An optimization Model for the Vehicle Routing Problem with Simultaneous Delivery and Pickup under Time windows for Environmental protection.

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By

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DEPARTMENT OF INDUSTRIAL AND PRODUCTION ENGINEERING
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CERTIFICATE OF APPROVAL

The thesis titled "AN OPTIMIZATION MODEL FOR THE VEHICLE ROUTING PROBLEM WITH SIMULTANEOUS DELIVERY AND PICKUP UNDER TIME WINDOWS FOR ENVIRONMENTAL PROTECTION" submitted by Mst. Anjuman Ara, Student No. 0413082035, Session –April 2013 has been accepted as satisfactory in partial fulfillment of the requirements for the degree of Master of Science in Industrial and Production Engineering on 13 February, 2019.

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Mst. Anjuman Ara

To the Almighty

To my Family

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ABSTRACT

The distribution of finished products from depots to customers is a practical and challenging problem in logistics management. Better routing and scheduling decisions can result in higher level of customer satisfaction because more customers can be served in a shorter time. The vehicle routing problem with simultaneous pickups and deliveries and time windows (VRP-SPDTW) is the problem of optimally integrating forward (good distribution) and reverse logistics (returning materials) for cost saving and environmental protection. This research develops a mathematical optimization model for VRPSDPTW called environmental vehicle routing problem with simultaneous delivery and pickup with time windows (EVRPSDPTW) model by using the traveling distance and the load of vehicle. The aim of this model is to determine the efficient vehicle route of a vehicle under cost optimization including fixed cost, variable cost, penalty cost for being tardy, fuel cost by optimizing fuel consumption and cost of carbon emission which results in reducing energy consumption as well as pollutant emissions in the air (GHG). A hybrid genetic algorithm is presented to address the Vehicle Routing Problem with simultaneous delivery and pickup with Time Window. In order to compare the operational efficiency of HGA, genetic algorithm (GA) is implemented to solve the EVRPSDPTW model. The computational experiment is conducted and the results of computational experiments show the performance of HGA is superior to that of GA in terms of the total cost consumption of a vehicle.

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LIST OF ABBREVIATIONS

VRP	Vehicle Routing Problem
SCM	Supply Chain Management
SC	Supply Chain
GA	Genetic Algorithm
OVRP	OpenVehicle Routing Problem
HGA	Hybrid Genetic Algorithm
NP	Nondeterministic Polynomial
MATLAB	Matrix Laboratory
BPC	Bangladesh Petroleum Corporation
SA	Simulated Annealing
TOHA	Time Oriented Heuristic algorithm
CVRP	Capacitated Vehicle Routing Problem
VRPTW	Vehicle Routing Problem with Time Windows
MDVRP	Multi Depot Vehicle Routing Problem
VRPSDP	VRP with Simultaneous Delivery and Pickup
VRPSDPTW	VRP with Simultaneous Delivery and Pickup with time windows
GHG	Green House Gas
VRPB	Vehicle Routing Problem with Backhauls
FCR	Fuel Consumption Rate
EVRP	Environment Friendly Vehicle Routing Problem
g-VRPSDP	Green Vehicle Routing Problem with Simultaneous Delivery and Pickup
TDVRP	Time Dependent Vehicle Routing Problem
TS	Tabu Search
ACO	Ant Colony Optimization
PDP	Pickup and Delivery Problems
DPP	Delivery and Pickup Problems
VRPPD	vehicle routing problem with pick-up and deliveries
PDPTW	Pickup and Delivery Problem with Time Windows
VRPB	Vehicle Routing Problem with Backhauls
SDPP	Simultaneous Delivery and Pickup Problem
SDPPTW	Simultaneous Delivery and Pickup Problem with Time Windows
TD	Travel Distance
DC	Distribution Center
CC	Collection Center
RC	Residual Capacity

RS	Radial Surcharge
RCRS	Residual Capacity And Radial Surcharge
FCR	Fuel Consumption Rate
MGCR	Multi-Mode Green Logistics Cargo Routing
HMOEA	Hybrid Multiobjective Evolutionary Algorithm
LP	Linear Programming
VRPMUV	vehicle routing problem with multiple use of vehicles
PSO	Particle Swarm Optimization

CHAPTER 1

INTRODUCTION

1.1 Background

Supply chain management includes all stages, directly or indirectly, manufacturers, suppliers, transporters, warehouses, retailers, and customers at which value is added in producing and delivering a product or service from suppliers (and their suppliers) to customers (and their customers) (Chopra and Meindl, 2007). It efficiently integrates suppliers, manufacturers, warehouses and retailers so, that merchandise produced and distributed in right quantities, to right locations, in order to lower the system cost while satisfying the service requirements needed (Basher). Logistics Management is the component of SCM. According to council of Logistics Management, Logistics can be defined broadly as the process of planning, implementing, and controlling the efficient, cost effective flow and storage of raw materials, in-process inventory, finished goods and related information from point of origin to point of consumption for the purpose of meeting customer requirements (Baris Kececi, 2014). It Includes movement of products from suppliers to manufacturers to distributors in both directions. Transportation plays an important role in the field of logistics due to the large part of final cost. Logistics movement of fields arrangement require considerable attention to reduce the transportation costs (Nagy & Salhi, 2003)

Traditional supply chain management has focused on the forward flow of materials which is called reverse logistics. Reverse logistics is one of the fields of logistics management. However, the new environmental regulations and the incentives for returning and reusing products have increased the reverse flows in supply chains in recent years (Gazpal & Abad, 2009). Reverse logistics is the process of effective flow of goods from the point of consumption to the point of origin and attempts to generate additional revenue by recapturing the value otherwise lost or underutilized in the supply chain (Biabchessi and Righini, 2007).

Sustainable logistics requires consideration of environmental issues as well as economic efficiency (Kazemian & Aref, 2017). Transportation is the greatest origin of pollution in logistics (Zhang et al., 2014). It is required to distinguish between four GHGs: (i) carbon dioxide (CO2), (ii) methane (CH4), (iii) nitrous oxide (N2O), and (iv) F-gases, which during 1970-2004 amounted, respectively, to 76.7 percent, 14.3 percent, 7.9 percent, and 1.1 percent (Bernhard G. Gunter, 2010). In Bangladesh, transportation accounted for 14% of greenhouse gas (GHG) emission in 2012 (world bank, 2014). Among GHGs, CO2 emissions are particularly the most concerning issues as they have direct effects on human health (Bektas and Laporte, 2011)During the last decades, a growing environmental awareness has lead to increasing efforts to protect the environment by reducing the amount of waste produced and energy consumed (Jan Dethloff, 2001). Among these, fuel consumptions are the most concerning as they not only are the main cost of the companies, but also cause serious pollution which has direct consequences on human health and environment. Rising fuel prices and growing concerns about GHG pollution of transportation on the environment call for revised planning approaches of road transportation to reduce fuel consumption (Jin Li, 2012). According to the information of BPC, total annual fuel consumption in Bangladesh is about 3.78 million metric ton (MT) of which 2.03 million MT is for transport sector. The total fuel consumption of transportation sector is about 54%, which is about 2.5 times higher than the agricultural 2 sector or 18 times higher than the industrial sector (BPC, 2008). Green transportation is a policy toward reduction of carbon emissions (Kou & Wang, 2011). Our purpose is to introduce a new variant vehicle routing where optimizing the VRP by minimizing the fuel consumption. (Jin Li, 2012)

From the above information, it is strongly evident that designing the transportation network is essential which minimizes the overall transportation costs of vehicles as well as optimize the fuel consumption of vehicles. So, this research focuses on controlling the GHG emissions by optimizing the fuel consumption of vehicles and minimizing the overall cost which are derived from the sum of its fixed costs, variable cost, penalty cost for being tardy, fuel cost and carbon emission cost in transportation phase.

Vehicle routing problem (VRP) is first introduced by Dantzig and Ramser towards the end of 1959 which is considered as an important issue in the field of transportation, distribution and logistics (Dantzig and Ramser, 1959). VRP is one of the most important model which deals with determining least cost routes from a depot to a set of scattered customers. Each route has to start and finish at the same depot and each customer has to be visited exactly once by one vehicle. The Vehicle Routing Problem with simultaneous delivery and pickup (VRPSPD) is an extension to the vehicle routing problem (VRP) where the vehicles are not only required to deliver goods to customer but also to pick some goods up at customer locations. Vehicle routing with simultaneous pickups and deliveries have practical application in beverage industry, grocery stores etc. VRPSPD with time windows is further extended where each customer must be serviced within a specified time interval (or time window) and penalties are imposed to the total cost in case the client delivery time window can’t be met. The lower and upper bounds of the time window define the earliest and latest time for the beginning of service at the customer. Hence, a vehicle is allowed to begin service with penalties at a customer location after its time window’s upper time. Moreover, if a vehicle reaches a customer before the lower bound it waits. Each customer also has a specified service time which is the time spent by the vehicle to load or unload the goods. Hence, the total route time of a vehicle is the sum of travel time (which is proportional to the distance traveled), waiting time and service time. Due to the growing concern of environmental deterioration because of transportation, this current research is intended to minimize the fuel consumption of a vehicle and thereby reduce the vehicle emissions with the objective of minimizing the overall cost of transportation. This research also designs a hybrid genetic algorithm (HGA) for solving the cost optimization model efficiently and effectively and minimizing overall costs including fixed cost, variable cost, penalty cost, fuel cost and carbon emission cost. The research uses filled soft drinks glass bottles as the goods for distribution and empty glass bottles as the goods for collecting in the reverse process.

1.2 Objectives with Specific Aims

The specific objectives of this research are-

1. Development of a cost optimization model for Vehicle Routing Problem with simultaneous delivery and pickup (VRPSDP) under time windows using fixed cost, variable cost, penalty cost for being tardy, fuel cost and carbon emission cost by optimizing fuel consumption.

2. Development of a Hybrid Genetic Algorithm (HGA) for solving the cost optimization (VRPSDPTW) model efficiently and effectively.

The outcomes of this research work are counted that cost minimization model for VRPSDPTW will address important sustainable development in environment by collecting recyclable waste and reducing CO_2.

1.3 Outline of Methodology

The research methodology is outlined below:-

a) Mathematical optimization model for VRPSDP under time windows is developed for cost optimization by considering the fixed cost, variable cost, penalty cost for being tardy, fuel cost and carbon emission cost.

b) Computational optimization procedure named Hybrid Genetic Algorithm (HGA) is designed to solve the optimization model (VRPSDPTW) under optimizing the cost of a vehicle.

c) HGA is developed by hybridizing the Genetic Algorithm with Sweep algorithm and Time oriented Heuristic method.

d) Genetic Algorithm (GA) is also applied to solve the EVRPSDP model in order to compare the operational efficiency of proposed HGA.

e) The computational experiments of HGA and existing GA are conducted based on hypothetical data and the performance of the proposed HGA is compared with existing GA based on several genetic operators.

1.4 Organization of the Thesis

The remaining structure of this thesis is organized as follows. Chapter 2 presents the literature review of all the relevant topics of the thesis. Chapter 3 describes the proposed cost optimization model. Chapter 4 presents the proposed HGA. In Chapter 5, the computational experiments are discussed with the necessary data. Chapter 6 illustrates the computational results and analysis of HGA and GA. Chapter 7 concludes the thesis with future directions.

CHAPTER 2
LITERATURE REVIEW

2.1Vehicle Routing Problem and its variants:

Rapid industrialization and increasing consumption of goods are increasing day by day due to prosperity and advances in technology. As a result, the importance of transportation in logistics management has been increased. Road freight transportation system is essential for the economic development, but it is also harmful to the environment and to human health. Until recently, the planning of freight transportation activities has mainly focused on cost minimization (see, e.g., Crainic, 2000; Forkenbrock, 2001). With an increasing worldwide concern for the environment, logistics providers and freight carriers have started paying more attention to the negative externalities of their operations. These include pollution, accidents, noise, resource consumption, land use deterioration, and climate change risk (Schreyer et al., 2004). The concentration of greenhouse gases (GHGs) in the earth's atmosphere has been increased markedly due to transportation. While the concentration of all types of GHGs has increased in the atmosphere, the focus is always on the CO2 emission, as it constitutes large share of GHG emission. Recently, Kirschstein and Meisel (2015) developed a mesoscopic model based on a simple, fundamental theory that GHG emissions are proportional to fuel consumption.

The vehicle routing problem was introduced by Dantzig and Ramser (1959). Since then variants of VRP have been studied for various situations in transportation. Vehicle Routing Problems (VRP) originally focused on how to dispatch a group of vehicles to serve a group of customers with a given demand regarding minimum operation cost. Deterministic VRPs by their classes of problems are reviewed at first, as shown in Fig.2.1 (Wang and Chen, 2012).

CVRP is a VRP in which a fixed fleet of delivery vehicles of uniform capacity must service known customer demands for a single commodity from a common depot at minimum transit cost. That is, CVRP is like VRP with the additional constraint that every vehicle must have uniform capacity of a single commodity. Within the framework of the CVRP, CVRP are extended into two major categories regarding routing activities: single activity CVRP which considers only pickup or delivery, and multiple activities which consider both pickup and delivery.

Multiple- Depot Capacitated Vehicle Routing Problem (MDVRP) and Vehicle Routing Problem with Time Windows (VRPTW) are the further extension of Single activity CVRP which have been studied extensively. In the MDVRP problem multiple depots exist from where vehicles could start traveling and where they could end up (Cordeau et al., 2001). In *open VRP* (OVRP) vehicles do not require to return to the depot (Brandao, 2004). The problem dealing with time windows constraints is called vehicle routing problem with time windows (VRPTW). Time window constraints define time frames when a customer can be serviced. A set of time windows for each customer could be also considered (VRP with Multiple Time-Windows). Also these time windows could be flexible depending on some extra costs (VRP with Soft Time-Windows).

Real situations can give another type of constraints where goods need not only to be brought from a depot to a customer, but also to be picked up from a number of customers and brought back to depot or to any other customer. Multi activity CVRP includes two sub problems: Pickup and Delivery Problems (PDP) and Delivery and Pickup Problems (DPP). PDP receives several requests for picking up an amount of goods at one location from a customer for a vehicle and delivering it to another location. This problem is known as a vehicle routing problem with pick-up and deliveries (VRPPD). PDP is further extended to the Pickup and Delivery Problem with Time Windows (PDPTW) to associate time windows with the customers (Ropke and Pisinger, 2006).

