CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION

Vehicular Routing Problems (VRP) have been dealt by many conventional algorithms in the past decade and the people who use exact methods attain best solution only for limited instances with restricted nodes. When the problem size grows, its complexity gets increased exponentially. On such instances, exhaustive search becomes a time consuming process and almost impractical for most of the cases. But these approaches lead space complexity to greater extent. In addition to that, as it was discussed, they get trapped into local optima and hence do not lead to optimal solutions in majority cases. As illustrated by numerous reviews (O. Bräysy and M. Gendreau, 2005; B. Golden et al., 2008) working on heuristic approaches like Tabu Search, Simulated Annealing gives hope within the limited extent. On the other hand, they are clearly meant for finding local optimal solutions.

Section 2.1 discusses the introduction of the conventional algorithm available for solving the VRP problems. Section 2.2 discusses the various solutions models for solving Vehicle Routing problems. The solution models for solving VRP problems are broadly classified into three categories are discussed. Section 2.3 discusses the optimisation based solution models for solving VRPs. The Genetic Algorithm based solution models for solving VRP problems and the various GA operators are discussed in the section 2.4. The PSO based solution models for the VRP instances are discussed in section 2.5. The ACO based solution models for the VRP instances are discussed in section 2.6. The Memetic algorithm based solution models for the VRP are discussed in section 2.7. The ABC algorithm based VRP solution models are discussed in section 2.8. The summary about the literature survey has been given in section 2.9.

2.2 VRP SOLUTION MODELS

This section discusses about the various solution models of VRP and their variants. Several researchers have proposed several techniques and approaches to
discover the optimal solution for the problem. The solution model is broadly classified into three categories and each category has different techniques shown in Fig. 2.1.

It is possible to get optimal solution or feasible solution from a set of routes; the solution models focused on that eliminated routes, proposed a dynamic programming method to that problem based on demand transportation (ODP). Previously the brute force method has been implemented to resolve the VRP’s, since the method is easy to implement the constraints of the VRP’s. Nevertheless the method is mainly applicable for solving small problem instances, in case of higher instances, this method become more complexity to find an optimal solution.

Fig 2.1 Flow of VRP Solution Models

There are some particular overviews in writing which cover the vast majority of these methodologies. The complete calculations in light of Branch-and-bound (Toth and
Branch-and-cut and Set-covering (Casco and Golden, 1988; Kelly and Xu, 1999) were individually performed. The researchers (Laporte and Nobert, 1987; Cordeau et al., 1997) elaborated the fundamental CVRP with accurate calculations. The most recent advancement with respect to the definite methodologies for tackling the CVRP was performed (Baldacci et al., 2007 & 2010). As per these creators, the best correct calculations proposed for the CVRP is Branch and Cut (BC) algorithm (Lysgaard et al. 2004). The strong Branch Cut and Price (BCP) algorithm (Fukasawa et al., 2006) and the Set Partitioning (SP) with extra cuts based calculation are proposed (Baldacci et al., 2008). Because of the vast number of heuristic based algorithms proposed for the CVRP, one will focus on those that have been created and the best results for two of the most utilized arrangements of benchmark examples (Christofides et al., 1979; Golden et al., 1998).

Various utilizations of the VRPSPD can be found in the beverage business, where beds or holders are gathered for re-use in stock transportation. A few clients can request that the conveyance and pickup administrations must to be performed in the meantime. Since, on the off chance that it is to be done independently, it may infer an extra expense and operational endeavours for these clients. The VRPSPD was first published in the late 1980's. The author (Min, 1989) introduced a heuristic method to illuminate a genuine issue concerning the conveyance and gathering of books of an open library.

As indicated by the order plan of (Berbeglia et al., 2007) this problem is considered as the multi-vehicle one-to-numerous and numerous-to-one PDP with single requests and blended arrangements. The author (Golden et al., 1989) recommended a stop-based backhaul insertion methodology, where paths are first produced for the conveyance clients and afterward, the pickup clients are assessed for insertion in these paths. In a purported burden based backhaul insertion system, in which it is related to the conveyance stack after pickup and consolidated to the insertion cost (Casco et al., 1988).

