances generated from the Solomon benchmark VRPTW study had been used for computation analysis in the study. An introductory part of the work was carried by another study Bruglieri et al. (2015b) where all most same scenario of the problem was considered but only differed in the mathematical formulation of the problem. In the study by Bruglieri et al. (2015a) considered MILP formulation under the constraints of total time and battery level at customer location where a study by Bruglieri et al. (2015b) considered optimization problem as MILP under the battery level constraint only. Keskin and Catay (2016) studied another electric-VRP with time window and partial recharge (EVRPTW-PR) problem. In EVRPTW, vehicle leave from the depot or recharging station with full-charged battery and return at the deport or station with any degree of charge but in EVRPTW-PR, the vehicle leaves the deport or recharging station at any level of charge and return at the depot or station with an empty charged battery. The recharge amount was considered as a continuous decision variable. The recharging amount was determined from the remaining charge level at depot or recharging station. The service starting time and remaining cargo load were also considered as decision variables. The objective was to minimize the total traveled distance in the routes. The problem was formulated as 0-1 mixed-integer linear programming (MILP) and generated an adaptive large neighborhood search (ALNS) algorithm to solve the problem optimally. The performance of the proposed algorithm was validated using EVPTW instances used in Schneider et al. (2014). Of them, the proposed approach improved the four problems. That consequence showed that partial recharging scheme improved the solution obtained for full-charging scheme in the problem. Sassi et al. (2015a) studied the vehicle routing problem with mixed fleet and time window. Mixed fleet vehicles include heterogeneous electric vehicles and conventional vehicles. The heterogeneity of electric vehicles was characterised in terms of dissimilar battery capacities and operating costs; and all conventional vehicles had identical carrying capacity. The electric vehicles were allowed to be partial recharging. The study differed from the other studies in such a way that recharging stations were different in terms of fast recharging technologies compatible with heterogeneous electric vehicles and recharging cost was time-dependent. The problem was considered for a specific time horizon [0, T], for example a day, which was divided into many time intervals having a time length and their time duration. Although there were several recharging stations, some of them offered maximum charging power during a time window and subject to time dependent recharging cost. Vehicles must have to wait to match the time period for that offer. Furthermore, three different charging technologies were considered named as, level 1- slowest charging with the power of 3.7 kW, level 2- medium charging with the power of 22KW, and level 3-fastest charging with the power of 53Kw. At various predefined time period, different charging technology was available at fixed recharging stations such as, during time period [0, T], a fixed number of level 1 charger were obtainable at the depot, during time period [T_0 -T] some predefined chargers of level-2 were available and so on. When charging happened, only the required amount of charge was added to the vehicle that was partial recharging. The objective function was aimed to minimize total costs for mixed fleet operation in routes. Total cost composed of five costs were routing cost linearly related to distance traveled and operating cost, recharging cost at the depot, recharging cost at other recharging station, total fixed cost and total waiting cost needed for EVs in case of their arrival out of preferred charging time. The computation results were conducted based on 9 real-life instances collected from a French company. The instances consisted of between 300 to 500 nodes and there were many charging stations ranges from 15 to 35 in number. A metaheuristic, multi-start iterated local search (ILS), was proposed to solve the problem. Overall the study (Sassi et al. 2015a) was a modified work of the study by Sassi and Oulamara (2014), where the joint scheduling and optimal charging of electric vehicle routing problem was investigated under the same contexts. Sassi and Oulamara (2014) modeled their optimization problem as a mixed-integer linear programming (MILP). The small and medium data instances were solved by the exact algorithm (CPLEX) and large instances were solved the heuristics algorithm. Sassi et al. (2015b) investigated the same problem with a mathematical optimization model solved by a different mathematic procedure called by the multi-start iterated tabu search (ITS) based on a large neighborhood search (LNS). The LNS was used in the intensification and diversification phase of the ITS. ITS-LNS showed better results than their previous studies that implied LNS adoption in ITS improved the solution as compared to other neighbourhood search algorithm procedures such as 2-opt search. Before that same optimization problem was studied by Sassi et al. (2014), where authors used a different meta-heuristic as distinct to solve the problem. Metaheuristic consisted of a charging routing heuristic to build initial solutions and then an inject-eject-based local search embedded with three different insertion strategies. Juan et al. (2014) studied a VRP with multiple (heterogamous) driving ranges (VRPMDR), an extension of CVRP. The heterogeneous fleet consisted of a number of electric and hybrid-electric vehicles. The driving ranges of the vehicles were not the same that implied that the total distance for each vehicle was limited to their available maximum driving range. The conventional internal combustion vehicles have an unlimited driving range. All vehicles, both electric and hybrid, have a maximum carrying capacity. The objective of the problem was to minimize the total cost of vehicles travel with alternative fleet subject to the vehicle carrying load and available different driving ranges of the vehicles, and to assess how total costs were changed as ICV substituted by electric vehicle. The mathematical formulation was formed as integer programming and the model was solved by a multi-round heuristic algorithm. A total number of twenty well-known classic VRP benchmark instances were chosen randomly from the website http://www.branchandcut.org for computation analysis in the study. Three types of vehicles such as internal combustion vehicle, plug-in hybrid electric vehicle with unlimited driving range, electric vehicle with medium driving range (up to 200 km), and electric vehicle with short driving range (up to 100 km) were considered in the study. Moreover, the electric vehicle in distribution logistics was studied in a survey work by Pelletier et al. (2015). Grandinetti et al. (2016) considered the electric vehicles pick-up and delivery problem with soft time windows. The problem was mathematically formulated as a multi-objective MILP model with the objective function of minimizing the total cost for the EVs used, the total travel distance, and the total penalty cost for the unsatisfied time windows. Moreover, a time dependent green CVRP was addressed by proposing a dynamic programming based solution method in Soysal and Çimen (2017). Mancini (2017) addressed a hybrid vehicle routing problem where the decision process was involved to decide both when to switch from a CV to an EV and when to recharge. A metaheuristic based on a large neighborhood search was developed to solve the problem and it was tested on the GVRP benchmark instances. Leggieri and Haouari (2017) designed a new exact solution method for solving the GVRP. Zhang et al. (2018) studied an electric VRP with recharging stations to minimize the energy consumption of the vehicles. An ant colony based solution approach was tested on newly generated instances. Andelmin and Bartolini (2019) investigated a green VRP considering AFVs and vehicle tour length constraint. The fuel consumption for the vehicles was assumed to be linearly related to the distance travelled. A multi-start local search heuristic method was designed to solve the problem. The proposed method was tested on 52 benchmark instances obtain from the literature. Bruglieri et al. (2019) designed a path-based solution method exact solution to solve a green vehicle routing with AFVs and their visit to the alternative fuel stations (AFSs). Zhang et al. (2020) considered a multi-depot green VRP to minimize CO_2 emissions of the vehicles. A two-stage ACO was designed to solve the problem and it was tested on newly generated problem instances.

2.6 Particle swarm optimization and neighbourhood search

Literature shows that heuristics and metaheuristic methods are hybridized to obtain good solution quality within reasonable CPU time. Local search schemes are used for most of the hybridization. This observation motivated us to hybridize the PSO to improve its performance in this study. Our study proposes a hybrid PSO based solution for CluVRP, and new variants of VRPB named as MFGVRPBTW and GCluVRPBTW in this thesis work. The PSO is a population-based combinatorial optimization solving technique originally introduced in Eberhart and Kennedy (1995). The technique has been inspired by social collective behaviors seen in many natural swarms. The PSO algorithm starts with a population (called swarm) of many feasible solutions (denoted as particles). Each solution is randomly initialized in a multidimensional solution space. Each particle is characterized by two vectors, such as position and velocity vector. The optimal solution is obtained through iterations. In iterations, particles update their vectors according to their inertial behavior, individual cognitive behavior, and social learning behavior; and follow their personal best solutions and the global best solution of the swarm. A predefined fitness function is used to evaluate the performance of each particle. The PSO has well been evidenced in the literature to be a very effective, powerful, and competitive algorithm for solving VRPs and their variants (Li et al. 2019; Marinakis et al. 2019).

For instance, Ai and Kachitvichyanukul (2009a) solved a VRP with simultaneous pickup and delivery by proposing a PSO algorithm. The proposed PSO was developed based on global-local-neighbor particle swarm optimization (GLNPSO). Local searches and route optimization methods were implemented to obtain a quality solution. Shao et al. (2009) studied a VRP with stochastic travel time and designed a hybrid PSO based algorithm to solve it. In the algorithm, an initial set of the solution was created by arranging randomly generated position values of particles in ascending order. The solutions were further improved by using the dynamic neighbor operator. Marinakis and Marinaki (2010) studied a CVRP and proposed a hybrid PSO based solution. In the hybrid PSO, the initial solution was created by using greedy randomized adaptive search procedure, a multiple phase neighborhood search, then standard PSO combined with a genetic algorithm, expanding neighborhood search strategy, and many local searches to obtain a competitive solution tested on benchmark instances. Marinakis et al. (2010) designed a hybrid PSO based solution method for a CVRP. Instead of using a randomly created solution, the initial solution was generated using the MPNS–GRASP. The solution was improved by adopting an expanding neighborhood search strategy. The path relinking strategy was used to obtain a local optimal and global optimum solution. Marinakis et al. (2013) proposed a hybrid algorithmic approach based on PSO for solving CVRP with stochastic demands. Initially, the routes of each particle were created from random nodes and velocity was initialized as zero. The 2-opt and 3-opt local search algorithms were used to improve the solution. The path relinking strategy was used to represent the solutions, where each element of the solutions was transformed into floating point interval (0, 1), velocity and position values of all particles were calculated, and then position values were converted back to integer values using relative position indexing method. Belmecheri et al. (2013) developed a PSO based solution approach to solve a heterogeneous fleet VRP with mixed backhauls and time windows. Vehicles were different in capacities and variable costs. The initial solutions were created by randomly generated position values in decreasing order. The solution was improved by using a local search method. The algorithm was validated on Solomon's instances. Xu et al. (2015) proposed a hybrid solution method combining PSO with a genetic algorithm for the VRP with time windows. The routes were decoded from a real number coding of particles, and the crossover operation of the genetic algorithm was used to find an optimal solution. The algorithm was tested on Solomon instances. Norouzi et al. (2017) introduced a modified PSO based algorithm to solve a time-dependent VRP. The algorithm resulted in reduced carbon emission from a minimal travel time of the vehicles. In the algorithm, initial solutions were created from randomly generated position values. The neighborhood searches, such as crossover and 2-opt operators were used to improve the solutions further. The Solomon's test cases were used for solution method evaluation. Li et al. (2019) designed a modified PSO algorithm for a green VRP for cold chain logistics considering the GHG emission and a total of six costs in the logistics. Initial solutions of each particle were created from randomly generated integer values. The solution approach was tested on a case study. Zhang et al. (2018) proposed an evolutionary scatter search PSO to solve a VRPTW to minimize the total travel distance. Chen and Shi (2019) introduced a multi-compartment VRP with time windows and proposed two PSO based solution approaches, i.e. hybrid PSO and conventional PSO based solutions. In both solution approaches, initial solutions were created by random scanning and greedy algorithm. Many local searches were used to find neighbor solutions and path relinking algorithm was used to obtain new solutions from two different solutions. In the hybrid PSO, simulated annealing was used to avoid the shortage of premature convergence of conventional PSO and to jump the solutions out of local optimum. Then a further better global optimal solution was obtained. The algorithms were tested and compared with each other on Solomon's instances. Marinakis et al. (2019) developed a multi-adaptive PSO algorithm to solve a VRP with time windows. In the unique solution approach, diversified initial solutions were created by an adaptive strategy based on GRASP. Another adaptive strategy denoted as adaptive combinatorial neighborhood topology, where a path relinking procedure was used for the movement of the particles from one solution to another. All parameters of the algorithm, including main iterations and local search iterations, were adapted during the procedure by the third adaptive strategy in the algorithm. A problem specific variable neighborhood search (VNS) was utilized on both the initial solution and iteration's solutions in each particle to obtain improved solutions. The algorithm was tested on Solomon's instances.

The variable neighborhood search (VNS) was first introduced by Mladenovic and Hansen (1997) to solve a traveling salesman problem in 1997. Usually, a VNS is used as a local search algorithm to obtain a local best solution. The VNS is also a widely used heuristic search method in VRPs (Hansen and Mladenovic, 2003). Many studies found using the VNS with the PSO for solving several optimization problems, where PSO solution was used as a global search algorithm. Marinakis et al. (2010) generated a hybrid PSO metaheuristic to solve a CVRP, by producing an initial solution from a greedy randomized adaptive search procedure and by improving the solution further by a VNS algorithm. Goksal et al. (2013) introduced a hybrid metaheuristic based on PSO and variable neighborhood descent (VND), a lower-level VNS, to solve a vehicle routing problem with simultaneous pickup and delivery. Besides, Marinakis et al. (2013) proposed a multi-adaptive PSO solution approach for a vehicle routing problem with time windows, where the PSO solutions were improved by applying VNS for each particle in the swarm. Zou et al. (2013) presented a novel PSO algorithm hybridized with VNS to solve a multi-objective VRP with pickup and delivery problem with time windows. Zhang et al. (2019) designed a hybrid solution based on VNS integrated with binary PSO to solve a location-routing problem (LRP). Marinakis (2015) hybridized a PSO combined with a VNS for solving a capacitated LRP. In another study, Moghaddam et al. (2015) used VNS in an advanced PSO based solution approach to solve a VRP with uncertain demands. A novel decoding algorithm was used to increase the efficiency of the solution approach. The decoding was designed for generating vehicle routes and updating particle values. Moreover, due to the dominant behavior of PSO in producing a strong global solution and VNS having the advantages of generating a best local solution, PSO and VNS have also been using widely in job scheduling problem (Moslehi and Mahnam 2011). Liu et al. (2006) used a hybrid metaheuristic based on PSO combined with VNS to solve a multi-objective flexible job-shop scheduling problem. In additional work by Pongchairerks and Kachitvichyanuku (2007), it was shown that a simpler VNS algorithm without hybridization with PSO produces a better quality solution with shorted CPU time than a hybrid PSO with a VNS algorithm for the job-shop scheduling problems. Furthermore, a hybrid metaheuristic combining a PSO and VNS algorithm was proposed for solving an unconstrained global optimization problem in Ali et al. (2014). In the study, the PSO was used to perform a wider diversification and deep intensification in the solution space, and VNS was used as a local search algorithm. Furthermore, a PSO-based hybrid metaheuristic was designed for a permutation flow shop scheduling problem (Zhang and Wu 2014). In the work, a PSO algorithm was incorporated with a stochastic VNS, a variant of VNS proposed in Hansen and Mladenovic (2001), hybridized with simulation annealing to enhance the exploration ability of PSO in the solution approach. Gumaida and Luo (2019) developed a new hybrid optimization technique based on PSO combined with a VNS to enhance the localization process in wireless sensor networks. Marinakis et al. (2017) designed a hybrid PSO incorporated with VNS to solve a constrained shortest path problem. Motivated by this observation, this thesis work embeds the VNS with the PSO to obtain a good quality solution of the CluVRP, MFGVRPBTW, and GCluVRPBTW problems.

2.7 Conclusion

The literature shows that the VRP, GVRP, and their variants were solved using various heuristics and metaheuristics algorithms. It is apparent that architecting a framework to integrate multiple algorithms with different characteristics extensively improves the overall performance of a hybrid algorithm. Motivated by this observation, this thesis work designs a hybrid PSO based solution approach to solve the problems and to obtain a good quality solution of the clustered VRP, MFGVRPBTW, GCluVRPBTW. The performances of the proposed algorithms are tested by comparing many state-of-the-art algorithms for different variants of CluVRP, VRPB, VRPTW, and VRPBTW.

CHAPTER THREE

Clustered vehicle routing problem

In this chapter, a variant of capacitated vehicle routing problem (CVRP), called the clustered VRP (CluVRP), is studied. In CluVRP, customers are partitioned into predefined groups called clusters. The customers corresponding to a single cluster must all be visited by the same vehicle before it leaves the cluster. The notion of clustering in VRP has been well known due to its economic implications and its reduced complexity in modeling and solving a great range of real-life applications (Expósito-Izquierdo et al. 2016). The CluVRP is a generalized form of the CVRP. As the CVRP is proven to be an NP-hard problem, the CluVRP is also NP-hard (Toth and Vigo 2002).

The comprehensive CluVRP introduced by Sevaux and Sörensen (2008) focused on a real-world parcel delivery problem in courier companies. The consignment parcels were arranged into the bins corresponding to the specific delivery zones. The consignees belonged to the same zone designated as a cluster. The CluVRP can also arise in many scenarios such as transporting elderly people when the customers prefer to move with friends or neighbors, providing service to gated communities, collecting urban solid waste, providing the services of common repairmen, delivering healthcare providing service in both precedence ordered multitude of emergency environments and in logistics operations in an order-picking (Schmid et al. 2013; Expósito-Izquierdo et al. 2016).

Sevaux and Sörensen (2008) proposed a mixed integer linear programming formulation of a CluVRP for a distribution operation in a famous courier services company. Barthélemy et al. (2010) designed a heuristic for a CluVRP, where a big value was added to all inter-cluster edges to convert the CluVRP into a CVRP and solve it by simulated annealing method. Pop et al. (2012) presented two integer programming based exact solution approaches for a CluVRP. In another study, based on the integer programming formulation, two exact solution approaches such as branch-and-cut and branch-and-cut-and-price were presented by Battarra et al. (2014). A new hybrid algorithm based on the genetic algorithm combined with simulated annealing was developed to solve a CluVRP by Marc et al. (2015). Vidal et al. (2015) proposed two hybrid metaheuristics for solving a CluVRP. The first one was based on the iterated local search (ILS) algorithm designed by Subramanian (2012) while the second one was based on the unified hybrid genetic search (UHGS). An approximate two-level optimization technique was suggested to solve a CluVRP in Expósito-Izquierdo et al. (2016). Defryn and Sörensen (2017) developed an efficient two-level variable neighborhood search (VNS) heuristic to solve a CluVRP. In a study by Pop et al. (2018) addressed a unique two-level optimization approach to solve a CluVRP. The problem was divided into two sub-problems: the upper-level (cluster) sub-problem and the lower-level (customer) sub-problem. In the approach, the route visiting the clusters was obtained by a genetic algorithm, then, the customers' visiting order within the clusters was determined by the Concorde TSP solver. The recent trend of metaheuristics shows its hybridization for performance improvement. Recently, Hintsch and Irnich (2018) presented a large multiple neighborhood search (LMNS) based metaheuristic algorithm for the CluVRP. The problem was broken down into three sub-problems: assigning clusters to the routes, intra-cluster routing, and routing the clusters. In the LMNS approach, multiple destroy and repair moves for clusters were used first, then a VND-based local search improvement scheme was employed for further optimization. The CluVRP in this thesis work is investigated by the hybridized PSO algorithm. The PSO is hybridized by variable neighborhood search (VNS) for solving a CluVRP.

3.1 Problem definition of CluVRP

The CluVRP can be defined on an undirected graph $G = (V,\ E)$, where $V = \{0, 1, 2 \dots \dots n\}$, a set of nodes (vertices) including the customers $\{1, 2 \dots \dots n\}$ and a depot 0. A homogenous fleet of vehicles is situated at the depot, where the vehicles start and end their trip while serving the customers. Customers are grouped into predefined clusters. The parameters and mathematical formulation for the CluVRP used in this work is inspired by the study (Expósito-Izquierdo et al., 2016).

Parameters

n	Total number of customers
C	Total number of clusters
0	The depot
$\mathrm{n_l}$	The number of customers for the l^{th} cluster
m	Individual vehicle
M	Total number of vehicles available in the network
r	Individual cluster (mutually exclusive non-empty disjoint), r ∈ R
R	Group of the clusters
$\mathrm{d_r}$	Demand of cluster, r (aggregated over all customers in the cluster), $\mathrm{d_r} > 0$
$\mathrm{tc_{ij}}$	The nonnegative travel cost for the edges from i to j, $(\mathrm{i, j}) \in \mathrm{E}$
Q	Maximum loading capacity of each vehicle, $\mathrm{Q} > 0$
$\mathrm{C_r}$	The group of customers within a cluster, $\mathrm{C_r} = \{\ \mathrm{i} \in \mathrm{n}\colon \mathrm{r_i} = \mathrm{r}\}, \forall\ \mathrm{r} \in \mathrm{R}$
V	Set of vertices
S	subset of vertices that is different from V
$\delta^{+}(S)$	Set of edges $(i, j) \in S \times N \backslash S$
$\delta^{-}(S)$	Set of edges $(i, j) \in N \backslash S \times S$

The binary decision variables are:

$$x_{ijm} = \begin{cases} 1 & \text{vehicle } m \text{ travels from customer } i \text{ to } j \\ 0 & \text{otherwise} \end{cases}$$

$$y_{im} = \begin{cases} 1 & \text{customer } i \text{ is served by vehicle } m \\ 0 & \text{otherwise} \end{cases}$$

The CluVRP can be formulated as follows:

Minimize $$\sum_{(i,j)\in E} \sum_{m=1}^{M} tc_{ij} x_{ijm} \qquad (1)$$

s.t.,

$$\sum_{m=1}^{M} y_{im} = 1 \qquad \forall i \in \{1,2,\dots\dots n\} \qquad (2)$$

$$\sum_{m=1}^{M} y_{0m} \le M \qquad (3)$$

$$y_{0m} \ge y_{im} \qquad \forall m \in \{1,2,\dots M\}, \forall i \in \{1,2,\dots\dots n\} \qquad (4)$$

$$\sum_{j=1}^{n} x_{ijm} = \sum_{j=1}^{n} x_{jim} = y_{im} \qquad \forall m \in \{1,2,\dots M\}, \forall i \in \{0,1,2,\dots n\} \qquad (5)$$

$$\sum_{i=0}^{n} d_i y_{im} \le Q \qquad \forall m \in \{1,2,\dots M\} \qquad (6)$$

$$\sum_{i\in S} \sum_{j\neq S}^{M} x_{ijm} \ge y_{hm} \qquad \forall S \subseteq \{1,2,\dots n\}, h \in S, m \in \{0,1,2,\dots M\} \qquad (7)$$

$$\sum_{(i,j)\in\delta^{+}(C_r)} \sum_{m=1}^{M} x_{ijm} = \sum_{(i,j)\in\delta^{-}(C_r)} \sum_{m=1}^{M} x_{ijm} = 1 \qquad \forall r \in R \qquad (8)$$

$$\sum_{i=1}^{n} d_i y_{im} \ge \sum_{i=1}^{n} d_i y_{im+1} \qquad \forall m \in \{1,2,\dots M-1\} \qquad (9)$$

$$x_{ijm} \in \{0,1\} \qquad \forall (i,j) \in E, \forall m \in \{1,2,\dots M\} \qquad (10)$$

$$y_{im} \in \{0,1\} \qquad \forall i \in \{0,1,2,\dots n\}, \forall m \in \{1,2,\dots M\} \qquad (11)$$

In CluVRP work, the objective of minimizing the total travel cost is determined by eq. (1). Constraint (2) guarantees that each customer is visited exactly once. Constraint (3) assures that the number of vehicles used does not exceed the number of available vehicles. Constraint (4) enforces the rule that each vehicle in the route should visit the depot. That the arriving and departing vehicle is the same for a given customer is ensured by constraint (5). Constraint (6) states the maximum loading capacity of the vehicles is satisfied. Constraint (7) represents the sub-tour elimination constraint. Constraint (8) ensures that each cluster can be visited exactly once by a unique vehicle. Constraint (9) is the inequality ensuring partial symmetry.

3.2 Proposed hybrid PSO for the CluVRP

The proposed approach is a hybrid PSO algorithm that combines the standard PSO and the VNS. The structure of VNS in the proposed approach is inspired by a study by Vidal et al. (2015). Generally, the performance of the PSO is largely affected by the accuracy of the problem mapping. Thus, the PSO is modified in accordance with problem specifications in this study. The main features of the proposed hybrid PSO are the use of two types of particles representing clusters and customers, and the use of improvement scheme for the personal best solutions. The pseudo-code of the proposed hybrid PSO for the CluVRP is shown in Algorithm 3.1.

The proposed hybrid PSO uses the following definition:

α_{il}	Current cluster position value of i^{th} particle in l^{th} dimension
γ_{ij}	Current customer position value of i^{th} particle in j^{th} dimension
β_{il}	Current cluster velocity value of i^{th} particle in l^{th} dimension
δ_{ij}	Current customer velocity value of i^{th} particle in j^{th} dimension
f_i	Fitness function of particle, i
α_{il}^{b}	Personal best cluster position value found so far for the i^{th} particle in the l^{th} dimension
γ_{ij}^{b}	The personal best customer position value found so far for the i^{th} particle in the j^{th} dimension
f_i^{b}	Fitness function of best particle, i
α_l^{*}	Global best cluster position value found in the l^{th} dimension
γ_j^{*}	Global best customer position value found in the j^{th} dimension
f^{g}	Fitness function of global best particle
w	Inertia coefficient
c_1	Cognitive coefficient
c_2	Social coefficient
r_1, r_2	Independent random numbers
K	Total number of the particles
X	Position matrix for customer swarm
Y	Position matrix for cluster swarm
U	Velocity matrix for customer swarm
V	Velocity matrix for cluster swarm
X^{b}/X^{G}	Customer personal best/global best position value for swarm
Y^{b}/Y^{G}	Cluster personal best/global best position value for swarm
S^{b}	Personal best solution for swarm

Algorithm 3.1: Pseudo-code of the proposed algorithm for CluVRP

```
Initialization
Set parameters: w = 0.7, c_1 = c_2 = 2, r_1 = r_2 = 0.5, K = n/4.
Initialize position matrix X, Y and velocity matrix U , V
Initialize the personal best fitness vector f^b
Initialize the global best fitness vector f^g
Main phase
    Do while
            S^s ← GenerateCluVRPSolution (X, Y, U, V)
            S^s ← VNS ( S^s)
            Update personal best matrix X^b, Y^b, fitness vector f^b, and personal best
                solution matrix S^b
            Improve personal best matrix using improvement scheme
            S^b ← Improvement scheme (S^b)
            Update the best particle X^G, Y^G and fitness vector f^g
            Update (X, Y, U, V)
    End Do
```

3.2.1 Initialization phase

The position and velocity vectors are initialized as follows:

$$\alpha_{il} = \alpha_{min} + (\alpha_{max} - \alpha_{min}) * U(0,1) \qquad \forall i \in \{1,2,\dots K\}, \forall l \in \{1,2,\dots c\} \tag{12}$$

$$\gamma_{il} = \gamma_{min} + \left(\gamma_{max} - \gamma_{min}\right) * U(0,1) \qquad \forall i \in \{1,2,\dots K\}, \forall j \in \{1,2,\dots n\} \tag{13}$$

$$\delta_{il} = \delta_{min} + (\delta_{max} - \delta_{min}) * U(0,1) \qquad \forall i \in \{1,2,\dots K\}, \forall l \in \{1,2,\dots c\} \tag{14}$$

$$\beta_{il} = \beta_{min} + (\beta_{max} - \beta_{min}) * U(0,1) \qquad \forall i \in \{1,2,\dots K\}, \forall j \in \{1,2,\dots n\} \tag{15}$$

Where $\alpha_{max} = \gamma_{max} = \delta_{max} = \beta_{max} = 4$; $\alpha_{min} = \gamma_{min} = \delta_{min} = \beta_{min} = -4$.