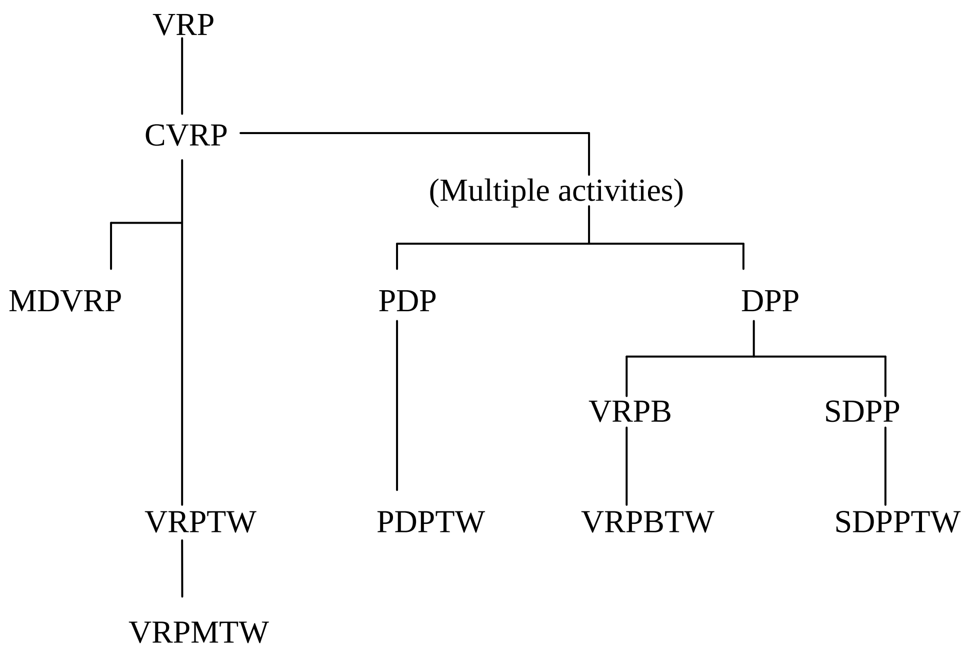

Fig. 2.1 Basic variants of VRP

Another problem of multi activity CVRP is DPP which is divided into two categories consisting of Vehicle Routing Problem with Backhauls (VRPB) and Simultaneous Delivery and Pickup Problem (SDPP). As in the VRPB, the customers are divided into two subsets. The first subset contains the linehaul customers, which are customers requiring a given quantity of product to be delivered. The second subset contains the backhaul customers, where a given quantity of inbound product must be picked up. Then all linehaul customers have to be visited before the backhaul customers in a route. In SDPP, Each customer is associated by two quantities, representing one demand to be delivered at the customer and another demand to be picked up from the same customer and returned to the depot. The vehicles must pickup and deliver items to the same customers in one visit. In addition to the constraint that the total pickup and total delivery on a route cannot exceed the vehicle capacity, also it has to ensure that this capacity is not exceeded at any point of the route. This problem, called simultaneous delivery and pickup problem (SDPP) and evolved from above strategy, has been studied extensively (Ai and Kachitvichyanukul (2009), Berbeglia et al. (2007), Bianchessi and Righini (2007), Chen and Wu (2006), Dell'Amico et al. (2006), Dethloff (2001), Min (1989), Montané and Galvao (2006), and Nagy and Salhi (2005).

When each customer is associated with a time interval and can only be served within this interval, which is termed as simultaneous delivery and pickup problem with time windows (SDPPTW). Ai and Kachitvichyanukul (2009) studied SDPPTW and proposed a model to formulate SDPPTW. Therefore, their model should be revised into a simpler form for SDPPTW so that both the number of vehicles and the traveling cost are minimized. Consequently a solution procedure should be developed accordingly.

Another special case of Vehicle routing problem is the green Vehicle routing problem (GVRP) where GVRP aims at including different environmental issues in the optimisation process, e.g. greenhouse gas emissions (Ubeda et al. 2011), pollution, waste and noise (Bektas¸ and Laporte 2011), effects of using 'greener' fleet configurations (Juan et al. 2014a), etc. An excellent and updated survey on GRVP can be found in (Demir et al. 2014).Carbon die oxide (CO_2) emissions are reduced.

As stated before, the problem is the vehicle routing problem with simultaneous pickup and delivery and time windows, in which goods are transported by a fleet of vehicles between the depot and customers within their time windows. In this problem, two main bodies of vehicle routing literature are relevant to our problem. The first one is the cost optimization model where cost is minimized considering fixed cost, variable cost, penalty cost for being late and environmental cost including fuel cost and carbon emission cost. The second one is to minimize fuel consumption for reducing CO_2 emission considering environmental protection.

Dethloff (2001) studied the cheapest insertion with four different insertion criteria: travel distance (TD), residual capacity (RC), and radial surcharge (RS) and their combination (RCRS).

For large-scale VRPSPD problems, research has been focusing on heuristic and meta-heuristic methods. Nagy and Salhi (2005) develop mathematical relationships to describe how route changes affect solution feasibility, based on which they propose an integrated heuristic method to solve the VRPSPD. It first finds a solution to the corresponding VRP and modifies the solution to make it feasible for the VRPSPD. They then apply composite improvement heuristics to improve the solution. Chen and Wu (2006) apply the cheapest insertion heuristic to construct an initial solution and then improve the solution based on the record-to-record travel, tabu lists, and route improvement procedures. Biabchessi and Righini (2007) represent and compare a variety of constructive, local search, and tabu search algorithms via numerical experiments. Ai T. J. et al (2009) examined the VRPSDP on the basis of the known information of vehicle model standard configuration, distribution route maximum service time and client node delivery volume, and proposed a particle swarm optimization algorithm for solving it.

Compared with first objective related to VRPSDPTW, there is an abundant body of research on the second objective related to VRPSDPTW. The cost of traveling with a vehicle along a route depends on many factors. Some of these factors such as distance, load, speed, road conditions, fuel consumption rate (FCR -fuel consumption per unit of distance), fuel price, etc. have direct effects on traveling schedule. Fuel consumption, as an influential factor, has been regarded as a fixed or variable cost in VRP. In addition, rise in transportation has increased the hazardous impacts on the environment such as resource consumption, land use, acidification, toxic effects on ecosystems and humans, noise and so on (MirHassani and Mohammadyari, 2014).

In the last years, following the Green Logistics emerging area, a number of studies on VRP taking account environmental considerations in their objective functions were published. Bektas and Laporte (2011) use the comprehensive modal emission model to include fuel consumption and carbon emissions in the capacitated vehicle routing problem and the variant with time windows (VRPTW). Xiao et al. add the load dependent fuel consumption rate (FCR) into the capacitated VRP, and develop a simulated annealing algorithm with a hybrid exchange rule to solve the problem. Their numerical experiments show that the proposed model can result in 5% fuel consumption savings on average as compared to the traditional CVRP model.

Kou (2010) added the vehicle velocity to the time-based VRP model besides the factors of passed distance and the carried load and solved the model through a Simulated Annealing (SA) algorithm.

This paper is distinguished from the previous work in this area, by including environmental aspects with cost factor from a multi-objective perspective. Furthermore, a heuristic algorithm for the problem resolution is presented. In multi-objective VRP there are lower research works than relating to our problem. Molina et al (2014) presented a new mixed-integer linear programming model for the Multi-Objective Vehicle Routing Problem with some realistic assumptions such as Heterogeneous Fleet and Time Windows. Siu et al (2012) proposed a multi-mode green logistics cargo routing (MGCR) problem with multi-objective approach of VRP incorporating the cost minimization and optimization of CO_2 emissions as a secondary objective of the problem as well as an additional constraint. Abbas et al (2006) proposed weather avoidance multi-objective heuristics using Ant Colony Optimization (ACO) in a free flight environment. Tan et al (2006) proposed a hybrid multiobjective evolutionary algorithm (HMOEA) to VRPTW that involves the optimization of routes for multiple vehicles in order to satisfy a set of constraints and to minimize multiple objectives, such as traveling distance and number of vehicles.

2.2 Different Methods to Optimize the cost under VRP

In the field of transportation and supply chain, VRP is used to design the delivery or pickup routes of vehicles to serve the customers (Goodson, 2010). The fundamental objectives of VRP are to find the minimal number of vehicles, the minimal travel time or the minimal costs of the travelled routes or minimal cost for fuel consumption. VRP continues to draw researchers' attention due to usefulness in real life like in transportation sector as well as in logistics. Since then, a large number of different approaches of VRP have been extensively developed and a number of different methods such as exact, heuristic and metaheuristic methods have been applied to solve VRP.

2.2.1 Exact methods

Exact methods generate optimal solution and are applied to small size problem. The computational time considerably increases with the increasing size of the problem. There are different types of exact method: branch-and-cut, branch-and-bound, dynamic programming, and set-partitioning methods.

2.2.1.1 Branch-and-Bound Method

In 1960, the branch-and-bound for discrete programming is discussed by Land and Doig (Land and Doig, 1960). In the extensive survey devoted to exact methods, Laporte and Nobert gave a complete and detailed analysis of the branch-and-bound algorithms proposed up until the late 1980s. It is the most commonly used tool for solving NP hard optimization technique (Clausen, 1999). Toth et al. (1994) applied this method for capacitated vehicle routing problem on directed graphs. Branch and bound exact algorithm is proposed in capacitated vehicle routing problem (CVRP) whose performance is enhanced by means of reduction procedures, dominance criteria and feasibility check. It searches of all possible solutions while discarding (pruning) a large number of non-promising solutions by estimating upper and lower bounds of the quantity to be optimized. The effectiveness of branch-and-bound algorithms largely depends on the quality of the lower bounds used to limit the search tree. Therefore, some elementary combinatorial relaxations such as the assignment problem, the degree-constrained shortest spanning tree, state-space relaxation and lagrangean relaxation are applied for estimating lower bound which ensures the effectiveness of branch and bound algorithm.

2.2.1.2 Branch and Cut Algorithm

Branch and Cut is a combinatorial optimization method for solving linear integer programming problem. Laporte et al. (1985) proposed the branch and cut method for the CVRP. This algorithm describes an integer linear programming algorithm for vehicle routing problems involving capacity and distance constraints. The method uses constraint relaxation and a new class of sub tour elimination constraints. This initial relaxation is iteratively strengthened by adding violated capacity constraints, which are heuristically separated by considering the connected components induced by the set of nonzero variables in the current LP solution. Exact solutions are obtained for problems involving two or three vehicles and up to sixty customers. Later, this method is applied extensively in different vehicle routing problem such as vehicle routing problem with multiple use of vehicles (VRPMUV) (Karaoglan, 2015).

2.2.1.3 Set-Partitioning Formulation

The Set-Partitioning formulation is originally proposed by Balinski and Quandt (1964) and contains binary variable formulation for each feasible route. The optimization version of the partition problem is to partition the multiset S into two subsets $S1$, $S2$. The objective is to minimize the difference between the sum of elements in $S1$ and the sum of elements in $S2$. The optimization version is NP-hard, but can be solved efficiently in practice. This technique is quite general and can consider several constraints at a time (Subramanian et al. 2012; Subramanian 2012). Novoa (2006) presented a set-partitioning-based modeling framework for the VRP with stochastic demands (VRPSD) to construct a minimum cost set of vehicle routes that visits all customers and satisfies demands without violating the vehicle capacity constraints.

2.2.2 Heuristic methods

A heuristic algorithm is a problem solving technique that is designed to solve a problem in faster and more efficient way than traditional method where optimality, accuracy, precision and completeness are sacrificed for speed. They do not guarantee that the best solution will be found and considered as sufficient but not accurate algorithms for immediate goals. These algorithms, usually find a solution close to the best one easily and fast. Heuristic algorithms often times used to solve NP-complete problems, a class of decision problems, to speed up the process of finding a satisfactory solution. Heuristic algorithms are most often employed when approximate solutions are sufficient and exact solutions are necessarily computationally expensive. These approaches start from null-solution and generate feasible solutions by achieving simple steps. These approaches are continued until a complete solution is achieved and termination criteria are met. Heuristics that are typically used for solving VRP as follows:

2.2.2.1 Savings Algorithm

The savings algorithm is a heuristic algorithm proposed by Clarke & Wright (1964) based on the concept of maximized saving, and therefore it does not provide an optimal solution to the problem with certainty. The method does, however, often yield a relatively good solution. That is, a solution which deviates little from the optimal solution. The cost saving concept is obtained by joining two routes into one route, rather than in two separate ones. The algorithm calculates all the savings from customer i to j If i is the last customer of a route and is the first customer of another route, the associated saving is defined as $S_{ij} = C_{i0} + C_{0j} - C_{ij}$. If S_{ij} is positive, then serving i and j consecutively in a route is profitable. Solving the role of routing by Clarke-Wright´s method is carried out by gradual steps. Firstly, the least preferred solution, which is then improved by each gradual step, is found. This method considers all customer pairs and sorts the savings in non increasing order. Starting with a solution in which each customer appears separately in a route, the customer pair list is examined and two routes are merged whenever this is feasible. Generally, a route merge is accepted only if the associated saving is nonnegative but, if the number of vehicles is to be minimized, then negative saving merges may also be considered. The Clarke and Wright algorithm is inherently parallel since more than one route is active at any time. However, it may easily be implemented in a sequential fashion. The resulting algorithm is quite fast but may have a poor performance.

2.2.2.2 Route-First Cluster-Second

Route-first, cluster-second methods construct giant tour in a first phase, disregarding side constraints, and decompose this tour into feasible vehicle routes in a second phase.

The construction starts from the initial route that visits all the nodes. The route is then split into several routes starting from the depot. Examples of such algorithms are given by Beasley (1983), Haimovich and Rinnooy Kan (1985), Bertsimas and Simchi-Levi (1996), and Bouzid et al (2013) but the performance of this approach is generally poor.

2.2.2.3 Cluster-First-Route-Second Method

In 1971, Wren and Carr first introduced the sweep algorithm in her book (Wren and Carr, 1971) and in 1972, Wren and Holliday mentioned in their paper (Wren and Holiday, 1972), but in the year of 1974, Gillet and Miller applied this algorithm for the vehicle dispatch problem with distance and load constraints for each vehicle. Sweep algorithm is an algorithmic paradigm that uses a conceptual sweep line or ray that originated from a center point to solve various problems in Euclidean space (Gillet and Miller, 1974). The idea behind the sweep algorithm is to imagine that a line (often a vertical line) is swept or moved across the plane at any point in time, stopping at some points. It stores the information along the sweep line. The vertical line can be moved in any angle in Euclidean space. Sweep algorithm is the basic and important problem in geographic information system. It can be Forward sweep and backward sweep. In forward sweep algorithm, the vertical line starts from center point that sweep clockwise to store information along the line. Similarly, in backward sweep algorithm, the vertical line starts from center point that sweep anticlockwise to store information along the line.