The author (Tarantilis et al., 2004) added two visit parcelling heuristics that comprises of breaking a visit into disjoint fragments, which are allocated to diverse
vehicles. The author (Dethloff, 2002) connected the VRPSPD insertion methodology grew in to the VRPMPD (Casco et al., 2001). An Ant Colony heuristic that incorporates a few components, for example, the fuse of a look ahead methodology into the visibility table and upgraded trail updating guidelines (Wade et al., 2003). After some decades, the author (Wassan et al., 2008) explored the relationship between the VRPSPD and the VPMPD, rather than exhibiting a Reactive TS heuristic taking into account the one produced for the VRPSPD.

The objective of MDVRP is to discover a possible set of tours with the minimum total travelled distance. Definite Branch-and-Bound (Laporte et al., 1984; Laporte et al., 1988) algorithms were proposed by the authors in 1980's. The first was equipped for example with up to 50 clients and 8 warehouses, while the recent figured out up to 80 clients and 8 stops. The authors (Baldacci and Mingozzi, 2009) set forward a SP based algorithm that uses bouncing methodology in view of straight unwinding and Lagrange an unwinding. Their system was intended to manage few VRPs, including the HFVRP, Site-subordinate VRP and the MDVRP. The same authors discovered better arrangements of MDVRP examples up to 200 clients and 4 warehouses. This circumstance can be regularly found and the HFVRP may be a suitable model for managing this sort of utilizations. In industry, an arrangement of vehicles is seldom homogeneous.

Later on, the exact algorithm has been applied to solve the VRP namely Branch and Bound algorithm (B&B) (A. H. Land and A. G. Doig, 1960) and Branch and Cut algorithm (B&C). Branch and bound algorithm (B&B) uses the depth first search to accomplish the set of possible solutions by eliminating the infeasible solutions. In Branch and Bound algorithm is applied to solve the CVRP, and the estimation of feasible solution that has been determined from upper bound and lower bound values (Fischetti et al., 1994). However the B&B is suitable for solving smaller problem instances and become more complex for higher instances. Consequently, to reduce the complexity, Branch and Cut algorithm has been proposed to solve CVRP (Blasum et al., 2000). In this a cutting plane phase is included for cutting the planes and then the bound values are
used to determine the solution. Later on constructive heuristic methods are proposed to solve the VRP and its variants at various strategies as savings algorithm, route-first cluster-second, cluster-first route-second insertion heuristics.

Solutions of the exact algorithm will be suitable for small instances of VRPs. Once the size of the instances gets increased then the solving methodology will be consuming time proportionally. There exist some algorithms as it is discussed in generic solution model methods in the previous sections like Tabu Search, Simulated Annealing, Two Phase Algorithm, Hill Climbing, etc., for finding optimal solutions. In the worst case scenario these algorithms lead to local optima since these are non-guided random search based methods. To get rid of this non-guided random search, evolutionary algorithms which are inspired from the nature were introduced for solving optimization problems. Optimization gives us a set of feasible solutions that may or may not be the best but never the worst. Optimization in VRPs evolves a great interest among the researchers since it holds many constraints and still searching for optimized feasible solutions.

Some of the evolutionary algorithms used to resolve vehicular routing problems includes Genetic Algorithm, Ant Colony Optimization, Particle Swarm Optimization, Memetic Algorithm, Shuffled Frog Leading, Bacterial Foraging Optimization, Harmony Search, Artificial Bee Colony, etc., These algorithms work in Vehicular Routing Problem both in standalone and could be focused with other algorithms in order to produce optimized results. These algorithms are still improvised by either hybridized or modified fashions in order to obtain better results.