Here, $U(0,1)$ represents a uniform random number generated between 0 and 1. The personal best fitness vector for the particle, i and fitness vector of a global particle are initialized as infinity.

$$f_i^b = \infty \quad \forall i \in \{1,2,\dots K\}$$
$$f^g = \infty$$

3.2.2 Mapping position vectors to generate CluVRP solution

The PSO usually maps the position values of the particles to generate the solution for a given problem. The two-phase approach is used in many studies to generate CluVRP solutions (Defryn and Sörensen 2017; Pop et al. 2018). In the proposed PSO, the solution is generated in two phases. In the first phase, the cluster route for the vehicles is generated, while the customer route for each cluster is generated in the second phase.

Phase 1: Generating cluster route

The generation of the cluster route starts with the empty trip for each vehicle, where the vehicles start and finish their trip at the depot. The clusters are iteratively added to the vehicle routes to find the complete solution. Firstly, the clusters with the highest position values are chosen for inclusion in the vehicle route, then the chosen cluster is inserted into the vehicle routes by using the cheapest insertion method. However, cluster insertion might face a situation where no vehicle has enough capacity for inserting a chosen cluster. In this situation, a tabu search based searching method is used to insert the chosen cluster. This method tries to maximize the available vehicle capacity using swap (1,1) and shift (1,0) neighborhood move. The selected swap move between cluster i and j is forbidden for next $U\left(\frac{c^2}{8},\frac{c^2}{4}\right)$ iteration. Similarly, in shift (1,0) move, insertion of cluster i is forbidden in cluster j for next $U\left(\frac{c*v}{8},\frac{c*v}{4}\right)$ iteration.

To understand the mapping procedure, consider an instance with 6 clusters and 2 vehicles with vehicle capacity 80. In any iteration t, consider the following position values and demands related to 6 clusters.

Clusters	1	2	3	4	5	6
Position values, γ_{ij}	1.99	3.67	-2.25	2.50	-0.09	1.08
Cluster demand, d_r	45	10	25	15	25	30

In the mapping, first clusters are arranged in non-increasing order of their position values. The resultant order will be π = 2-4-1-6-5-3. The two vehicles routes initially start with the first two clusters from π. The initial route will be {0-2-0; 0-4-0} and the remaining vehicle capacity for each vehicle is updated accordingly. Then, cluster 1 is chosen for insertion on vehicle routes. The insertion cost (i.e., increase in total route length) of cluster 1 is evaluated on every position of two routes {0-2-0; 0-4-0}. Suppose the cheapest insertion of cluster 1 is obtained by inserting at position 3 of vehicle 2. Then the new route will be {0-2-0; 0-4-1-0}. In the next iteration, cluster 6 is chosen for insertion. Suppose the cheapest insertion of cluster 6 is obtained by inserting at position 3 of vehicle 1. Then the new route will be {0-2-6-0; 0-4-1-0}. In the next iteration, cluster 5 is chosen for insertion. Suppose the cheapest insertion of cluster 5 is obtained by inserting at position 2 of vehicle 1. Then the new route will be {0-5-2-6-0; 0-4-1-0}. At this point, the remaining capacities for the two vehicles will be 15 and 20. But the demand for unassigned cluster 3 is 25 and no vehicle has the required capacity to accommodate cluster 3. In this situation, we use the tabu search with swap (1, 1) and shift (1, 0) with the objective function of maximizing remaining vehicle capacity. The tabu search is stopped when objective function (i.e., remaining vehicle capacity) becomes at least 25. Let assume the tabu search finds the new routes as {0-4-5-2-6-0; 0-1-0}. The remaining capacities will be 0 and 35 for vehicle 1 and vehicle 2 respectively. Finally, cluster 3 is chosen for insertion. Suppose the cheapest insertion of cluster 3 is obtained by inserting at position 3 on vehicle 2. Consequently, the final routes will be {0-4-5-2-6-0; 0-1-3-0}.

Phase 2: Generating customer route

Once the clusters routes are constructed, a sequence of the customers for each cluster is generated to find the complete solution of the CluVRP. The sequence of the customers is generated by selecting customers similar to the clusters routes generation method described in phase 1.

3.2.3 Variable neighborhood search (VNS) for CluVRP

The proposed PSO considers the position vector as a region instead of a particular point. The solution generated in the mapping phase represents one solution in the region, which might not be the best solution of the region. Therefore, the VNS is employed to achieve the local optima. The VNS procedure consists of three local search moves, which are inter-route search, intra-route search, and intra-cluster search. Both of the inter-route search and intra-route search focus on the cluster level; whereas, the intra-cluster search focuses on the customer level. The neighborhood operators which are used at cluster level: shift, shift2, swap, swap (2,1), swap (2,2), and 2-opt in the inter-route search; and shift, or-opt2, or-opt3, 2-opt, and swap in the intra-route search. The NL_c is the list of all inter-route neighbourhood searches. The neighborhood operators that are adopted for intra-cluster search (customer level) are shift, 2-opt, and swap; these explore all moves within each cluster. The detail of the operators can be found in the literature (Vidal et al. 2015; Subramanian 2012; Subramanian et al. 2010). The structure of each operator is shown in Fig.1 and Fig. 2. The first move adoption strategy is adopted for all local search moves. In this strategy, the solution is updated whenever an improved solution is found.

In all local searches, all neighbourhood move is selected only once for possible improvement instead of iterative strategy. The overall structure of the VNS for the CluVRP is shown in Algorithm 3.2.

Algorithm 3.2: Variable neighborhood search (VNS) for the CluVRP

Method VNS:
Initial solution, s;
Do
    Set previous solution, $s^{initial} = s$;
    List (NL_c) for the inter-route search;
        While $NL_c \neq \emptyset$
            Choose randomly a neighborhood from NL_c;
            Find best $s^{\neg}$ of $s \in$ neighbourhood;
            if $f(s^{\neg}) < f(s)$
                $s \leftarrow s^{-}$;
                $s \leftarrow$ Intra-route search(s)
                Update NL_c;
            Else
                Remove neighbourhood from NL_c;
        end While
    $s \leftarrow$ Intra-cluster search (s);
While ($s < s^{initial}$)
return s;
end *VNS*;

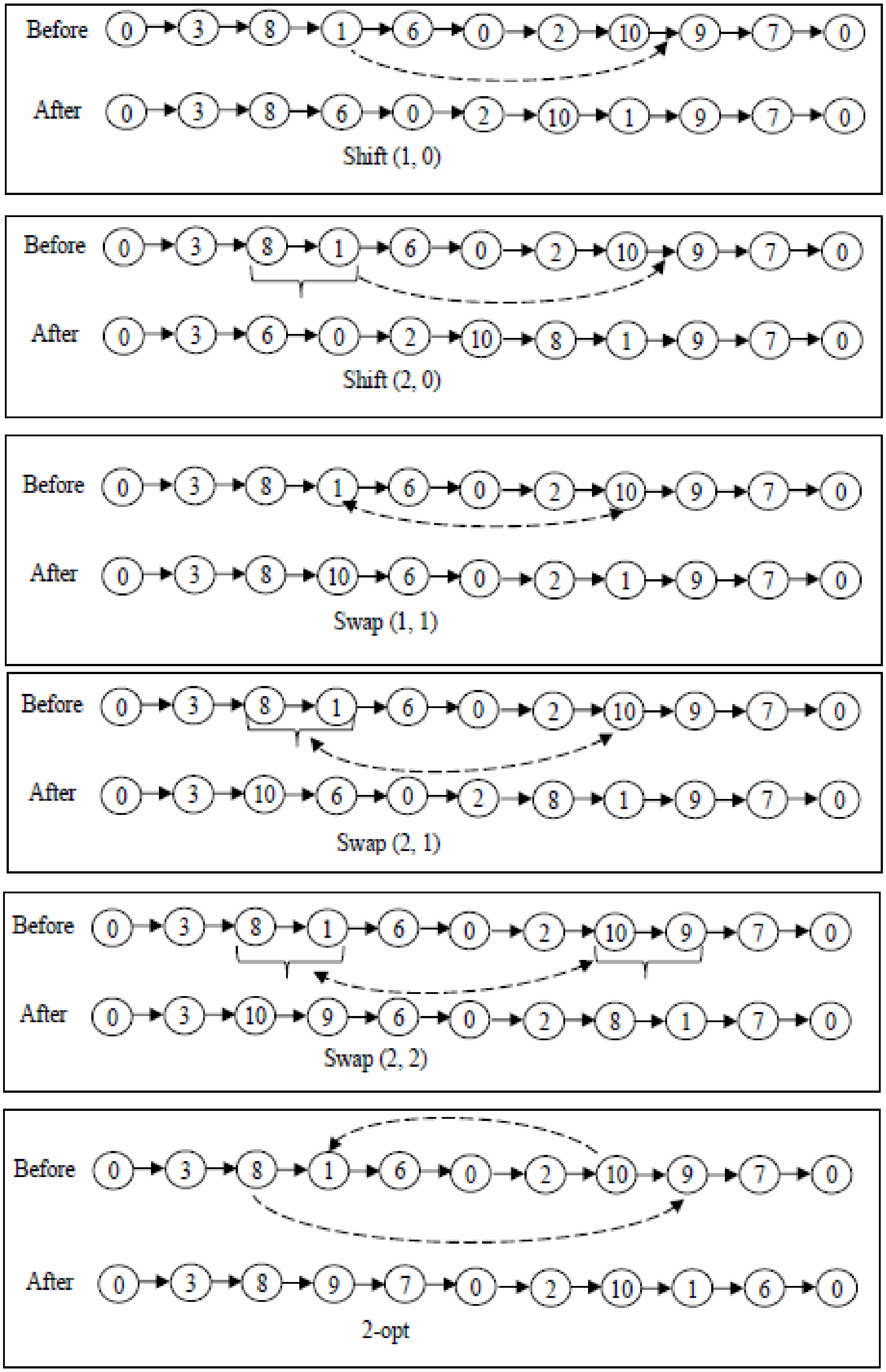

Fig.3.1: Inter-route neighbourhood search operators

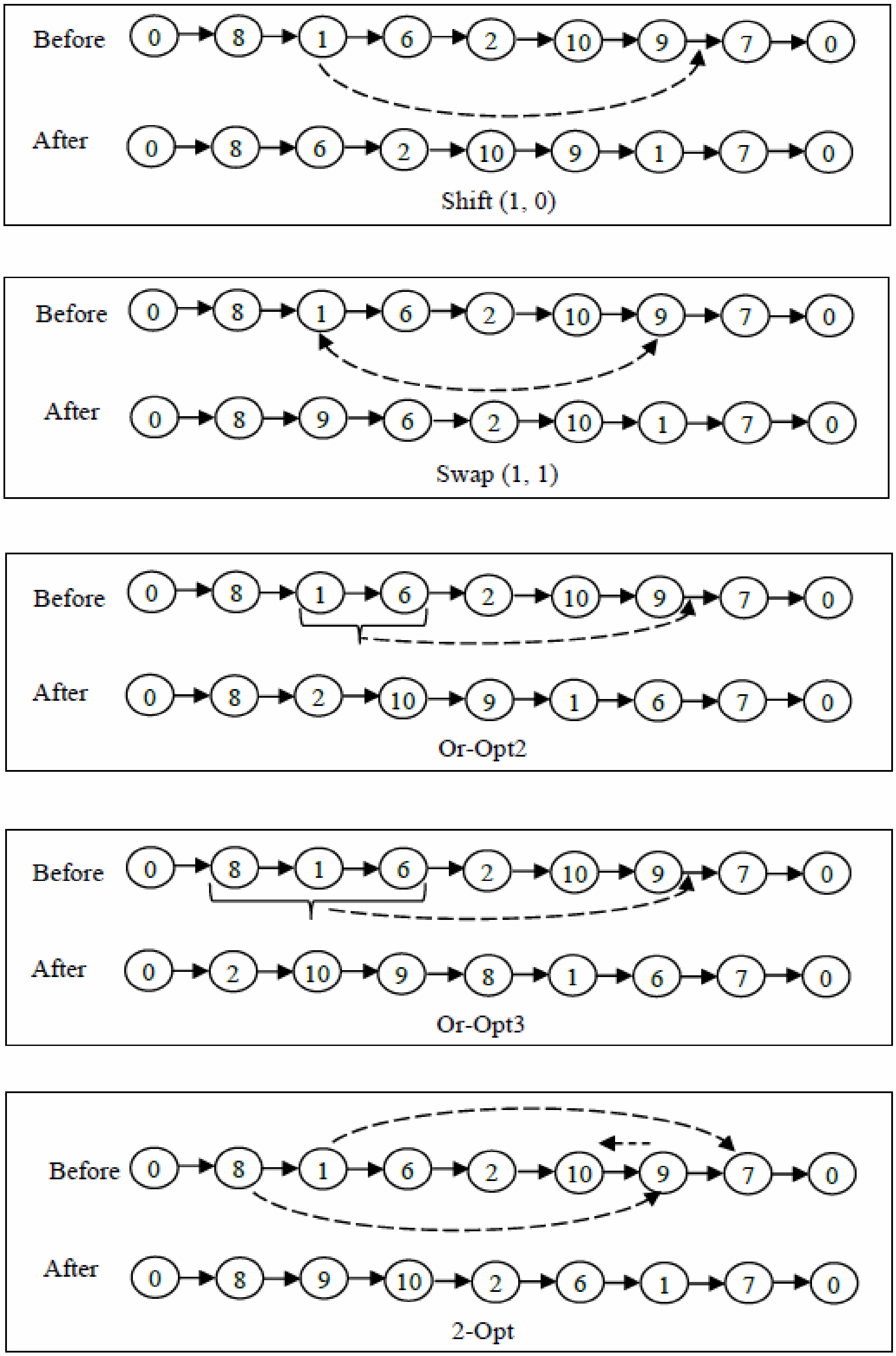

Fig. 3.2: Intra-route and inter-cluster neighbourhood search operators

3.2.4 Updating position and velocity vectors

The personal best position value for each particle is updated if the current solution is obtained better than the current personal best solution. Similarly, the global best value is updated if the new best solution is found better than the current global best value.

The velocity and position vectors are updated as follows:

$$\delta_{il} = w\delta_{il} + c_1r_1\left(\alpha_l^p - \alpha_{il}\right) + c_2r_2(\alpha_l^* - \alpha_{il}) \qquad \forall i \in \{1,2, \dots K\}, \forall l \ \{1,2, \dots c\} \tag{16}$$

$$\beta_{il} = w\beta_{il} + c_1r_1\left(\gamma_j^p - \gamma_{il}\right) + c_2r_2\left(\gamma_j^* - \gamma_{il}\right) \qquad \forall i \in \{1,2, \dots K\}, \forall j \ \{1,2, \dots n\} \tag{17}$$

$$\alpha_{il} = \alpha_{il} + \delta_{il} \qquad \forall i \in \{1,2, \dots K\}, \forall l \ \{1,2, \dots c\} \tag{18}$$

$$\gamma_{il} = \gamma_{il} + \beta_{il} \qquad \forall i \in \{1,2, \dots K\}, \forall j \ \{1,2, \dots n\} \tag{19}$$

3.2.5 Improvement scheme

The improvement scheme is used to improve the personal best solution. This is one of the new features of PSO used in this study. In our knowledge, this feature is not used in the existing literature of PSO. In the improvement scheme, at first, the solution is perturbed to generate a new solution. The perturbed solution is then optimized using the VNS scheme. A perturbation technique is implemented in both cluster and customer levels. In the perturbation scheme, firstly the Δ_1/Δ_2 number of clusters/customers are removed and then reinserting again using the cheapest insertion method. The structure of the improvement scheme used in hybrid PSO for CluVRP is shown in Algorithm 3.3. The parameters Δ_1 and Δ_2 are randomly generated between [0.5c, 0.75c] and $[0.5n_l, 0.75n_l]$ respectively.

Algorithm 3.3: Improvement scheme used in hybrid PSO for CluVRP

Method Improvement scheme:
    Initial solution, s;
    $s^* \leftarrow$ Perturbation (s)
    $s^{**} \leftarrow$ VNS (s^*)
    Update s
        if $f(s^{**}) < f(s)$
        $s = s^{**}$
return s;
end Improvement scheme;

3.3 Computational experiments

The proposed hybrid PSO algorithm for CluVRP is implemented using the C++ programming language to solve several benchmark datasets from the literature of CluVRP. The experiments are run on a Linux server with four 2.1GHz processors with 16-core each and a total of 256GB of RAM.

3.3.1 The benchmark CLuVRP instances

The performance of the hybrid-PSO is tested on the CluVRP benchmark instances composed of 20 major customers groups named as, A, B, P, M, and Golden instances (Golden 1 to Golden 20) with a total of 298 individual instances. These CluVRP instances are originally adopted from the GVRP instances by Bektas et al. (2011). The characteristics of the benchmark dataset are summarized in Table 3.1.

Table 3.1: The summary of the benchmark instances

Instance type	No. of instances	No. of customers	No. of Clusters	Vehicle capacity (No. of vehicles)	Source
A	27	31-79	11-27	100 (2-5)	Bektas et al. (2011)
B	23	30-77	11-23	100 (2-5)	Bektas et al. (2011)
M	4	100-261	34-76	200 (3-8)	Bektas et al. (2011)
P	24	15-100	6-51	35-400 (1-8)	Bektas et al. (2011)
Golden	220	201-483	17-97	550-1000 (4-12)	Battarra et al. (2014)

The following notations are used for the results reporting purpose in this study:

Notations	Algorithms
BC	The branch and cut method of Battarra et al. (2014)
UHGS	The unified hybrid genetic search approach of Vidal et al. (2015)
Two-level	The two level algorithm results of Expósito-Izquierdo et al. (2016)
Two-level VNS	The two level variable neighborhood search results of Defryn and Sorensen (2017)
Decomposition-based method	The decomposition method of Horvat-Marc et al. (2015)
Two-level optimization	The two-level optimization approach by Pop et al. (2012)
LMNS	The large multiple neighborhood search result of Hintsch and Irnich (2018)
Hybrid PSO	The algorithm proposed in this work for CluVRP

The PSO parameters are set by performing sensitivity analysis using the problem instances of sets A, B, M, and P. We use PSO solution without VNS and without improvement scheme for 100 iterations to set the parameters. The sensitivity analysis is started with the parameter values found in the literature (Marinakis et al. 2013; Ai and Kachitvichyanukul 2009b; Marinakis et al. 2010). The parameter values are set one by one in the order of w, c_1, c_2, r_1, r_2, and K. A number of different alternative values for each parameter are tested as w = {0.5, 2}; c_1= {2, 5}; c_2= {2, 5}; r_1= {0, 1}; r_2 = {0, 1}. Finally we set our best parameters as w = 0.7; $c_1 = c_2 = 2$; $r_1 = r_2$ = 0.5; $K = n/4$. The proposed hybrid PSO is run for 500 iterations (i.e., algorithm termination criterion) to maintain reasonable CPU time. We observe that the improvement of results after 500 iterations is very marginal.

3.3.2 Performance evaluation of different algorithms

All the results in this study are evaluated by comparing the results reported by the Battarra et al. (2014) using the branch and cut (BC) algorithm to solve the CluVRP problem. They could not achieve the optimal solutions for all the problem instances but reported the best feasible upper bound solutions obtained during the execution of their algorithms. The solutions by Battarra et al. (2014) are denoted by UB. Overall, the performance of the algorithms, including algorithms obtained from the literature, is evaluated by two criteria. The first criterion is that in how many instances does the algorithm finds a better solution than the upper bound, UB solution. It is reported in the tables under the "No. of improved UB". The second criterion is the improvement% of the algorithm compared to the UB. It is measured by the eq. (20), where Sol is used to denote the solutions found by the other algorithms. The improvement% of a group instance is reported as "improvement%" in the tables. Furthermore, the processing time (CPU time) is reported as t(s). The following formula is used to calculate improvement% from the UB.

$$Improvement\% = \frac{UB - Sol}{UB} \times 100 \qquad (20)$$

Table 3.2 and Table 3.3 show all the results of this study including reported results from the literature.

In the performance evaluation, a statistical test, non-parametric Friedman test is used to check any significant difference exists in the performance of algorithms. The statistical software IBM SPSS version 19 is used to run the Friedman test using $\alpha = 0.05$ as the level of significance.

3.3.2.1 Performance evaluation for A, B, M and P instances

Table 3.2 reports the results for the instances groups A, B, M, and P. The two-level VNS algorithm, decomposition-based method, two-level optimization, and the hybrid PSO are evaluated in the table. The comparison shows that all of the two-level VNS, the decomposition-based method, and the two-level optimization obtain the improved UB solution for one instance out of 75 instances; whereas, the hybrid PSO is capable of obtaining the improved UB solution for a total of 2 instances out of 78. In addition, the overall improvements obtained are -0.03%, -5.00%, and -1.7% respectively in the two-level VNS, decomposition-based method, and two-level optimization, which shows that all the two-level VNS, the decomposition-based method, and two-level optimization are inferior to BC solutions. In the case of the hybrid PSO solution, the overall improvement is found to be 0.05% compared to BC solution, which also indicates that the hybrid PSO solution is superior to the two-level VNS by 0.08% (from -0.03% to 0.05%), decomposition-based method by 5.05% (from -5.00% to 0.05%), and to two-level optimization approach by 1.12% (from -1.7% to 0.05%). Although the CPU time is observed to be better in two-level VNS (0.23 sec) compared to the hybrid PSO algorithm (1.31 sec). In the Friedman test, it is found to be a significant statistical difference in comparing the performance of hybrid PSO with all algorithms (p values=0.000).

Table 3.2: Summarised results of A, B, M, and P instances

Instances in BC			Two-level VNS			Decomposition-based method			Two-level optimization			Hybrid PSO		
Group	No. of instances	No. of Cust-omer	No. of improved UB	Improve -ment %	t(s)	No. of improved UB	Improve -ment %	t(s)	No. of improved UB	Improve -ment %	t(s)	No. of improved UB	Improve -ment %	t(s)
A	27	31-79	0/24	-0.07%	0.05	1	-2.6%	...	1	-1. 21%	…	0	0.00%	0.46
B	23	30-77	0	-0.03%	0.04	0	-3.0%	…	0	-1.63%	…	0	0.00%	0.50
M	4	100-261	1	0.11%	3.48	0	-32.3%	…	0	-5.32%	…	1	0.16%	15.05
P	24	15-100	0	-0.01%	0.07	…	…	…	…	…	…	1	0.13%	0.75
Total	78	…	1/75	…	…	1/78	…	…	1/78	…	…	2/78	…	…
Avg	…	…	…	-0.03%	0.23	…	-5.00%	…	…	-1.7%	…	…	0.05%	1.31

The Fig.3.3 reveals that the two-level optimization algorithm obtains negatively dispersed results from the UB for most of the instances. The two level VNS achieves nearly closer results with the UB but the proposed hybrid PSO achieves more nearest results to the UB. The decomposition-based method omitted in Fig.3 because the results of the algorithm are far away from the UB for the instances.

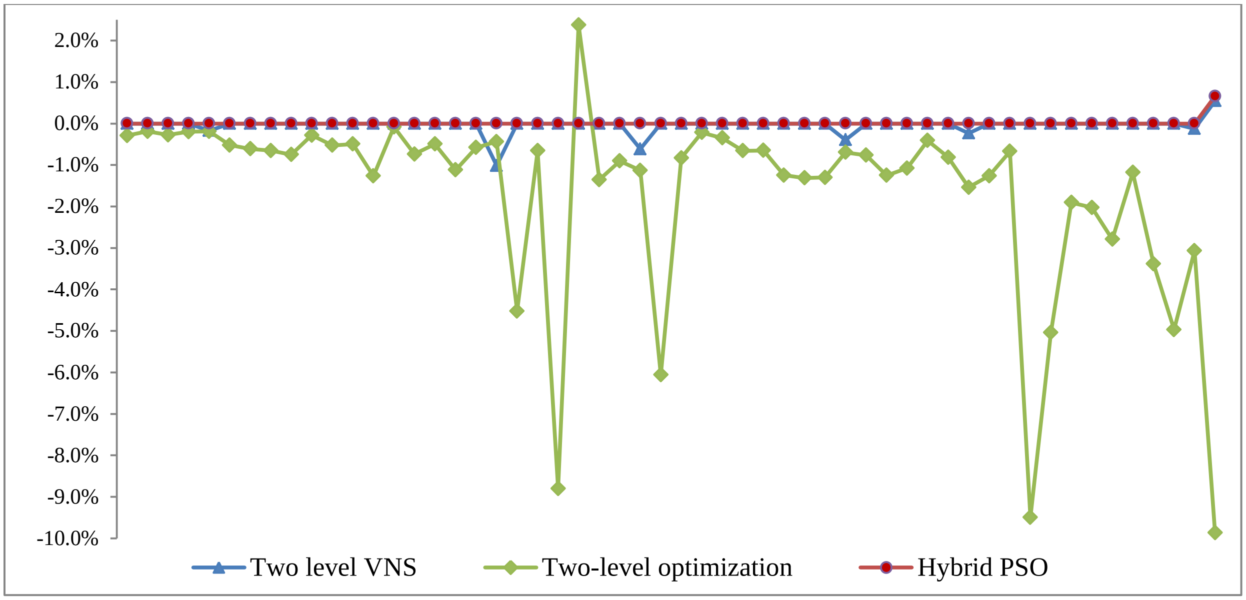

Fig. 3.3: Improvement% of the algorithms results for A, B, M instances.