2.2.2.4 Nearest Neighbor Heuristic (NNH)

Firstly, Reinelt (1994) introduced the nearest neighbor algorithm to solve the travelling salesman problem. The basic principle of the Nearest Neighbor method that is developing the travel route, each vehicle serves the closest city from the last city until all have been visited that has not been visited before. In other word, the method solves the problem by determining the closest point with the shortest distance and it quickly yields a short tour, but usually not the optimal one. It is a simple method to solve these problems and has an early solution. This heuristic has been effectively hybridized with other heuristics and metaheuristics for large scale problem. Du and He (2012) studied VRP and they developed an effective hybrid metaheuristics which combines Nearest Neighbor Search and Tabu Search algorithm. It was highly competitive method than others.

2.2.3 Metaheuristic Methods

Optimization is an important subject with many important applications and in the simplest sense, an optimization can be considered as a minimization or maximization problem. Algorithms for optimization are diverse with a wide range of successful applications. Among these optimization algorithms, modern metaheuristics are becoming increasingly popular, leading to a new branch of optimization, called metaheuristic optimization. A metaheuristic is a higher-level procedure designed to find or generate a sufficiently good solution to an optimization problem, especially with incomplete or imperfect information or limited computation capacity. The state-of-the-art optimization methods are explored ranging from local searches over evolutionary computation methods and memetic algorithms to estimation of distribution algorithms. This will be able to recognize problems where "traditional" techniques will fail (e.g., run too long) and know how to find good solutions for them within feasible time. Today more advanced metaheuristics use search experience (embodied in some form of memory) to guide the search for solving VRP such as:

2.2.3.1 Simulated Annealing (SA)

Simulated annealing approaches are designed for global optimization, i.e. for searching the global optimum in the entire search space. The method is invented in 1983 by Kirkpatrick, Gel-lat and Vecchi (based on earlier work by Metropolis) (Kirkpatrick et al., 1983) which is an adaptation of the Metropolis–Hastings algorithm, a Monte Carlo method to generate sample states of a thermodynamic system and published by N. Metropolis et al. in 1953 (Metropolis et al., 1953). The simulated annealing algorithm was originally inspired from the process of annealing in metal work. In annealing process, a material is first heated and cooled to alter its physical properties due to the changes in its internal structure. After the metal cools, a permanent new structure is formed which causing the metal to retain its newly obtained properties. In simulated annealing a temperature is kept variable to simulate this heating process. The temperature set high and then allow it to cool slowly as the algorithm runs. The probability of accepting depends on the temperature. When the temperature is high, there is a high chance to accept degraded solution than current solution. The ability to jump out of any local optimums is achieved by this. As the temperature is reduced so is the chance of accepting worse solutions, a close to optimum solution can be found by gradually focusing in the search space. This gradual 'cooling' process makes the simulated annealing algorithm remarkably effective at finding a close to optimum solution when dealing with large problems which contain numerous local optimums. Different researchers used simulated annealing algorithm to solve VRP with different objectives. Harmanani et al., (2011) applied SA algorithm in Capacitated VRP. The algorithm uses a combination of random and deterministic operators that are based on problem knowledge information. The Capacitated Vehicle Routing Problem (CVRP) is a combinatorial optimization problem where a fleet of delivery vehicles must service known customer demands from a common depot at a minimum transit cost without exceeding the capacity constraint of each vehicle. Similarly, Cordeau et al. (2005), Vidal et al. (2013) studied simulated annealing algorithm to solve variants of VRP.

2.2.3.2 Tabu Search (TS)

Tabu Search is a Global Optimization algorithm and a Metaheuristic or Meta-strategy for controlling an embedded heuristic technique. With roots going back to the late 1960's and early1970's, TS was proposed in its present form a few years ago by Glover (1986), and has now become an established optimization approach that is rapidly spreading to many new fields. The idea of the tabu search is to prevent a move in the search that is already performed during specified amount of last iterations. In such approach restrictions are stored in memory so called tabu list. Application of tabu search prevents cycling in search and allows moving the search to unexplored search space. It is used extensively to solve different VRP problems. Gendreau (1994) proposed a tabu search heuristic for the vehicle routing problem with capacity and route length restrictions. Montané and Galvão (2006) developed a Tabu Search (TS) algorithm to solve VRPSPD. Three types of movements: the relocation, interchange and crossover movements are used to obtain inter-route solutions and *2-opt* procedure is used to obtain alternative intra-route solutions.

2.2.3.3 Ant Colony Optimization (ACO)

Ant Colony optimization (ACO) was introduced by Marco Dorigo and colleagues the first ACO algorithms in the early 1992 (Dorigo, 1992).The development of these algorithms was carried out by the observation of ant colonies. The optimal paths are searched following the behavior of ants seeking a path between their colony and a source of food. Their behavior is governed by the goal of colony survival rather than being focused on the survival of individuals. When searching for food, ants initially explore the area surrounding their nest in a random manner. Ants leave a chemical pheromone trail on the ground during their movement. Other ants move by smelling pheromone and they tend to choose paths marked by strong pheromone concentrations with higher probability. When an ant finds a food source, it evaluates the quantity and the quality of the food and carries some of it back to the nest. During their coming back, the quantity of pheromone that an ant leaves on the ground may depend on the quantity and quality of the food. Other ants will guided by the pheromone trail to the food source. The indirect communication between the ants via pheromone trails enables them to find shortest paths between their nest and food sources. ACO has been known to find high quality solutions to vehicle routing problems for its many applications by many researchers. Gajpal and Abad (2009) used Ant Colony Optimization (ACO) algorithm to solve Vehicle Routing Problem with simultaneous delivery and pickup (VRPSPD). The proposed ACS algorithm used a construction rule with two multi-route local search schemes. It was shown that in general the proposed ACS gives better results compared to the existing solution methods for VRPSDP both in terms of the solution quality and the CPU time.

2.2.3.4 Genetic Algorithm

A genetic algorithm is a search heuristic developed by John Holland and his students and colleagues at the University of Michigan in the early 1970's (Holland, 1970). This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation. GAs has been mainly inspired by Charles Darwin’s theory of natural evolution. Algorithm is started with a set of solutions (represented by chromosomes) called population (Darwin, 1809-1882). Solutions from one population are taken for mating them and used to form a new population. There is a hope that the new population will be better than the old one. Solutions which are selected to form new solutions (offspring) are selected according to their fitness - the more suitable they are the more chances they have to reproduce. The genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

- In Selection rules, individuals are selected (called parents) for contributing to the population at the next generation.
- In Crossover rules, two parents are mated together to form children for the next generation.
- In Mutation rules random changes are applied to individual parents to form children.

Genetic Algorithms are used extensively in different field of Vehicle Routing Problems by different researchers. For example, Pop and Chira (2014) developed a hybrid genetic algorithm to solve VRP. They used single depot and clustered customers to form group. To find optimum clustered route for the above problem, genetic algorithm was used in combination with local global approach. Shahdaei and Rahimi (2016) proposed a new genetic algorithm for vehicle routing problem with simultaneous delivery and pickup (VRPSPD). In this algorithm, two types of crossover operator and two types of mutation operator with new features are designed which during the process can be replaced with each other and its efficiency is shown.

2.2.3.5 Particle Swarm Optimization

Particle Swarm Optimization (PSO) was invented by Russell Eberhart and James Kennedy in 1995 inspired by the flocking and schooling patterns of birds and fish (Kennedy and Eberhart, 1995). Originally, these two was trying to develop computer software simulations based on birds flocking around food sources, then later realized that the algorithms worked very well on optimization problems. It is a population based stochastic optimization technique. Swarm-based algorithms such as PSO emerged as a powerful family of optimization techniques where the set of candidate solutions to the optimization problem is defined as a swarm of particles which move in search space to find shortest distance between source and destination. Each particle keeps track of its coordinates in the problem space which are associated with the achieving the best solution (fitness). The particle swarm optimization concept consists of changing the velocity of (accelerating) each particle at each step toward its gbest (global best) and lbest (local best) locations. Acceleration is weighted by a random term, with generation of separate random numbers for acceleration toward pbest and lbest locations.

Compared to the evolutionary computation techniques such as Genetic Algorithms (GA), PSO has no evolution operators such as crossover and mutation. The system is initialized with a population of random solutions and optima are searched by updating generations. PSO has been successfully applied in many research and application areas in the past several years. Ai and Kchitvichyankul (2009) proposed a particle swarm optimization (PSO) algorithm for solving the vehicle routing problem with simultaneous pickup and delivery (VRPSPD) with the purpose of explaining the mechanism of the PSO for solving VRPSPD and to demonstrate the effectiveness of the proposed method.

CHAPTER 3
COST OPTIMIZATION MODEL

3.1 Vehicle Routing Problem with Simultaneous Delivery and Pickup and Time Windows

The importance of reverse logistics has increased day by day from the last few decades due to the environmental and economical issues. The new environmental regulations and the incentives for returning and reusing products have increased the reverse flows in supply chains in recent years. Routing of vehicles is one of the most critical issues that affect the performance of the reverse logistics. The importance of reverse logistics increased the importance of Vehicle routing problem with simultaneous pick-up and delivery (VRPSPD). So it is decided to focus on VRPSPDTW and its related studies.

The VRP with Simultaneous Deliveries and Pickups (VRPSDP) is a case of combined demands where customers require simultaneous pick-up of goods from their location and are collected at the depot in addition to delivery of goods to their location originated from depot. Various types of service appear in practical situations, where customers require simultaneous pick-up of goods from their location in addition to delivery of goods to their location and a fleet of vehicles originated in a depot serves customers with pick-up and deliveries from/to their locations. Such as in soft drink industry or gas distribution industry, empty containers/cylinders must be returned in the delivery to grocery stores, where reusable pallets/containers/cylinders are used for the transportation of merchandise. In this regard, separate service for the delivery and pick-up the goods may not accepted because a handling effort is necessary for both activities. Therefore, this effort may be considerably reduced by a simultaneous operation. In this research, the soft drinks containers are considered. The vehicle routing problem with simultaneous deliveries and pickups VRPSDP is explained in Fig. 3.1(Shahdaei & Rahimi, 2016). In following Fig.3.1 black circles indicate customer nodes while black rectangle indicates the depot, solid arrows indicate deliveries while dotted arrows indicate pick-ups in customer nodes and solid lines are the arcs between customer nodes. A number of routes are sought for number of vehicles with homogenous capacity, that minimize the total transportation cost of routes while satisfying the pick-up and delivery demands of the number of customer nodes simultaneously. Each vehicle has to depart and return to the depot and each customer node has to be visited exactly once by one vehicle.

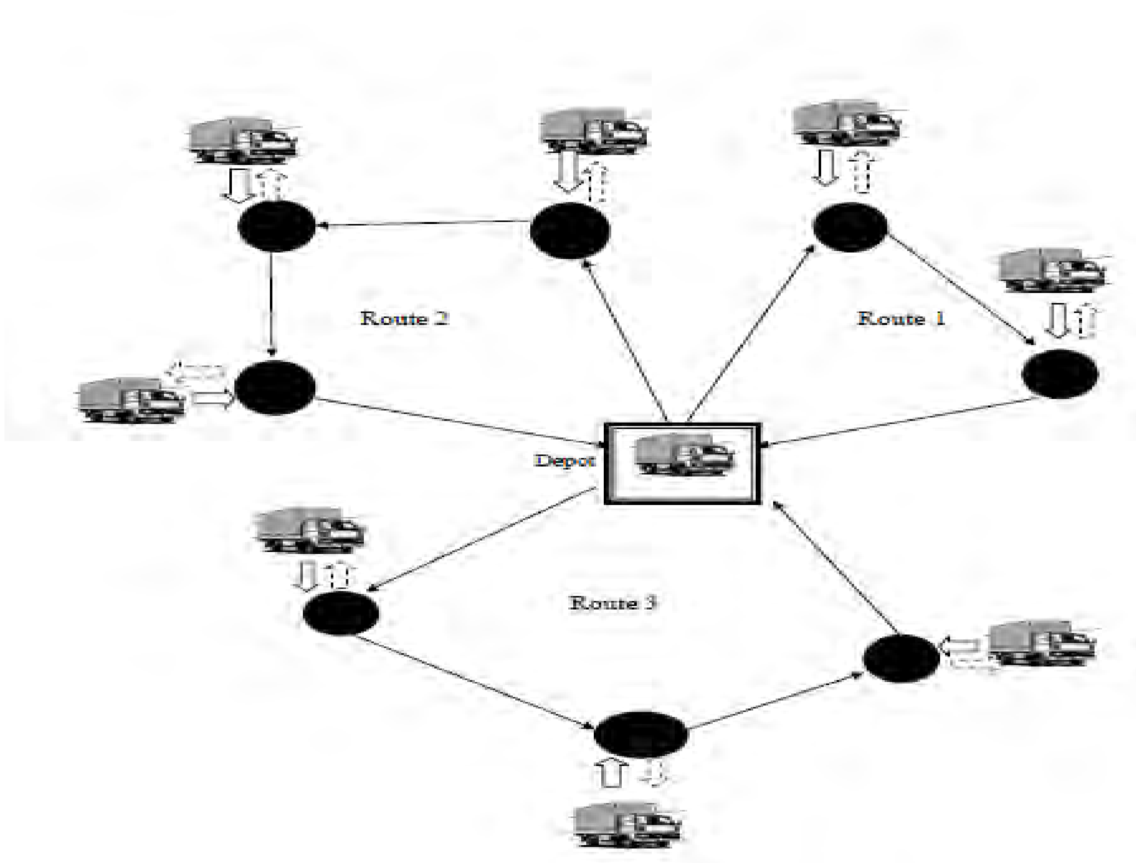

Fig. 3.1 Vehicle Routing Problem with Simultaneous Delivery and Pickup

There are two strategies found for servicing customer by pickup and delivery that creates two types of vehicle routing problem; first is the Vehicle Routing Problem with Backhauls (VRPB) and the second is Vehicle Routing Problem with Simultaneous Pick-up and Delivery (VRPSDP) (Berbeglia et al., 2007). Both VRPSPD and VRPB consider pick-up and delivery of goods to/from customers. In VRPB, at first, delivering to customers will be done and then, in return the pick-up will be done (Ropke and Pisinger, 2006). Osman and Wassan (2002) studied VRPB to design the set of minimum cost. Initial solutions were generated based on the saving-insertion and saving-assignment procedures, respectively. The initial solutions were then improved by a reactive tabu search meta-heuristic. Many researchers such as Liu and Chung (2009), Ropke and Pisinger, (2006) etc also studied the vehicle routing problem with Backhauls (VRPB) that are found in literature to handle the transportation optimization.