2.3 OPTIMIZATION BASED SOLUTION MODELS FOR VRPs

Vehicular Routing Problem has been solved by many of the optimization algorithms including their constraints. Since there are many types of VRP, researchers modified these existing evolutionary algorithms based on their representation and constraints in order to make it adaptable. In this literature study, solution models for vehicular problems based on evolutionary algorithms have been discussed. The author
(Marshall et al., 1981) addresses the issue by depicting certain qualities of some genuine VRPs. During the air express dispatch, the airplanes leave from a stop city, convey their payload to an arrangement of clients topographically spread and after that gather the payload from the same arrangement of clients by following their courses back to the warehouse. The author (Bodin et al., 1983) has displayed a contextual investigation of this sort of use at the FedEx Express organization. Other than limit imperatives, different confinements like time windows and courses length of time were considered. The issue was tackled by a procedure of the (Clarke and Wright, 1964) reserve funds heuristic.

The Open VRP discussions remained for all intents and purposes unaltered for about two decades until it was return (Sariklis and Powell, 2000). The authors (Bodin and Golden, 1981) proposed a cluster-first, course second approach where the first stage comprises in gathering the clients as per the limit imperatives, while the second stage comprises of a Minimum Spanning Tree (MST) heuristic that incorporates a punishment technique. The author (Letchford et al., 2007) introduced an ILP(Inductive Logic Programming) detailing, an arrangement of legitimate disparities, and a BC(Big Crunch) algorithm that is predominantly taking into account the one depicted (Lysgaard et al., 2004). Their technique is fit for unravelling to optimality and this work is the accurate methodologies that have been managed.

The author (Cordeau et al., 2012) proposed a parallel iterated Tabu Search Heuristic for the Vehicle Routing Problems. A perpetration mechanism has been introduced along with Tabu search for better exploration of multiple routes in the search space. An efficient heuristic has been implemented in parallel. It has been designed not only for a particular class of VRPs, but also for other variants including classical VRP, periodic VRP, multiple depot induced VRP, site depended VRP and time-window variant VRP. The author (Gehring et al., 2001) proposed a parallel two-phase meta-heuristic for routing problems with time windows. The Tabu Search has been collaborated with other evolutionary strategies for efficient results for VRP variants. In the first phase, the number of vehicles used to travel has been minimized in an efficient manner and in the second phase, the objective has been fixed as minimizing the total tour cost. This meta-
heuristic approach has been tested with larger set of VRP instances and the results prove that the method works well for other VRP instances.

2.4 GENETIC ALGORITHMS BASED VRP SOLUTION MODELS

Genetic Algorithms manipulates the survival of the fittest among the population from repeated generation for optimizing a problem. On each iteration, it usually consists of a set of individuals in the form of array which is also called as chromosome in DNA. Each chromosome represents a solution in the search space and a set of feasible solution. The chromosomes in the population undergoes to the process of evolution in order to find optimized solution.

_Crossover_ (John Holland, 1975): Crossover is one of the processes in genetic algorithm which is used to generate the individuals for next generation by changing or swapping the positions of genes between two chromosomes. It closely resembles the reproductive systems that happen in biological factors. To state precisely, crossover is the process of fusing or crossing two parents and generating two children in which both holds the properties of both the parents. Many types of crossover algorithms have been proposed which makes the crossover to be suitable for all kinds of problems. Some of the crossover operators are One-point crossover, Two-point crossover, Cut and splice, Uniform and half uniform crossover and Three parent crossover. These crossovers will be used for the chromosome where direct swapping can be applied. Since this type of crossovers is not possible to apply all optimization problems where as some other variants of crossovers have been proposed.

_Ordered Crossover_ (Davis,1999): Contingent upon how representation of individuals or chromosomes, an immediate swap may not be conceivable. One such case is the point at which the chromosome is a requested rundown, for example, in a travelling salesman problem the problem exists with the existing crossover methods. The swapping is not possible since repetitions are not allowed in TSP solution representation. There are numerous crossover routines for requested chromosomes. The N-point crossover can be connected for requested chromosomes. Likewise, this requires a relating repair process
constantly and some requested crossover routines have been received from the ideas. Once in a while a crossover of chromosomes produce recombination which disregards the limitation of requesting and that should be repaired. A few cases for crossover administrators protecting a given sets are Partially mapped crossover, Cycle crossover, Order crossover, Order-based crossover, Position based crossover, Voting recombination crossover, Alternating position crossover and Sequential constructive crossover.