3.3.2.2 Performance evaluation for Golden instances

Table 3.3 reports the result for the Golden instances. This set includes a total of 220 instances. The results by the UHGS, the two-level, two-level VNS, LMNS, and by the hybrid PSO are evaluated in the table. In the comparison study (in table 3.3), we omit 5 instances out of 220 instances (2 instances from instance group n = 360 and 3 instances from group n = 420), because the results produced by the proposed PSO is found to be exceptionally better than other algorithms. Although we report all results of the CluVRP study in the appendix tables (Table A1 to Table A7). The comparison shows that the LMNS improves the UB solution for 114 instances and the UHGS improves for 4 instances; whereas, the hybrid PSO improves a total of 154 instances. The two-level algorithm and two-level VNS algorithm obtain no improved UB solution of the Golden instances.

The overall average improvement for Golden instances using LMNS, UHGS, the two-level, two-level VNS is -0.18%, -0.03%, -2.40%, and -1.08% respectively. The hybrid PSO obtains an overall average improvement of 0.57%, which is better than all existing algorithms. In terms of solution quality, our nearest competitor is LMNS and UHGS. The CPU time for the LMNS and UHGS is as 9.5 seconds and 626.70 seconds respectively; whereas, the CPU time for the hybrid PSO is 59.10 seconds only. The hybrid PSO uses a Linux server with four 2.1GHz processors with 16-core each and a total of 256 GB of RAM. And, the UHGS uses a Xeon CPU with 3.07 GHz with 16 GB of RAM running under Oracle Linux Server 6.4. In terms of speed, these two computers are comparable. Therefore, it can be concluded that the hybrid PSO is superior to UHGS in terms of both solution quality and CPU time.

The statistical analysis here again shows that there are significant differences in the comparison of the performance of hybrid PSO to all algorithms in the Friedman test

$(p\ values = 0.000)$. However, it is important to mention that Friedman's test only reveals the significant difference exists between two algorithms instead of showing which particular group is different from each other in comparison (Ezugwu et al. 2017).

As it can be noted from Fig. 3.4, the hybrid PSO improves the solution for most instances group. The two-level algorithm obtains relatively worse results followed by the two-level VNS algorithm. The LMNS algorithm generates comparatively better results but not as good as UHGS algorithm results. The UHGS finds the results nearly close to the UB for most of the instances.

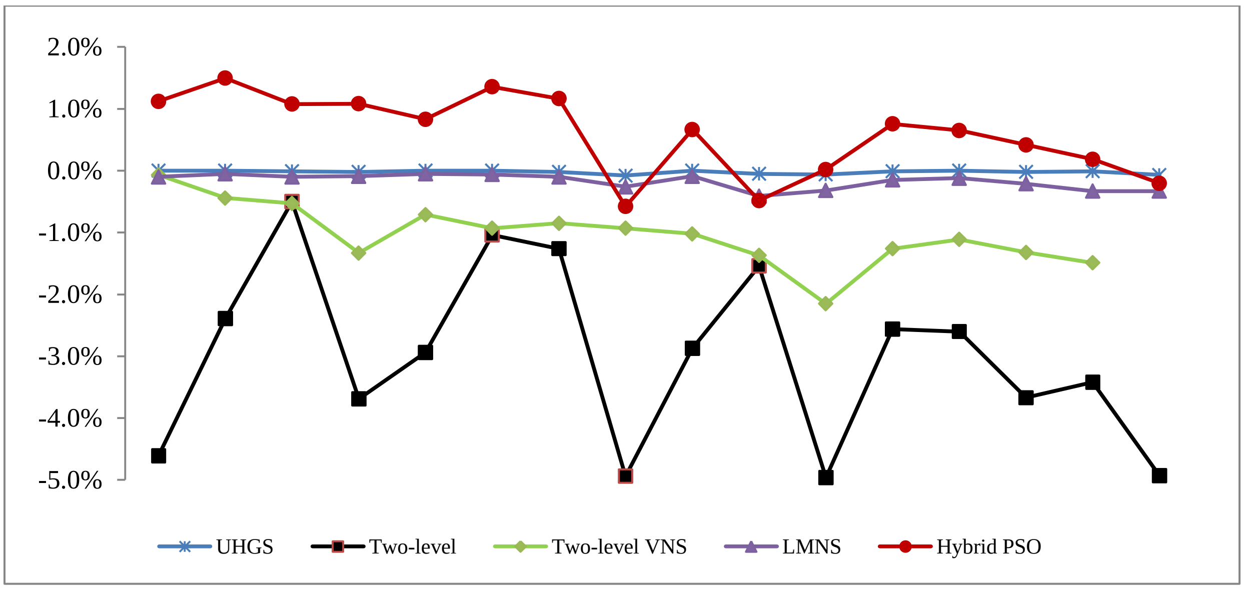

Fig. 3.4: Improvement% of the algorithms results for 16 groups of Golden instances.

Table 3.3: Summarised results of Golden instances

Golden instance		UHGS			Two-level			Two-level VNS			LMNS			Hybrid PSO		
n	No of instances	No of improved UB	Improve-ment %	t (s)	No of improved UB	Improve-ment %	t(s)	No of improved UB	Improve-ment %	t(s)	No of improved UB	Improve-ment %	t(s)	No of improved UB	Improve-ment %	t(s)
200	11	0	0.00%	2866.56	…	-4.61%	10	0	-0.07%	10	8	-0.10%	9.9	8	1.12%	13.00
240	22	0	0.00%	154.93	…	-2.39%	10	0	-0.44%	10	17	-0.05%	3.7	15	1.14%	17.90
252	11	0	-0.01%	127.15	…	-0.50%	10	0	-0.53%	10	8	-0.10%	1.4	11	1.08%	16.38
255	11	0	-0.02%	135.45	…	-3.69%	10	0	-1.33%	10	8	-0.09%	2.1	11	1.08%	16.04
280	11	0	0.00%	3848.31	…	-2.94%	10	0	-0.71%	10	7	-0.05%	20.1	8	0.82%	31.18
300	11	0	0.00%	197.93	…	-1.04%	10	0	-0.93%	10	8	-0.06%	6.3	11	1.36%	27.91
320	22	0	-0.02%	202.49	…	-1.26%	10	0	-0.85%	10	13	-0.10%	4.9	22	0.87%	41.54
323	11	0	-0.08%	175.74	…	-4.94%	10	0	-0.93%	10	6	-0.26%	2.6	0	-0.58%	30.73
360	20	0	0.00%	1250.15	…	-2.87%	10	0	-1.02%	10	17/22	-0.09%	17.9	14	0.60%	60.36
396	11	0	-0.05%	292.26	…	-1.54%	10	0	-1.37%	10	1	-0.41%	2.4	4	-0.49%	66.03
399	11	0	-0.06%	225.26	…	-4.96%	10	0	-2.15%	10	4	-0.32%	2.8	5	0.02%	58.98
400	11	0	-0.01%	1384.18	…	-2.56%	10	0	-1.26%	10	3	-0.15%	19.5	11	0.76%	94.89
420	8	0	0.00%	361.86	…	-2.60%	10	0	-1.11%	10	8/11	-0.12%	15.4	8	0.65%	111.77
440	11	0	-0.02%	1017.64	…	-3.67%	10	0	-1.32%	10	2	-0.21%	19.9	10	0.42%	90.00
480	22	0	-0.01%	1434.94	…	-3.42%	10	0/21	-1.49%	10	6	-0.33%	15.6	13	0.09%	136.07
483	11	4	-0.07%	405.87	…	-4.93%	10	0	-2.23%	10	1	-0.33%	2.9	3	-0.22%	127.90
Total	215	4/220	…	…	…	…	…	0/219	…	…	114/220	….		154/215	…	…
Avg.		…	-0.03%	626.70	…	-2.40%	10	…	-1.08%	10	….	-0.18%	9.5	…	0.57%	59.10

The CPU time of some algorithms (LMNS, two-level VNS, and two level algorithm) are approximately 10 seconds, which is lower than the CPU time of our algorithm. In order to make a valid comparison, we observe the results of our algorithm for 100 iterations. The improvement% of our algorithm is 0.17% (with 9.33 seconds CPU time) when it is executed for 100 iterations. The improvement% of LMNS, two-level VNS, and two-level algorithms are -0.18%, -1.08%, and -2.40% respectively. The results indicate the superiority of our algorithm compared to other existing algorithms.

3.3.2.3 Effect of hybridizing and improvement scheme on PSO's performance

The effect of hybridizing the proposed PSO on solution quality is presented in Table 3.4. The performance of the hybridization of the PSO is evaluated for the 20 major customers groups with a total of 298 instances under three settings: PSO without VNS and without improvement scheme; PSO with VNS and without improvement scheme; and the proposed PSO (i.e., PSO with VNS and with improvement scheme). The number of iterations for each setting is changed to maintain approximately the same computational time. All other parameters in the PSO framework are the same for all settings.

Table 3.4 shows that hybridizing the PSO with VNS and without improvement scheme improves the solution quality of the PSO without VNS and without improvement scheme by 73.74% (from -74.55% to -0.81%). The solution quality of the PSO with VNS and without improvement scheme is further improved by 12.4% (from -0.81% to 0.43%) by hybridizing the PSO with VNS and improvement scheme. Thus, the table denotes that the performance of PSO is enhanced if hybridization with VNS and with improvement scheme. These results justify the hybridization of the PSO with the VNS and with the inclusion of the improvement scheme in PSO.

In the pure improvement scheme, we implement the improvement scheme on the randomly generated initial solution for a specified number of iterations. In the scheme, the initial solution is perturbed, and then local searches of the improvement scheme are implemented. The process is repeated until the specified number of iterations is reached. Thus, the pure improvement scheme without PSO can be called as iterative local searches (ILS) (Macrina et al. 2019; Vidal et al. 2015). The result of the pure improvement scheme is found as the improvement% of 0.16% and it improves the UB solution for 121 instances with CPU time of 56.79. The total iterations for pure improvement are 70000. The result of the proposed hybrid PSO is found as the improvement% of 0.43%, which is 0.27% (from 0.16% to 0.43%) superior to the pure improvement scheme result. The result of the improvement scheme is close to the proposed PSO algorithm. This observation brings an interesting fact about the potential of ILS. A further investigation is needed to design an efficient ILS for solving the clustered vehicle routing problem.

Table 3.4: Effect of hybridization on CluVRP solution quality

Degree of hybridization	Number of iterations	No. of improved UB	Improvement %	t(s)
PSO without VNS and without improvement scheme	15000	0	-74.55%	60.80
PSO with VNS and without improvement scheme	1800	2	-0.81%	57.37
Pure improvement scheme	70000	121	0.16%	56.79
Proposed PSO	500	156	0.43%	51.86

3.4 Conclusion

The combinatorial optimization problem, CluVRP, is considered in this chapter. The objective of the problem is to find the optimal distribution costs for the logistic network serving all customers by using the available vehicles. A new hybrid PSO algorithm is designed to solve the CluVRP. Here, the intensification capabilities of VNS obtaining local optimal with the swarm based diversification abilities of the PSO are combined to form the hybridized PSO algorithm. The algorithm is tested on the benchmark instances found in CluVRP literature. The new best-known solutions for a total of 156 instances out of 293 benchmark instances are generated with an average CPU time of 43.71 seconds by the proposed hybrid PSO. The new features in the PSO algorithm have been added such as the use of two types of particles and improvement scheme for the personal best solution. By considering the architecture of the proposed algorithm, it is believed that the proposed hybrid PSO algorithm to have great potential for solving instances other variants of VRP. With the capability of a quality solution on relatively acceptable CPU time, the algorithm has the perspective to use in many practical scenarios such as distribution logistics with CO_2 emission cap leading to a penalty, the problem of perishable items, and transportation problems in military operations, etc.

CHAPTER FOUR

Mixed fleet green vehicle routing problem with backhaul and time windows

Improving operational practices, and fuel efficiency, transferring to cleaner fuels, lowering travel demand are effective approaches to reduce the CO_2 emission in transportation (Fukasawa et al., 2016). In this light, a hydrogen and mixed fleet based green vehicle routing problem with backhaul with time windows (MFGVRPBTW) is proposed in this chapter of thesis work. The routing problem consists of a heterogeneous fleet of conventional internal combustion vehicles (CVs) and fuel cell hydrogen vehicles (HVs) characterized by different CO_2 emission models and carrying capacities. Time windows of all nodes, upper limit (cap) of CO_2 emission for the network, and vehicle capacity are considered as constraints. In this research work, the fuel cell hydrogen vehicle (HV) is introduced in the vehicle routing field. The HVs have better fuel economies but almost the same driving range compare to CVs. Besides, the HVs have almost the same fuel economies but higher driver range compare to electric vehicles. So, HVs are considered to have better fuel economies than the CVs and no visit to refueling or recharging stations is measured for vehicles in this study.

The vehicle routing problem with backhauls (VRPB) is an importation variant of VRP that addresses a realistic scenario of logistic operation considering the pickup and delivery problem. The VRPB comprises two sets of customers, identified as linehauls for the delivery problem on outbound trip and backhauls for pickup problem on the return trip.

Each vehicle serves both sets of customers in a manner that linehaul customers must be served first followed by backhaul customers that result in a reduced number of total vehicles and a shorter routing time compare to a conventional VRP for the delivery customer or pickup customer only. Contrary to the conventional VRP where vehicle returns to the depot with an empty load, vehicles pick up the backhaul loads and return to the depot with total picked up loads after serving all linehaul customers. In practice, VRPB is seen in many instances where delivery customers need priority than pickup customers. For instance, in the grocery industry, the supermarkets and shops are linehaul customers; and grocery suppliers are backhaul customers (Walmart 2017); in the drink distribution industry, delivering full bottles are linehaul customers and collecting empty bottles are backhaul customers (Coca-Cola 2017). In reverse logistics, delivering new products are linehaul customers, and damaged or non-conforming or recycling products are backhaul customers (ex., Tesco retails, DS Smith 2017). In the manufacturing business, final products are delivered to final customers (linehaul), raw materials are picked up from distributions (backhauls) to the depot. Similar applications are found in airline scheduling, railway fleet routing, and scheduling problems (Thangiah et al. 1996).

Over the last decades, many variants of VRPB have been seen in literature, for examples, the mixed VRPB (introduced by Wade and Salhi 2002), multi-depot VRPB (first studied by Salhi and Nagy 1999), VRPB with time windows (first studied by Gelinas 1991), VRPB with heterogeneous fleet (introduced by Tavakkoli-Moghaddam et al. 2006), single VRP with unrestricted backhaul (first proposed by Süral and Bookbinder 2003), mixed VRPB (Hoffet al. 2009), time-dependent VRPB (Wang and Wang 2009), VRPB with inventory control decisions (introduced by Liu and Chung 2009), VRP with clustered backhauls (Belloso et al. 2015), VRP with clustered back- hauls and with 3D loading constraints (Bortfeldt et al. 2015), VRP with clustered and mixed backhauls (Belloso et al. 2017a), multi-objective VRPB (García-Nájera et al. 2015), multi-trip VRPB (Wassan et al. 2016), and Green VRPB (Pradenas et al. 2013). Adding the time windows constrain into the VRPB forms a new variant, known as VRP with backhauls with time windows (VRPBTW), where customers are defined with a time windows where they prefer to be visited. The VRPBTW provides a great perspective for reducing environmental impact and cost of transportation, as it reduces running of empty vehicles and fuel consumptions from better utilization of vehicle capacity combining two different services in the distribution services (Corlu et al. 2020; Santos et al. 2019; Pradenas et al. 2013). As the capacitated VRP is proven to be an NP-hard problem, the VRPBTW is also NP-hard (Thangiah et al. 1996; Kücükoglu and Öztürk 2015).

The objective of the MFGVRPBTW problem is to determine the cost effective optimal routes of the vehicles serving all customers. As a variant of VRP, the MFGVRPBTW is an NP-hard problem and it is hard to solve by exact method within a reasonable computation time. Therefore, it is intended to develop a hybrid particle swarm optimization (PSO) based solution approach to solve the problem. Moreover, metaheuristics integrated by local searches or route construction heuristics can be more effective and powerful solution method for the combinatorial optimization problem (Kücükoglu and Öztürk 2015). In this response, a hybrid particle swarm optimization (PSO) based solution approach is designed to solve the problem. This hybrid PSO integrating a classical PSO with a neighborhood search and improvement scheme is targeted to achieve a better solution quality for the different VRPB instances.

Toth and Vigo (2002) presented the first review work on VRPB literature until 2002. Parragh et al. (2008) reviewed the VRPB until 2007. Irnich et al. (2014) briefly reviewed various VRPB papers published from 2002-2014. Koç and Laporte (2018) comprehensively reviewed the VRPBs until 2017. Recently Santos et al. (2019) presented a review study on VRPB with a sustainability perspective suggesting the sustainability concern would be the future researches line in the field of VRPB.

Since its introduction, the standard VRPB and its variants have been extensively studied. Yang et al. (2020) considered a VRP with mixed backhauls and time windows (VRPMBTW). In the problem, the linehaul and backhaul customers were visited in any order of sequence, in contrast to the pure backhaul problem where backhaul customers are served only after linehaul customers. An augmented lagrangian relaxation approach was proposed as a solution approach. The variant, standard VRPB with time windows (VRPBTW) have also gained popular attention. Gelinas (1991) developed an exact solution using a branch-and-bound algorithm for the VRPBTW consists of up to 100 customers (Goetschalckx and Jacobs-Blecha 1993). Thangiah et al. (1996) studied a VRPBTW by proposing a route construction heuristic inspired by the study of Kontoravdis and Bard (1992). The proposed heuristics were tested on a total number of 45 Gélinas et al. (1992) instances and 24 newly generated instances involving up to 500 customers. Potvin et al. (1996) proposed a greedy insertion heuristic coupled genetic algorithm for solving a VRPBTW. Duhamel et al. (1997) developed a tabu search based solution approach for the VRPB with time windows. Reimann et al. (2002) presented an insertion based ant system solution approach for the VRPB with time windows. Another study by Cho and Wang (2005) generated a metaheuristic for solving VRPBTW. The metaheuristic was based on the threshold accepting heuristics coupled with modified nearest neighbor and exchange procedures. In addition, Ropke and Pisinger (2006) proposed a large neighborhood search algorithm to solve a VRPB with time windows. The proposed algorithm was found superior to the previous solution when tested on both benchmark Gélinas et al. (1992) and Thangiah et al. (1996) instances. Reimann and Ulrich (2006) studied a VRPBTW and generated an ant colony optimization (ACO) based solution method. Zhong and Cole (2005) investigated a VRPB with time windows with and without customer precedence. A proposed guided local search approach heuristic was tested on benchmark instances and compared to Potvin et al. (1996). Küçükoglu and Öztürk (2014) developed a differential evolution algorithm to solve a VRPBTW. Küçükoglu and Öztürk (2015) presented an advanced hybrid metaheuristic algorithm to solve a VRPBTW. The hybrid algorithm was comprised of simulated annealing and tabu search algorithm. The proposed algorithm was tested for VRPTW on Solomon's R1 instances and for VRPBTW on Gélinas et al. (1995) instances. Tuntitippawan and Asawarungsaengkul (2016) presented an artificial bee colony algorithm to solve the VRPBTW. Brandão (2018) studied a VRPBTW by designing an iterated local search based algorithm and tested on benchmark instance of Gélinas et al. (1992) and Thangiah et al (1996). Worawattawechai et al. (2019) developed an artificial bee colony algorithm for the VRPBTW. Quila et al. (2020) investigated a VRPBTW by proposing a new mathematical model. The problem was formulated based on the study of Küçükoglu and Öztürk (2015). The proposed model was tested on newly generated instances with customer size up to 30 customers. Eguia et al. (2013) presented a green VRPBTW with a heterogeneous fleet and different fuel types. A mixed VRPBTW with heterogeneous fleet was studied by Belmecheri et al. (2013). The problem was solved by a hybrid PSO metaheuristic, where classical PSO was combined with ACO and with many local searches. Pradenas et al. (2013) introduced a GHG emissions function in a VRPBTW. The author developed a scatter search heuristic based solution approach and tested on the Gélinas et al. benchmark instances.

This thesis work designs a new hybrid PSO based solution approach for MFGVRPBTW to obtain a good quality solution. The performance of the proposed algorithm is tested by comparing many state-of-the-art algorithms for different variants of VRPB.

4.1 Problem definition and mathematical formulation

4.1.1 Problem definition

The MFGVRPBTW is defined on a complete, directed graph $G = (N,\ A)$, where N is a set of nodes. The set has three separate sets, $N = \{0, L, B\}$. The node 0 is the depot, the nodes set $L = \{1, 2 \dots \dots n\}$ is the linehaul customers, and nodes set $B = \{n + 1, \dots \dots n + m\}$ is the backhaul customers. The arc set A denotes all possible connections between the nodes, defined as $\{(i, j): i, j \in N, i \neq j\}$. Each customer is either linehaul customer or backhaul customer that implies each customer requires either delivery service or pick up service but can't be requiring both services. Each node $i \in N$ is associated with a non-negative amount of load either to be delivered (a_i) or picked up (b_i) in the routes and a hard time windows $[e_i, l_i]$, where e_i and l_i are the earliest and latest arrival time at the nodes respectively with a s_i non-negative service time (loading or unloading) of the vehicles. A hard time window specifies vehicles are not allowed to start their service late but waiting in case of early arrival at the nodes is possible. Each node also has the following properties such as Euclidian distance d_{ij}, travel speed v_{ij}, and travel time $t_{ij} = \frac{d_{ij}}{v_{ij}}$. A mixed fleet of heterogeneous vehicles consists of a number of k_{cv} conventional vehicles and k_{hv} hydrogen vehicles are located at depot. Both the conventional and hydrogen vehicles are used to serve both linehaul and backhaul customers to generate the best routes in the network. Linehaul customers must be visited before the backhaul customer are served in the vehicle routes. The heterogeneity of the vehicles includes different vehicle capacities and CO_2 emission amounts. The capacities of conventional and hydrogen vehicles are denoted by Q_{cv} and Q_{hv} respectively. Let k is any vehicle of the fleet size of K. M_* is a very large value. T_{max} is the maximum allowable driving time for vehicle k. E_{cap} is the given CO_2 emission cap for the logistics network. The vehicle's tailpipe emission is calculated from the instantaneous fuel consumption model (Barth et al. 2005; Bektas and Laporte 2011). The pragmatic fuel consumption model for the vehicles in this study is realistically considered as a function of traveled distance, speed, and cargo load over the arcs, instead of only distance function (Li et al. 2018; Goeke and Schneider 2015). Because considering the fuel consumption model as a linear function of the traveled distance of vehicles only is not useful in studying green logistics of businesses. The fuel consumption model of hydrogen vehicle for an arc (i, j) is estimated by Eq. (21), (22), and (23) used in Bektas, et al. (2016), and Goeke and Schneider (2015) for AFV.

$$Cb_{ij} \approx \alpha_{ij}(w_0 + u_{ijk})d_{ij} + \beta v_{ij}^2 d_{ij} \quad (21)$$

$$\alpha_{ij} = a + g sin\theta_{ij} + g C_r cos\theta_{ij} \quad (22)$$

$$\beta = 0.5 C_d A \rho \quad (23)$$

The fuel consumption model of conventional vehicle for an arc (i, j) is estimated as follows:

$$Cf_{ij} \approx FE_{factor} \ . \{\alpha_{ij}(w_0 + u_{ijk})d_{ij} + \beta v_{ij}^2 d_{ij}\} \quad (24)$$

Where, Cb_{ij} and Cf_{ij} are the fuel consumption amount by the hydrogen vehicle and conventional vehicle respectively in the arc (i, j). Here α_{ij} is the arc specific constant, β is the vehicle specific constant, u_{ijk} is the on-board cargo load for the vehicle, k, on the arc (i, j). $FE_{factor} = 1.2$ is the fuel economy factor used for the conventional vehicle compared to the hydrogen vehicle (Thomas 2009). The typical values of all parameters in the emission models are shown in Table 4.1. The fuel consumption amount is found by the equations in joules

($\mathrm{J} = \mathrm{kg}\frac{\mathrm{m}^2}{\mathrm{s}^2}$), which can be converted into kilowatt-hour (kWh). The $\mathrm{CO_2}$ emission of the vehicle for traveling on the arc (i, j) is calculated as estimated in Shin et al. (2019) in kgram = 207.68 *fuel consumption amount (in kWh).

Table 4.1: Parameters used in emission models (adopted from Demir et al. 2014)

Notation	Description	Typical value
w_0	Curb weight (empty vehicle weight) (kg)	6,350
a	Acceleration in the (i, j).	0
θ	Gradient in the (i, j).	0
g	Gravitation constant (m/s^2)	9.81
C_d	Coefficient of aerodynamic drag	0.7
ρ	Air density (kg/m^3)	1.2041
A	Frontal surface area	3.912
C_r	Coefficient of rolling resistance	0.01
$v_{i,j}$	Speed limit for the vehicle in the arc (meter/second)	5.5 ~ 20.83 (20~75 kilometer/hour)

4.1.2 Mathematical formulation

Similar to VRP in the MFGVRPBTW problem, many geographically located customers are given with their demand. There are two types of customers: linehaul customers who need deliveries, and backhaul customers who need pickup services. Multiple conventional and hydrogen heterogeneous vehicles located on a single depot are utilized to serve the customers. The decision variables are defined as follows:

x_{ij}^k = 1 if arc (i, j) is travelled by vehicle k otherwise *0*.

y_i^k = 1 if linehaul customer i is visited by vehicle k otherwise *0*.

z_i^k = 1 if backhaul customer i is visited by vehicle k, otherwise *0*.

u_{ijk} Specifies the on-board cargo load in the vehicle, k, while in the arc (i, j).

$T_{i,k}$ Service start time of vehicle k for customer, i.