Due to additional cost of separate delivery and pick-up, the VRPSPD was introduced. This problem was introduced by Min (1989). Min recognized the possibility of simultaneous pickup and delivery at the same node in practical situations and introduced the vehicle routing problem with simultaneous pickups and deliveries (VRPSPD).He investigated the distribution of a public library with 22 library and two vehicles based on the central library. Vehicles serve branch libraries everyday with deliveries and pick-ups at each branch library. Gendreau et al., (1999) studied the vehicle routing problem with simultaneous delivery and pick-up for solving travelling salesman problem at first; and then organized travelling salesman routing problem. Dethloof (2001) studied the relation between VRPSPD and other types of vehicle routing problem and presented a mathematical formula for this problem. He expanded 40 species to test in his proposed algorithm and comprised its results with Salhi and Nagy's result (1999). He also discussed about the relation between VRPSPD and VRPB (Dethloff, 2002). Huang et al (2012) studied green VRPSPD (GVRPSPD) problem by considering fuel consumption and carbon emissions and formulated a two-index commodity flow based linear integer programming model for VRPSPD. Gan et el (2012) studied a case of the VRPTW with simultaneous delivery and pickup service. The objective of the proposed VRPTW-SDP is minimizing the transport costs with uncertain number of vehicles. An efficient multiswarm cooperative particle swarm optimization (MCPSO) algorithm is applied and compared with genetic algorithm (GA) and particle swarm optimization (PSO) algorithm, the MCPSO algorithm performs best for solving this problem. In MCPSO, each particle should contain two aspects of the customers, the order of served by which vehicle. Thus two dimensions encoding methods in MCPSO are proposed and used for the VRPTW-SDP. Many studies about VRPSPD were conducted (Chen and Wu (2006), Dell'Amico et al (2006), Nagy and Salhi (2005) & Zachariadis et al., (2010)). Toth and Vigo (1999) was also presented an efficient innovative method for creating appropriate initial solutions by genetic algorithm. Montane and Galvao (2002) proposed a mathematical model for this problem and solved it with improved heuristic algorithm for travelling salesman problem with simultaneous delivery and pick-up. Later, they were successful to make a mathematical model for vehicle routing with distance limitations and pick-up, and then solved it by using tabu search algorithm and combinational local algorithms.

3.2 Model Development

Given a number of customers who require both forward supply service and reverse recycling service within a certain time period, the problem concerned in this paper is how to send out a fleet of capacitated vehicles, stationed at a distribution center (DC), to meet the requests with the minimum number of vehicles and traveling cost. Based on the simultaneous delivery and pick-up activities of a vehicle, all vehicles should return to the collection center (CC) to unload the recycled material. The distribution center is the same as the collection center, then CC = DC.
This problem is also considered as green VRPSPDTW problem where CO_2 emission is reduced and cost of fuel consumption is included in the objective function. Since the CO_2 emissions depend on the fuel consumption, the fuel consumption rate is minimized.

The vehicle routing problem with simultaneous pickups and deliveries and time windows (VRP-SPDTW) is the following problem: a set of customers is located on a transportation network; each customer i requires both a delivery and a pickup operation of a certain amount of goods (d_i) and returning materials (p_i) and must be visited once for both operations. The customers has to be serviced with a given fleet of vehicles of limited capacities (Q) which are usually assumed to be identical; each vehicle leaves the depot carrying an amount of goods equal to the total amount it must deliver and returns to the depot carrying an amount of returning materials equal to the total amount it pick-up. Each customer must be serviced within a specified time interval (or time window) $[a_i,b_i]$. The lower (a_i) and upper bounds (bi) of the time window define the earliest and latest time for the beginning of service at the customer. A vehicle is not allowed to begin service at a customer location after bi. Moreover, a waiting time arises if a vehicle reaches a customer before a_i. Each customer also has a specified service time (t_i) which is the time spent by the vehicle to load and unload the goods. Hence, the total route time of a vehicle is the sum of travel time (which is proportional to the distance traveled), waiting time and service time. The total route distance should not exceed the maximum route distance of the vehicle. In each point along its tour no vehicle can carry load greater than its capacity. The goal is to minimize the overall cost of the tours. In addition to minimizing the distance-related cost and fixed cost of vehicles as in the traditional VRPSPDTW model, the VRPSPDTW problem also includes the costs of fuel consumption, cost of carbon emission and penalty cost in the objective function. The following notation will help in the description of the methods used for solving the VRP-SPDTW.

Sets

J = Set of customer nodes {1, 2, 3, 4,......................n}

J_0 = Set of all nodes including customer locations and depot {0, 1, 2, 3, 4..............n}

V = Set of vehicles {1, 2, 3,.............m}

Parameters:

(X_i, Y_i) = Coordinates of node i, i = 0, 1, 2, 3,..........n, node 0 represents the depot

C_{ij} = Distance between node i and j, $i, j \in J_0, i \neq j$

F = Total fuel consumption

d_j = Delivery amount demanded by customer node j, $j \in J$

p_j = Pickup amount of customer node j, $j \in J$

n =Number of nodes, $n = |J_0|$

Q = Vehicle capacity

M = A very large number used in Big-M technique

$$M = \max\left\{\sum_{j \in J}(d_j + p_j), \sum_{i \in J_0}\sum_{j \in J_0} C_{ij}\right\}$$

r = Number of routes; the same as the number of vehicles being used

D_n = Total delivery amount

P_n = Total pickup amount

μ = Carbon emission rate

C_v = Fixed cost

C_d = variable cost

C_p = penalty weight factor

C_f = fuel cost

C_e = Carbon emission cost

A_i = arrival time of assigned vehicle at node i

D_i = departure time of assigned vehicle at node i

W_i = waiting time

$T_{i\,=}$ tardiness time

S_i = service time

t_{ij} = time taken to vehicle v to travel from node i to j

e_i = the earliest time that node i can be serviced by a vehicle

l_i = the latest time that node i can be serviced by a vehicle

Arrival time at a destination node j

$A_j = D_i + t_{ij}$

Waiting time, $W_i = e_i - A_i$

The departure from node i, $D_i = A_i + S_i$

The departure and service time of a depot, $D_i = S_i = 0$

The tardiness time, $T_i = \max\{0, (D_i - l_i)\}$

Decision variables:

l_v' : Initial loads of Vth vehicle when leaving the depot

l_j : Load of vehicle after having serviced customer j, $j \in J$

K_j : Intermediate variable used to prohibit sub tours; can be interpreted as position of node $j \in J$ in the route

X_{ijv} : Binary decision variable that indicates whether V^{th} vehicle travels from node i to j

X_{ijv} = 1, if vehicle V ^{traverses} arc (i, j)

X_{ijv} = 0, if vehicle V does not traverses arc (i, j)

T_i = 1, if $D_i - l_i$ is positive

0, if $D_i - l_i$ is negative

3.2.1 Measurement of Fuel consumption

In addition to minimizing the distance related cost, fixed cost of the vehicles and penalty cost for being tardy as in the traditional VRPSPDTW model, the g-VRPSPDTW problem also includes the cost of fuel consumption and carbon emission in the objective function. The fuel consumption during VRPSPDTW routes are affected by many factors, e.g. travel distance, speed, road gradient, and load. Most studies fail to properly integrate these factors. The fuel consumption is proportional to the driving distance and linear with the vehicle load. That is,

Fuel consumption = (a * load + b) * distance and

Carbon emissions = μ * fuel consumption,

Where a and b are the coefficients of vehicle fuel consumption and μ is the carbon emission rate of fuel consumption.

Let X_{ij} be the binary variable to indicate whether arc (i, j) is visited on the route. Y_{ij} denotes the demand picked up from customers routed up to node i and transported on arc (i, j); Z_{ij} denotes the demand to be delivered to customers routed after node i and transported on arc (i, j). With the vehicle load variables Y_{ij} and Z_{ij}, the fuel consumption from node i to node j can be calculated as $d_{ij}[a(Y_{ij} + Z_{ij}) + b]$ and the carbon emissions can be calculated as $\mu d_{ij} [a(Y_{ij} + Z_{ij}) + b]$.

3.2.2 Cost minimization VRPSPDTW Model

Let C_d denote the unit distance-related cost, C_v denote the fixed cost of a vehicle, C_f denote the unit fuel cost, Cp denote the penalty cost for violating time windows and C_e denote the environmental cost for carbon emission. Considering the environmental effect, the complete objective function for the vehicle routing problem with simultaneous delivery and pickup and time windows is presented in the following:

Objective Function:

Minimize $C_{cost} = C_v \sum_{j=1}^{n} \sum_{v=1}^{n} X_{0jv} + C_d \sum_{i=0}^{n} \sum_{j=1}^{n+1} d_{ij} X_{ijv} + C_p \sum_{i=0}^{n} \sum_{j=1}^{n} \sum_{v=1}^{n} T_{ij} X_{ijv} +$

$$C_f \sum_{i\in J_0} \sum_{j\in J_0} \sum_{v\in V} d_{ij} [a(Y_{ij} + Z_{ij}) + b] + C_e\, \mu \sum_{i\in J_0} \sum_{j\in J_0} \sum_{v\in V} d_{ij} [a(Y_{ij} + Z_{ij}) + b]$$

Subject to,

$$\sum_{i\in J_0}^{n} \sum_{v\in V}^{m} X_{ijv} = 1, \quad j \in J \qquad \text{....................................1}$$

Constraint (1) ensures that each customer is serviced exactly once.

$$\sum_{i\in J_0}^{n} X_{isv} = \sum_{j\in J_0}^{n} X_{sjv}, \quad s \in J, v \in V \qquad \text{………………………….2}$$

Constraint (2) guarantees that every vehicle that arrives to a customer node must leave that customer node.

$$l'_v = \sum_{i\, \varepsilon\, J_0} \sum_{i\, \varepsilon\, J} d_j X_{ijv}, \quad v \varepsilon V \qquad \text{....................................3}$$

Constraint (3) defines the vehicle’s initial load that is the accumulated demand of all customer nodes assigned to this vehicle.

$$l_j \geq l'_v - d_j + p_j - M(1 - X_{ojv}), \quad j \varepsilon J, v \varepsilon V \qquad \text{..................................4}$$

Constraint (4) means that the amount of vehicle load after it has serviced the first customer node on their route.

$$l_j \geq l_i - d_j + p_j - M\left(1 - \sum_{v \varepsilon V}^{m} X_{ijv}\right), \quad i \varepsilon J, j \varepsilon J \qquad \text{..................................5}$$

Constraint (5) gives the amount of vehicle load en route.

$$l'_v \leq Q, \quad v \varepsilon V \qquad \text{..................................6}$$

Constraint (6) guarantees that the initial vehicle loads do not exceed the vehicle capacity.

$$l_j \leq Q, \quad j \varepsilon J \qquad \text{..................................7}$$

Constraint (7) means that the vehicle loads en route do not exceed the vehicle capacity.

$$S_j \geq S_i + 1 - n\left(1 - \sum_{v \varepsilon V}^{m} X_{ijv}\right), \quad i \varepsilon J,\ j \varepsilon J,\ j \neq i \qquad \text{..................................8}$$

Constraint (8) ensures sub tour elimination.

$$S_j \geq 0, \quad j \varepsilon J \qquad \text{..................................9}$$

Constraint (9) ensures the non-negativity of intermediate variables used to prohibit sub-tours.

$$X_{ijv} \, \varepsilon \{0,1\}, \quad i \varepsilon J_0, \quad j \varepsilon J_0, \quad v \varepsilon V \qquad \text{..................................10}$$

Constraint (10) states the decision variable is a binary variable.

$(A_{iv} + W_i + S_i + t_{ij})\, X_{ijv} \leq A_{jv}$ ……………………………11

$A_i \leq l_{i,}$ $i \epsilon J_0$ ……. ……………..……..... 12

$e_i \leq A_i + W_i \leq l_{i\,,}$ $i \epsilon J_0$ …………………………………13

Equation 11, 12 & 13 are time windows constraints

CHAPTER 4
HYBRID GENETIC ALGORITHM

4.1 Genetic Algorithms Based Solution Approach

VRP-SPD belongs to the class of NP-hard problems, for that reason the exact solution methods become highly time-consuming as the problem instances increase in size. Therefore, due to the combinatorial nature of the VRP and the GAs' efficiency in solving combinatorial problems, a GA based approach is developed to solve the vehicle routing problem.

Genetic algorithm is an optimization computational algorithm where different areas of the solution space are searched effectively by considering a set of points of solution space in each iteration. In genetic algorithm, design space, which includes different solutions of the problem, must be converted to genetic space. Therefore, genetic algorithm works with a series of coded variables.

The Genetic Algorithms (GA) were invented by John Holland and his colleagues in the early 1970s (Holland, 1970), inspired by Darwin's theory. The British naturalist Charles Darwin (1809-1882) proposed the Theory of Natural Selection in 1859 (Darwin, 1809-1882). The theory states that individuals with certain favorable characteristics are more likely to survive and reproduce whereas Individuals with less favorable characteristics will gradually disappear from the population. The fittest individuals consequently pass their characteristics on to their offsprings. In nature, the genetic inheritance is stored in chromosomes and made of genes. The characteristics of every organism are controlled by the genes, which are passed on to the offsprings when the organisms mate. Once in a while a mutation causes a change in the chromosomes. Due to natural selection, the population will gradually improve on the average as the number of individuals having the favorable characteristics increases.

The idea behind GA is to model the natural evolution by using genetic inheritance together with Darwin's theory. In GA, the population consists of a set of solutions or individuals instead of chromosomes. The creation of new generation of individuals involves primarily four major steps or phases: representation, selection, recombination (crossover), and mutation. The representation of the solution space consists of encoding significant features of a solution as a chromosome, defining an individual member of a population. Typically pictured by a bit string, a chromosome is made up of a sequence of genes, which capture the basic characteristics of a solution. A selection procedure, simulating the natural selection, selects a certain number of parent solutions, which the crossover uses to generate new solutions, also called offsprings. A crossover operator plays the role of reproduction and a mutation operator is assigned to make random changes in the solutions. The recombination or reproduction process makes use of genes of selected parents to produce offspring that will from the next generation. It combines characteristics of chromosomes to potentially create offspring with better fitness. As for mutation, it consists of randomly modifying gene(s) of a single individual at a time to further explore the solution space and ensure, or preserve, genetic diversity. The occurrence of mutation is generally associated with low probability. A new population replaces those from the old one. A proper balance between genetic quality and diversity is therefore required within the population in order to support efficient search. At the end of each iteration, the offsprings together with the solutions from the previous generation form a new generation, after undergoing a selection process to keep a constant population size. The solutions are evaluated in terms of their fitness values identical to the fitness of individuals.