**Mutation Operator** (John Holland, 1975): Mutation is the process of altering a single gene's position or replacing a gene with another random gene in a chromosome. This type of operation in genetic operator will give diversity in finding optimal solutions over a large search space. Mutation operator helps in exploration of search space in genetic algorithm. Because of mutation, an individual may avoid local optima and finds global optima. For mutation, user defines the probability factors that represents on what basis the mutation process can be carried over in Genetic Algorithm. The problem with mutation is, if it set with higher range of values then genetic algorithm may turn its nature to random search. The different types of mutation include Bit string mutation, Flip-bit mutation, Boundary mutation, Non-uniform mutation, Uniform mutation and Gaussian mutation.

The author (Vidal et al., 2013) proposed a hybrid genetic algorithm with adaptive diversity management for vehicle routing problems with time-windows. A penalty function has been introduced which handles infeasible solutions and worked on it to make it feasible. Once the infeasible solutions are repaired, it will be included into feasible sub populations. If, the solutions are improved, the process will be carried over as instructed method. If not, the diversity in population will be introduced and the penalty function will be adjusted in order to improve the solution quality (Thangiah et al., 1999) proposed a Hybrid Genetic Algorithm, which combine the benefits of Simulated Annealing and Tabu Search heuristic for vehicle routing problems with time windows. This approach exploits the local search in a well versed manner, which converge the algorithm flow sooner. But exploration of search space was not given much importance in their research.
The developed an improved Genetic Algorithm for Multi Depot Probabilistic Vehicle Routing Problems with a Time Window author (Samantha et al., 2011). This variant of Genetic Algorithm was tested in small sized instances that include 14, 25 and 51 nodes. It shows better results for smaller instances but the large sized nodes are not tested, which shows that there are no promising results with the help of this proposed method to solve VRP.

A Fuzzy Logic Guided Genetic Algorithms (FLGA) which is used to solve the MDVRP (Surekha, et al., 2011). In this the genetic operators such as crossover and mutation are tuned for each ten generations by fuzzy logic. An agent based, modified traditional auction-based model to solve the VRPTW (Zhenggang et al., 2009). A negotiation radius has been formed within the radius agent and negotiation takes place with the help of scheduling agent. A different approach of three phase algorithm is proposed to solve the CVRPTW. The customers are clustered in the first phase followed by using the beam search algorithm resulting in the construction of feasible solutions. Finally to improve the quality of the solutions a local search model has been applied. Exploring the search space is inadequate, as a consequence of local search alone. In (Yucenur et al., 2011) a new form of genetic clustering algorithm is proposed that is based on the geometric shapes. As inspired from (Wang et al., 2009), the customers are clustered based on the circle drawn from the depot with different radius and then the customers are gathered using genetic algorithm.

The Cellular Genetic Algorithm (Nebro et al., 2009; Alba et al., 2004) has been proposed to solve VRP’s, in which each node is interacting with the overlapped neighbour nodes and the routes are constructed. The partial routes present in the constructed routes are improved through the local search techniques. In (Alba et al., 2006) the same Cellular Genetic Algorithm has been applied to solve the CVRP. Here the solutions are constructed using integer permutation which consists of the customers and router splitters. In a 2D toroidal grid, the population has been structured and a binary tournament selection has been applied to select the customers. Finally the crossover and mutation process has been applied; significantly the results are better compared to other
existing algorithms. Even though the performance and computation time of GA is better, it is applicable for CVRP alone.

In a robust heuristic approach (Bent et al., 2004) has been proposed to solve the VRPTW using GA and set partitioning formulation. The core objective of this approach is to assemble the local optimal solutions consuming virtuous quality and transformed as a new solution. In an efficient hybrid genetic search with advanced diversity control to solve VRPTW is proposed (vidal et al., 2013). To improve the neighbourhood search in GA operation process, a new operator has been introduced called ‘education’. The infeasible solutions in the population are direct to the repair process; however some of them may be infeasible. Then the feasibility of the solution has been restored through education process. The quality of the solution and the computation time has been improved through this approach.