Objective function:

Minimize total travel distance = $\sum_{i=0}^{n+m} \sum_{j=0}^{n+m} \sum_{k=1}^{K} d_{i,j} \, . x_{i,j}^{k}$ (25)

Constraints:

$$\sum_{i=1}^{n} a_i \, y_i^k \leq Q_k \qquad \forall k \in K \tag{26}$$

$$\sum_{i=n+1}^{n+m} b_i \, z_i^k \leq Q_k \qquad \forall k \in K \tag{27}$$

$$\sum_{j=0}^{N} \left(x_{ij}^{k_{cv}} + x_{ij}^{k_{hv}} \right) = 1 \qquad \forall i \in N \tag{28}$$

$$\sum_{k=1}^{K} y_i^k = 1 \qquad i = 1, \ldots, n \tag{29}$$

$$\sum_{k=1}^{K} z_i^k = 1 \qquad i = n+1, \ldots, n+m \tag{30}$$

$$\sum_{j=1}^{n+m} x_{0,j}^{cv} \leq k_{cv} \tag{31}$$

$$\sum_{j=1}^{n+m} x_{0,j}^{hv} \leq k_{hv} \tag{32}$$

$$\sum_{i=0}^{n+m} x_{ij}^k = \begin{cases} y_j^k, & if \ j = 1, \ldots \ldots n \\ z_j^k, & if \ j = 0, n+1, \ldots \ldots n+m \end{cases} \qquad \forall k \in k_{cv} \tag{33}$$

$$\sum_{j=0}^{n+m} x_{ij}^k = \begin{cases} y_i^k, & if \ i = 1, \ldots \ldots n \\ z_i^k, & if \ i = 0, n+1, \ldots \ldots n+m \end{cases} \qquad \forall k \in k_{cv} \tag{34}$$

$$\sum_{i=0}^{n+m} x_{ij}^k = \begin{cases} y_j^k, & if \ j = 1, \ldots \ldots n \\ z_j^k, & if \ j = 0, n+1, \ldots \ldots n+m \end{cases} \qquad \forall k \in k_{hv} \tag{35}$$

$$\sum_{j=0}^{n+m} x_{ij}^{k} = \begin{cases} y_i^k, & if\ i = 1, \ldots\ldots n \\ z_i^k, & if\ i = 0, n+1, \ldots\ldots n+m \end{cases} \qquad \forall k \in k_{hv} \tag{36}$$

$$\sum_{i=0}^{n} \sum_{j=0,n+1}^{n+m} x_{ij}^{k} = 1 \qquad \forall k \in K \tag{37}$$

$$T_{j,k} \geq T_{i,k} + (s_i + t_{ij})(x_{ij}^k) - M_{*}.(1 - x_{ij}^k) \qquad \forall i \in N, \ \forall j\ N, \ \forall k \in K \tag{38}$$

$$e_i \leq T_{i,k} \leq l_i \qquad \forall i \in N \quad \forall k \in K \tag{39}$$

$$0 \leq T_{0,k} \leq T_{Max} \quad \forall k \in K \tag{40}$$

$$\sum_{i=0}^{n+m} \sum_{j=0}^{n+m} \sum_{k=1}^{k_{cv}} \sum_{k=1}^{k_{hv}} \left(Cf_{i,j}.x_{ij}^{k_{cv}} + Cb_{i,j}.x_{ij}^{k_{hv}} \right) \leq E_{cap} \tag{41}$$

$$\sum_{j=0;j\neq i}^{n+m} u_{jik} - \sum_{j=0;j\neq i}^{n+m} u_{ijk} = \begin{cases} a_i, & if\ j = 1, \ldots\ldots n \\ b_i, & if\ j = 0, n+1, \ldots n+m. \end{cases} \quad i,j = 1, \ldots n+m. \quad k = 1, ., K \tag{42}$$

$$a_{i-1}.x_{i,j}^k \leq u_{ijk} \leq (Q_k - a_i).x_{i,j}^k \qquad i,j = 1, \ldots n+m; \qquad k = 1, \ldots, K \tag{43}$$

$$b_{i-1}.x_{i,j}^k \leq u_{ijk} \leq (Q_k - b_i).x_{i,j}^k \qquad i,j = 1, \ldots n+m; \qquad k = 1, \ldots, K \tag{44}$$

$$x_{ij}^k \in \{0,1\} \quad \forall i \in N, \quad \forall k \in K \tag{45}$$

$$T_{i,k} \geq 0; \qquad \forall i \in N, \quad \forall k \in K \tag{46}$$

In this MFGVRPBTW problem, the objective function (25) minimizes the total distance traveled by the vehicles in the routes. Constraints (26), and (27) ensure the capacity of conventional and hydrogen vehicles cannot be exceeded while serving linehaul and backhaul customers. Constraint (28) restricts each customer visit has only one successor which means that each customer (vertex) has only one arc enters and one arc leaves. Constraint (29), and (30) guarantee each linehaul and backhaul customer must be served by exactly one vehicle.

Constraints (31) and (32) ensure the maximum number of used vehicles for each type in the route must follow the fleet composition. Constraint (33), (34), (35), and (36) represent the flow conservation ensuring each node must have an incoming number of arcs equal to outgoing arcs for each vehicle. Constraint (37) enforces the priority assigned to the linehaul customers where all linehaul customers are served first before the backhaul customers for each vehicle. The time window constraints are confirmed by the constraints (38), and (39). The constraint (38) becomes $T_{j,k} \geq T_{i,k} + (s_i + t_{ij})(x_{ij}^k)$ if arc (i,j) is traveled by a vehicle of k_{cv} or k_{hv} otherwise, it remains $T_{j,k} \geq T_{i,k} + (s_i + t_{ij})(x_{ij}^k) - M_*.(1 - x_{ij}^k)$. Constraint (40) guarantees the route length restriction for each vehicle. Constraint (41) ensures the total amount of CO_2 emissions in the model must not go beyond the emission Cap, E_{Cap}. Constraint (42), (43), and (44) confirm flow balance, that denotes the flows as increasing (for linehaul customers) or decreasing (for backhaul customers) by the amount of each customer demand. Constraint (45), and (46) define the decision variables in the model.

4.2 The proposed hybrid PSO for the MFGVRPBTW

The MFGVRPBTW problem becomes a very complex model after considering all the constraints. The hybrid PSO based algorithm is designed in this study to solve the MFGVRPBTW model and obtain an optimal solution within a reasonable computation time. To the best of our knowledge, a hybrid PSO based solution method has not been proposed so far in the literature to solve a green vehicle routing problem with backhaul and time windows. The proposed hybrid PSO approach is a combination of standard PSO and neighborhood search algorithms. The neighborhood search consists of four renowned local search methods. The neighborhood search algorithm is adopted to overcome the shortage of premature convergence attributes of standard PSO and to obtain an improved solution quality of the algorithm. Using neighborhood search in PSO and another technique of hybridizing PSO are seen in many studies in the literature. But the novelties of the proposed algorithm include neighborhood search that is not only applied on all initial solutions but also through an improvement scheme on a list of best solutions (named as Elitist solutions). A perturbation technique is proposed and used on each best solution before going through the additional neighborhood search. The pseudo-code of the proposed hybrid PSO for the MFGVRPBTW is shown in Algorithm 4.1.

The proposed hybrid PSO uses the following definition:

α_{il}	Current position value of i^{th} particle in l^{th} dimension
γ_{il}	Current velocity value of i^{th} particle in l^{th} dimension
F_i	Fitness function of particle, i
α_{il}^{b}	Personal best position value found so far for the i^{th} particle in the l^{th} dimension
F_i^b	Fitness function of best particle, i
α_l^*	Global best position value found in the l^{th} dimension
F^g	Fitness function of global best particle
w, c_1, c_2	Inertia, Cognitive, Social coefficient respectively
r_1, r_2	Independent random numbers
M	Total number of the particles
X	Position matrix for swarm
Z	Velocity matrix for swarm
X^b/X^G	Personal best/global best position value for swarm
S^b	Personal best solution for swarm
E^b	Number of best solutions, Elitist solutions
$Purb_{Num}$	Number of perturbation

Algorithm 4.1: Pseudo-code of the proposed algorithm for the MFGVRPBTW

```
1:  Initialization
2:  Set parameters
3:  Initialize position matrix X, velocity matrix Z
4:  Initialize the personal best fitness vector, F_i^b
5:  Initialize the global best fitness vector, F^g
6:  Main phase
7:      Do while
8:          S ← GenerateH-MFGVRPBTWSolution (X, Z)
9:          S ← Neighborhood search (S)
10:         Update  personal best matrix X^b, fitness vector  F_i^b, personal best solution
                matrix S^b, and  Elitist solution matrix E^b
11:         Improve personal best matrix using improvement scheme
            E^{b*} ← Improvement Scheme (E^b)
12:         Update the best particle X^G and fitness vector F^g
13:         Update (X,  Z)
14:     End Do
```

One of the important features of the proposed algorithm is the introduction of the improvement scheme for the personal best solution as indicated in line 11. The proposed PSO maintains a pool of best solutions encountered so far. Usually, the solutions remain stagnant after a few iterations. Our proposed method tries to diversify the solutions using the mutation operator for diversification. Another feature of the proposed PSO is the consideration of vector as a region and not a particular point. The competitiveness of the proposed hybrid PSO algorithm can be attributed to these new features.

4.2.1 Initialization phase

The PSO parameters are set by performing sensitivity analysis within a limited time period for a few instances. The parameters are initialized as $w = 0.7$, $c_1 = c_2 = 2$, $r_1 = r_2 = 0.5$, $E^b = 20$, $Purb_{Num} = 4,$ and $M = 20, Iteration = 100$.

The position and velocity vectors are initialized as follows:

$$\alpha_{il} = \alpha_{min} + (\alpha_{max} - \alpha_{min}) * U(0,1) \qquad \forall i \in \{1,2, \dots M\}, \qquad \forall l \in \{1,2,, \dots n + m\} \qquad (47)$$

$$\gamma_{il} = \gamma_{min} + (\gamma_{max} - \gamma_{min}) * U(0,1) \qquad \forall i \in \{1,2, \dots M\}, \qquad \forall l \in \{1,2, \dots, n + m\} \qquad (48)$$

Where $\alpha_{max} = \gamma_{max} = 4$; $\alpha_{min} = \gamma_{min} = -4$. Here $U(0,1)$ represents a uniform random number generated between 0 and 1. The personal best fitness vector for the particle, i and fitness vector of a global particle are initialized as infinity.

$$F_i^b = \infty \quad \forall i \in \{1,2, \dots M\}$$

$$F^g = \infty$$

4.2.2 Mapping position vectors to generate MFGVRPBTW solution

The PSO usually maps the position values of the particle to generate the solution (S^b) for a given problem. The generation of the customer route starts with the empty trip for each vehicle, where the vehicles start and finish their trip at the depot while serving linehaul and backhaul customers. The linehaul customers with the highest position values are iteratively added to each vehicle route first given to vehicle capacity constraint, and then backhaul customers are started serving. All customers are chosen for inclusion in the vehicle route in a similar fashion to complete the solution. The generated solutions can be infeasible if the constraints of time windows of each customer and CO_2 emissions cap of the network are not respected. The neighborhood search is used to establish the solutions feasible and also to improve the solutions.

4.2.3 Neighborhood search

The proposed PSO considers the position vector as a region instead of a particular point. The solution generated in the mapping phase represents one of the solutions of the region, which might not be the best solution of the region. Therefore, the neighborhood search is employed to find the local optima. The neighborhood search includes customer shift (1, 0), shift (2, 0), swap (1, 1), and swap (2, 1) based on the current solution. In shift (1, 0) move, one customer is shifted from one route to another route, i.e., reinserting. In shift (2, 0) move, two consecutive customers from a route, either linehauls or backhauls, are shifted from one route to another route in a similar sequence. In swap (1, 1), one customer is interchanged between two routes. In Swap (2, 1), two consecutive customers, either linehauls or backhauls, are interchanged with a customer from another route. In the neighborhood search iterations, local searches are randomly selected one by one. Each local search is started with an additional penalty function of three constraints, such as vehicle capacity, time windows, and CO_2 emission constraints. In the iterations, the penalty for each constraint is increased if infeasible routes are generated from the constraints, and vice versa. A list of feasible personal best solutions, E^b, (named as Elitist solutions) is generated at the end neighborhood search iterations.

4.2.4 Updating position and velocity vectors

The personal best position value for each particle is updated if the current solution is found better than the current personal best solution. Similarly, the global best value is updated if the new best solution is found better than the current global best value.

The velocity and position vectors are updated as follows:

$$\gamma_{il} = w\gamma_{il} + c_1 r_1\left(\alpha_{il}^{b} - \alpha_{il}\right) + c_2 r_2\left(\alpha_{l}^{*} - \alpha_{il}\right) \qquad \forall i \in \{1,2,\dots,n+m\}, \forall l\ \{1,2,\dots M\} \qquad (49)$$

$$\alpha_{il} = \alpha_{il} + \gamma_{il} \qquad \forall i \in \{1,2,\dots,n+m\}, \forall l\ \{1,2,\dots M\} \qquad (50)$$

4.2.5 Improvement scheme

The improvement scheme is used to improve the personal best solution. This is one of the new features of PSO used in this study. To our best knowledge, this feature is used for the first time in the literature of PSO. In the improvement scheme, each solution from the list of elitist solutions (E^{b}) is perturbed to generate a new solution. The perturbed solution is then improved using a neighborhood scheme. In the perturbation mechanism, a customer is removed randomly from a route and reinserted in a random position in another route. In traditional PSO, a monotonic learning pattern is used to follow the same strategy for all the particles. As a result, the algorithm may easily get trapped in a local optimum that requires the population of the algorithm to be more diversified for solving a complex problem especially. The perturbation technique can be used to strengthen the algorithm by increasing the diversity of the population. However, all input data are deterministic in conventional VRPs, so a small perturbation on input data can lead to impractical or suboptimal results by a solution method as local optima can be far away from the global optimum as a result of ineffective diversification (Moghaddam et al. 2012). Thus, the perturbation technique is imperatively needed to be effective in the proposed hybrid PSO through a perturbation operator. In the hybrid PSO, the perturbation technique runs for a time of $\mathrm{Purb}_{\mathrm{Num}}$ on each solution. The structure of the improvement scheme used in the proposed hybrid PSO for the MFGVRPBTW is shown in Algorithm 4.2. Overall, both intensification of local searches and an effective diversification behavior of the perturbation technique are employed in the light of enhancing the performance of PSO in the proposed algorithm.

Algorithm 4.2: Improvement scheme used in proposed hybrid PSO for MFGVRPBTW

```
1:  Method Improvement scheme:
2:      Personal best solution, S^b;
3:      S^b* ← Perturbation ( S^b)
4:      S^b** ← Neighborhood search ( S^b*)
5:      Update S^b
6:              if f( S^b**) < f( S^b)
7:                  S^b = S^b**
8:  return S^b;
9:  end Improvement scheme;
```

4.3 Numerical experiments

The proposed hybrid PSO algorithm is implemented using the C++ programming language to solve the MFGVRPBTW. The experiments are run on a Linux server with four 2.1GHz processors with 16-core each and a total of 256GB of RAM. The proposed algorithm is tested on several MFGVRPBTW instances modified from benchmark VRPBTW instances of Gelinas et al. (1995) study. The proposed MFGVERBTW is a generalized version of the many variants of the VRP problem. Hence, the algorithm developed for H-MFGVRPTW can solve many variants of VRP.

We tested our algorithm on many benchmark instances for the VRPB, VRPTW, and VRPBTW studies found in the literature to test the effectiveness of the proposed algorithm. Overall, when tested on these benchmark instances, the performance of the proposed algorithm is evaluated by two criteria. The first criterion is how many new best solution (BS) is generated by proposed the algorithm. The literature already has reported best known solutions (BKS) from existing algorithm for different variations of VRPB. Our algorithm found new best solutions which are denoted as a new BS. The second criterion is the relative deviation % of the obtained solution by the proposed algorithm compared to the BKS. The relative deviation % of an instance is reported as "%Gap" in the tables of results. It is measured by the eq. (31), where Sol denotes the solutions (total distance) found by the other algorithms. In addition, the processing time (CPU time) is reported as *t* in second. The following formula is used to calculate %Gap from the existing best known solution (BKS).

$$\%\text{Gap} = \frac{Sol - BKS}{BKS} \times 100\% \tag{51}$$

It is worth mentioning that a negative value of %Gap means improved solution quality, and a positive value of %Gap means worse solution quality with respect to existing BKS. Moreover, distances refer to the corresponding Euclidian distances. Double precision distances with no rounding or truncation are considered in entire computational experiments.

4.3.1 Numerical experiments on MFGVRPBTW

The primary objective of this study is to solve the hydrogen and mixed fleet based green vehicle routing problem with backhaul and time windows (MFGVRPBTW). The datasets for the MFGVRPBTW are created from the Gelinas et al. (1995) VRPBTW instances which include 100 customers. In the Gelinas et al (1995) instances, the travel time of the vehicle between two nodes is equal to the distance between two nodes, because vehicle speed is considered as 1 kilometer/hour. However, in the newly generated 15 datasets for this study of MFGVRPBTW, each node is designated with a randomly chosen speed of the vehicle from a speed range of 20~75 kilometer/hour. The datasets consist of a mixed fleet of conventional and hydrogen vehicles. Each vehicle type has a specific number of vehicles but the total number of vehicles remains the same as Gelinas et al. (1995) instances. The heterogeneity of the vehicles also includes different vehicle capacity and CO_2 emission amount for each type of vehicle. Moreover, each instance has a CO_2 emission cap for the network. The capacity of conventional vehicles is considered as 200 the same as Gelinas et al. (1995) instances but the capacity of hydrogen vehicles is chosen as 150. All other attributes of Gelinas et al. instances remain the same in the newly generated instances for the MFGVRPBTW.

Since the MFGVRPTW problem is proposed for the first time in this work, we report the improvement of the proposed algorithm from the first iteration to the last iteration as %Gap. Table 4.2 represents the comparative results between initial solutions and the final solutions of hybrid PSO when it is tested on the newly generated MFGVRPBTW instances for 100 customers in this study. Initial solutions refer to the solution obtained in the first iteration of complete hybrid PSO, and final solutions denote the final solution of the complete hybrid PSO algorithm. Here, the %Gaps are calculated for final solutions by comparing them with the initial solution of hybrid PSO. Results show that the hybrid PSO algorithm improves solution quality for all new H-MFGVRPBTW instances. The overall %Gap is found as -6.18% with a CPU time of 163.83 seconds, with an average result of initial solutions and final solutions are

1371.38 and 1287.10 respectively. The results also indicate that solution improvement usually increases when the percentage of backhaul increases.

4.3.2 Effect of elitist solution on PSO's performance

One of the novel features of the proposed algorithm is the introduction of tracking a set of elitist solutions. The set of elitist solutions are the best solutions obtained so far. The elitist solutions are improved using perturbation and local search schemes in every iteration of PSO. The effect of using the elitist solution with the proposed PSO on the solution quality is presented in Table 6. The performance of the PSO is evaluated on the newly generated MFGVRPBTW instances for 100 customers under two settings: PSO without elitist solutions and the hybrid proposed PSO (i.e., PSO with elitist solution scheme). The effect of elitist solutions is shown as %Gap. The number of iterations for each setting is changed to maintain approximately the same computational time. All other parameters in the PSO framework are the same for all settings. Table 4.3 shows that the elitist solutions with the PSO scheme improve the solution quality of the PSO without elitist solution by -2.15% from its solution 1315.11. Thus, the table denotes that the performance of PSO is enhanced if elitist solutions are employed with the hybrid PSO and it justifies the use of elitist solutions with the PSO.

Table 4.2: Comparison results between initial solutions and final solutions of hybrid PSO on newly generated MFGVRPBTW instances for 100 customers

Instance type	%BH	Initial Solutions of Hybrid PSO		Final solutions of Hybrid PSO		
		Distance	t (s)	Distance	%GAP	t (s)
	10	1514.87	1.16	1476.1	-2.56%	143.67
New R101	30	1641.81	1.21	1564.01	-4.74%	132.30
	50	1736.83	1.23	1593.84	-8.23%	123.40
	10	1378.5	1.65	1307.02	-5.19%	172.76
New R102	30	1474.47	1.42	1387.26	-5.91%	151.67
	50	1511.72	1.50	1432.18	-5.26%	140.41
	10	1150.69	2.01	1127.15	-2.05%	198.23
New R103	30	1283.77	1.64	1215.12	-5.35%	173.21
	50	1298.38	1.48	1217.98	-6.19%	158.85
	10	1054.05	2.04	976.985	-7.31%	218.05
New R104	30	1110.24	1.86	999.706	-9.96%	202.95
	50	1120.68	1.67	1023.91	-8.63%	189.87
	10	1359.59	1.49	1302.06	-4.23%	165.0
New R105	30	1446.43	1.39	1329.62	-8.08%	150.12
	50	1488.65	1.26	1353.53	-9.08%	136.85
Average		1371.38	1.53	1287.10	-6.18%	163.83

Table 4.3: Effect of elitist solutions on the solution quality for MFGVRPBTW instances for 100 customers

PSO without elitist solution			Proposed hybrid PSO (PSO with elitist solution)		
Iteration	Solution	t(s)	Iteration	%Gap	t(s)
140	1315.11	178.65	100	-2.15%	163.83

4.3.3 Numerical experiments on VRPB

Performance of the proposed hybrid PSO on VRPB is evaluated using the well-known Goetschalckx and Jacobs-Blecha's (1989) benchmark instances. The instances contain 14 primary problem sets (A-N) which include a total of 62 instances with different vehicle capacities and various numbers of vehicles. Several algorithms from literature (shown in Table 4.4) are used to compare the obtained solutions of the proposed algorithm. Detailed comparison results are shown in Table 4.5. It is found that the proposed hybrid PSO generates a total of 12 are new BS out of 62 instances. The overall %Gap is obtained as 0.37% with a CPU time of 190 seconds, which is 3.51% superior to the FMOP algorithm (from 3.88% to 0.37%). The most successful algorithms for VRPB are MACO (Gajpal and Abad 2009b), UHGS (Vidal et al. 2014), and ILSA (Brandão 2016) as they produce better solution qualities with a %Gap of 0.1%~0.3% with reasonable CPU time.

Table 4.4: List of algorithms used in the evaluation of proposed algorithm for VRPB

Notations	Algorithms
TS	Tabu search by Brandão (2006)
ALNS	Adaptive large neighborhood search in Ropke and Pisinger (2006)
MACO	Multi-ant colony optimization by Gajpal and Abad (2009b)
LS	Local search algorithm in Zachariadis and Kiranoudis (2012)
ILS	Iterated local search algorithm by Cuervo et al. (2014)
UHGS	Unified hybrid genetic search in Vidal et al. (2014)
FMOP	Fuzzy multi-objective programming algorithm in Yalcın and Erginel (2015)
ILSA	Iterated local search algorithm in Brandão (2016)
ILS-SP	ILS combined with set partitioning in Subramaniana and Queiroga (2020)
Hybrid PSO	The algorithm proposed in this chapter of the thesis work

4.3.4 Numerical experiments on VRPTW

The proposed hybrid PSO is also evaluated for VRPTW on the mostly used 56 instances of Solomon's benchmark with 100 customers. The instances have six sets of problems: C1, C2, R1, R2, RC1, and RC2. Existing algorithms (shown in Table 4.6) are used to compare their results with the proposed hybrid PSO algorithm results. Table 4.7 exhibits the entire comparison results for VRPTW. As can be noted, the first column refers to instances, the second column refers to the BKS found in the literature, the algorithm used for BKS is stated