Recently, Hybrid genetic algorithms (HGAs) have received significant attention as the most prevalent algorithms in recent years and are being increasingly used to solve hard optimization problems such as, the PCB component scheduling problem (Ho and Ji, 2003, 2004), the logistics distribution problem (Gen and Syarif, 2005), the water distribution network design (Keedwell and Khu, 2005), the bankruptcy prediction (Min et al., 2006), the flow shop scheduling problem (Wang et al., 2006), and so on. Hybrid genetic algorithms are based on the complementary view of search methods where Genetic and other search methods are brought together as complementary tools to achieve an optimization goal. In these hybrids, a genetic algorithm incorporates one or more methods to improve the performance of the genetic search. There are several ways in which a search or optimization technique can complement the genetic search. The HGA combines the general working procedure of genetic algorithm with other heuristic or meta heuristic methods (i.e sweep algorithm, clarke and wright savings algorithm, tabu search, ant colony algorithm and so on) to improve the solution quality. In addition, the required constraints in the developed cost optimization model forces to diverse the existing GA algorithm.

Therefore, based on the existing GA algorithm, a hybrid GA algorithm is developed to solve the cost optimization model effectively. Furthermore, none of the researchers have developed the HGA to solve the VRPSDPTW.

The main phases of the GA approach and proposed HGA in this study is shown in Fig. 4.1. In GA, the initial population is generated randomly in which it would take long time for the algorithm to converge to the solution. HGA is hybridized to generate initial population using some form of heuristics such as sweep heuristic for routing, the nearest neighbor heuristic (NNH) for sequencing and then the chromosomes (solutions) are improved by iterated swap procedure (ISP). The procedure of the HGAs is explained as follows: The GA parameters such as the iteration number, the population size, the crossover rate, and the mutation rate have been set initially. Feasible clusters of customers are initially formed by sweep algorithm and then vehicle route is obtained for each cluster. So there are two phases found in sweep algorithm i.e clustering phase and routing phase. In the cluster phase, the customers are clustered by rotating a ray centered at the depot having the smallest angle and in the second phase routes are constructed based on vehicle capacity and customer demand for each vehicle. After routing phase, the delivery sequence of vehicles in each route is determined by time oriented heuristic procedure. After getting predetermined number of initial chromosomes, the ISP is applied to improve the chromosomes. Fitness function is applied in each chromosome to measure their fitness for evaluation. The rank selection operator is employed to select some chromosomes for the genetic operations.

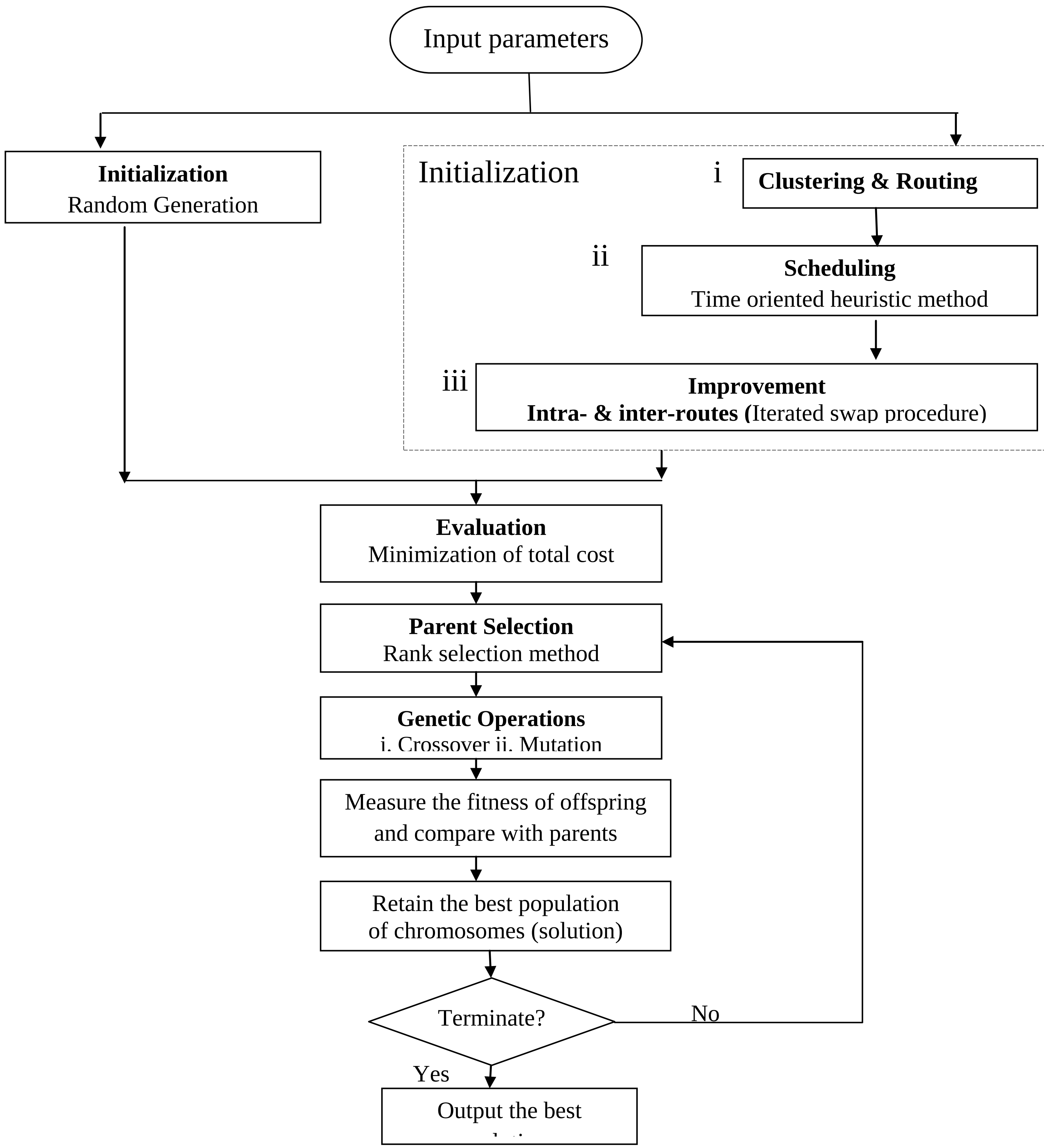

Fig. 4.1 The Operation Procedure of Designed HGA and Existing GA.

After genetic operations a new chromosome or offspring is produced and the fitness of the offspring is measured. If the offspring possesses a relatively good quality, it is then considered as a member of the population. The overall steps of iteration and then rank selection is performed again to start the next iteration. The HGA will continue unless the predetermined number of iterations is conducted.

4.2 Operation Procedure of GAs to Cost Optimization Model

GAs are developed by three key elements Gene, individual (Chromosome) and population (Fig. 4.2). A chromosome contains genes. Each gene contains a parameter of the problem represented by the whole chromosome. An individual is any possible single solution while the population is the set of individuals currently involved in the search process. The chromosome is a set of parameters or in this case, it can be said sequence (permutation) of customer nodes which define a proposed solution to the problem that is tried to solve by the genetic algorithm. An individual or chromosome represents a potential solution to the problem (Carter and Ragsdale, 2006). It is a member of population. A population is a group of all individuals. A population consists of a number of individual being tested, the phenotype parameters defining the individuals. The population size (PopSize) is the number of chromosomes in each generation;

population	Chromosome-1	1 2 5 9 7 8
	Chromosome-2	5 9 8 7 6 3
	Chromosome-3	5 2 1 9 4 3
	Chromosome-4	1 9 4 6 2 3
	Chromosome-5	3 6 2 8 7 5

Fig.4.2 Example of Key Elements

4.2.1 Chromosome representation

The representation of a feasible solution in a chromosome structure may be much more complex for the VRP than other problems. Chromosome is represented by encoding method. It is required to find an optimal route for each vehicle with satisfying all the constraints. The process of standard representation of individual genes in chromosome is called encoding. Hence, permutation encoding is used for chromosome representation of the VRPSDPTW. In permutation encoding, the customers are listed in the order in which they are visited. Chromosome is represented by integer string of length where the length of the chromosome is determined by the number of customer nodes that are served by the vehicles. Routes are determined by the capacities of vehicles and maximum allowable operating time. For example, there are 10 customer nodes with three vehicles where a chromosome is generated randomely1 3 6 8 9 5 4 10 2 7, which can be interpreted as r =3 feasible routes: 0-1-3-6-0, 0-8-9-5-0, and 0-4-10-2-7-0. If vehicle (v) >= r, then this chromosome is legal; otherwise, it is illegal. Vehicle capacity and time window constraints are hard constraints, which mean that the conditions must be met or the possible solution will be discarded by the algorithm.

4.2.2 Population initialization

The representation of a feasible solution in a chromosome structure is more complex for the VRP than other problems. In addition to the problem of finding an optimal route for each vehicle, there is also the problem of distributing visits required for each customer in the planning horizon by satisfying all the constraints. For this reason, different heuristics methods are applied to generate initial solution based on all constraints.

The population initialization procedure under proposed HGA is explained as follows:

In the stage of population initialization, three heuristics procedure are followed to generate a feasible initial solution. The first step is to cluster the customers to each of n links using Sweep Heuristics that is, the grouping problem.

Step 1: sweep approach

Sweep method was first found in a book by Wren (1971) and in a paper by Wren and Holliday (1972) but It was popularized by Gillett and Miller (1974) as a heuristic algorithm that have been developed for solving vehicle dispatch problems with load and distance constraints for each vehicle. The objective of sweep algorithm is to clustering the given nodes i.e. the customers are grouped into clusters.

There are two sweeping methods i.e. forward sweep and backward sweep for clustering the customer nodes. Before starting the clustering, forward sweep method is specified to determine the order of clustering. A cluster is a group of nodes that satisfies certain constraint where the nodes are joined based on their angles. After locating all customer nodes, the angle of each node is calculated by the following equation;

$$\sin\alpha = \frac{node_{\,i+1}\,Y - node_{\,i}\,Y}{\sqrt{(node_{\,i+1}\,X - node_{\,i}X)^2 + (node_{\,i+1}\,Y - node_{\,i}\,Y)^2}}$$

The depot is a place like a warehouse where goods are temporarily stored in large quantities for meeting customer demand. In the clustering stage, the depot is considered as center point and the ray or line acts as a vehicle. The ray starts from depot at 0^0 angle and move clockwise to cluster the customers. The ray encompasses at surrounding to assign each customer one by one to the current cluster according to the capacity of the vehicle and demand of the customer. Clustering is executed by joining the nearest to any node which has smallest sin angle and this process is continued by joining the second closest, the third, and so forth until the capacity constraint is satisfied. The capacity here is the maximum amount of load that a vehicle can carried out.

When the vehicle capacity is violated for adding a certain customer node, then this node becomes the first node of the second cluster. This process is continued until all nodes are included in the clusters. Each cluster represents a single route of vehicle based on the capacity constraint for the vehicle routing problem.

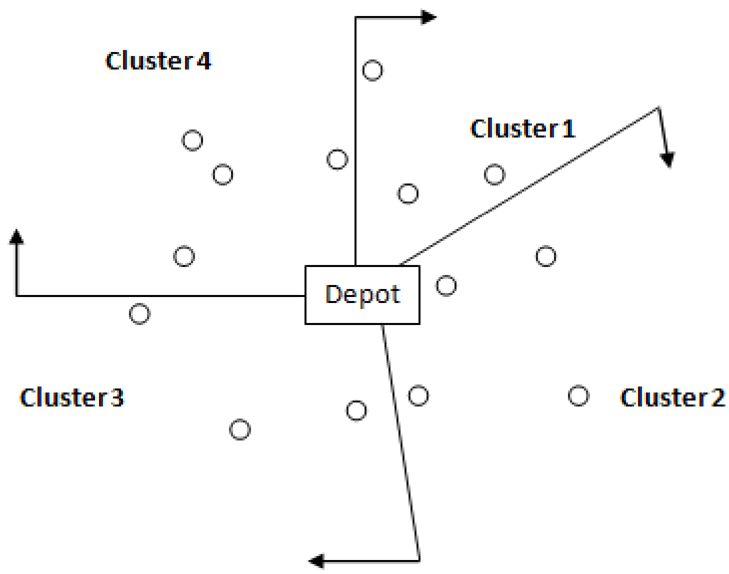

Fig.4.3 Clustering Process

Step 2: Time Oriented Heuristic algorithm (TOHA)

A time oriented heuristics algorithm is proposed in this step for sequencing of customer nodes in each vehicle route based on time windows constraint. The sequence of nodes in each cluster is determined on the basis of travel time and the customer's waiting time by using TOHA. The basic principle of time oriented heuristic method is that to develop the travel route, each vehicle serves the closest city from the last city until all have been visited that has not been visited before. The service at a customer, say i, i = 1, ..., n, involving pickup and delivery of goods or services can begin at time bi with s_i service time within a time window defined by the earliest time e_i and the latest time l_i that customer i will permit the start of service. Hence, if a vehicle travels directly from customer i to customer j and arrives too early at j, it will wait, that is, b_j =

max $\{e_j, b_i + s_i + t_{ij}\}$, where t_{ij} is the direct travel time between i and j. Note that the times b_i for i = 1, ..., n, at which services begin are decision variables.

Details for several notations are as follows:

θ_i = time when a vehicle completes service of customer *i*, where $\theta_i = b_i + s_i$

j′ = spatially closest unvisited customer from customer *i*,

N′ = set of unvisited customers,

The heuristic algorithm process is proposed as follows:

Step1. The algorithm is initialized and the number of iterations (η) is set equal to 1.

Step2. Set *j′* equal to 0, θ_0 equal to a_0,

Step3. Set *i* equal to *j′* and find the unvisited customer *j′* that is within the time window and spatially closest to customer *i*. The customer is denoted as described elsewhere:

$$j' \in \arg\min_{j \in N} \{ t_{ij} + \max \{a_j - \theta_i - t_{ij}, 0\}\}$$

If more than one unvisited customer is found, then the customer *j′* with the minimum travel distance is selected.

Step4. Insert customer *j′* into the current route of vehicle *k*, and the time when customer *j′* is visited can be expressed as

$$\theta_j = \theta_i + t_{ij'} + \max \{ a_{j'} - \theta_i - t_{ij'}, 0\}$$

Step5. Set η equal to η + 1, return to Step 2, and repeat until all customers are served.

This procedure is continued until all nodes are selected to be linked in the same cluster. The same procedure is performed for each cluster.