The Machine Scheduling and Vehicle Routing with Time Windows are integrated and Genetic Algorithm is used to solve integrated problems (Christian et al., 2013). Significantly, the problem is divided into sub problems and the solutions of the sub problem have been merged to produce the feasible solution. The Hybrid Genetic Algorithms (HGA) has been proposed namely HGA-1 and HGA-2 to solve MDVRP (Ho et al., 2009). Random population seeding technique has been applied in HGA-1 to generate the initial population. In HGA-2, the initial population has been generated by combining the Clarke and Wright savings algorithm and Nearest Neighbour heuristic. The performance of HGA-2 is better than the HGA-1. A novel Hybrid Genetic Algorithm (HGA) has been proposed is (Mirabi et al., 2010) comprises of three stages: at the first stage, the initial population has been generated through the nearest addition method (NAM); subsequent in second stage, to optimize the probability of crossover and mutation, the Response Surface Methodology (RSM) has been applied and at last, an improved sweep algorithm has been applied to improve the diversity of the GA.
A decomposition technique (Lian et al., 2009) has been proposed to solve the VRPTW; the main objective of the decomposition technique is the main problem that has to be divided into different sub-problems and finally the sub-problems are optimized through GA. Localized Optimization Framework (LOF) has been proposed in which consists of optimization and de-optimization (Ursani et al., 2011). This technique is applied in GA for optimization, which is named as Localized Genetic Algorithm (LGA). The LGA is then applied to solve the VRPTW as a domain space and exhibited with better results.

2.5 PSO BASED VRP SOLUTION MODELS

A Multi Depot Vehicle Routing Problem with Pickup and Delivery, in which the VRP is represented in the SD1 (Sequential Dynamics) form (P. Sombuntham et al., 2010). This type of representation ignores the source and destination point which are given at the time of request and construct the solutions based on customer priority list. Though this, SD1 technique gives efficient result, but the computational time gets increased even for smaller instance of VRPs. To overcome this, the authors (Kachitvichyanukul et al., 2015) proposed two solution representations for solving multi-depot vehicle routing problem with multiple pickup and delivery requests via PSO. They used SD2 and SD3 representations for solving this type of VRP. The SD2 generates the solution for next generation based on the position of the particles; SD2 technique also proposed with its decoder for efficient representation of candidate solutions in PSO. In SD3 representation vehicle orientation points are used with its radius coverage for vehicle assignment.

The authors (Ai et al., 2009) proposed a Particle Swarm Optimization (PSO) approach for solving vehicle routing problem with time windows. The PSO works well on VRP and provide better results for small instance problems, but it was not tested on high dimensional datasets and the consistency of algorithm was not proved. The same authors proposed a particle swarm optimization and two solution representations for solving the capacitated vehicle routing problem in which they proposed SR1 and SR2 techniques for solving capacitated VRP as solution representation schemas (Ai et al.,
These lead PSO to be adaptable for discrete problems. These solution representations are as same as SD1 and SD2.

A multiple social learning structures (Sombuntham et al., 2010) imposed in PSO multi-depot vehicle routing problem with simultaneous pickup and delivery and time window from practical point of view. SD1 technique has been discussed earlier in this research work that was imposed in solving this VRP problem. The author (Gong et al., 2012) proposed a set-based PSO to improve the VRPTW in which an arc set of customers formed by nearest neighbor heuristic (NNH) for the search space. During route construction, the Hamiltonian cycle is formed first and later converted to feasible routes of the vehicles through constrain-based decoder. Initially the vehicle follows the Hamiltonian cycle by visiting the customers. In case of failure in the VRPTW constraint, the depot is added in between the nodes and the single arc may be split into two arcs. The route is conserved and a new vehicle starts from the depot. The constraint of VRPTW is accomplished by set-based PSO which obtains the feasible solution. Subsequently, in the formation of Hamiltonian cycle the possibility of attaining the optimal solution is lower for large instances.