Table 4.5: Comparison results of Goetschalckx and Jacobs-Blecha (1989) for VRPB

Instance	n	BKS	TS (2006)		ALNS (2006)		MACO (2009)		LS (2012)		ILS (2014)		UHGS(2014)		ILSA (2016)		ILS-SP (2020)		FMOP (2015)		Hybrid PSO		
			%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	Distance	%GAP	t(s)
A1	25	229,886	0.00%	40	0.00%	7	0.00%	1.00	0.00%	2.7	0.00%	…	0.00%	7	0.00%	1.0	0.00%	0.1	0.00%	1.762	229886	0.00%	1.09
A2	25	180,119	0.00%	25	0.00%	8	0.00%	1.75	0.00%	1.6	0.00%	…	0.00%	7	0.00%	1.2	0.00%	0.1	0.78%	1.127	180119	0.00%	1.75
A3	25	163,405	0.00%	25	0.00%	9	0.00%	3.00	0.00%	1.1	0.00%	…	0.00%	8	0.00%	1.2	0.00%	0.1	3.25%	0.873	155796	-4.66%	2.89
A4	25	155,796	0.00%	14	0.00%	11	0.00%	1.88	0.00%	1.6	0.00%	…	0.00%	10	0.00%	0.8	0.00%	0.1	8.48%	1.011	155796	0.00%	2.90
B1	30	239,080	0.00%	53	0.00%	9	0.00%	2.13	0.00%	7.5	0.00%	…	0.00%	8	0.00%	1.3	0.00%	0.1	1.53%	5.737	239080	0.00%	2.00
B2	30	198,048	0.00%	24	0.00%	10	0.00%	2.50	0.00%	6.4	0.00%	….	0.00%	9	0.00%	1.3	0.00%	0.2	1.33%	1.709	198048	0.00%	3.35
B3	30	169,372	0.00%	18	0.00%	14	0.00%	2.00	0.00%	2.7	0.00%	…	0.00%	11	0.00%	0.9	0.00%	0.1	4.19%	0.127	169372	0.00%	5.42
C1	40	249,448	0.44%	75	0.44%	13	0.44%	3.88	0.44%	11.8	0.44%	…	0.45%	13	0.44%	2.2	0.44%	0.3	1.55%	12.89	250557	0.44%	3.90
C2	40	215,020	0.00%	80	0.00%	16	0.00%	4.13	0.00%	10.7	0.00%	…	0.00%	14	0.00%	2.5	0.00%	0.3	8.04%	2.106	215020	0.00%	6.07
C3	40	199,346	0.00%	37	0.00%	18	0.00%	4.88	0.00%	6.4	0.00%	…	0.00%	14	0.00%	2.1	0.00%	0.4	1.30%	0.421	195367	-2.00%	10.1
C4	40	195,366	0.00%	37	0.00%	19	0.00%	3.88	0.00%	4.8	0.00%	…	0.00%	14	0.00%	1.8	0.00%	0.4	0.98%	3.137	195367	0.00%	10.04
D1	38	322,530	0.00%	115	0.00%	12	0.00%	6.13	0.00%	9.7	0.00%	….	0.00%	11	0.00%	2.5	0.00%	0.3	0.05%	5.242	316709	-1.80%	2.76
D2	38	316,709	0.00%	113	0.00%	12	0.00%	6.25	0.00%	8	0.00%	…	0.00%	10	0.00%	2.2	0.00%	0.3	0.56%	20.97	316709	0.00%	2.72
D3	38	239,479	0.00%	136	0.00%	13	0.00%	5.63	0.00%	5.4	0.00%	…	0.00%	11	0.00%	2.0	0.00%	0.3	0.13%	3.844	239479	0.00%	4.90
D4	38	205,832	0.00%	99	0.00%	15	0.00%	6.50	0.00%	5.9	0.00%	…	0.00%	14	0.00%	2.6	0.00%	0.3	1.45%	3.245	205832	0.00%	7.92
E1	45	238,880	0.00%	134	0.00%	18	0.00%	6.75	0.00%	14.5	0.00%	…	0.00%	16	0.00%	3.9	0.00%	0.3	1.18%	2.369	238880	0.00%	8.41
E2	45	212,263	0.00%	172	0.00%	22	0.00%	6.50	0.00%	10.7	0.00%	…	0.00%	19	0.00%	2.2	0.00%	0.5	0.87%	0.724	212263	0.00%	15.92
E3	45	206,659	0.00%	123	0.00%	26	0.00%	10.38	0.00%	11.8	0.00%	….	0.00%	22	0.19%	2.6	0.00%	0.6	5.43%	1.307	206659	0.00%	20.63
F1	60	263,173	0.00%	249	1.48%	29	0.00%	11.13	0.00%	18.2	0.00%	…	0.00%	23	0.00%	8.7	0.00%	0.9	2.26%	275.7	263173	0.00%	19.52
F2	60	265,213	0.11%	210	0.00%	28	0.00%	9.13	0.00%	19.3	0.00%	…	0.00%	23	0.00%	4.6	0.00%	1.0	3.19%	75.84	263174	-0.77%	19.32
F3	60	241,120	0.00%	138	0.35%	35	0.00%	11.25	0.00%	15	0.00%	…	0.00%	29	0.00%	7.0	0.00%	1.1	0.38%	0.72	241970	0.35%	33.83
F4	60	233,861	0.00%	201	0.56%	42	0.00%	15.00	0.00%	17.2	0.00%	…	0.00%	32	0.00%	5.7	0.00%	1.2	6.19%	5.054	234342	0.21%	47.23
G1	57	306,306	0.00%	342	0.00%	22	0.08%	18.00	0.00%	20.4	0.00%	…	…	…	0.00%	9.4	0.00%	0.9	3.37%	54.59	305002	-0.43%	12.96
G2	57	245,441	0.00%	371	0.00%	27	0.00%	10.38	0.00%	17.2	0.00%	….	0.00%	23	0.00%	4.9	0.00%	0.8	2.71%	25.58	245441	0.00%	26.28
G3	57	229,507	0.00%	196	0.00%	30	0.00%	14.25	0.00%	16.6	0.00%	…	0.00%	26	0.00%	6.8	0.00%	0.8	5.67%	15.32	231045	0.67%	35.97
G4	57	232,521	0.00%	183	0.00%	31	0.00%	21.75	0.00%	20.4	0.00%	…	0.00%	27	0.00%	7.5	0.00%	0.8	5.51%	3.543	231045	-0.63%	35.79
G5	57	221,730	0.00%	242	0.00%	35	0.00%	20.38	0.00%	17.2	0.00%	…	0.00%	28	0.00%	6.5	0.00%	1.0	4.81%	6.826	218485	-1.46%	48.99
G6	57	213,457	0.00%	213	0.00%	39	0.00%	20.63	0.00%	13.4	0.00%	…	0.00%	32	0.00%	6.4	0.00%	1.1	6.60%	3.739	213457	0.00%	63.95
H1	68	268,933	0.00%	363	0.00%	39	0.00%	24.50	0.00%	20.4	0.00%	…	0.00%	37	0.00%	10.3	0.00%	1.7	2.29%	37.76	268933	0.00%	48.20
H2	68	253,365	0.00%	398	0.00%	47	0.00%	21.50	0.00%	18.8	0.00%	….	0.00%	34	0.00%	9.2	0.00%	1.8	2.61%	4.617	253365	0.00%	69.06

H3	68	247,449	0.00%	345	0.00%	53	0.00%	20.25	0.00%	19.3	0.00%	…	0.00%	38	0.00%	8.6	0.00%	2.0	2.16%	2.032	247449	0.00%	92.07
H4	68	250221	0.00%	167	0.00%	52	0.00%	27.13	0.00%	21.5	0.00%	…	0.00%	35	0.00%	10.4	0.00%	1.9	4.29%	2.193	247449	-1.11%	91.88
H5	68	246,121	0.00%	188	0.00%	55	0.00%	26.00	0.00%	18.8	0.00%	…	0.00%	37	0.00%	9.6	0.00%	2.2	1.84%	3.234	251505	2.19%	113.92
H6	68	249,135	0.00%	161	0.00%	55	0.00%	30.25	0.00%	22.5	0.00%	…	0.00%	35	0.00%	9.9	0.00%	2.3	4.64%	3.647	246121	-1.21%	112.49
I1	90	350246	0.05%	648	0.00%	52	0.00%	41.63	0.00%	35.9	0.00%	…	0.00%	53	0.00%	27.3	0.00%	3.7	3.05%	1001	349160	-0.31%	53.75
I2	90	309,944	0.00%	542	0.00%	63	0.00%	37.50	0.00%	32.7	0.00%	….	0.00%	51	0.00%	20.4	0.00%	3.4	7.65%	457.2	314141	1.35%	84.71
I3	90	294507	0.00%	574	0.00%	81	0.00%	43.88	0.00%	29.5	0.00%	…	0.00%	59	0.00%	25.6	0.00%	4.2	4.25%	5.827	297173	0.91%	153.73
I4	90	295988	0.00%	630	0.00%	76	0.00%	46.63	0.00%	35.4	0.00%	…	0.00%	55	0.42%	21.6	0.00%	4.3	3.19%	16.04	298581	0.88%	159.05
I5	90	301226	0.00%	504	0.00%	74	0.00%	47.38	0.00%	38.6	0.00%	…	0.00%	49	0.38%	20.9	0.00%	4.3	1.83%	1.941	298588	-0.88%	159.44
J1	94	335007	0.00%	965	0.00%	56	0.00%	66.63	0.00%	52	0.00%	…	0.00%	50	0.00%	33.3	0.00%	3.3	2.55%	428.7	336325	0.39%	90.94
J2	94	310417	0.12%	946	0.00%	65	0.00%	59.25	0.00%	48.3	0.00%	…	0.00%	50	0.00%	41.7	0.00%	5.0	2.77%	53.72	311307	0.29%	292.62
J3	94	279219	0.03%	764	0.00%	84	0.00%	77.63	0.00%	41.8	0.00%	….	0.00%	56	0.00%	30.6	0.00%	4.5	10.53%	27.2	281917	0.97%	273.86
J4	94	296533	0.11%	859	0.00%	72	0.00%	62.75	0.00%	47.2	0.00%	…	0.00%	67	0.36%	37.2	0.00%	4.9	1.87%	26.42	297141	0.21%	415.92
K1	11	394071	0.23%	1334	0.08%	81	0.26%	104.8	0.00%	54.2	0.00%	…	0.00%	80	0.26%	36.9	0.00%	10	3.83%	2941	399201	1.30%	337.17
K2	11	362130	0.47%	1302	0.00%	96	0.00%	96.88	0.00%	44	0.00%	…	0.00%	84	1.00%	37.3	0.00%	7.7	4.64%	972.3	365181	0.84%	329.40
K3	11	365694	0.15%	1204	0.00%	95	0.00%	114.2	0.00%	48.3	0.00%	…	0.00%	78	0.92%	47.6	0.00%	7.5	4.50%	1030	365943	0.07%	244.00
K4	11	348950	0.69%	1150	0.00%	108	0.26%	106.0	0.00%	46.7	0.00%	…	0.00%	77	0.39%	58.2	0.00%	8.1	2.75%	70.66	352220	0.94%	342.06
L1	15	417897	2.03%	2366	1.94%	149	0.01%	148.3	0.00%	88.5	0.00%	….	0.00%	236	0.13%	86.8	0.00%	19.2	6.81%	1004	417616	-0.07%	446.70
L2	15	401228	0.23%	2477	0.00%	176	0.00%	142.0	0.00%	72.9	0.00%	…	0.00%	178	0.18%	89.1	0.00%	20.3	8.10%	1013	414427	3.29%	575.12
L3	15	402678	0.43%	2333	0.00%	174	0.00%	160.6	0.00%	92.8	0.00%	….	0.00%	164	0.12%	95.2	0.00%	17.9	5.71%	1911	415353	3.15%	572.75
L4	15	384637	0.09%	2287	0.00%	205	0.00%	159.5	0.00%	75.1	0.00%	…	0.00%	141	0.24%	87.2	0.00%	19.6	7.85%	1250	394351	2.53%	551.28
L5	15	387565	0.38%	2258	0.00%	200	0.00%	158.0	0.00%	82.6	0.00%	…	0.00%	163	0.25%	92.0	0.00%	20.6	5.78%	190.8	387826	0.07%	569.08
M1	12	398593	0.45%	1858	0.08%	102	0.03%	229.5	0.00%	70.8	0.00%	…	0.00%	95	0.72%	65.7	0.05%	21.4	3.81%	127	398871	0.07%	498.75
M2	12	396917	0.51%	1913	0.61%	100	0.10%	183.3	0.00%	64.4	0.00%	…	0.00%	143	0.60%	53.4	0.04%	64.7	3.69%	289.8	402361	1.37%	440.84
M3	12	375695	0.46%	1878	0.40%	114	0.43%	183.7	0.00%	56.8	0.00%	…	0.00%	162	0.61%	90.5	0.13%	28.7	5.98%	2259	385296	2.56%	462.71
M4	12	348140	0.27%	1858	0.08%	137	0.08%	164.1	0.00%	50.4	0.00%	….	0.00%	103	0.15%	99.5	0.00%	13.3	4.81%	19.42	360777	3.63%	450.58
N1	15	408101	0.35%	2468	0.66%	155	0.00%	213.8	0.00%	103	0.00%	…	0.00%	163	0.14%	70.3	0.00%	22.4	5.36%	1003	423010	3.65%	494.04
N2	15	408066	0.05%	2430	0.32%	153	0.00%	214.3	0.00%	90.6	0.00%	…	0.00%	153	0.32%	90.7	0.00%	24.8	5.63%	1003	409060	0.24%	439.48
N3	15	394338	0.00%	2441	0.00%	170	0.00%	199.7	0.00%	77.2	0.00%	…	0.00%	148	0.05%	73.8	0.00%	20.3	5.05%	71.1	406002	2.96%	593.09
N4	15	394788	1.07%	2298	1.06%	170	0.00%	219.0	0.00%	105.1	0.00%	…	0.00%	142	0.05%	83.3	0.00%	22	5.00%	20.5	396681	0.48%	585.26
N5	15	373477	0.82%	2494	0.00%	210	0.07%	272.0	0.00%	81.5	0.00%	…	0.00%	187	1.47%	112.7	0.01%	20.8	6.57%	39.07	376022	0.68%	596.73
N6	15	373759	0.27%	2468	0.00%	209	0.00%	255.0	0.00%	91.2	0.00%	….	0.00%	205	0.84%	101.8	0.00%	22.2	7.23%	32.46	379036	1.41%	579.97
Average		*290,558*	*0.16%*	*815*	*0.13%*	*69*	*0.03%*	*67.56*	*0.01%*	*35.1*	*0.01%*	*….*	*0.01%*	*63.52*	*0.17%*	*30.49*	*0.1%*	*10.5*	*3.88%*	*288*	*292,201*	*0.37%*	*190.00*

in parenthesis in the column, and other columns refer to the algorithm's results and their %Gap.

The comparison shows that the proposed hybrid PSO algorithm obtains a total of 11 new BS solutions out of 56 instances. The hybrid PSO obtains the average %Gap of 0.47% for the problems, which is 0.07% (from 0.54% to 0.47%), 0.44%, and 0.72% superior to the algorithm of HS, CGH, and hybrid ACS respectively. The hybrid GA attains 0.17% overall %Gap, which is 0.30% (from 0.47% to 0.17%) better than the hybrid PSO algorithm. Table 4.8 shows the comparative results for each problem type of Solomon's instances. Average results comparison shows that hybrid PSO improves the existing BKS for the problem class of R1 by 0.60% (from 1179.95 to 1172.90). The results for problem classes of C1 and C2 are found as their BKS (%Gap=0).

Table 4.6: List of algorithms used in the evaluation of proposed algorithm for VRPTW

Notations	Algorithms
TS	Tabu search with probabilistic diversification and intensification technique by Rochat and Taillard (1995)
GLS	Guided local search by Kilby et al. (1997)
AGA	A messy genetic algorithm by Tan et al. (2001)
Hybrid GA	Hybrid genetic algorithm by Jung and Moon (2002)
CGH	Column generation heuristic by Alvarenga et al. (2007)
HS	Hybrid search that combines simulated annealing with non-monotonic temperature control, random start and hill-climbing by Oliveira and Vasconcelos (2010)
Hybrid ACS	A hybrid ant colony system with brain storm optimization algorithm by Shen et al. (2019)
MAPSO	Multi-adaptive particle swarm optimization algorithm by Marinakis et al. (2019)
Hybrid PSO	The algorithm proposed in this chapter of the thesis work

Table 4.7: Comparison results of Solomon's 56 instances with 100 customers for VRPTW

Instance	BKS	TS (1995)		mGA (2001)		Hybrid GA (2002)		CGH (2007)		HS (2010)		Hybrid ACS (2019)		Hybrid PSO	
		Distance	%GAP	Distance	%GAP	Distance	%GAP	Distance	%GAP	Distance	%GAP	Distance	%GAP	Distance	%GAP
C101	828.94 (TS)	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%
C102	828.94 (TS)	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%
C103	828.06 (TS)	828.07	0.00%	859.78	3.83%	828.06	0.00%	828.06	0.00%	828.06	0.00%	828.06	0.00%	828.07	0.00%
C104	824.78 (TS)	824.78	0.00%	893.23	8.30%	824.78	0.00%	824.78	0.00%	824.78	0.00%	824.78	0.00%	824.78	0.00%
C105	828.94 (TS)	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%
C106	828.94 (TS)	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%
C107	828.94 (TS)	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%
C108	828.94 (TS)	828.94	0.00%	830.94	0.24%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%
C109	828.94 (TS)	828.94	0.00%	849.03	2.42%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%	828.94	0.00%
C201	591.56 (TS)	591.56	0.00%	591.56	0.00%	591.56	0.00%	591.56	0.00%	591.56	0.00%	591.56	0.00%	591.56	0.00%
C202	591.56 (TS)	591.56	0.00%	591.56	0.00%	591.56	0.00%	591.56	0.00%	591.56	0.00%	591.56	0.00%	591.56	0.00%
C203	591.17 (TS)	591.17	0.00%	618.00	4.54%	591.17	0.00%	591.17	0.00%	591.17	0.00%	591.17	0.00%	591.17	0.00%
C204	590.60 (TS)	590.60	0.00%	609.02	3.12%	590.60	0.00%	590.60	0.00%	590.60	0.00%	590.60	0.00%	590.60	0.00%
C205	588.88 (TS)	588.88	0.00%	616.32	4.66%	588.88	0.00%	588.88	0.00%	588.88	0.00%	588.88	0.00%	588.88	0.00%
C206	588.49 (TS)	588.49	0.00%	615.92	4.66%	588.49	0.00%	588.49	0.00%	588.49	0.00%	588.49	0.00%	588.49	0.00%
C207	588.29 (TS)	588.29	0.00%	636.62	8.22%	588.29	0.00%	588.29	0.00%	588.29	0.00%	588.29	0.00%	588.29	0.00%
C208	588.32 (TS)	588.32	0.00%	611.29	3.90%	588.32	0.00%	588.32	0.00%	588.32	0.00%	588.32	0.00%	588.32	0.00%
R101	1642.87 (HGA)	1650.80	0.48%	1648.86	0.36%	1642.88	0.00%	1642.87	0.00%	1642.88	0.00%	1642.88	0.00%	1615.46	-1.67%
R102	1472.62 (CGH)	1486.12	0.92%	1486.71	0.96%	1472.81	0.01%	1472.62	0.00%	1475.35	0.19%	1479.55	0.47%	1439.10	-2.28%
R103	1213.62 (HGA)	1213.62	0.00%	1234.43	1.71%	1213.62	0.00%	1213.62	0.00%	1222.68	0.75%	1225.31	0.95%	1212.09	-0.13%
R104	976.61 (HGA)	982.01	0.55%	1024.38	4.89%	976.61	0.00%	986.10	0.97%	990.78	1.45%	1002.62	2.59%	974.89	-0.18%
R105	1360.78 (HGA)	1377.11	1.20%	1372.71	0.88%	1360.78	0.00%	1360.78	0.00%	1363.74	0.22%	1365.66	0.36%	1358.78	-0.15%
R106	1240.47 (HGA)	1252.03	0.93%	1271.11	2.47%	1240.47	0.00%	1241.52	0.08%	1244.58	0.33%	1249.51	0.72%	1244.90	0.36%
R107	1073.34 (HGA)	1159.85	8.06%	1106.19	3.06%	1073.34	0.00%	1076.13	0.26%	1081.88	0.80%	1091.21	1.64%	1067.35	-0.56%
R108	947.55 (HGA)	980.05	3.43%	992.12	4.70%	947.55	0.00%	948.57	0.11%	952.37	0.51%	960.23	1.32%	949.46	0.20%
R109	1101.37 (mGA)	1235.68	12.19%	1101.37	0.00%	1151.84	4.58%	1151.84	4.58%	1153.89	4.77%	1165.71	5.52%	1151.08	4.51%
R110	1072.41 (HGA)	1080.36	0.74%	1119.12	4.36%	1072.41	0.00%	1092.35	1.86%	1087.94	1.45%	1090.92	1.70%	1066.52	-0.55%
R111	1053.50 (HGA)	1129.88	7.25%	1083.05	2.81%	1053.50	0.00%	1053.50	0.00%	1053.80	0.03%	1063.69	0.96%	1047.37	-0.58%
R112	953.63 (HGA)	953.63	0.00%	1020.52	7.01%	953.63	0.00%	960.68	0.74%	973.34	2.07%	976.28	2.32%	947.82	-0.61%
R201	1147.80 (HS)	1281.58	11.66%	1198.15	4.39%	1149.68	0.16%	1148.48	0.06%	1147.80	0.00%	1161.20	1.15%	1150.29	0.22%
R202	1034.35 (HGA)	1088.07	5.19%	1057.56	2.24%	1034.35	0.00%	1049.74	1.49%	1039.32	0.48%	1058.83	2.31%	1030.12	-0.41%
R203	874.87 (HGA)	948.74	8.44%	922.38	5.43%	874.87	0.00%	900.08	2.88%	874.87	0.00%	883.42	0.97%	874.87	0.00%
R204	735.80 (HS)	869.29	18.14%	791.78	7.61%	736.52	0.10%	772.33	4.96%	735.80	0.00%	756.93	2.79%	746.59	1.47%

R205	954.16 (HS)	1063.24	11.43%	1015.99	6.48%	955.82	0.17%	970.89	1.75%	954.16	0.00%	978.47	2.48%	973.67	2.04%
R206	879.89 (HGA)	912.97	3.76%	884.65	0.54%	879.89	0.00%	898.91	2.16%	884.25	0.50%	906.27	2.91%	888.29	0.95%
R207	797.99 (HS)	814.78	2.10%	875.76	9.75%	799.86	0.23%	834.93	4.63%	797.99	0.00%	812.35	1.77%	821.82	2.99%
R208	705.45 (HGA)	738.60	4.70%	778.38	10.34%	705.45	0.00%	723.61	2.57%	705.62	0.02%	725.05	2.70%	722.92	2.48%
R209	859.39 (HGA)	944.64	9.92%	920.34	7.09%	859.39	0.00%	879.53	2.34%	860.11	0.08%	879.01	2.23%	876.36	1.97%
R210	910.70 (HGA)	967.50	6.24%	961.18	5.54%	910.70	0.00%	932.89	2.44%	910.98	0.03%	923.43	1.38%	912.76	0.23%
R211	755.82 (HS)	949.50	25.63%	820.23	8.52%	755.96	0.02%	787.51	4.19%	755.82	0.00%	776.17	2.62%	759.13	0.44%
RC101	1623.58 (TS)	1623.58	0.00%	1659.68	2.22%	1643.41	1.22%	1639.97	1.01%	1642.83	1.19%	1643.78	1.23%	1641.08	1.08%
RC102	1461.23 (HGA)	1477.54	1.12%	1492.10	2.11%	1461.23	0.00%	1466.84	0.38%	1480.46	1.32%	1464.63	0.23%	1480.95	1.35%
RC103	1249.86 (mGA)	1262.02	0.97%	1249.86	0.00%	1277.54	2.21%	1264.71	1.19%	1308.64	4.70%	1275.65	2.02%	1271.56	1.74%
RC104	1135.52 (CGH)	1135.83	0.03%	1202.12	5.87%	1136.81	0.11%	1135.52	0.00%	1162.75	2.40%	1156.92	1.85%	1160.04	2.16%
RC105	1518.58 (HGA)	1733.56	14.16%	1585.34	4.40%	1518.58	0.00%	1518.60	0.00%	1534.60	1.05%	1535.78	1.12%	1534.98	1.08%
RC106	1377.35 (CGH)	1384.92	0.55%	1449.30	5.22%	1381.23	0.28%	1377.35	0.00%	1386.82	0.69%	1378.45	0.08%	1378.18	0.06%
RC107	1212.83 (HGA)	1230.95	1.49%	1303.36	7.46%	1212.83	0.00%	1212.83	0.00%	1247.53	2.86%	1216.65	0.31%	1202.66	-0.84%
RC108	1117.53 (HGA)	1170.70	4.76%	1197.13	7.12%	1117.53	0.00%	1117.53	0.00%	1135.87	1.64%	1134.28	1.48%	1136.60	1.71%
RC201	1265.56 (HGA)	1438.89	13.70%	1354.96	7.06%	1265.56	0.00%	1274.54	0.71%	1266.11	0.04%	1284.71	1.49%	1277.90	0.98%
RC202	1095.64 (HGA)	1165.57	6.38%	1151.46	5.09%	1095.64	0.00%	1113.53	1.63%	1096.75	0.10%	1127.02	2.78%	1099.54	0.36%
RC203	926.89 (HS)	1079.57	16.47%	1018.09	9.84%	928.51	0.17%	945.96	2.06%	926.89	0.00%	943.13	1.72%	941.14	1.54%
RC204	786.38 (HGA)	806.75	2.59%	865.51	10.06%	786.38	0.00%	799.67	1.69%	786.38	0.00%	807.71	2.64%	796.72	1.31%
RC205	1157.55 (HGA)	1333.71	15.22%	1225.69	5.89%	1157.55	0.00%	1161.81	0.37%	1157.55	0.00%	1170.98	1.15%	1176.82	1.66%
RC206	1054.61 (HGA)	1212.64	14.98%	1122.23	6.41%	1054.61	0.00%	1059.89	0.50%	1056.21	0.15%	1093.64	3.57%	1054.76	0.01%
RC207	966.08 (HGA)	1085.61	12.37%	1047.86	8.47%	966.08	0.00%	976.40	1.07%	966.08	0.00%	986.70	2.09%	969.56	0.36%
RC208	779.31 (HGA)	833.97	7.01%	854.75	9.68%	779.31	0.00%	795.39	2.06%	780.72	0.18%	785.60	0.80%	787.34	1.03%
Average	*976.21*	*1021.97*	*4.55%*	*1016.69*	*4.32%*	*978.20*	*0.17%*	*984.54*	*0.91%*	*982.51*	*0.54%*	*988.48*	*1.19%*	*980.64*	*0.47%*

Table 4.8: Comparative results of each problem type of Solomon's 56 instances with 100 customers for VRPTW

Instance type	BKS	TS (1995)		GLS (1997)		mGA (2001)		Hybrid GA (2002)		CGH (2007)		HS (2010)		MAPSO (2019)		Hybrid ACS (2019)		Hybrid PSO	
		Distance	%GAP	Distance	%GAP	Distance	%GAP	Distance	%GAP	Distance	%GAP	Distance	%GAP	Distance	%GAP	Distance	%GAP	Distance	%GAP
C1	828.38	828.45	0.01%	830.75	0.29%	859.81	3.79%	828.38	0.00%	828.38	0.00%	828.38	0.00%	828.38	0.00%	828.38	0.00%	828.38	0.00%
C2	589.86	590.32	0.08%	592.24	0.40%	617.10	4.62%	589.86	0.00%	589.86	0.00%	589.86	0.00%	589.86	0.00%	589.86	0.00%	589.86	0.00%
R1	1179.95	1202.31	1.89%	1200.33	1.73%	1260.71	6.84%	1179.95	0.00%	1196.80	1.43%	1186.94	0.59%	1209.99	2.55%	1192.80	1.09%	1172.90	-0.60%
R2	878.71	969.29	10.31%	966.56	10.00%	1058.52	20.46%	878.71	0.00%	899.90	2.41%	878.79	0.01%	952.06	8.35%	896.47	2.02%	886.98	0.94%
RC1	1341.70	1368.03	1.96%	1388.15	3.46%	1447.06	7.85%	1343.64	0.14%	1341.70	0.00%	1362.44	1.55%	1384.18	3.17%	1350.77	0.68%	1350.76	0.67%
RC2	1004.20	1155.47	15.06%	1133.42	12.87%	1169.41	16.45%	1004.20	0.00%	1015.90	1.17%	1004.59	0.04%	1119.60	11.49%	1024.94	2.07%	1012.97	0.87%

4.3.5 Numerical experiments on VRPBTW

The proposed hybrid PSO algorithm is evaluated for VRPBTW using Gelinas et al. (1995) benchmark instances. Gelinas et al. (1995) instances were generated from the first five datasets of Solomon's R1-type VRPTW instances comprising 100 customers. These instances were created by randomly selecting backhaul customers of 10%, 30%, and 50% nodes given the same all other attributes. Additionally, 30 instances were constructed by considering only first 25 or 50 customers from Solomon's R1-type VRPTW instances for 100 customers. Thus a total of 45 Gelinas et al. (1995) VRPBTW instances are used to evaluate the performance of the proposed algorithm and the results are compared with the BKS retrieved from the literature algorithms solutions (shown in Table 4.9). All the results of Gelinas et al. (1995) instances are summarized in Tables 4.10, 4.11, and 4.12. The used algorithms for BKS generation are stated in parenthesis.