The encoding together with the above two steps to generate a feasible initial solution of the VRPSDPTW problem is explained as below:

Example: the customers are clustered into routes based on vehicle capacity and customer demand as below using Sweep heuristic method.

Route 1 for vehicle no. 1 = 2 4 7

Route 2 for vehicle no. 2 = 3 8 5

Route 3 for vehicle no. 3 = 1 9 6 10

Now for each cluster, the sequences of customer nodes are found in each route or cluster using TOHA method as like;

Route 1 for vehicle no. 1 = 0 4 2 7 0

Route 2 for vehicle no. 2 = 0 5 3 8 0

Route 3 for vehicle no. 3 = 0 9 10 1 6 0

The path representation for all customers can be represented as

Chromosome 1 = 0 4 2 7 0 5 3 8 0 9 10 1 6 0

This same procedure of population initialization is continued by creating the first ray at different angles from depot to cluster the customer nodes along with route construction. That is the initial population size. In addition, the design of population size varies with the angle of ray or sweep hand.

Step-3: Iterated Swap procedure (ISP)

Iterated Swap procedure (ISP) (Ho and Ji, 2003, 2004) is generally used to improve the solutions of the hard optimization problems like VRPSDPTW. Here, ISP is used in third step to improve the links of each initial solution. If a new solution generated is better than the original one, or parent, in terms of quality, it will replace and become the parent. Although, it increases the computational time because every two swaps are examined but it increases the efficiency of HGA. During iteration, the depot is not considered.

The procedure of the ISP is as follows:

Step 1: Select two genes randomly from a link of a parent.

Step 2: Exchange the alleles of the two genes to form an offspring.

Step 3: Swap the neighbors of the two genes to form four more offspring.

Step 4: Evaluate all offspring based on minimization of fuel consumption and find the best one.

Step 5: If the best offspring is better than the parent, replace the parent with the best offspring and go back to Step 1; otherwise, stop.

There are two types of improvement techniques i.e the intra-route improvement and inter-route improvement are used in case of ISP. In intra-route improvement, The ISP interchanges the customers within the same route. Similarly, in inter-route improvement, customers are exchanged from one route to another route.

Example:

Parent:	4	2	**7**	5	3	8	9	**10**	1	6
Offspring 1:	4	2	**10**	5	3	8	9	**7**	1	6
Offspring 2:	4	2	**5**	**10**	3	8	9	**7**	1	6
Offspring 3:	4	**10**	**2**	5	3	8	9	**7**	1	6
Offspring 4:	4	2	**10**	5	3	8	9	**1**	**7**	6
Offspring 5:	4	2	**10**	5	3	8	**7**	**9**	1	6

Fig. 4.4 Iterated Swap Procedure

Each offspring generated by swap procedure are validated by capacity and time windows constraint before evaluation of fitness function.

4.2.3 Fitness function evaluation

The initial population created is evaluated based on fitness function. To do it, fitness function, which called cost function in this study equal to sum of total cost including distance related cost, fixed cost, fuel cost, carbon emission cost and penalty cost for violating time windows is minimized.

Let C_d denote the unit distance-related cost, C_v denote the fixed cost of a vehicle, C_f denote the unit fuel cost, C_e denote carbon emission cost and C_p denote the penalty cost for violating time windows. The mathematical model of VRPSPDTW can be formulated as below.

$$\text{Minimize } C_{cost} = C_v \sum_{j=1}^{n} \sum_{v=1}^{n} X_{0jv} + C_d \sum_{i=0}^{n} \sum_{j=1}^{n+1} d_{ij} X_{ijv} + C_p \sum_{i=0}^{n} \sum_{j=1}^{n} \sum_{v=1}^{n} T_{ij} X_{ijv} + C_f \sum_{i \in J_0} \sum_{j \in J_0} \sum_{v \in V} d_{ij} [a(Y_{ij} + Z_{ij}) + b] + C_e \mu \sum_{i \in J_0} \sum_{j \in J_0} \sum_{v \in V} d_{ij} [a(Y_{ij} + Z_{ij}) + b]$$

Where X_{ij} be the binary variable to indicate whether arc (i, j) is visited on the route. Y_{ij} denotes the demand picked up from customers routed up to node i and transported on arc (i, j); Z_{ij} denotes the demand to be delivered to customers routed after node i and transported on arc (i, j). d_{ij} represents distance from i to j and T_{ij} represents penalty factor of customer j.

4.2.4 Parent selection

In Genetic Algorithm for crossover operations, chromosomes are selected from the population to be parents to crossover. The problem is how to select these chromosomes. According to Darwin's evolution theory the best ones should survive and create new offspring. There are many methods how to select the best chromosomes, for example roulette wheel selection, Boltzman selection, tournament selection, rank selection, steady state selection and some others.

The rank selection operator (Baker, 1985) is adopted to select some chromosomes to undergo the genetic operations. Rank selection operator is selected to ensure the fittest chromosome in this problem. Rank selection first ranks the population based on value of fitness function and then every chromosome receives fitness from this ranking. The fitness value for each chromosome is ranked according to ascending order to undergo genetic operations. Therefore, there is a high chance to select the fitter chromosome according to desired requirements. This means that the chromosomes (solutions) incurred less total cost are selected from the population to produce fitter offsprings based on desired population size (n). Due to super individuals, it helps to prevent premature convergence.

4.2.5 Genetic operations

Crossover and mutation are the two essential genetic operations used in genetic algorithm to guide the algorithm towards a solution to a given problem for the progress of the genetic searching procedure. Generally, the crossover operator combines existing solutions into new solutions while the mutation operator maintains genetic diversity and explores a wider search space.

4.2.5.1 Crossover

Crossover plays a vital role in GAs, which simulates a reproduction between two parents. It works on a pair of solutions and recombines them in a certain way generating one or more offsprings. The offsprings share some of the characteristics of the parents and in that way the characteristic are passed on to the future generations. It is not able to produce new characteristics. Crossover operator is applied to the mating pool with the hope that it creates a better offspring. After the selection (reproduction) process, the population is enriched with better individuals by this operation. A lot of crossover operators have been proposed in literature and all have their significant importance. The genetic crossover operators i.e. one point crossover, two point crossover and cyclic crossover are adopted for the genetic operations in the EVRPSDP model.

1. Single point crossover

   This crossover uses the single point fragmentation of the two parents randomly and designates the fragmentation point as crossover point. The tails to the right of the crossover point are swapped between the two parent chromosomes and then combine the parents at the crossover point to create the offspring or child.

Parent-1	0	1	2	3	4	**5**	**6**	**7**	**8**	**9**
Parent-2	5	8	9	7	3	**1**	**0**	**6**	**4**	**2**

Offspring-1	0	1	2	3	4	**1**	**0**	**6**	**4**	**2**
Offspring-2	5	8	9	7	3	**5**	**6**	**7**	**8**	**9**

Fig. 4.5 Single point Crossover

2. Two point crossover

   The two-point crossover selects two crossover points within a chromosome and then the bits in between the two points are swapped between two parent chromosomes to produce two new offsprings.

Parent-1	0	1	2	**3**	**0**	**5**	6	7	8	9
Parent-2	0	8	9	**7**	**0**	**3**	5	6	1	2

Offspring-1	0	1	2	**7**	**0**	**3**	6	7	8	9
Offspring-2	0	8	9	**3**	**0**	**5**	5	6	1	2

Fig. 4.6 Two point Crossover

3. Cycle crossover

The cycle crossover (CX) operator was proposed by Oliver et al. (1987). It attempts to create offspring in such a way that each gene and its position is occupied by a corresponding element from one of the parents. Cycle crossover occurs by picking some cycles from one parent and the remaining cycles from the alternate parent. All the elements in the offspring occupy the same positions in one of the two parents. First a cycle of alleles from parent 1 is created. Then the alleles of the cycle are put in child 1. Other cycle is taken from parent 2 and the process is repeated.

<u>Step-1: Cycle identification</u>

Parent-1	1	2	3	4	5	6	7	8	9
Parent-1	9	3	7	8	2	6	5	1	4

Parent-1	1	**2**	**3**	4	**5**	**6**	**7**	8	9
Parent-2	9	3	7	8	**2**	**6**	**5**	1	4

<u>Step-2 Offspring Identification</u>

Parent-1	1	2	3	4	5	**6**	7	8	9
Parent-2	9	3	7	8	2	**6**	5	1	4
Offspring-1	1	3	7	4	2	**6**	5	8	9
Offspring-2	9	2	3	8	5	**6**	7	1	4

Fig. 4.7 Cycle Crossover

4.2.5.2 Mutation

Mutation mechanism is applied on the new off springs that produce by crossover. The purpose of the mutation operation is to promote diversity of the population. The mutation mechanism prevents the algorithm to be trapped in a local optimum and premature convergence. It maintains the diversity in the population by some sudden changes on the traits of individuals according to a predefined mutation probability parameter (Negnevitsky, 2002). Mutation is applied to a single solution with a certain probability that makes small random changes in the solution. These random changes will gradually add some new characteristics to the population, which could not be supplied by the crossover. The genetic mutation operators i.e. inverse and swap mutation are adopted in the EVRPSDP.

1. Inversion mutation

The inversion operator is a mutation operation, which is used to increase the diversity of the population. The inversion operator selects a substring from a parent and flips it to form an offspring. However, the inversion operator works with one chromosome only.

Parent	3	9	**5**	**4**	**6**	**2**	7	1	8
Offspring	3	9	**2**	**6**	**4**	**5**	7	1	8

Fig. 4.8 Inversion Mutation

2. Swap mutation

The swap mutation randomly selects two alleles in the chromosome and interchanges their positions. It is also known as the exchange mutation (Banzhaf, 1990) operator, also known as reciprocal exchange mutation or swapping (Oliver et al., 1987).

Parent	3	9	**5**	4	6	2	**7**	1	8
Offspring	3	9	**7**	4	6	2	**5**	1	8

Fig. 4.9 Swap Mutation

4.2.6 Chromosome replacement

Chromosome replacement is a steady-state approach used in GA and HGA for sorting eligible chromosome. In this case, the eligible offsrings enter into the population and at the same time, the inferior offspring is being removed. Thus, the size of the population is kept constant. Additionally, to ensure the meeting of constraints (capacity and time windows), a backtracking method is used. If a new offspring violates the constraints, the GA and HGA engine backtracks towards one of the parents of the child, changing the child until it falls within the valid solution space.

4.2.7 Termination criteria (change)

In genetic algorithm, different termination conditions are followed such as improvement rate, reaching number of generations and achieving defined objective value. To provide more chances for optimization, the two termination criteria are set in this study: (1) fitness threshold and (2) number of total generations (upper bound). For instance, if the upper bound is set to be 1000 generations, the integer for checking the improvement is 150 and the maximum change of fitness value is set to be 0.01%. The GA and HGA engine will continuously check whether the target cell is improved at least 0.01% in the last 150 generations while it's running. If this ‘‘change criterion’’ is not met, the engine will stop optimization no matter whether the 1000 generation upper bound is reached or not. If the improvement is greater or equal to 0.01% in the past 150 generations, the engine will continue to optimize until either it does not meet the ‘‘change criterion’’ or reaches 1000 generations.

4.2.8 Chromosome decoding

Once the termination criterion is fulfilled, the chromosome with the smallest fitness value is selected as the near-optimal solution. The chromosome is an array that should be translated into a form of vehicle routing solution that can be understood by others. An additional process is performed to transform the chromosome into a complete vehicle plan with near-optimal total cost consumption.

CHAPTER 5

COMPUTATIONAL EXPERIMENT

In this section, the computational experiments have been carried out to compare the performance of developed HGA and existing GA to solve VRPSDPTW for the cost optimization of vehicle. In addition, the computational study is conducted to evaluate the operational efficiency of two algorithms. . In order to assess the effectiveness of proposed HGA with existing GA, the routes are designed to deliver demands of customer related to soft drinks glass bottles and the same hypothetical data is considered for both methods. In this case, Time and capacity constraints are controlled during each solution scenario. In computational experiments, the three crossover operators (single point, two point and cycle) and two mutation operators (swap and inversion) are adopted. These computational experiments are executed under six scenarios such as swap mutation with one point crossover, swap mutation with two-point crossover, swap mutation with cyclic crossover, inverse mutation with one point crossover, inverse mutation with two point crossover and inverse mutation with cyclic crossover. The three different customer sizes are considered for computational experiments. Under each customer base, three different vehicle capacity levels are chosen for each customer base.

5.1 Data Set

The customers' locations are specified randomly over the geographical area on a Euclidean Plan. The coordinates of the customers are uniformly distributed over the interval [0,100]. The delivery amounts of customers are uniformly distributed over the interval [50,100] and the pick-up demand p_i corresponding to the delivery demand d_i is computed by using a random number r_i that is uniformly distribution over the interval [0.5,1] such that $p_i = d_i* r_i$. The vehicle capacities are taken into consideration, too. The customers' demand level, pickup level and the capacity of the vehicles are considered in terms of quantity (pieces) in all cases. The lower bounds a_i of time windows are uniformly distributed over the interval [0, 10], and the upper bounds b_i are computed by using a random number λ_i that is uniformly distributed over the interval [1, 2] such that $b_i= (a_i + \lambda_i)$. The service time s_i of each customer is set as 30 minutes for each customer. The travel time t_i is considered equal to the corresponding Euclidean distances. Instances with different vehicle capacities are generated by choosing the minimal number of vehicles required.

Random test instances with different customer size and different parameters of controlled variable for both algorithms are considered. When customer size is 30, three levels of vehicle capacity are 800 Pieces, 1000 Pieces and 1500 Pieces. Same levels of vehicle capacity are adopted when customer size is 50 and 80. Here identical soft drink containers are considered. The soft drinks are delivered to the customer and the empty glass bottles are returned from the customers as the required amount.

5.2 Parameter Settings

The algorithms are coded in MATLAB language version 2016b and stochastic simulations are performed in fixed Computer hardware. Computational experiments are performed on DHP pavilion g series with Intel Core i5 560 GHz CPU and 2.0 GB of RAM. From the historical data, with the help of statistical goodness of fit test, the parameter of GA and HGA such as population size (pop_size), the probability of crossover (Pc), probability of mutation (Pm) and the maximum number of generations (ngener) is set in the experiment that are shown in Table 5.1. The population size is set large enough to ensure it does not stuck at a local optimum in all cases. During the computational experiments, the constraints of developed cost optimization model are satisfied. To evaluate the average performance 10 independent trials were carried out for each cases of both the GA and HGA and the result with the best fitness value among all trials is selected as the final solution for each case. The parameters such as FCR constant (a and b) and Carbon emission rate (μ) are considered based on the practical case study of Huang et al. (2012). The parameters used in the model are presented in the table below.