The authors proposed a new hybrid algorithmic approach based on PSO (Marinakis et al., 2013) for solving the VRP with stochastic demands. The main idea of this proposal is to find the suitable mapping between the vehicle routing problems with stochastic demands. To find the optimal route in VRP using the PSO, the initial population or the routes are generated randomly and then based on the fitness function the routes are ranked.

2.6 ACO BASED VRP SOLUTION MODELS

The author (Pureza, et al., 2012) dealt vehicle routing with multiple delivery men for the class of VRPTW. Two heuristic functions namely, Ant Colony Optimisation (ACO) and Tabu Search (TS) are introduced based on which route optimizations have been carried out. Both optimization algorithms include a heuristic approach, insertion based solution construction, local search to improve exploitation in common and an
adaptive Tabu Search procedure for constructing population for next iteration. An efficient pheromone initialization and update has been made in pheromone table for choosing efficient ideology. The authors proposed a combination of multiple ant colony (Ting et al., 2009) system and simulated annealing for solving the multi depot vehicle routing problem with time windows. In this work, a research methodology has been proposed for solving VRP variants with the fusion of simulated annealing and ant colony system. This ant colony system is another variant of ant colony optimization. Feature of simulated annealing is used to find the depot and the ant colony system is used to find the efficient routing between the cities. These two heuristic techniques were used to solve the VRP variants in an efficient manner. The experiment shows better results when it has been compared with its predecessors.

The ACO is modified with semi-greedy state transition rule (Chen et al., 2012). The initial population is generated by Greedy Randomizing Adaptive Search Procedure (GRASP). Furthermore, to choose the customers, a Restricted Candidate List (RCL) is added with GRASP. In this research work, two phases are followed: the first phase is assignment phase, to find and assign the best customer to the vehicle; the second phase is making span minimization in which the shortest routing distance is solved using NEH heuristic approach. It is observed that the size of RCL is very high and hence computing the state transition rule is more complex and results in high computational complexity.

The solution construction mechanism of ACO has been altered and introduced a new hybrid ACO algorithm namely ACO with Scatter Search (SS_ACO)( Zhang et al., 2009). The initial solutions are generated using ACO and greedy heuristic, preceded by the VRP has been solved by scatter search. The main benefit of this approach is that the solution search space is explored to determine the optimal solution. An improved ACO namely Hybrid Ant Colony Optimization (HACO) has been proposed to overcome these problems and experimented in VRPTW (Sedighpour et al., 2014). To avoid the local optima struck, a disaster operator has been introduced to adjust the pheromone approach. Subsequently the ACO has been integrated with savings algorithm and λ interchange mechanism to improvise the computational speed.
An another variant of ACO is proposed with hybrid meta-heuristic for close-open vehicle routing problems with time windows and fuzzy constraints (J.Britoa et al., 2015). In this work, they have picked a VRP variant as close-open VRP. In this variant, the vehicles which are used in goods delivery system are not necessary to reach the depot. That is, from the problem point of view, the cost of returning to the depot need not to be considered, this in turn reduces the problem solving constraints to some extent. In (Chen et al., 2012) the ACO is modified with semi-greedy state transition rule, where the initial population is generated by Greedy Randomizes Adaptive Search Procedure (GRASP). GRASP is the technique which is used to construct the solution at the initial phase. The construction of solution in this GRASP will be inserting one node at one stage of GRASP. This kind of initialization also includes random process on the restricted candidates. VNS procedures will be used for the improvement of the constructed phase solutions after the iteration gets over by ACO. This VNS finds the best fitness value provided individually and keeps track on it. It also reduces the pheromone table values which are known as pheromone update.

The author (Chen-Yang et al., 2015) proposed a method using hybrid approach based on the particle swarm optimization and ant colony optimization to solve a joint order batching and picker routing problem. This is another variant of VRP in which it is used to concentrate on pick-up the delivery since it is a repetitive process. This problem has some constraints such as capacitated vehicle, where the vehicle has a maximum capacity limit to load, limited vehicles for pickup. For solving this efficiently, a hybrid system has been proposed by fusing ACO and PSO. PSO finds the best plan from all the batches which holds minimum travelling distance among other batches; ACO generates the multiple paths where it finds better results on that run.