Table 4.10 reports the results for 25 customers' instances. The overall %Gap found by the hybrid PSO is 0.31% with a CPU time of 3.23 seconds, which is better than all existing algorithms. The overall %GAP is 0.07% better than the HMA (from 0.38% to 0.31%) and 0.09% superior to the GA algorithm. The hybrid PSO improves the solution quality of the HA algorithm by 1.96% (from 2.27% to 0.31%).

Table 4.11 shows the results for 50 customers' instances. Here, the hybrid PSO generates solutions with an overall %Gap of 0.38%, which is also superior to all the available algorithms. For example, overall hybrid PSO's result is 0.34% better than the HMA algorithm (from 0.72% to 0.38%). The results are 0.85% and 2.41% better than the GA and HA algorithm respectively.

Table 4.12 denotes the results for 100 customers' Gelinas et al. instances. The hybrid PSO obtains a total of 9 new BS out of 15 instances. The overall %Gap between BKS and the proposed hybrid PSO is noted as -0.38% that indicates the improvement in solution quality of hybrid PSO compared to all existing solutions. The hybrid PSO is found to be 1.38% better than the HMA algorithm (from 1.00% to -0.38%), following 2.73% and 2.98% superior to the GA and UH algorithms respectively.

Overall, the proposed hybrid PSO generates a better solution for Gelinas et al. instances compared to the existing BKS available in the literature. The proposed hybrid PSO improves the solution quality for 25 customers by 0.07% compared to its nearby competitor algorithm, HMA. The solution quality is also improved by 0.34% compared to its closest competitor algorithm, HMA, in the case of the hybrid PSO algorithm for 50 customers. A noticeable improvement is seen for large sizes instances with 100 customers, when hybrid PSO obtains 9 new BS out 15 instances with an improved solution quality of -0.38% compared to previous BKS. The result is 1.38% improvement over its nearby competitor, HMA algorithm.

Table 4.9: List of algorithms used in the evaluation of the proposed algorithm for VRPBTW

Notations	Algorithms
B&B	Branch-and-bound approaches based on column generation in Gelinas et al. (1995)
GA	Genetic Algorithm in Potvin et al. (1996)
HA	Heuristic Approaches in Thangiah et al. (1996)
ASA	Ant System approach based on Insertion algorithm by Reimann et al. (2002)
GLSA	Guided local search approach in Zhong and Cole (2005)
UH	A unified heuristic in Ropke and Pisinger (2006)
HMA	Hybrid simulated annealing and tabu search algorithm in Küçükoglu and Öztürk (2015)
Hybrid PSO	The algorithm proposed in this chapter of the thesis work

4.4 Conclusion

A new combinatorial optimization problem, the hydrogen and mixed fleet based green vehicle routing problem with backhaul and time windows (MFGVRPBTW), is introduced in this chapter of the thesis paper. The sustainability concerns are brought in the proposed model with the constraints of CO_2 emission cap for the network and the maximum route length in the distribution logistic. The problem is proposed to optimize the routes of heterogeneous vehicles serving the linehaul and backhaul customers with time windows. The hybrid PSO algorithm is designed to solve the introducing MFGVRPBTW. The efficiency of the newly designed algorithm is proved by testing it on the newly generated MFGVRPBTW instances and also on the benchmark instances of VRPB, VRPTW, and VRPBTW available in the literature. The suggested hybrid PSO algorithm generates 11 new best known solutions out of 56 instances Solomon VRPTW, 12 new best known solutions out of 62 Goetschalckx and Jacobs-Blecha VRPB instances, and attains 9 new best known solutions out of 15 Gelinas et al. (1995) VRPBTW instances for 100 customers. Overall, the comparative result ensures the superiority of the proposed algorithm to the state-of-the-art algorithms on the VRPB, VRPTW, and VRPBTW. Thus, considering both of the features of the problem and the proven efficiency of the proposed algorithm, this study has great potential in the field of green VRP with backhaul and time windows.

Table 4.10: Comparison results on Gelinas et al. (1995) VRPBTW instances for 25 customers

Instance type	%BH	B&B (1995)	BKS	GA (1996)		HA (1996)		HMA (2015)		Hybrid PSO		
		Optimal solution		%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	Distance	%GAP	t(s)
R101	10	643	643 (B&B)	0.06%	…	6.02%	…	0.06%	0.5	644.759	0.27%	3.29
	30	711.1	711.1 (B&B)	1.50%	…	0.83%	…	1.50%	0.3	712.369	0.18%	2.81
	50	674.5	674.5 (B&B)	1.16%	…	3.87%	…	0.34%	0.3	675.932	0.21%	2.5.5
R102	10	563.5	563.5 (B&B)	0.00%	…	0.27%	…	0.00%	1.4	564.617	0.20%	3.60
	30	622.3	622.3 (B&B)	0.00%	…	1.40%	…	0.93%	1.4	629.128	1.10%	3.07
	50	584.4	583 (B&B)	0.24%	…	0.00%	…	0.24%	2	585.577	0.44%	2.86
R103	10	476.6	476.6 (B&B)	0.00%	…	4.07%	…	0.46%	1.6	477.739	0.24%	4.17
	30	507	507 (B&B)	0.00%	…	2.56%	…	0.00%	1.4	508.309	0.26%	3.24
	50	475.6	475.6 (B&B)	1.56%	…	6.18%	…	1.56%	2.4	477.022	0.30%	2.97
R104	10	452.5	452.5 (B&B)	0.07%	…	1.88%	…	0.29%	3.2	453.761	0.28%	4.11
	30	467.6	467.6 (B&B)	0.19%	…	0.51%	…	0.19%	2.3	468.736	0.24%	3.22
	50	446.8	446.8 (B&B)	0.00%	…	0.27%	…	0.00%	2.9	448.057	0.28%	3.15
R105	10	565.1	565.1 (B&B)	0.00%	…	4.71%	…	0.00%	1.6	566.364	0.22%	3.89
	30	623.5	623.5 (B&B)	1.07%	…	1.14%	…	0.00%	0.8	624.787	0.21%	2.86
	50	591.1	591.1 (B&B)	0.17%	…	0.30%	…	0.17%	1.5	592.529	0.24%	2.57
Average		560.31	560.21	0.40%	…	2.27%	…	0.38%	1.57	561.98	0.31%	3.23

Table 4.11: Comparison results on Gelinas et al. (1995) VRPBTW instances for 50 customers

Instance type	%BH	B&B (1995)	BKS	GA (1996)		HA (1996)		HMA (2015)		Hybrid PSO		
		Optimal solution		%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	Distance	%GAP	t(s)
R101	10	1122.3	1122.3 (B&B)	1.42%	...	3.39%	...	1.20%	5	1122.9	0.05%	24.04
	30	1191.5	1191.5 (B&B)	0.10%	...	2.78%	...	0.01%	3.2	1194.38	0.24%	22.95
	50	1168.6	1168.6 (B&B)	1.31%	...	3.65%	...	1.31%	3.5	1168.58	0.00%	25.64
R102	10	974.7	974.7 (B&B)	0.22%	...	0.44%	...	0.22%	9	977.063	0.24%	25.58
	30	1024.8	1024.8(B&B)	0.43%	...	1.39%	...	2.07%	10	1052.85	2.74%	24.03
	50	1057.2	1057.2(B&B)	0.24%	...	0.45%	...	0.42%	7	1060.06	0.27%	26.21
R103	10	811.4	811.4(B&B)	0.23%	...	4.63%	...	0.51%	25	813.988	0.32%	27.78
	30	882.8	882.8(B&B)	1.12%	...	5.46%	...	0.74%	17	884.837	0.23%	25.52
	50	882.1	882.1(B&B)	0.39%	...	2.37%	...	0.63%	10	884.307	0.25%	27.91
R104	10	…	687.7(HMA)	0.22%	...	0.48%	...	0.00%	34	688.569	0.13%	32.80
	30	…	736.8(HMA)	2.00%	...	0.98%	...	0.00%	38	737.349	0.07%	27.92
	50	733.6	733.6(B&B)	1.06%	...	4.42%	...	0.63%	42	736.339	0.37%	29.41
R105	10	970.6	970.6(B&B)	3.29%	...	2.64%	...	0.81%	13	973.174	0.27%	26.42
	30	1007.5	1007.5(B&B)	4.00%	...	5.26%	...	1.91%	10	1010.4	0.29%	24.60
	50	993.4	993.4(B&B)	2.48%	...	3.54%	...	0.28%	12	996.221	0.28%	27.05
Average		986.19	949.67	1.23%	...	2.79%	...	0.72%	15.91	953.40	0.38%	26.52

Table 4.12: Comparison results on Gelinas et al. (1995) VRPBTW instances for 100 customers

Instance type	%BH	B&B (1995)	BKS	GA (1996)		HA (1996)		ASA(2002)		GLSA (2005)		UH (2006)		HMA (2015)		Hybrid PSO		
		Optimal solution		%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	%GAP	t(s)	Distance	%GAP	t(s)
R101	10	1767.9	1767.9(B&B)	2.66%	...	4.21%	...	3.6%	...	0.05	25.00	2.9%	109	2.47%	76	1773.43	0.31%	107.45
	30	1877.6	1877.6(B&B)	1.01%	...	2.72%	...	6.5%	...	0.08	27.00	4.4%	103	0.72%	90	1884.97	0.39%	108.99
	50	1895.1	1895.1(B&B)	0.57%	...	2.24%	...	2.6%	...	0.09	27.00	2.3%	101	0.85%	108	1900.7	0.30%	108.44
R102	10	1600.5	1600.5(B&B)	1.40%	...	3.35%	...	4.8%	...	…	…	3.3%	121	1.45%	105	1605.4	0.31%	120.05
	30	1639.2	1639.2(B&B)	2.98%	...	7.63%	...	7.0%	...	….	….	6.8%	114	5.17%	90	1652.27	0.80%	120.13
	50	1721.3	1721.3(B&B)	0.84%	...	1.42%	...	3.5%	...	….	….	3.2%	113	2.24%	132	1722.42	0.07%	118.80
R103	10	…..	1343.7(GA)	0.00%	...	2.08%	...	0.4%	...	….	….	3.3%	128	0.24%	124	1339.11	-0.34%	125.58
	30	…..	1381.6(GA)	0.00%	...	6.95%	...	1.0%	...	….	….	0.6%	115	0.31%	102	1367.77	-1.00%	128.96
	50	…..	1456.48(UH)	0.01%	...	5.95%	...	0.8%	...	….	….	0.0%	115	0.58%	87	1433.92	-1.55%	119.90
R104	10	…..	1084.17(UH)	3.09%	...	12.56%	...	11.2%	...	….	….	0.0%	132	0.85%	182	1081.35	-0.26%	143.71
	30	…..	1128.3(ASA)	3.62%	...	15.44%	...	0.0%	...	….	….	2.4%	122	0.74%	176	1122.38	-0.52%	136.54
	50	…..	1189.6(HMA)	1.19%	...	13.20%	...	1.6%	...	….	….	0.1%	119	0.00%	194	1160.78	-2.42%	134.23
R105	10	…..	1516(HMA)	6.93%	...	2.47%	...	1.9%	...	0.05	34.00	3.0%	109	0.00%	80	1502.46	-0.89%	110.19
	30	…..	1581.5(HMA)	4.51%	...	7.90%	...	0.7%	...	0.05	55.00	0.1%	102	0.00%	81	1577.93	-0.23%	128.14
	50	…..	1604.1(HMA)	6.40%	...	3.32%	...	1.8%	...	0.06	64.00	6.6%	100	0.00%	78	1593.68	-0.65%	126.84
Average		1750.27	1519.14	2.35%	...	6.1%	...	3.2%	...	6.3%	38.67	2.60%	113.53	1.00%	113.67	1514.57	-0.38%	122.53

CHAPTER FIVE

Green clustered vehicle routing problem with backhaul and time windows

In this chapter, we introduce a new variant of the capacitated vehicle routing problem (CVRP) called as the green clustered vehicle routing problem with backhaul and time windows (GCluVRPBTW). The GCluVRPBTW is a generalized form of standard CVRP because it includes some additional constraints compared to the CVRP. Additional constraints are customers are partitioned into clusters, there are two sets of customers: linehaul customers and backhaul customers, time window constraint for each customer. Customers in each set are partitioned into predefined clusters, which imply linehaul clusters consisting of linehaul customers and backhaul clusters consisting of backhaul customers. Linehaul clusters must be served in the vehicle routes before the backhaul clusters are visited. Linehaul clusters require delivery operations and backhaul clusters need pickup operations in the problem. The customers belonging to a cluster (linehaul or backhaul cluster) must be served by the same vehicle before the vehicle visits customers from a different cluster or before it returns to the depot. Each cluster of linehaul and backhaul clusters has aggregated positive demand, which is to be delivered or picked up, over all customers in the cluster. The objective of the work is to obtain a set of feasible vehicle routes with minimum travel distance serving each customer and each cluster exactly once given to satisfying all constraints in the problem.

The clustered vehicle routing problem with backhaul appears in many practical situations where linehaul and backhaul customers are grouped into clusters. For example, in the grocery distribution networks, the supermarkets and shops (customers) located in specific locations are served as linehaul clusters and grocery suppliers of identical products or located in specific locations are visited as backhaul clusters; in the gas cylinders distribution network, delivering same gas cylinders are linehaul clusters and pulling empty cylinders of same type are backhaul clusters; in the drink distribution network, delivering identical bottles are linehaul clusters and collecting identical empty bottles are backhaul clusters; in the patient transportation services, dropping off service on outbound trips for similar type of patients as linehaul clusters, and picking up same types of patients are backhaul cluster on return trip; in reverse logistics, delivering identical products of different types are linehaul clusters and collecting recycling or damaged products of different groups are backhaul clusters, distributing similar goods and collecting identical goods to and from rough, remote geographical places or gated communities are linehaul clusters and backhaul clusters respectively; and in the healthcare service, delivering similar types of medicines are linehaul clusters and collecting same types of testing samples are backhaul clusters.

In our best knowledge, the clustered vehicle routing problem with backhaul has not been studied so far in the literature. So, this is the first work to introduce the problem. In the pathway of decarbonizing transportation, the CO_2 emission cap for the network is also considered as a constraint for this problem in addition to considering a mixed fleet of conventional and hydrogen vehicles in the network. The fuel consumption model for the vehicles is also realistically considered as a function of traveled distance, speed, and cargo load over the arcs, instead of considering only distance function. As a variant of VRP, the GCluVRPBTW is an NP-hard problem and it is hard to solve by exact method within a reasonable computation time. Therefore, it is intended to develop a metaheuristic method to investigate the problem.

5.1. Problem definition and mathematical formulation

5.1.1 Problem definition

The GCluVRPBTW is defined on a complete, directed graph $G = (N,\ A)$, where N is a set of nodes. The set has three separate sets, $N = \{0, L, B\}$. The node 0 is the depot, the nodes set $L = \{1, 2 \ldots \ldots n\}$ is the linehaul customers, and nodes set $B = \{n + 1, \ldots \ldots n + m\}$ is the backhaul customers. The arc set A denotes all possible connections between the nodes, defined as $\{(i, j): i, j \in N, i \neq j\}$.

Parameters

R	: Total number of clusters
c_L	: set of linehaul clusters $c_L \in R$
c_B	: set of backhaul clusters $c_B \in R$
r	: Individual cluster (mutually exclusive non-empty disjoint), $r \in R$
C_r	The group of customers within a cluster, $C_r = \{\ i \in n: r_i = r\}, \forall\ r \in R$
a_r	: Delivery demand of a linehaul cluster (a non-negative aggregated over all customers in the cluster)
b_r	: Pickup load of a backhaul cluster (a non-negative aggregated over all customers in the cluster)
n_l	: The number of customers for the l^{th} cluster
$[e_r, l_r]$	: A hard time windows where e_r and l_r are the earliest and latest arrival time at the nodes respectively with a s_r non-negative service time (loading or unloading) of the vehicles
d_{ij}	: Euclidian distance
v_{ij}	: Travel speed, and travel time $t_{ij} = \frac{d_{ij}}{v_{ij}}$
k	: Individual vehicle
k_{cv}	: Numbers of conventional vehicles

k_{hv} : Numbers of hydrogen vehicles
K : Total number of vehicles available in the network
Q_{cv}, Q_{hv} : Capacities of conventional and hydrogen vehicles respectively
M_* : A very large value
E_{cap} : Given CO_2 emission cap for the logistics network
S Set of vertices that is different from V
$\delta^+(S)$ Set of edges $(i,j) \in S \times V \backslash S$
$\delta^-(S)$ Set of edges $(i,j) \in V \backslash S \times S$

Similar to the hydrogen and mixed fleet based green vehicle routing problem with backhaul with time windows (MFGVRPBTW) work, the heterogeneity of the vehicles in the GCluVRPBTW includes different vehicle capacities and CO_2 emission amounts. The emissions of both types of vehicles are calculated similarly to the MFGVRPBTW work in chapter four.

5.1.2 Mathematical formulation

Each cluster and customer must be served only once by multiple conventional and hydrogen heterogeneous vehicles located on a single depot. The decision variables are defined as follows:

x_{ij}^k = 1 if arc (i,j) is traveled by vehicle k otherwise *0*.
y_i^k = 1 if linehaul customer i is visited by vehicle k otherwise *0*.
z_i^k = 1 if backhaul customer i is visited by vehicle k, otherwise *0*.
u_{ijk} Specifies the on-board cargo load in the vehicle, k, while in the arc (i,j).
$T_{i,k}$ Service start time of vehicle k for customer, i.

Objective function:

Minimize total travel distance = $$\sum_{i=0}^{n+m}\sum_{j=0}^{n+m}\sum_{k=1}^{K} d_{i,j}\,.\,x_{i,j}^{k} \tag{52}$$

Constraints:

$$\sum_{i=1}^{n} a_i\, y_i^k \le Q_k \qquad \forall k \in K \tag{53}$$

$$\sum_{i=n+1}^{n+m} b_i\, z_i^k \le Q_k \qquad \forall k \in K \tag{54}$$

$$\sum_{j=0}^{N}\left(x_{ij}^{k_{cv}} + x_{ij}^{k_{hv}}\right) = 1 \qquad \forall i \in N \tag{55}$$

$$\sum_{k=1}^{K} y_i^k = 1 \qquad i = 1,..,n \tag{56}$$

$$\sum_{k=1}^{K} z_i^k = 1 \qquad i = n+1,..,n+m \tag{57}$$

$$\sum_{(i,j)\in\delta^{+}(C_r)}\sum_{k=1}^{K} x_{ij}^{k} = \sum_{(i,j)\in\delta^{-}(C_r)}\sum_{k=1}^{K} x_{ij}^{k} = 1 \qquad \forall r \in R \tag{58}$$

$$\sum_{j=1}^{n+m} x_{0,j}^{cv} \le k_{cv} \tag{59}$$

$$\sum_{j=1}^{n+m} x_{0,j}^{hv} \le k_{hv} \tag{60}$$

$$\sum_{i=0}^{n+m} x_{ij}^{k} = \begin{cases} y_j^k, & if\ j = 1,\ldots..n \\ z_j^k, & if\ j = 0, n+1,\ldots..n+m \end{cases} \qquad \forall k \in k_{cv} \tag{61}$$

$$\sum_{j=0}^{n+m} x_{ij}^{k} = \begin{cases} y_i^k, & if\ i = 1,\ldots..n \\ z_i^k, & if\ i = 0, n+1,\ldots..n+m \end{cases} \qquad \forall k \in k_{cv} \tag{62}$$

$$\sum_{i=0}^{n+m} x_{ij}^{k} = \begin{cases} y_j^k, & if\ j = 1, \ldots ..n \\ z_j^k, & if\ j = 0, n+1, \ldots ..n+m \end{cases} \qquad \forall k \in k_{hv} \tag{63}$$

$$\sum_{j=0}^{n+m} x_{ij}^{k} = \begin{cases} y_i^k, & if\ i = 1, \ldots ..n \\ z_i^k, & if\ i = 0, n+1, \ldots ..n+m \end{cases} \qquad \forall k \in k_{hv} \tag{64}$$

$$\sum_{i=0}^{n} \sum_{j=0,n+1}^{n+m} x_{ij}^{k} = 1 \qquad \forall k \in K \tag{65}$$

$$T_{j,k} \geq T_{i,k} + (s_i + t_{ij})(x_{ij}^k) - M_{*}.(1 - x_{ij}^k) \qquad \forall i \in N,\ \forall j\ N,\ \forall k \in K \tag{66}$$

$$e_i \leq T_{i,k} \leq l_i \qquad \forall i \in N \quad \forall k \in K \tag{67}$$

$$0 \leq T_{0,k} \leq T_{Max} \quad \forall k \in K \tag{68}$$

$$\sum_{i=0}^{n+m} \sum_{j=0}^{n+m} \sum_{k=1}^{k_{cv}} \sum_{k=1}^{k_{hv}} \left(Cf_{i,j}.x_{ij}^{k_{cv}} + Cb_{i,j}.x_{ij}^{k_{hv}} \right) \leq E_{cap} \tag{69}$$

$$\sum_{j=0;j\neq i}^{n+m} u_{jik} - \sum_{j=0;j\neq i}^{n+m} u_{ijk} = \begin{cases} a_i, & if\ j = 1, \ldots ..n \\ b_i, & if\ j = 0, n+1, ..n+m. \quad i,j = 1, ..n+m. \quad k = 1, ., K \end{cases} \tag{70}$$

$$a_{i-1}.x_{i,j}^k \leq u_{ijk} \leq (Q_k - a_i).x_{i,j}^k \quad i,j = 1, ..n+m; \quad k = 1, .., K \tag{71}$$

$$b_{i-1}.x_{i,j}^k \leq u_{ijk} \leq (Q_k - b_i).x_{i,j}^k \quad i,j = 1, ..n+m; \quad k = 1, .., K \tag{72}$$

$$x_{ij}^k \in \{0,1\} \quad \forall i \in N, \quad \forall k \in K \tag{73}$$

$$T_{i,k} \geq 0; \quad \forall i \in N, \quad \forall k \in K \tag{74}$$

The objective function (52) minimizes the total distance traveled by the vehicles in the routes. Constraints (53), and (54) ensure the capacity of conventional and hydrogen vehicles cannot be exceeded while serving linehaul and backhaul customers. Constraint (55) restricts each customer visit has only one successor. Constraint (56), and (57) guarantee each linehaul and backhaul customer must be visited by exactly one vehicle. Constraint (58) specifies that each cluster is served exactly one time. Constraints (59) and (60) restrict the maximum number of used vehicles for each type in the route that must follow the fleet composition. Constraint (61), (62), (63), and (64) represent the flow conservation ensuring each node must have an incoming number of arcs equal to outgoing arcs for each vehicle. Constraint (65) enforces the priority assigned to the linehaul customers where all linehaul customers are served first before the backhaul customers for each vehicle. The time window constraints are confirmed by the constraints (66), and (67). The constraint (66) becomes $T_{j,k} \geq T_{i,k} + (s_i + t_{ij})(x_{ij}^k)$ if arc (i,j) is traveled by a vehicle of k_{cv} or k_{hv} otherwise it remains $T_{j,k} \geq T_{i,k} + (s_i + t_{ij})(x_{ij}^k) - M_*.(1 - x_{ij}^k)$. Constraint (68) guarantees the route length restriction for each vehicle. Constraint (69) ensures the total amount of CO_2 emissions in the model must not go beyond the emission Cap, E_{Cap}. Constraint (70), (71), and (72) confirm flow balance, where constraint (71) denotes the flows are increasing for linehaul customers and constraint (72) ensures flows are decreasing for backhaul customers by the amount of respective customer demand. Constraint (73), and (74) define the decision variables in the model.

5.2 Proposed hybrid PSO for the GCluVRPBTW

The hybrid PSO based solution approach is architected to solve the newly introduced green clustered vehicle routing problem with backhaul and time windows (GCluVRPBTW). The proposed hybrid PSO is a combination of standard PSO and neighborhood search (NS) algorithms. The neighborhood search includes several renowned local searches in both cluster level and customer level. The PSO structure is designed following the problem specifications of the GCluVRPBTW. Two types of particles denoting clusters and customers are used in the proposed hybrid PSO algorithm for the GCluVRPBTW. The pseudo-code of the proposed hybrid PSO for the GCluVRPBTW is shown in Algorithm 5.1.

The proposed hybrid PSO uses the following definition:

α_{il}	Current cluster position value of i^{th} particle in l^{th} dimension
γ_{ij}	Current customer position value of i^{th} particle in j^{th} dimension
β_{il}	Current cluster velocity value of i^{th} particle in l^{th} dimension
δ_{ij}	Current customer velocity value of i^{th} particle in j^{th} dimension
f_i	Fitness function of particle, i
α_{il}^{b}	Personal best cluster position value found so far for the i^{th} particle in the l^{th} dimension
γ_{ij}^{b}	The personal best customer position value found so far for the i^{th} particle in the j^{th} dimension
f_i^{b}	Fitness function of best particle, i
α_l^{*}	Global best cluster position value found in the l^{th} dimension
γ_j^{*}	Global best customer position value found in the j^{th} dimension
f^{g}	Fitness function of global best particle
w	Inertia coefficient
c_1	Cognitive coefficient
c_2	Social coefficient
r_1, r_2	Independent random numbers
M	Total number of the particles
X	Position matrix for customer swarm
Y	Position matrix for cluster swarm
U	Velocity matrix for customer swarm
V	Velocity matrix for cluster swarm
X^{b}/X^{G}	Customer personal best/global best position value for swarm
Y^{b}/Y^{G}	Cluster personal best/global best position value for swarm
S^{b}	Personal best solution for swarm
IT^{Max}	Maximum iteration number, the algorithm termination criterion.