Table 5.1: The parameter settings of GA and HGA

Parameter	Explanation	
HGA and **GA** algorithm	Crossover rate	0.85
	Mutation rate	0.05
	Population size	100
	Termination criteria	Stops if either (1) target cell does not improve at least 0.015% in the last 150 generations, or (2) number of generations reaches 1000.
Model	Fixed Cost, C_v (TK)	1000
	Variable Cost, C_d (TK)	1
	Fuel Cost, C_f (TK)	70
	Penalty Cost, C_p(TK)	25
	Carbon emission cost, C_e (TK)	30
	Carbon emission rate, μ	2.68
	FCR Constant, a	6.208×10^{-3}
	FCR Constant, b	0.2125

CHAPTER 6
RESULTS AND ANALYSIS

The results from the computational experiments for two algorithms are analyzed in this section. The near-optimal results derived by running the GA and HGA are first presented here. In order to assess the operational efficiency of the proposed HGA approach for the cost optimization of vehicle, the best solution between HGA and existing GA for each instance with different vehicle capacity are compared. The results of comparison between the proposed HGA and existing GA are discussed as follows in several main findings.

6.1 Operational Performance of HGA and GA under Swap Mutation

The operational competency of proposed HGA approach and GA approach on solving VRPSDPTW are compared and the results of two algorithms under the swap mutation with three crossover operators are summarized in Tables 6.1, 6.2 and 6.3. In each table, column CS represents customer size, column VC represents the vehicle capacity in units and weight, column BSIP represents the best one solution in the initial population (minimum cost), column FBS represents the final best solution (minimum cost), column GN represents the number of generation to reach the final best solution, column TTD represents the total traveling distance in km for the final best solution, column IR (%) represents the cost optimization improving rate, the column PCS (%) represents the percentage of cost savings in the HGA and the column DR (%) represents the percentage of distance reduction in the HGA.

The following equations are used to calculate the fuel optimization improving rate, the percentage of cost savings and the percentage of distance reduction are. If the savings of cost and distance (PCS and DR) value is positive, the total cost and final traveling distance is less in HGA than the GA and vice versa on solving cost optimization model.

$$IR=\frac{\text{Best initial Cost}-\text{Final best cost}}{\text{Best Initial Cost}}\times 100\% \quad 6.1$$

$$PCS=\frac{\text{Final Best Cost in GA}-\text{Final best cost in HGA}}{\text{Best Initial Cost in GA}}\times 100\% \quad 6.2$$

$$PDR=\frac{\text{Final toal travelling distance in GA}-\text{Final total travelling distance in HGA}}{\text{Best total travelling distance in GA}}\times 100\% \quad 6.3$$

The experimental results show that the HGA produces most of the best outcomes under the swap mutation with one point crossover, swap mutation with two point crossover and swap mutation with cyclic crossover in terms of all indexes including total consumption, total distance, no of generations. The performance of proposed HGA is superior to that of GA in terms of the solutions' quality. First reason is that, the best initial solutions generated by HGA are much better than those generated by GA. For example, in case of the 50-customer with 1000 pieces of vehicle capacity with swap mutation and one point crossover, the obtained best initial solution in HGA (1429900 TK) is much better than that obtained by GA (1224700 Tk). Therefore, the improvement rate in the HGA is less than in the GA for the optimization of consumed cost in VRPSDPTW. The second reason and the most important, HGA generates better final solutions than GA. For example, when the customer size is 50 while the vehicle capacity is 1000 pieces, the obtained final best solution in HGA (1071200TK) is much better than that obtained by GA (1135800 TK). As a result, the total traveling distance for different customer sizes in the HGA is less than in the GA. Finally, the average savings reflect that the savings is largest in the HGA than GA in terms of distance and consumed cost. Therefore, the following results demonstrate that the economic cost (total cost) is evidently lower in HGA than GA.

Table 6.1: Computational results of HGA and GA for the VRPSDPTW model under the swap mutation with one point crossover

CS	VC	GA						HGA						PCS	PDR
		IS	FBS	GN	IR	TTD	T	IS	FBS	GN	IR	TTD	T		
25	500	547650	369970	1000	32%	853	90	385070	321380	1000	17%	734	35	13%	14%
	1000	1003800	630570	1000	37%	788	82	688710	547510	1000	21%	677	33	13%	14%
	1500	1336700	927530	1000	31%	1086	77	1015500	821040	1000	19%	694	34	11%	36%
50	500	1224700	648880	1000	47%	1499	164	809780	549950	1000	32%	1270	63	15%	15%
	1000	2217700	1135800	1000	49%	1475	168	1429900	1071200	1000	25%	1315	67	6%	11%
	1500	3316000	1715900	1000	48%	1453	162	2075700	1633300	1000	21%	1389	64	5%	4%
80	500	2387500	1325300	1000	44%	3092	287	1591700	1210500	1000	24%	2829	107	9%	9%
	1000	4309800	2321900	1000	46%	2906	262	2949700	2079800	1000	29%	2583	107	10%	11%
	1500	6101800	3099000	1000	49%	2637	265	4072300	2818600	1000	31%	2390	105	9%	9%

Table 6.2: Computational results of HGA and GA for the VRPSDPTW model under the swap mutation with two point crossover

CS	VC	GA						HGA						PCR	PDR
		IS	FBS	GN	IR	TTD	T	IS	FBS	GN	IR	TTD	T		
25	500	531630	364550	1000	31%	861	87	386460	326180	1000	18%	828	34	11%	4%
	1000	997530	632970	1000	37%	785	91	686930	601640	1000	14%	772	35	5%	2%
	1500	1386900	959600	1000	31%	855	84	1021800	886740	1000	15%	793	35	8%	7%
50	500	1222400	811530	1000	34%	1960	170	795410	671240	1000	18%	1592	68	17%	19%
	1000	2327100	1634700	1000	30%	2065	175	1453200	1148300	1000	27%	1534	67	30%	26%
	1500	2988300	2221100	1000	26%	2268	172	2063900	1756800	1000	17%	1501	68	21%	34%
80	500	2351500	1792900	1000	24%	4314	302	1540600	1386300	1000	11%	3306	119	23%	23%
	1000	4121700	3101900	1000	25%	3999	289	2899500	2599200	1000	12%	3355	118	16%	16%
	1500	6278400	4428700	1000	29%	3832	284	3993200	3513700	1000	14%	3369	112	21%	12%

Table 6.3: Computational results of HGA and GA for the VRPSDPTW model under the swap mutation with cyclic point crossover

CS	VC	GA						HGA						PCS	PDR
		IS	FBS	GN	IR	TTD	T	IS	FBS	GN	IR	TTD	T		
25	500	535050	426050	1000	20%	1185	73	383910	351020	1000	9%	1141	32	18%	4%
	1000	998550	685290	1000	31%	974	69	705790	683610	1000	3%	992	51	0%	-2%
	1500	1436800	1098200	1000	24%	1013	69	1007000	993240	1000	1%	960	29	10%	5%
50	500	1250600	1074200	1000	14%	2578	118	819100	819100	1000	0%	2518	49	24%	2%
	1000	2294700	1914300	1000	17%	2638	115	1481700	1431400	1000	3%	2593	48	25%	2%
	1500	3319400	2633800	1000	21%	2621	112	2094700	2094700	1000	0%	2447	46	20%	7%
80	500	2336300	2096800	1000	10%	5501	188	1606400	1606400	1000	0%	5161	73	23%	6%
	1000	4359300	4020800	1000	8%	5164	178	2855700	2855700	1000	0%	5077	68	29%	2%
	1500	6495300	5872500	1000	10%	5084	173	4001500	3808900	1000	5%	4662	67	35%	8%

6.2 Operational Performance of HGA and GA under Inverse Mutation

In order to assess the operational competency of the designed HGA approach and GA approach are compared for the optimization of consumed cost of vehicle. The experimental results of HGA with existing GA under inverse mutation with one point crossover, inverse mutation with two point crossover and inverse mutation with cyclic crossover for each instance with different vehicle capacity are studied. The computational results of the VRPSDPTW under two algorithms are presented in Tables 6.4, 6.5 and 6.6. The indexes in the tables are the same as those in Table 6.1, 6.2 and 6.3 and perform the same calculations. The computational results in each table show that the performance of developed HGA is beneficial than GA in terms of the solutions' quality including total cost consumption (TK), total distance (km) and no of generations. This study indicates that the hybridized heuristics for the initialization procedure improve the solutions' quality greatly. It is found that the solutions generated by using these heuristics are already near optimal

Table 6.4: Computational results of HGA and GA for the VRPSDPTW model under the inverse mutation with one point crossover

CS	VC	GA						HGA						PCS	PDR
		IS	FBS	GN	IR	TTD	T	IS	FBS	GN	IR	TTD	T		
25	500	491330	412490	1000	16%	960	91	419980	331940	1000	21%	764	34	20%	20%
	1000	1018500	734900	1000	28%	916	85	665270	649400	1000	2%	808	35	12%	12%
	1500	1456400	1012700	1000	30%	863	79	1007000	871110	1000	13%	736	34	14%	15%
50	500	1201300	993060	1000	17%	2340	175	821870	685560	1000	17%	1600	65	31%	32%
	1000	2232500	1770300	1000	21%	2232	164	1460600	1216400	1000	17%	1671	67	31%	25%
	1500	3300400	2672700	1000	19%	2291	158	2042700	1791300	1000	12%	1524	67	33%	34%
80	500	2382200	2036800	1000	14%	4899	279	1527200	1395100	1000	9%	3284	112	32%	33%
	1000	4302000	3382200	1000	21%	4921	275	2911100	2461100	1000	15%	3080	109	27%	37%
	1500	6436200	5024700	1000	22%	4320	276	3986200	3416400	1000	14%	2911	108	32%	33%

Table 6.5: Computational results of HGA and GA for the VRPSDPTW model under the inverse mutation with two point crossover

CS	VC	GA						HGA						PCS	PDR
		IS	FBS	GN	IR	TTD	T	IS	FBS	GN	IR	TTD	T		
25	500	539270	354290	1000	34%	1242	91	389590	345950	1000	11%	896	36	2%	28%
	1000	960250	776600	1000	19%	1011	89	678520	572950	1000	16%	737	35	26%	27%
	1500	1466400	1059600	1000	28%	937	86	1020200	890640	1000	13%	760	35	16%	19%
50	500	1212300	870350	1000	28%	2064	175	812010	668570	1000	18%	1689	68	23%	18%
	1000	2271700	1712400	1000	25%	2182	169	1423800	1231200	1000	14%	1557	68	28%	29%
	1500	3350900	2325300	1000	31%	2056	168	2071400	1661300	1000	20%	1456	68	29%	29%
80	500	2411000	1884300	1000	22%	4561	295	1487600	1404200	1000	6%	3309	119	25%	27%
	1000	4361300	3665700	1000	16%	4647	287	2897500	2510500	1000	13%	3175	116	32%	32%
	1500	6422600	5030300	1000	22%	4382	281	4025300	3629000	1000	10%	3197	117	28%	27%

Table 6.6: Computational results of HGA and GA for the VRPSDPTW model under the inverse mutation with cyclic crossover

CS	VC	GA						HGA						PCS	PDR
		IS	FBS	GN	IR	TTD	T	IS	FBS	GN	IR	TTD	T		
25	500	538760	446440	1000	17%	1104	73	409110	400030	1000	2%	1065	29	10%	4%
	1000	1014200	779170	1000	23%	1098	70	702270	666500	1000	5%	1042	29	14%	5%
	1500	1348000	1130000	1000	16%	1147	70	1015500	944930	1000	7%	1085	28	16%	5%
50	500	1205000	1110000	1000	8%	2762	120	806500	806500	1000	0%	2687	49	27%	3%
	1000	2268500	1970400	1000	13%	2759	121	1458700	1421600	1000	3%	2579	47	28%	7%
	1500	3274800	2832300	1000	14%	2819	119	2077000	2067400	1000	0%	2424	46	27%	14%
80	500	2335700	2121600	1000	9%	5535	197	1525000	1517700	1000	0%	5080	75	28%	8%
	1000	4283900	4034600	1000	6%	5416	181	2963200	2718700	1000	8%	4906	70	33%	9%
	1500	6521400	5867700	1000	10%	5396	180	4022100	3839000	1000	5%	4798	69	35%	11%

The optimization progress of proposed HGA and GA under the 50-customer with 1500 units load on solving VRPSDPTW under two mutation operators are shown in Fig. 6.1-6.4, respectively. The fitness value and the number of generation are represented in Y-axis and X-axis in these figures. The optimization progress in the scenario of the VRPSDPTW model with 50 customers where 1500 (Pieces) units of vehicle capacity under the swap and inverse mutation with two point crossover that obtained by HGA are reflected in the fig. 6.1 and 6.2. The curve in the fig. 6.3 and 6.4 show the trend of the optimization progress in the scenario of the VRPSDPTW model with 50 customers while 1500 (Pieces) units of vehicle capacity under the swap and inverse mutation with two point crossover that obtained by GA.

These figures are showing that the GA takes more generations than HGA to reach the final near-optimal solutions. In addition, the following curves represent that GA is great at the beginning of initial better solution and proposed HGA generate much better initial solutions than GA. This is because HGA incorporates the sweep algorithm and the TOHA for generating the initial chromosomes. This can reduce total amount of consumed cost and total traveling distance of a vehicle significantly. Although GA converges significantly in VRPSDPTW, the curves representing HGA are slightly lower than those representing GA. In other words, the heuristics hybridized for the initialization procedure play an important role in the VRPSDPTW. Due to the NP-hard nature of VRPSPDTW, GA, approach cannot solve the problem within an acceptable period while HGA perform well within significantly shorter period. Considering these results and CPU times, it can be stated that, HGA based proposed approach is efficient and performs well.