2.7 MEMETIC ALGORITHM BASED VRP SOLUTION MODELS

The author (Nagata et al., 2010) introduced a penalty-based edge assembly memetic algorithm for VRPs with time windows. A new crossover named existing Edge Assembly Crossover (EDX) (Nagata, 1999) has been introduced for efficient unambiguous selection process for next group of population. Along with that a novelty
based penalty function was also been introduced to handle the violations that occurs during the process of EDX crossover. The overall performance has been measured with larger set of instances with better results.

Multi-objective optimization problems are considered to be a challenging from the evolutionary algorithms point of view. Achieving more than one objective with multiple constraints are considered to be the most important and predominant work to optimize a problem. An evolutionary algorithm with multi-objective phase in decomposition is a framework for solving such problems. Decomposition states that it breaks the problem as sub-problems so that it can be solved efficiently. But when applying this decomposition technique in VRPs with multi-objective theory faces redundancy in best solutions. In some pareto optimal solutions, the path gets repeated and faced some challenging schema. To solve this issue, an optimal ideology has been proposed (Qi et al., 2015) for solving the multi-objective VRP with time windows. A set of selection operators have been included in this memetic algorithm. Along with that, three other local search methods have been imposed in order to enhance the performance of memetic algorithm. The proposed memetic algorithm obtains more diverse set of non-dominated solutions than other algorithms for the instances which hold long time windows.

The author (Sema et al., 2014) proposed a method to solve vehicle routing to multiple warehouses using a Memetic Algorithm. This work has been considered as a memetic method for saving VRP variant because it uses the algorithm which is the fusion of genetic algorithm that imposes with a local heuristic algorithm. The two opt heuristic used in this algorithm has been proposed (Croes et al., 1958), where each route cuts it into two sub-routes. Now these four routes will be joined by any fusion or in any order and new set of routes will be discovered. The author (Karaoglana et al., 2015) proposed a work on memetic algorithm for the capacitated location-routing problem with mixed backhauls. There are two phases used in this algorithm for including the local search in genetic algorithm: first phase is called improving the solution where simulated annealing comes into phase, where the solutions get improvised; the second phase is known as
facility location problem, where the current set of solutions is reconfigured for improvising the results.

2.8 ABC ALGORITHM BASED VRP SOLUTION MODELS

Artificial Bee Colony (ABC) algorithms are another set of Swarm Intelligence category work well on non-deterministic problems due to colonial behaviour. This is inspired from natural life style of Bee Colony. The author (Iqbal et al., 2015) proposed a method for solving the Multi-objective VRP with Soft Time Windows with the help of bees. Along with artificial bee colony algorithm two-step constrained local search has been imposed for neighbour search. Foraging behaviour of bees is used to solve this VRP with time windows by which the balance between exploration and exploitation has been done. This balance helps the bee colony algorithm to avoid local optima and explore global optimal solution. This algorithm has been applied for Solomon’s problem in order to find the efficiency of algorithm.

The author (Marinakisa et al., 2014) proposed a Bumble Bees Mating Optimization Algorithm (BBMOA) for the open VRP. In this work, a local search procedure has been placed instead of movement of drones outside the hive. With the help of this local search procedure the algorithm turns its capability to handle combinatorial problems. The basic Bumble Bee Algorithm is used to handle continuous problems where there exists a scenario of accepting repeated variables. In BBMOA, after the initialization random solutions will be generated. After the generation of random solutions, each Bumble Bee fitness function will be calculated. Total tour cost will be projected as fitness value in Bumble Bee Algorithm. The bee which represents the best fitness value will be elected as queen and the rest will be considered as drones of that particular iteration. From the group of drones some drones are elected for mating with the queen bee. Then the local search procedure will be applied in order to make it feasible solution after it completes the mating process. The bee which represents the best fitness value at the end of each run will be considered as optimal solution.
The author (Bitama et al., 2013) proposed a Bee Life-based Multi Constraints Multicast Routing Optimization for Vehicular Ad-hoc Networks. A novel bee colony algorithm which is also known as Bee Life Algorithm (BLA) has been used to solve this kind of VRP variant. There are two predominant behaviours in bee life algorithm which dominates other algorithms, namely reproduction and food foraging technique of bees. After the initialization, based on the fitness value, the fittest bee will be considered as queen, the rest will be considered as drones and workers. Then the reproduction and food foraging behaviour will play its major role in finding VRP optimal route. In the reproduction phase, broods will be generated with the help of crossover and mutation. Then its fitness values will be calculated and its fittest brood will be compared with the existing queen. If the best brood is better than the existing queen, then the best brood will be replaced with the existing queen. The drones and workers are then isolated for food foraging behaviour. Only the worker bees are used for food foraging in BLA.