Algorithm 5.1**:** Pseudo-code of the proposed algorithm for the GCluVRPBTW

Initialization
Set parameters
Initialize position matrix X, Y and velocity matrix U , V
Initialize the personal best fitness vector f^b
Initialize the global best fitness vector f^g
Main phase
    Do while
        S← Generate GCluVRPBTWSolution (X, Y, U, V)
        S ← neighborhood search (S)
        Update personal best matrix X^b, Y^b, fitness vector f^b, and personal best solution matrix S^b
        Update the best particle X^G, Y^G and fitness vector f^g
        Update (X, Y, U, V)
    End Do

5.2.1 Initialization phase

The PSO parameters are set by performing sensitivity analysis within a limited time for a few instances. The parameters are initialized as $w = 0.7$, $c_1 = c_2 = 2$, $r_1 = r_2 = 0.5$, $M = 20$, and IT^{Max}=100.

The position and velocity vectors are initialized as follows:

$$\alpha_{il} = \alpha_{min} + (\alpha_{max} - \alpha_{min}) * U(0,1) \qquad \forall i \in \{1,2, \dots M\}, \forall l \in \{1,2, \dots c\} \tag{75}$$

$$\gamma_{il} = \gamma_{min} + \left(\gamma_{max} - \gamma_{min}\right) * U(0,1) \qquad \forall i \in \{1,2, \dots M\}, \forall j \in \{1,2, \dots n\} \tag{76}$$

$$\delta_{il} = \delta_{min} + (\delta_{max} - \delta_{min}) * U(0,1) \qquad \forall i \in \{1,2, \dots M\}, \forall l \in \{1,2, \dots c\} \tag{77}$$

$$\beta_{il} = \beta_{min} + (\beta_{max} - \beta_{min}) * U(0,1) \qquad \forall i \in \{1,2, \dots M\}, \forall j \in \{1,2, \dots n\} \tag{78}$$

Where, $\alpha_{max} = \gamma_{max} = \delta_{max} = \beta_{max} = 4; \quad \alpha_{min} = \gamma_{min} = \delta_{min} = \beta_{min} = -4.$ Here $U(0,1)$ represents a uniform random number generated between 0 and 1. The personal best fitness vector for the particle, i and fitness vector of a global particle are initialized as infinity.

$$f_i^b = \infty \quad \forall i \in \{1,2, \dots K\}$$

$$f^g = \infty$$

5.2.2 Mapping position vectors to generate GCluVRPBTW solution

In PSO, the initial solution(S) of a given problem is usually generated by mapping the position values of the particles. In the proposed PSO for GCluVRPBTW, the solution is generated in hierarchical two phases. The solution consists of an assignment of clusters sub-problems in phase-1, and an assignment of customers' sub-problem in phase-2.

Phase 1: Assignment of clusters sub-problem

In phase-1, cluster routes for linehaul and backhaul clusters are generated. The assignment of cluster sub-problem starts with an empty load for each vehicle in the routes, where all vehicles start and finish their trip at the depot while serving linehaul and backhaul clusters. The clusters are assigned one by one into the vehicles to complete the solution. Firstly, linehaul clusters with highest position values are assigned one by one to each vehicle subject to vehicle capacity constraint, then backhaul cluster with highest position values are similarly assigned one by one to the vehicle subject to vehicle capacity constraint. All clusters in the network are added to the vehicle route in a similar way to generate the complete solution of a problem. While assigning clusters to the route, we do not impose constraints on the CO_2 emission cap. Therefore, the assignment of clusters in the routes can generate an infeasible solution if constraints of time windows of each customer and CO_2 emissions cap of the network are not satisfied. The neighborhood search (NS) is designed in such a way in this work that it establishes the solutions feasible and also improves the solutions.

Phase 2: Assignment of customers' sub-problem

After the phase-1, where cluster routes are generated, a sequence of the customers for each cluster is generated to obtain the complete solution of the GCluVRPBTW. In the assignment of customers' sub-problem, the assignment of the customers for each of linehaul and backhaul cluster is completed by selecting customers similar to the clusters routes generation method described in phase 1.

5.2.3 Neighborhood search (NS)

The proposed PSO considers the position vector as a region instead of a particular point. The solution generated in the mapping phase represents one of the solutions of the region, which might not be the best solution of the region. Therefore, the neighborhood search is employed to find the local optima. The neighborhood search consists of several local search moves applied on the cluster level and customer level. The customer level neighborhood searches are shift (1,0), shift(2,0), and 2-opt moves based on the current solution. The cluster level neighborhood searches are swap (1, 1), swap (2, 1), shift (1, 0), and shift (2, 0) moves based on the current solution. The moves at both the customer level and cluster level are selected randomly one by one. The customer level moves are applied on the customers within a cluster and it continues for all clusters one after another. The cluster level moves are applied on the clusters both on within same route and different routes. The detailed structures of the operators are explained in chapter three and chapter four. Each local search move in the cluster level is started with an additional penalty function of three constraints, such as vehicle capacity, time windows, and CO_2 emission constraints. In the iterations, the penalty for each constraint is increased if infeasible routes are generated from the constraints, and vice versa. The overall structure of the NS used with the hybrid PSO for the GCluVRPBTW is shown in Algorithm 5.2.

Algorithm 5.2: Neighborhood search (NS) used with hybrid PSO for the GCluVRPBTW

Method NS:
Initial solution, s;
Set previous solution, $s^{initial} = s$;
    $s \leftarrow$ Intra-cluster search (s);
    update s
        if $f(S^b) < f(s)$
            $s = S^b$
    return s
Set previous solution, $s^{b*} = s$;
    $s^{b*} \leftarrow$ Intra-route and inter-route search (s);
    update s
        if $f(S^{b*}) < f(s)$
            $s = S^{b*}$
    return s
end *NS*;

5.2.4 Updating position and velocity vectors

The personal best position value for each particle is updated if the current solution is found better than the current personal best solution. Similarly, the global best value is updated if the new best solution is found better than the current global best value.

The velocity and position vectors are updated as follows:

$$\delta_{il} = w\delta_{il} + c_1 r_1\left(\alpha_l^p - \alpha_{il}\right) + c_2 r_2(\alpha_l^* - \alpha_{il}) \qquad \forall i \in \{1,2, \dots M\}, \forall l\ \{1,2, \dots c\} \tag{79}$$

$$\beta_{il} = w\beta_{il} + c_1 r_1\left(\gamma_j^p - \gamma_{il}\right) + c_2 r_2\left(\gamma_j^* - \gamma_{il}\right) \qquad \forall i \in \{1,2, \dots M\}, \forall j\ \{1,2, \dots n\} \tag{80}$$

$$\alpha_{il} = \alpha_{il} + \delta_{il} \qquad \forall i \in \{1,2, \dots M\}, \forall l\ \{1,2, \dots c\} \tag{81}$$

$$\gamma_{il} = \gamma_{il} + \beta_{il} \qquad \forall i \in \{1,2, \dots M\}, \forall j\ \{1,2, \dots n\} \tag{82}$$

5.3 Numerical experiments

Similar to CluVRP and MFGVERBTW, the proposed hybrid PSO algorithm is implemented using the C++ programming language to solve the GCluVRPBTW. The experiments are run on a Linux server with a total of 256GB of RAM and four 2.1GHz processors with 16-core each. As the GCluVRPBTW is studied for the first time in this work, the proposed algorithm is tested on several newly generated GCluVRPBTW instances. The new GCluVRPBTW instances are generated from benchmark VRPBTW instances of Gelinas et al. (1995) study for 100 customers with 30% backhaul and 50% backhaul customers. A number of 20 GCluVRPBTW instances are generated from VRPBTW instances for 100 customers with 30% backhaul customer by selecting both clusters' number (linehaul and backhaul clusters) of 15%, 20%, 25%, and 30% given all other attributes the same. Similarly, A number of 20 additional GCluVRPBTW instances are generated from VRPBTW instances for 100 customers with a 50% backhaul customer by selecting both clusters' number (linehaul and backhaul clusters) of 15%, 20%, 25%, and 30% given all other attributes the same. However, in the newly generated 40 datasets for this study of GCluVRPBTW, each node is designated with a randomly chosen speed of the vehicle from a speed range of 45~90 kilometer/hour. The datasets consist of a mixed fleet of conventional and hydrogen vehicles. Each vehicle type has a specific number of vehicles but the total number of vehicles remains the same as Gelinas et al. (1995) instances. The heterogeneity of the vehicles includes different vehicle capacity and CO_2 emission amount for each type of vehicle. Moreover, each instance has a CO_2 emission cap for the network. The capacity of conventional vehicles is considered as 200 the same as Gelinas et al. (1995) instances but the capacity of hydrogen vehicles is chosen as 150. All other attributes of Gelinas et al. instances remain the same in the newly generated instances for the GCluVRPBTW. The proposed GCluVRPBTW is a generalized version of the many variants of the CluVRP problem. Hence, the algorithm developed for GCluVRPBTW can solve many variants of CluVRP.

The performance of the proposed hybrid PSO is also evaluated on the instances for CluVRPB, CluVRPTW, and CluVRPBTW. The 40 instances for each of the CluVRPB, CluVRPTW, and CluVRPBTW are generated in a similar way to the GCluVRPBTW from VRPBTW instances of Gelinas et al. (1995) study for 100 customers with 30% backhaul and 50% backhaul customers. In the studies of CluVRPB, CluVRPTW, and CluVRPBTW, instead of a mixed fleet of heterogeneous vehicles, a homogeneous fleet of conventional vehicles with a capacity of 200 is considered and the vehicle speed is considered as 1 kilometer/hour. Thus, a total of 160 instances are used to evaluate the performance of the proposed hybrid PSO for the GCluVRPBTW.

5.3.1 Numerical experiments on GCluVRPBTW

The GCluVRPBTW in this study is a problem with a mixed fleet of conventional and hydrogen vehicles. Table 5.1 represents the hybrid PSO results for the GCluVRPBTW with a mixed fleet, GCluVRPBTW with conventional vehicles only, and with hydrogen vehicle only. The average solutions (total travel distances), CPU time (in seconds), CO_2 emission (in gram) for each problem instance are reported in the table. Table 5.1 shows that average distance, average CPU time, and the average CO_2 emission of the mixed fleet are 2290.36, 42.39, and 1407.43 respectively. The average distance, average CPU time, and the average CO_2 emission of hybrid PSO with conventional vehicles only are 2275.48, 83.65, and 1598.56 respectively. The result indicates that the average distance is obtained as 0.64% less for the GCluVRPBTW with conventional vehicles only than the GCluVRPBTW with mixed fleet results. But the average CO_2 emission for the GCluVRPBTW with conventional vehicles only is 13.58% greater than the results with the mixed fleet. It also specifies that if only conventional vehicles are employed in the routes, it reduces total travel distances but increases CO_2 emission in the network, as expected because of higher vehicle capacity and higher CO_2 emission rate of conventional vehicles. Moreover, the average distance, average CPU time, and the average CO_2 emission of hybrid PSO with hydrogen vehicles only are 2336.31, 41.63, and 1172.62 respectively. The result indicates that the average distance is found as 2.00% greater with hydrogen vehicles only than the mixed fleet results. But the average CO_2 emission for the GCluVRPBTW with hydrogen vehicles only is 16.68% less than the results for the GCluVRPBTW with mixed fleet results. It also specifies that if only hydrogen vehicles are employed in the routes, it increases total travel distances but decreases CO_2 emission in the network, as expected because of lower vehicle capacity and lower CO_2 emission rate of conventional vehicles. Thus considering real-life scenarios of distribution networks, we consider the mixed fleet of conventional and hydrogen vehicles in the routes in the work. The mixed fleet of conventional and hydrogen vehicles help to keep the CO_2 emission within the considered CO_2 emission cap in the distribution network.

5.3.2 Numerical experiments on GCluVRPBTW, CluVRPB, CluVRPTW, and CluVRPBTW

This section presents the GCluVRPBTW problem as a generalized version of the many VRP problems such as GCluVRPBTW, CluVRPB, CluVRPTW, and CluVRPBTW. Here, we compare the results of GCluVRPBTW with the CluVRPB, CluVRPTW, and CluVRPBTW. The purpose of this analysis is to observe the effect of solution parameters on a different version of the reduced problems. Table 5.2 shows the hybrid PSO results for the GCluVRPBTW, CluVRPB, CluVRPTW, and CluVRPBTW.

In the CluVRPB, some constraints are relaxed compared to the GCluVRPBTW such as CO_2 emission for the vehicles in the network and time window constraints; and one additional constraint is imposed. The additional constraint is a vehicle route is not permitted to consist entirely of backhaul clusters and each route must have at least one linehaul cluster. In addition, the travel time of the vehicle between two nodes is equal to the distance between two nodes, because vehicle speed is considered as 1 kilometer/hour. Table 5.2 shows that the average solution for GCluVRPBTW is 2290.36 with the CPU time of 42.39 seconds; and the average solution for CluVRPB is 2152.84 with the CPU time of 21.71 seconds, which is 5.94% less than the average solution of GCluVRPBTW. The results highlight the effect of CO_2 emission calculation for the vehicles and time window constraint for customers in the network. The reduced solution with less CPU time for CluVRPB can also be seen as the effect of considering homogenous conventional vehicles in the CluVRPB.

In CluVRPTW, the constraint of CO_2 emission for the vehicles in the network is relaxed compared to the GCluVRPBTW and there are no backhaul clusters and customers in the problem of CluVRPTW. The travel time of the vehicle between two nodes is also equal to the distance between two nodes because vehicle speed is considered as 1 kilometer/hour. Table 5.2 shows the average solution for CluVRPTW is 2279.98 with the CPU time of 128.1 seconds, which is 0.45% less than the average solution of GCluVRPBTW and 5.90% higher than the average solution of CluVRPB. The results highlight the effect of CO_2 emission calculation for the vehicles in the network. The reduced solution with comparatively higher CPU time for CluVRPTW can also be seen as the effect of considering homogenous conventional vehicles in the CluVRPB.

In CluVRPBTW, the constraint of CO_2 emission for the vehicles in the network is relaxed compared to the GCluVRPBTW. The additional constraint for the vehicle route of not permitted entirely of backhaul clusters is also relaxed in CluVRPBTW compared to CluVRPB. So, routes are permitted to consist of entirely linehaul clusters, mixed of linehaul and backhaul clusters, and entirely backhaul clusters. The travel time of the vehicle between two nodes is also equal to the distance between two nodes because vehicle speed is considered as 1 kilometer/hour. Table 5.2 shows the average solution for CluVRPTW is 2279.94 with the CPU time of 59.70 seconds, which is 0.46% less than the average solution of GCluVRPBTW. The results highlight the effect of CO_2 emission calculation for the vehicles in the network. The reduced solution with comparatively higher CPU time for CluVRPTW can also be seen as the effect of considering homogenous conventional vehicles in the CluVRPB.

Table 5.1: The hybrid PSO results for GCluVRPBTW with mixed fleet, conventional vehicle only, and with hydrogen vehicle only

Instance type	%BH	% Cluster	With mixed fleet			With conventional vehicles only			With hydrogen vehicles only		
			Distance	t (s)	CO_2 Emission	Distance	t (s)	CO_2 Emission	Distance	t (s)	CO_2 Emission
GCluVRPBTW-R101	30	15	2049.04	157.73	1223.12	2062.17	159.29	1407.74	2089.05	157.24	1106.29
		20	2065.49	23.27	1385.92	2055.87	24.14	1506.6	2092.23	22.73	1050.84
		25	2293.94	41.11	1165.98	2261.15	41.58	1601.72	2328	39.9	1105.97
		30	2452.68	61.67	1693.94	2423.62	66.38	1632.96	2481.28	59.81	1159.38
	50	15	2254.92	16.54	1514.17	2238.66	15.93	1556.59	2302.84	14.89	1104.27
		20	2274.88	23.58	1280.39	2257.83	23.04	1592.44	2317.88	22.96	1237.32
		25	2436.61	39.24	1301.79	2399.17	44	1659.78	2471.93	37.94	1196.94
		30	2335.82	58.97	1395.15	2313.69	68.91	1646.48	2380.35	57.57	1169.65
GCluVRPBTW-R102	30	15	2120.81	17.6	1393.43	2120.81	14.98	1498.44	2311.75	22.87	1108.68
		20	2253.39	23.01	1396.26	2239.78	23.05	1483.63	2272.45	23.47	1142.56
		25	2462.94	37.97	1686.79	2439.62	84.12	1847.62	2513.73	46.57	1310.14
		30	2707.21	61.62	1691.03	2670.82	1210.48	1888.15	2730.75	59.61	1288.25
	50	15	2294.8	17.9	1587.44	2282.05	17.82	1628.73	2317.82	16.49	1279.32
		20	2340.37	23.53	1433.57	2331.16	22.97	1588.76	2492.37	22.86	1220.67
		25	2450.1	39.33	1351.04	2437.98	45.53	1608.6	2462.17	38.42	1156.83
		30	2342.08	57.69	1511.18	2313.16	81.99	1739.31	2372.55	56.23	1155.86
GCluVRPBTW-R103	30	15	2061.05	18.51	1496.86	2042.78	16.29	1503.18	2093.18	17.67	1217.31
		20	2065.99	24.06	1401.62	2042.73	24.47	1613.87	2113.54	22.87	1121.02
		25	2292.66	41.13	1503.16	2255.17	41.69	1605.85	2333.13	40.06	1166.39
		30	2482.24	61.02	1527.29	2453.61	76.99	1682.02	2504.61	59.13	1236.97
	50	15	2235.46	17.27	1472.89	2224.72	16.27	1560.23	2292.37	16.29	1234.29
		20	2277.43	23.76	1346.37	2292.65	23.31	1521.53	2328.14	22.63	1196.37
		25	2437.87	39.54	1393.21	2449.13	42.03	1573.57	2505.33	38.18	1286.97
		30	2319.86	57.94	1416.89	2327.02	74.81	1530.17	2375.92	56.57	1062.64
GCluVRPBTW-R104	30	15	2052.71	18.27	1248.78	2029.82	16.38	1519.44	2087.57	17.84	1089.47
		20	2045.36	23.87	1126.83	2040.42	24.51	1435.53	2078.21	23.03	1028.02
		25	2297.18	40.42	1493.46	2260.87	41.17	1564.31	2334.74	39.33	1116.37
		30	2430.99	60.86	1205.55	2406.97	79.57	1712.76	2463.64	58.99	1155.29
	50	15	2154.3	18.43	1530.75	2142.07	17.31	1481.93	2203.48	19.39	1213.53
		20	2383.52	23.39	1443.47	2364.24	67.8	1721.56	2485.79	22.48	1283.08
		25	2287.97	184.36	1326.43	2278.02	190.8	1479.48	2320.54	175.95	1139.11
		30	2538.32	58.13	1356.89	2531.04	337.52	1754.25	2579.71	56.87	1249.78
	30	15	2099.66	19.24	1243.38	2080.64	16.9	1448.99	2124.31	18.93	1138.72
		20	2073.31	23.82	1326.07	2045.84	24.39	1452.52	2089.7	23.01	1063.84
		25	2257.65	40.81	1342.06	2253.34	41.98	1459.98	2313.38	39.65	1008.63
		30	2417.46	61.78	1423.48	2401.35	70.36	1733.92	2447.76	60.23	1249.88

GCluVRPBTW-R105	50	15	2205.35	16.13	1406.43	2205.35	15.57	1537.3	2278.41	15.87	1242.47
		20	2316.35	23.71	1368.2	2283.43	23.54	1595.24	2338.36	24.84	1246.19
		25	2422.85	39.69	1421.73	2435.73	44.03	1716.71	2447.8	38.95	1175.24
		30	2324.12	58.74	1464.54	2324.91	74.46	1850.78	2375.96	57.13	1190.59
Average			2290.36	42.39	1407.43	2275.48	83.65	1598.56	2336.31	41.63	1172.62

Table 5.2: The hybrid PSO results for GCluVRPBTW, CluVRPB, CluVRPTW, and CluVRPBTW

Instance type	%BH	% Cluster	GCluVRPBTW		CluVRPB		CluVRPTW		CluVRPBTW	
			Distance	t (s)	Distance	t (s)	Distance	t (s)	Distance	t (s)
GCluVRP BTW- R101	30	15	2049.04	157.7	1989.19	10.9	2086.47	200.	2059.65	190.0
		20	2065.49	23.27	1947.11	15.2	2087.59	23.8	2042.48	25.88
		25	2293.94	41.11	2145.59	25.2	2286.57	46.7	2269.37	44.06
		30	2452.68	61.67	2258.05	37.7	2402.52	72.8	2442.72	66.15
	50	15	2254.92	16.54	2136.67	10.4	2301.31	33.1	2230.98	37.62
		20	2274.88	23.58	2198.85	14.3	2288.81	23.8	2287.07	24.35
		25	2436.61	39.24	2288.7	24.0	2406.38	46.8	2421.26	42.1
		30	2335.82	58.97	2137.38	36.9	2285.63	73.7	2322.47	64.15
GCluVRP BTW- R102	30	15	2120.81	17.6	2058.21	10.5	2162.55	13.6	2109.74	15.78
		20	2253.39	23.01	2124.79	14.6	2249.68	482.	2239.18	24.36
		25	2462.94	37.97	2275.86	22.8	2418.86	41.8	2445.31	39.61
		30	2707.21	61.62	2514.87	37.5	2669.71	755.	2677.68	478.5
	50	15	2294.8	17.9	2136.67	10.4	2289.15	12.2	2278.62	17.27
		20	2340.37	23.53	2198.85	14.4	2301.09	78.8	2324.99	24.64
		25	2450.1	39.33	2288.7	24.0	2395.27	46.2	2434.14	41.61
		30	2342.08	57.69	2258.05	37.8	2389.14	72.2	2469.88	65.17
GCluVRP BTW-`R103	30	15	2061.05	18.51	1989.19	10.9	2109.57	13.9	2042.39	16.6
		20	2065.99	24.06	1947.11	15.2	2069.27	24.2	2055.59	26.13
		25	2292.66	41.13	2145.59	25.1	2293.65	152	2268.97	44.33
		30	2482.24	61.02	2137.38	36.8	2289.6	73.7	2304.98	61.98
	50	15	2235.46	17.27	2136.67	10.4	2314.08	223.	2238.57	16.83
		20	2277.43	23.76	2198.85	14.4	2307.55	23.9	2291.8	24.74
		25	2437.87	39.54	2288.7	24.1	2391.47	46.5	2433.91	41.93
		30	2319.86	57.94	2137.38	36.8	2275.35	73.2	2305.38	62.3
GCluVRP BTW-R104	30	15	2052.71	18.27	1989.19	10.9	2085.88	13.8	2045	16.94
		20	2045.36	23.87	1947.11	15.3	2063.9	202.	2031.38	138.4
		25	2297.18	40.42	2145.59	25.1	2268.51	46.4	2272.59	43.62
		30	2430.99	60.86	2258.05	37.7	2428.71	72.8	2424.87	66.89
	50	15	2154.3	18.43	1991.93	10.3	2097.32	93.1	2136.78	17.17
		20	2383.52	23.39	2254.75	14.9	2373.69	24.1	2360.39	24.92
		25	2287.97	184.3	2121.88	21.8	2246.45	258.	2285.96	219.2
		30	2538.32	58.13	2365.29	35.9	2515.87	73.1	2554.14	63.2
GCluVRP BTW- R105	30	15	2099.66	19.24	1989.19	10.9	2077.62	13.7	2092.19	18.23
		20	2073.31	23.82	1947.11	15.2	2080.43	23.8	2057.49	25.58
		25	2257.65	40.81	2145.59	25.1	2248.17	46.3	2245.09	44.3
		30	2417.46	61.78	2258.05	37.7	2375.82	73.5	2441.79	67
	50	15	2205.35	16.13	2136.67	10.4	2299.91	12.4	2226.87	16.46
		20	2316.35	23.71	2198.85	14.3	2277.56	24.0	2303.43	24.59
		25	2422.85	39.69	2288.7	24.0	2415.29	46.6	2408.68	43.09
		30	2324.12	58.74	2137.38	36.8	2273.04	74.2	2314.16	62.5
Average			2290.36	42.39	2152.84	21.7	2279.98	128.	2279.94	59.70

5.4 Conclusion

This chapter introduces the green clustered vehicle routing problem with backhaul and time windows (GCluVRPBTW). The objective of the GCluVRPBTW is to optimize the routing of a mixed fleet of the problem. Similar to the MFGVRPBTW, the mixed fleet consists of several conventional vehicles and hydrogen vehicles. In the problem, all the predefined linehaul and backhaul clusters and customers must be served only once respecting all constraints of the problem. The new problem of the GCluVRPBTW has many real-life applications such as in the health care system, gas cylinder distribution system, drink distribution system, grocery distribution system, and good distribution system in remote and gated communities, etc. In order to address the problem, we design the PSO based solution approach that is hybridized by the neighborhood search method. The neighborhood search includes the many well-known local search moves in both customer level and cluster level. The neighborhood search is intended to find the local optima. Thus, the proposed hybrid PSO algorithm is a well architecture of the intensification behavior of local search and diversification behavior of PSO that aimed to solve the problem. The newly generated GCluVRPBTW instances are used to evaluate the performance of the proposed hybrid PSO in this introducing work. The newly generated instances of CluVRPB, CluVRPTW, and CluVRPBTW are also tested to check the performance of the hybrid PSO algorithm. The key contributions of the work include introducing a new green clustered vehicle routing problem with backhaul and time windows (GCluVRPBTW), formulating a mathematical model of the problem, developing a new hybrid PSO algorithm based solution approach, generating new instances for GCluVRPBTW, CluVRPB, CluVRPTW, and CluVRPBTW, and obtaining solutions for each of the problems. Overall the GCluVRPBTW is believed to be an important contribution in the field of green VRP, clustered VRP, and also in VRP with backhaul areas.