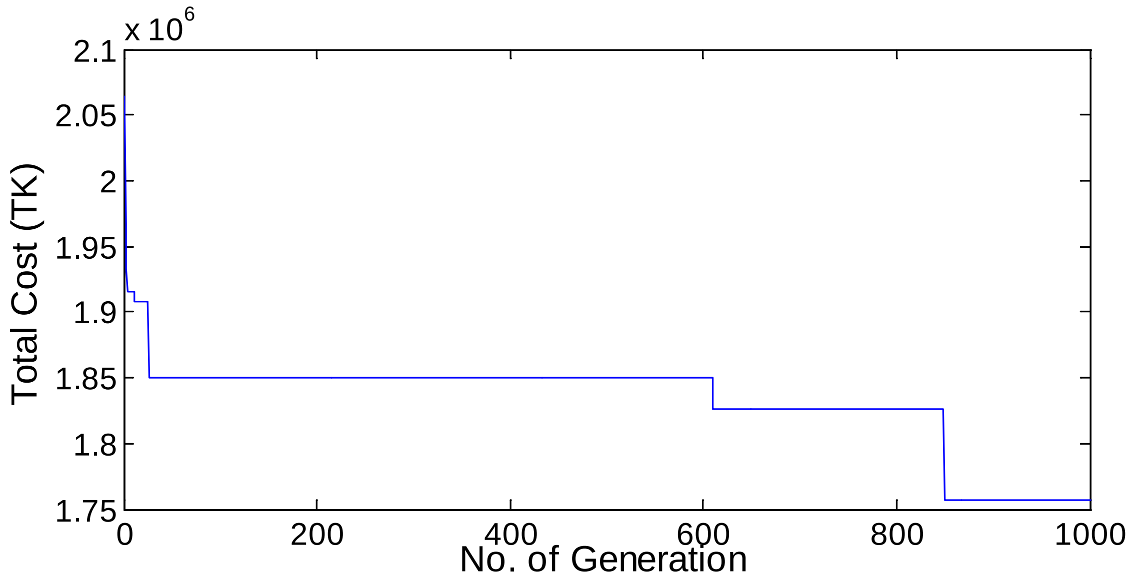

Fig. 6.1 Optimization progress of 50-customer, 1500 capacity, HGA scenario for swap mutation with two point crossover.

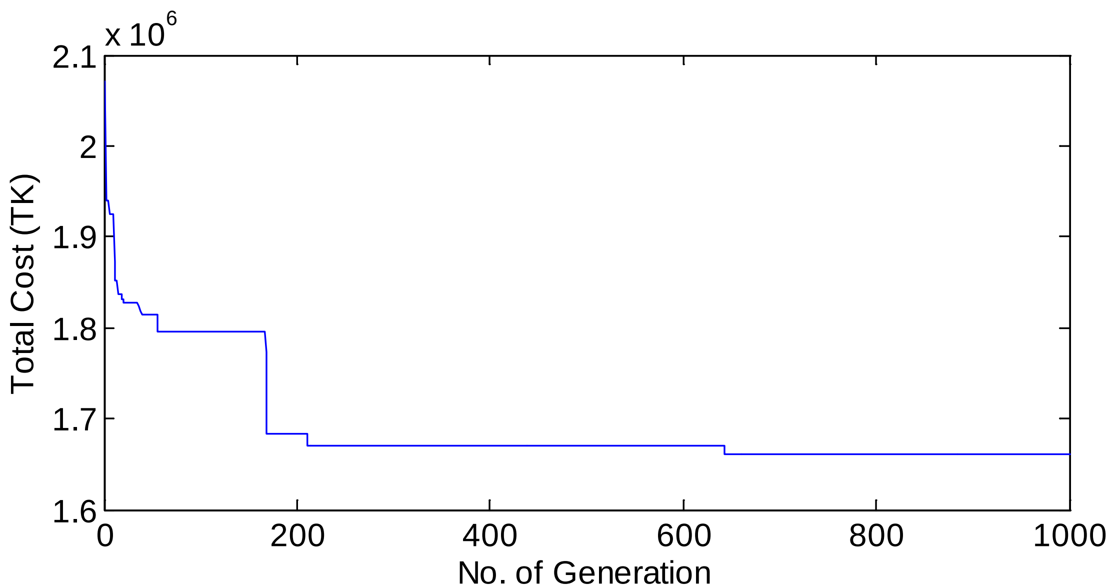

Fig. 6.2 Optimization progress of 50-customer, 1500 capacity, HGA scenario for inverse mutation with two point crossover

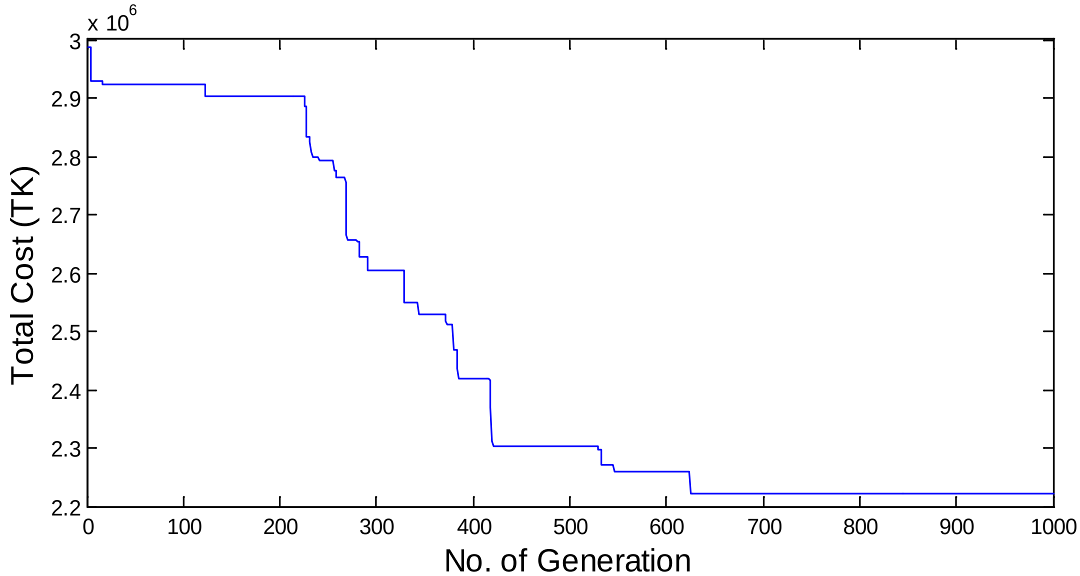

Fig. 6.3 Optimization progress of 50-customer, 1500 capacity, GA scenario for swap mutation with two point crossover**.**

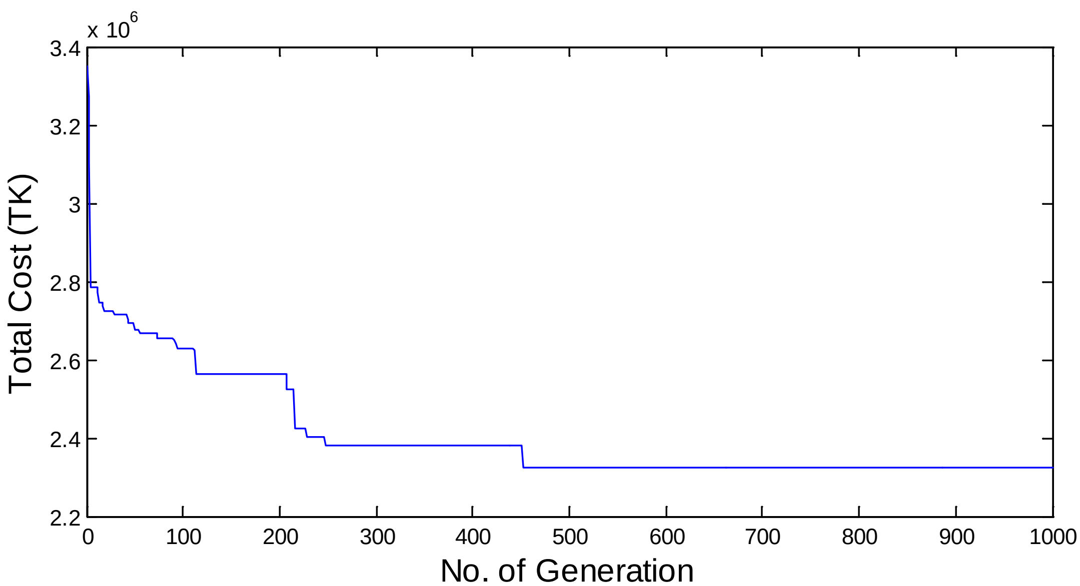

Fig. 6.4 Optimization progress of 50-customer, 1500 capacity, GA scenario for inverse mutation with two point crossover

6.3 Genetic Operator Analysis under the Designed HGA

The computational experiment of HGA are conducted by adopting genetic operators such as crossover operators (i.e. one point crossover, two point crossover and cyclic crossover) and mutation operators (i.e. inverse mutation and swap mutation) . The computational results of two mutation operators with three crossover operators under the HGA are compared in Table 6.7, 6.8 and 6.9 in which the total cost consumption, no of generation and total traveling distance of the instances in each class are included. Here, the percentage of cost consumed and distance reduction are calculated by following the equation (6.2) and (6.3). If the savings (CS and DR) value is positive, the total cost consumption and final traveling distance in the inverse mutation is less than in the swap mutation and vice versa on solving VRPSDPTW. The experimental results in each table show that the designed HGA is efficient to optimize the cost consumption in swap operation for one point crossover. But in case of two point crossover and cyclic crossover, inverse mutation shows comparatively better result than swap mutation.

Table 6.7: Computational results of HGA under the swap and inverse mutation with one point crossover

Cs	VC	Swap Mutation			Inverse Mutation			PCR	PDR
		FBS	GN	TTD	FBS	GN	TTD		
	500	321380	1000	734	331940	1000	764	-3%	-4.18%
25	1000	547510	1000	677	649400	1000	808	-19%	-19.31%
	1500	821040	1000	694	871110	1000	736	-6%	-6.00%
	500	549950	1000	1270	685560	1000	1600	-25%	-25.93%
50	1000	1071200	1000	1315	1216400	1000	1671	-14%	-27.04%
	1500	1633300	1000	1389	1791300	1000	1524	-10%	-9.68%
	500	1210500	1000	2829	1395100	1000	3284	-15%	-16.10%
80	1000	2079800	1000	2583	2461100	1000	3080	-18%	-19.22%
	1500	2818600	1000	2390	3416400	1000	2911	-21%	-21.80%

Table 6.8: Computational results of HGA under the swap and inverse mutation with two-point crossover

Cs	VC	Swap Mutation			Inverse Mutation			PCR	PDR
		FBS	GN	TTD	FBS	GN	TTD		
	500	326180	1000	828	345950	1000	896	-6%	-8.16%
25	1000	601640	1000	772	572950	1000	737	5%	4.62%
	1500	886740	1000	793	890640	1000	760	0%	4.17%
	500	671240	1000	1592	668570	1000	1689	0%	-6.09%
50	1000	1148300	1000	1534	1231200	1000	1557	-7%	-1.51%
	1500	1756800	1000	1501	1661300	1000	1456	5%	3.04%
	500	1386300	1000	3306	1404200	1000	3309	-1%	-0.07%
80	1000	2599200	1000	3355	2510500	1000	3175	3%	5.37%
	1500	3513700	1000	3369	3629000	1000	3197	-3%	5.11%

Table 6.9: Computational results of HGA under the swap and inverse mutation with cyclic crossover

Cs	VC	Swap Mutation			Inverse Mutation			PCR	PDR
		FBS	GN	TTD	FBS	GN	TTD		
	500	351020	1000	1141	400030	1000	1065	-14%	6.64%
25	1000	683610	1000	992	666500	1000	1042	3%	-5.02%
	1500	993240	1000	960	944930	1000	1085	5%	-13.07%
	500	819100	1000	2518	806500	1000	2687	2%	-6.72%
50	1000	1431400	1000	2593	1421600	1000	2579	1%	0.57%
	1500	2094700	1000	2447	2067400	1000	2424	1%	0.93%
	500	1606400	1000	5161	1517700	1000	5080	6%	1.57%
80	1000	2855700	1000	5077	2718700	1000	4906	5%	3.37%
	1500	3808900	1000	4662	3839000	1000	4798	-1%	-2.91%

CHAPTER 7
CONCLUSION AND RECOMMENDATION

7.1 Conclusion

In this study, Vehicle Routing Problem with Simultaneous pick-up and delivery and time windows is discussed with previous studies in this field. This research has studied the VRPSPDTW form economic considerations (cost optimization) with environmental considerations (fuel consumption and carbon emission). This model considers the environmental factors, such as and tries to decline the amount of CO2emission and fuel consumption which may increase the cost depended on economic factors. The goal of the model is to strike a balance between economic and environmental factors.

This cost optimization model is developed with the objective of optimizing the total cost of vehicles by considering the fixed cost, variable cost, penalty cost for being tardy, carbon emission cost and fuel cost. This paper contributed to a vehicle routing problem with simultaneous pickups and deliveries and time windows in the following respects: (a) An integer programming mathematical model of VRP-SPDTW was proposed for finding the optimal solutions (b) An improved hybrid genetic algorithm to solve the vehicle routing problem with simultaneous pickups and deliveries and time windows is proposed, focusing on minimization of total cost of vehicles in the operation process. The most two common constraints such as capacity and time are considered. Other factors, such as the vehicle speed, road condition, weather and traffic are ignored. This model is applicable for logistics purpose for cost optimization.

Then, computational optimization procedure is conducted for a Hybrid Genetic Algorithm (HGA) and Genetic algorithm (GA) to solve the VRPSDPTW model. Both methods are adopted in order to compare the operational efficiency and to optimize the consumed cost on solving VRPSDPTW model. The computational experiments of two algorithms under different customer sizes with different vehicles capacity to optimize cost are carried out. From the computational results, it is seen that the designed HGA algorithm outperforms better result than the existing GA significantly in less cost consumption. The reason for better performance of the proposed HGA is the procedure of generating initial solution. In HGA, the initial population is generated from adopting some heuristics. First, the sweep algorithm is used to cluster the customer in each route i.e. route construction. Second, the TOHA is used to determine the delivery sequence of vehicles in each route. Third, after the predetermined number of initial chromosomes is generated, the ISP is adopted to improve the links of all chromosomes. On the other hand, in existing GA initial solutions are generated randomly. So, this research concludes that the HGA is a viable approach to the solution of EVRPSDP as an optimization method. Experimental results indicate both environmental and economic benefits by minimising the consumption of fuel as well as CO_2 emission. The results from the model provides an insight to the trade-offs involved in environmental-friendly vehicle routing.

7.2 Recommendation

Future work will be conducted to further improve this research to some possible directions. . The computational cost of key genetic operators will be reduced by examining alternate metaheuristic features and insertion procedures. The proposed models only focus on the shipment flow between distribution centers and end-customers in a single-echelon supply chain system. The concept of this model for economic improvement with environmental awareness can be extended into multi-echelon system. The proposed method is effective and the researchers as well as the supply chain members can have the guideline to implement it into other VRP variants, such as multi-depot VRPSDP, VRP with split delivery, VRP with consideration of traffic conditions. Accordingly, the improved procedure will be tested and compared over larger problem instances.

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