CHAPTER SIX

Conclusions

6.1 Overview

This thesis focuses on the sustainable development of road transportation by investigating a comprehensive VRP model. First, the CluVRP model is considered, followed by the mixed fleet green VRPBTW model. Finally, the thesis combines these two VRP models and presents a comprehensive VRP model that can be considered as a generalization of many VRP models. We develop an effective and integrated hybrid metaheuristic solution approach to solve the problems. The solution approach is enabled to deal with many situations such as mixed fleet vehicles, fuel consumption calculation, CO_2 emission cap, backhauling, and time windows constraints in the distribution networks. The fuel consumption model is realistically considered as a function of traveled distance, speed, and on-board cargo load. The proposed solution approaches help to obtain new best-known solutions for the studied problems and to generate benchmark solutions for the other two new problems with a minimized CO_2 emission discharged by the vehicles in the distribution network.

In the first model, the clustered vehicle routing problem (CluVRP) is considered with the aim of finding the optimal distribution costs for the logistic network serving all customers by using the available vehicles. In the CluVRP, customers are partitioned into predefined clusters. The same vehicle is assigned to serve all customers consecutively under a cluster before it moves to another cluster or returns to the depot. Our proposed hybrid PSO algorithm is tested on the benchmark instances found in CluVRP literature. The hybrid PSO solution approach finds the new best-known solutions for a total of 156 instances out of 293 benchmark instances with an average CPU time of 43.71 seconds.

In the second model, a mixed fleet based green vehicle routing problem with backhaul and time windows (MFGVRPBTW), is introduced. The work brings sustainability concerns in the proposed model by considering backhaul customers, hydrogen AFV, as well as CO_2 emission cap imposed by the government for the distribution logistic. The problem is proposed to optimize the routes of heterogeneous vehicles serving the linehaul and backhaul customers with time windows. The CO_2 emission cap for the network and the maximum route length constraints are included in the problem. The efficiency of the proposed algorithm is proved hereby testing it on the newly generated MFGVRPBTW instances and also on the benchmark instances of VRPB, VRPTW, and VRPBTW available in the literature. While testing on Solomon's VRPTW benchmark instances, the hybrid PSO metaheuristic generates 11 new best known solutions out of 56 instances. The VRPB is tested on the Goetschalckx and Jacobs-Blecha' benchmark instances and obtains a total of 12 new best known solutions out of 62 instances. The proposed hybrid PSO is tested for VRPBTW using Gelinas et al. benchmark instances and attains 9 new best known solutions out of 15 instances for 100 customers.

In the third model, we introduce the green clustered vehicle routing problem with backhaul and time windows (GCluVRPBTW) to optimize the routing of a mixed fleet green CluVRP with backhaul and time windows. The mixed fleet also consists of several conventional vehicles and hydrogen vehicles. In the problem, customers are apportioned into predefined linehaul and backhaul clusters. All customers in a cluster must be served one by one by the same vehicle before it starts serving another cluster or returns to the depot. Since the GCluVRPBTW is the first work in this study, the performance of the proposed hybrid algorithm is evaluated by testing on newly generated GCluVRPBTW instances. The proposed hybrid PSO algorithm for GCluVRPBTW is tested on newly generated instances of CluVRPB, CluVRPTW, and CluVRPBTW. The proposed hybrid PSO algorithm solves each of the problems successfully.

In addition to generating many new best-known solutions for the CluVRP, VRPB, VRPTW, and VRPBTW benchmark instances, this thesis contributed by adding new features in the PSO algorithm such as the use of two types of particles and improvement scheme for the personal best solution in the newly designed hybrid PSO. In the improvement scheme, the personal best solutions of the swarm are further improved by adopting the perturbation and VNS method. With the complementary nature of the hybrid PSO which combines the local optimal improvement capabilities of neighborhood search with the swarm based diversification abilities of the PSO. Hence, the proposed algorithm has great potential for solving instances of other variants of VRP. With the capability of a quality solution on relatively acceptable CPU time, the algorithm has the perspective to use in many practical scenarios in VRPs.

6.2 Limitations of the thesis and future research directions

We acknowledge some limitations of this thesis work. Firstly, the scenario of traffic congestion on the road is not included in the problem. Moreover, the fuel consumption of the vehicles while they are on stops is not considered in this research. It is assumed that no energy for the vehicles is required during the vehicle service is being provided to both of the customers, linehaul, and backhaul customers. All parameters used in the problems are assumed to be deterministic but in practical, some parameters in the routing problem are known to be uncertain.

Future research could be done in the following areas to address the limitations mentioned above. Traffic road congestion could be considered to minimize CO_2 emission in the case of VRP with backhaul problem. There are many VRP works available in the literature working on congestions, but no VRP with backhaul problem has yet considered the traffic congestion for the vehicles. Similarly, no VRP with backhaul problem has yet measured the energy consumption on stops while vehicle service is being provided. Moreover, time-dependent parameters are practical in the urban and city logistics, it would be realistic to comprise time dependencies on the green VRP with backhaul. As some parameters are realistically known to be dynamic instead of deterministic, it would be more convincing to consider a dynamic version of green VRP with backhaul. Finally, in our knowledge, no study has yet been considered electric vehicles for VRP with backhaul and time window. Our thesis work introduces the hydrogen vehicle for the first time in VRP with backhaul and time window. We strongly believe that there are still exist meaningful and significant research opportunities on AFVs VRPB extensions.

Research outcomes

The thesis is designed from the following research events:

Journal papers:

- Md. Anisul Islam, Yuvraj Gajpal, and Tarek Elmekkawy (2020). Mixed Fleet Green Vehicle Routing Problem with Backhaul and Time Windows. Transportation Research Part E: Logistics and Transportation Review (submitted).
- Md. Anisul Islam, Yuvraj Gajpal, and Tarek Elmekkawy (2018). Hybrid Particle Swarm Optimization Algorithm for Solving the Clustered Vehicle Routing Problem. Applied Soft Computing (revised version submitted).

Working paper:

- Md. Anisul Islam, Yuvraj Gajpal, and Tarek Elmekkawy (2020). Green Clustered Vehicle Routing Problem with Backhaul and Time Windows. Preparing to submit to the European Journal of Operational Research.

Conference presentations and proceeding:

- Md. Anisul Islam, Gajpal, Y. and ElMekkawy, T. Y. (2019). A hybrid particle swarm optimization algorithm for mixed fleet of hydrogen and conventional vehicles routes. Administrative science association of Canada (ASAC). May 24-27, 2019, the Goodman school of business, Brock University, Niagara region of Ontario, Canada.

- Md. Anisul Islam, Gajpal, Y. and ElMekkawy, T. Y. (2018). Heuristics and metaheuristic solutions for mixed fleet of hydrogen and conventional vehicles. Administrative science association of Canada (ASAC). May 27-29, 2018, Ryerson University, Toronto, Canada.
- Md. Anisul Islam, Gajpal, Y. and ElMekkawy, T. Y. (2017). Route design for mixed fleet of hydrogen and conventional vehicles. The 21th conference of the international federation of operational research societies (IFORS), July 17-21, 2017, Quebec City convention center, Quebec, Canada.
- Md. Anisul Islam, Gajpal, Y. and ElMekkawy, T. Y. (2016). A hybrid particle swarm optimization algorithm for the clustered vehicle routing problem. The 5th biennial supply chain management conference, December 15–16, 2016, Indian Institute of management Bangalore (IIMB), Bengaluru, India.
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Appendix A: The detailed computational results for CluVRP study

Table A1: Results for the instances A, B for CluVRP study

Instance				BC	Hybrid PSO		
Group	*n*	*c*	*m*	UB	Solution	CPU t(s)	Improvement %
A	31	11	2	522	522	0.079	0.00%
A	32	11	2	472	472	0.122	0.00%
A	32	11	2	562	562	0.094	0.00%
A	33	12	2	547	547	0.13	0.00%
A	35	12	2	588	588	0.149	0.00%
A	36	13	2	569	569	0.183	0.00%
A	36	13	2	615	615	0.151	0.00%
A	37	13	2	507	507	0.143	0.00%
A	38	13	2	610	610	0.191	0.00%
A	38	13	2	613	613	0.157	0.00%
A	43	15	2	714	714	0.199	0.00%
A	44	15	3	712	712	0.315	0.00%
A	44	15	3	664	664	0.307	0.00%
A	45	16	3	664	664	0.354	0.00%
A	47	16	3	683	683	0.356	0.00%
A	52	18	3	651	651	0.577	0.00%
A	53	18	3	724	724	0.542	0.00%
A	54	19	3	653	653	0.493	0.00%
A	59	20	3	787	787	0.679	0.00%
A	60	21	4	682	682	0.817	0.00%
A	61	21	3	778	778	0.777	0.00%
A	62	21	4	801	801	0.827	0.00%
A	62	21	3	865	865	0.594	0.00%
A	63	22	3	773	773	0.89	0.00%
A	64	22	3	725	725	0.809	0.00%
A	68	23	3	814	814	0.898	0.00%
A	79	27	4	972	972	1.637	0.00%
B	30	11	2	375	375	0.097	0.00%
B	33	12	2	416	416	0.128	0.00%
B	34	12	2	562	562	0.12	0.00%
B	37	13	2	431	431	0.142	0.00%
B	38	13	2	321	321	0.155	0.00%
B	40	14	2	476	476	0.19	0.00%
B	42	15	2	415	415	0.219	0.00%
B	43	15	3	447	447	0.279	0.00%
B	44	15	2	506	506	0.265	0.00%
B	44	15	2	391	391	0.221	0.00%
B	49	17	3	467	467	0.415	0.00%
B	49	17	3	666	666	0.455	0.00%
B	50	17	3	585	585	0.394	0.00%
B	51	18	3	427	427	0.481	0.00%
B	55	19	3	433	433	0.556	0.00%
B	56	19	3	634	634	0.654	0.00%
B	56	19	3	753	753	0.601	0.00%
B	62	21	3	685	685	0.641	0.00%
B	63	22	4	526	526	0.832	0.00%

B	65	22	3	687	687	0.934	0.00%
B	66	23	4	626	626	1.09	0.00%
B	67	23	3	588	588	0.983	0.00%
B	77	26	4	721	721	1.65	0.00%

Table A2: Results for the instances M, P for CluVRP study

Instance				BC	Hybrid PSO		
Group	n	c	m	UB	Solution	CPU t(s)	Improvement %
M	100	34	4	607	607	3.506	0.00%
M	120	41	3	691	691	7.559	0.00%
M	150	51	4	804	804	13.048	0.00%
M	199	67	6	914	908	36.083	+0.66%
P	100	51	5	679	658	7.163	+3.09%
P	15	6	4	253	253	0.016	0.00%
P	18	10	2	186	186	0.013	0.00%
P	19	7	1	200	200	0.011	0.00%
P	20	7	1	190	190	0.017	0.00%
P	21	8	1	202	202	0.018	0.00%
P	21	8	4	365	365	0.047	0.00%
P	22	8	3	279	279	0.037	0.00%
P	39	14	2	396	396	0.212	0.00%
P	44	15	2	440	440	0.252	0.00%
P	49	17	4	491	491	0.403	0.00%
P	49	17	3	447	447	0.441	0.00%
P	49	17	3	460	460	0.357	0.00%
P	50	17	4	537	537	0.433	0.00%
P	54	19	4	500	500	0.55	0.00%
P	54	19	6	595	471	0.577	0.00%
P	54	19	3	462	462	0.565	0.00%
P	54	19	3	471	595	0.524	0.00%
P	59	20	4	552	552	0.703	0.00%
P	59	20	5	611	611	0.611	0.00%
P	64	22	4	619	619	0.969	0.00%
P	69	24	4	643	643	1.196	0.00%
P	75	26	2	581	581	1.421	0.00%
P	75	26	2	581	581	1.395	0.00%

Table A3: Results for the Golden instances 1– 4 for CluVRP study

Instance				BC	Hybrid PSO		
Group	*n*	*c*	*m*	UB	Solution	CPU t(s)	Improvement %
Golden 1	240	17	4	4831	4750	23.067	1.68%
Golden 1	240	18	4	4847	4757	17.04	1.86%
Golden 1	240	19	4	4872	4787	17.071	1.74%
Golden 1	240	21	4	4889	4790	17.132	2.02%
Golden 1	240	22	4	4908	4821	17.476	1.77%
Golden 1	240	25	4	4899	4821	18.47	1.59%
Golden 1	240	27	4	4934	4848	17.088	1.74%
Golden 1	240	31	4	5050	4951	18.657	1.96%
Golden 1	240	35	4	5102	5047	20.981	1.08%
Golden 1	240	41	4	5097	5058	25.569	0.77%
Golden 1	240	49	3	5000	4949	34.797	1.02%
Golden 2	320	22	4	7716	7613	44.146	1.33%
Golden 2	320	23	4	7693	7578	43.227	1.49%
Golden 2	320	25	4	7668	7568	40.281	1.30%
Golden 2	320	27	4	7638	7526	39.301	1.47%
Golden 2	320	30	4	7617	7529	36.109	1.16%
Golden 2	320	33	4	7640	7547	35.296	1.22%
Golden 2	320	36	4	7643	7550	37.713	1.22%
Golden 2	320	41	4	7738	7640	42.795	1.27%
Golden 2	320	46	4	7861	7786	48.713	0.95%
Golden 2	320	54	4	7920	7825	58.271	1.20%
Golden 2	320	65	4	7892	7824	82.016	0.86%
Golden 3	400	27	4	10540	10465	111.31	0.71%
Golden 3	400	29	4	10504	10374	87.507	1.24%
Golden 3	400	31	4	10486	10385	64.024	0.96%
Golden 3	400	34	4	10465	10392	68.672	0.70%
Golden 3	400	37	4	10482	10397	75.34	0.81%
Golden 3	400	41	4	10501	10434	78.611	0.64%
Golden 3	400	45	4	10485	10374	78.444	1.06%
Golden 3	400	51	4	10583	10510	83.915	0.69%
Golden 3	400	58	4	10776	10724	96.522	0.48%
Golden 3	400	67	4	10797	10747	125.7	0.46%
Golden 3	400	81	4	10614	10552	173.75	0.58%
Golden 4	480	33	4	13598	13568	108.73	0.22%
Golden 4	480	35	4	13643	13634	100.26	0.07%
Golden 4	480	37	4	13520	13523	148.29	-0.02%
Golden 4	480	41	4	13460	13395	124.67	0.48%
Golden 4	480	44	4	13568	13516	115.78	0.38%
Golden 4	480	49	4	13758	13744	109.78	0.10%
Golden 4	480	54	4	13760	13743	115.54	0.12%
Golden 4	480	61	4	13791	13737	148.57	0.39%
Golden 4	480	69	4	13966	13938	147.53	0.20%
Golden 4	480	81	4	13975	13953	170.61	0.16%
Golden 4	480	97	4	13775	13759	242.04	0.12%

Table A4: Results for the Golden instances 5– 8 for CluVRP study

Instance				BC	Hybrid PSO		
Group	n	c	m	UB	Solution	CPU t(s)	Improvement %
Golden 5	200	14	4	7622	7462	16.546	2.10%
Golden 5	200	15	3	7424	7424	15.15	0.00%
Golden 5	200	16	3	7491	7491	15.408	0.00%
Golden 5	200	17	3	7434	7434	14.172	0.00%
Golden 5	200	19	4	7576	7484	10.54	1.21%
Golden 5	200	21	4	7596	7489	10.195	1.41%
Golden 5	200	23	4	7643	7532	12.029	1.45%
Golden 5	200	26	4	7560	7436	10.795	1.64%
Golden 5	200	29	4	7410	7299	11.318	1.50%
Golden 5	200	34	4	7429	7321	12.35	1.45%
Golden 5	200	41	4	7241	7130	14.518	1.53%
Golden 6	280	19	3	8624	8636	43.251	-0.14%
Golden 6	280	21	3	8628	8633	37.288	-0.06%
Golden 6	280	22	3	8646	8651	30.392	-0.06%
Golden 6	280	24	4	8853	8727	27.107	1.42%
Golden 6	280	26	4	8910	8770	27.943	1.57%
Golden 6	280	29	4	8936	8839	23.312	1.09%
Golden 6	280	32	4	8891	8799	23.379	1.03%
Golden 6	280	36	4	8969	8860	25.362	1.22%
Golden 6	280	41	4	9028	8920	28.009	1.20%
Golden 6	280	47	4	8923	8823	35.821	1.12%
Golden 6	280	57	4	9028	8969	41.084	0.65%
Golden 7	360	25	3	9904	9950	58.636	-0.46%
Golden 7	360	26	3	9888	9934	54.108	-0.47%
Golden 7	360	28	3	9917	9960	55.438	-0.43%
Golden 7	360	31	4	10021	9937	55.158	0.84%
Golden 7	360	33	4	10029	9975	49.814	0.54%
Golden 7	360	37	4	10131	10042	59.732	0.88%
Golden 7	360	41	4	10052	9979	68.169	0.73%
Golden 7	360	46	4	10080	9990	53.545	0.89%
Golden 7	360	52	4	10095	10009	66.216	0.85%
Golden 7	360	61	4	10096	10023	70.67	0.72%
Golden 7	360	73	4	10014	9931	93.347	0.83%
Golden 8	440	30	4	10866	10755	72.164	1.02%
Golden 8	440	32	4	10831	10743	73.996	0.81%
Golden 8	440	34	4	10847	10738	75.17	1.00%
Golden 8	440	37	4	10859	10804	79.01	0.51%
Golden 8	440	41	4	10934	10881	76.273	0.48%
Golden 8	440	45	4	10960	10936	77.094	0.22%
Golden 8	440	49	4	11042	11018	68.908	0.22%
Golden 8	440	56	4	11194	11202	77.402	0.07%
Golden 8	440	63	4	11252	11235	91.29	0.15%
Golden 8	440	74	4	11321	11288	122.7	0.29%
Golden 8	440	89	4	11209	11208	175.96	0.01%

Table A5: Results for the Golden instances 9– 12 for CluVRP study

Instance				BC	Hybrid PSO		
Group	n	c	m	UB	Solution	CPU t(s)	Improvement %
Golden 9	255	18	4	300	296	14.349	1.33%
Golden 9	255	19	4	299	295	14.152	1.34%
Golden 9	255	20	4	296	293	13.991	1.01%
Golden 9	255	22	4	290	289	13.698	0.34%
Golden 9	255	24	4	290	288	13.588	0.69%
Golden 9	255	26	4	288	285	13.27	1.04%
Golden 9	255	29	4	292	291	13.531	0.34%
Golden 9	255	32	4	297	292	14.866	1.68%
Golden 9	255	37	4	294	289	17.3	1.70%
Golden 9	255	43	4	295	291	20.277	1.36%
Golden 9	255	52	4	296	293	27.451	1.01%
Golden 10	323	22	4	367	369	25.743	-0.54%
Golden 10	323	24	4	361	363	24.971	-0.55%
Golden 10	323	25	4	359	359	24.41	0.00%
Golden 10	323	27	4	361	365	24.98	-1.11%
Golden 10	323	30	4	367	371	25.642	-1.09%
Golden 10	323	33	4	373	377	26.215	-1.07%
Golden 10	323	36	4	385	388	26.106	-0.78%
Golden 10	323	41	4	400	401	28.454	-0.25%
Golden 10	323	47	4	398	399	33.684	-0.25%
Golden 10	323	54	4	393	394	41.718	-0.25%
Golden 10	323	65	4	387	389	56.109	-0.52%
Golden 11	399	27	5	457	452	42.24	1.09%
Golden 11	399	29	5	455	455	42.692	0.00%
Golden 11	399	31	5	455	459	42.905	-0.88%
Golden 11	399	34	5	455	456	43.153	-0.22%
Golden 11	399	37	5	459	461	44.32	-0.44%
Golden 11	399	40	5	461	459	45.737	0.43%
Golden 11	399	45	5	462	461	50.074	0.22%
Golden 11	399	50	5	458	457	56.757	0.22%
Golden 11	399	58	5	456	453	69.104	0.66%
Golden 11	399	67	5	454	456	87.073	-0.44%
Golden 11	399	80	5	451	453	124.7	-0.44%
Golden 12	483	33	5	535	539	65.866	-0.75%
Golden 12	483	35	5	537	539	66.781	-0.37%
Golden 12	483	38	5	535	540	66.963	-0.93%
Golden 12	483	41	5	537	541	67.389	-0.74%
Golden 12	483	44	5	535	542	116.86	-1.31%
Golden 12	483	49	5	533	540	75.547	-1.31%
Golden 12	483	54	5	535	540	138.84	-0.93%
Golden 12	483	61	5	538	542	118.95	-0.74%
Golden 12	483	70	5	546	537	202.09	1.65%
Golden 12	483	81	5	546	541	260.03	0.92%
Golden 12	483	97	5	560	548	227.61	2.14%

Table A6: Results for the Golden instances 13– 16 for CluVRP study

Instance				BC	Hybrid PSO		
Group	n	c	m	UB	Solution	CPU t(s)	Improvement %
Golden 13	252	17	4	552	548	13.953	0.72%
Golden 13	252	19	4	549	543	14.783	1.09%
Golden 13	252	20	4	548	540	14.458	1.46%
Golden 13	252	22	4	548	540	12.803	1.46%
Golden 13	252	23	4	548	542	12.666	1.09%
Golden 13	252	26	4	542	535	14.404	1.29%
Golden 13	252	29	4	540	535	13.561	0.93%
Golden 13	252	32	4	543	537	15.948	1.10%
Golden 13	252	37	4	545	541	19.711	0.73%
Golden 13	252	43	4	553	548	20.997	0.90%
Golden 13	252	51	4	560	554	26.903	1.07%
Golden 14	320	22	4	692	687	41.384	0.72%
Golden 14	320	23	4	688	683	24.206	0.73%
Golden 14	320	25	4	678	675	37.666	0.44%
Golden 14	320	27	4	676	674	37.577	0.30%
Golden 14	320	30	4	678	676	28.588	0.29%
Golden 14	320	33	4	682	679	36.76	0.44%
Golden 14	320	36	4	687	680	24.754	1.02%
Golden 14	320	41	4	690	686	31.529	0.58%
Golden 14	320	46	4	694	691	35.407	0.43%
Golden 14	320	54	4	699	698	45.384	0.14%
Golden 14	320	65	4	703	699	62.841	0.57%
Golden 15	396	27	4	842	850	46.669	-0.95%
Golden 15	396	29	4	843	852	46.33	-1.07%
Golden 15	396	31	4	837	849	46.639	-1.43%
Golden 15	396	34	4	838	851	45.11	-1.55%
Golden 15	396	37	4	845	853	48.034	-0.95%
Golden 15	396	40	4	849	851	50.478	-0.24%
Golden 15	396	45	5	853	852	57.041	0.12%
Golden 15	396	50	5	851	848	65.184	0.35%
Golden 15	396	57	5	850	849	77.337	0.12%
Golden 15	396	67	5	855	853	102.31	0.23%
Golden 15	396	80	5	857	857	141.17	0.00%
Golden 16	480	33	5	1030	1026	85.664	0.39%
Golden 16	480	35	5	1028	1024	85.726	0.39%
Golden 16	480	37	5	1028	1026	88.754	0.19%
Golden 16	480	41	5	1032	1032	85.406	0.00%
Golden 16	480	44	5	1028	1029	90.299	-0.10%
Golden 16	480	49	5	1031	1031	97.59	0.00%
Golden 16	480	54	5	1022	1022	116.76	0.00%
Golden 16	480	61	5	1013	1015	131.57	-0.20%
Golden 16	480	69	5	1012	1015	162.17	-0.30%
Golden 16	480	81	5	1018	1022	217.37	-0.39%
Golden 16	480	97	5	1018	1021	300.39	-0.29%

Table A7: Results for the Golden instances 17– 20 for CluVRP study

Instance				BC	Hybrid PSO		
Group	n	c	m	UB	Solution	CPU t(s)	Improvement %
Golden 17	240	17	3	418	419	14.967	-0.24%
Golden 17	240	18	3	419	421	14.56	-0.48%
Golden 17	240	19	3	422	423	13.351	-0.24%
Golden 17	240	21	3	425	426	13.796	-0.24%
Golden 17	240	22	3	424	425	14.085	-0.24%
Golden 17	240	25	3	418	419	12.844	-0.24%
Golden 17	240	27	3	414	414	12.952	0.00%
Golden 17	240	31	4	421	411	13.566	2.38%
Golden 17	240	35	4	417	406	14.73	2.64%
Golden 17	240	41	4	412	403	17.777	2.18%
Golden 17	240	49	4	414	404	23.884	2.42%
Golden 18	300	21	4	592	586	28.133	1.01%
Golden 18	300	22	4	594	589	27.81	0.84%
Golden 18	300	24	4	592	587	28.314	0.84%
Golden 18	300	26	4	590	578	24.567	2.03%
Golden 18	300	28	4	577	570	21.963	1.21%
Golden 18	300	31	4	578	571	22.187	1.21%
Golden 18	300	34	4	582	574	22.884	1.37%
Golden 18	300	38	4	586	578	24.77	1.37%
Golden 18	300	43	4	594	584	26.842	1.68%
Golden 18	300	51	4	601	590	33.65	1.83%
Golden 18	300	61	4	599	590	45.928	1.50%
Golden 19	360	25	10	925	806	54.799	12.86%
Golden 19	360	26	10	924	803	52.665	13.10%
Golden 19	360	28	4	808	813	54.733	-0.62%
Golden 19	360	31	4	811	816	50.376	-0.62%
Golden 19	360	33	4	797	800	47.209	-0.38%
Golden 19	360	37	5	799	789	42.522	1.25%
Golden 19	360	41	5	789	775	46.074	1.77%
Golden 19	360	46	5	788	774	51.689	1.78%
Golden 19	360	52	5	800	787	57.843	1.63%
Golden 19	360	61	5	807	796	72.84	1.36%
Golden 19	360	73	5	810	802	99.174	0.99%
Golden 20	420	29	11	1220	1079	99.2	11.56%
Golden 20	420	31	12	1232	1069	84.198	13.23%
Golden 20	420	33	12	1208	1056	78.686	12.58%
Golden 20	420	36	5	1059	1053	80.535	0.57%
Golden 20	420	39	5	1052	1043	83.127	0.86%
Golden 20	420	43	5	1052	1045	87.669	0.67%
Golden 20	420	47	5	1053	1047	95.474	0.57%
Golden 20	420	53	5	1058	1050	84.69	0.76%
Golden 20	420	61	5	1058	1049	123.07	0.85%
Golden 20	420	71	5	1049	1053	145.61	0.57%
Golden 20	420	85	5	1049	1045	193.98	0.38%