2.9 POPULATION SEEDING TECHNIQUES

Random population seeding technique is the most commonly used population generation technique. In literature the statement “generate an initial population,” mostly refers to generation of initial population using random technique. Random population seeding technique is widely used because the technique works even when there is a lack of prior information about the problem to be solved. (Katayama et al., 2000; Liangsheng et al., 1999) have proposed different types of random number generation method such as Uniform Random Sequence, Sobol Random and Quasi Random.

In random initialization technique, for vehicle routing problem, the successive customers of the initial solutions are chosen randomly. During the generation of each individual, a random number is generated randomly between 1 and ‘n’, if the generated number is already in the current individual, then a new number is generated or else the generated number is appended to the current individual and it is repeated again until the size of the individual reaches ‘n’.
Nearest Neighbor (NN) population seeding technique is a well-known choice, in substitute for random population initialization, to construct the initial population of solutions for solving TSP with GAs (Kaur and Murugappan, 2008; Xiao-Ping Liao. 2009; Ting et al., 2013; Cheng-Fa Tsai et al., 2002). In NN technique, each individual starts with a random customer and then add the next nearest customer to the starting customer. Since individuals in the NN population seeding are constructed with customer nearest to the current customer, such good individuals can refine the subsequent search in the next generations (Shubhra Sankar Ray et al., 2007). If the nearest customer from the current customer was not in the partially built individual then it’s added. The same procedure is repeated until all the customers are included in the current individual.

Gene Bank technique is a population seeding technique which generates population based their distance. The GB technique is intended to generate the initial population of solutions with better quality and diversity. The individuals in the population that is generated from the GB are of above-average fitness and short defining length (Yingzi et al., 2007) proposed a Greedy Genetic Algorithm (GGA), in which the population seeding is performed using Gene Bank (GB). The GB is built by assembling the permutation of ‘n’ cities based on their distance.

In Sorted Population (SP) technique, the initial population is generated and sorted in based on their fitness values and individuals with lower fitness are removed which results in population with above average fitness value. This approach is similar to the random initialization technique, but the opportunity of having good fitness individuals is relatively higher than random technique and it is assumed that with a large initial population there is a high probability of having good solutions in the population. Olga et al., 2008 proposed a modified GA with sorted initial population method with the concept that the better parents would produce better offspring.

The selective initialization technique was proposed by Rong Yang, 1997. In this technique the K-nearest neighbour sub graph is formulated based on the distance matrix. The technique works by generating a list of k-nearest neighbor for each city in advance.
In the heuristic population seeding techniques for TSP increases the quality of solution, convergence diversity and nearest neighbor ratio factor (M. Shanmugam et al., 2013)

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<tr>
<td>2013)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brute force method (Akos Kovacs, 2008)</td>
<td>To implement the constraints</td>
<td>The method is mainly applicable for solving small problem instances, in case</td>
</tr>
<tr>
<td></td>
<td>of the VRP’s</td>
<td>of higher instances, this method become more complexity to find an optimal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>solution</td>
</tr>
<tr>
<td>Fuzzy Logic Guided Genetic Algorithms</td>
<td>To solve the MDVRP</td>
<td>Genetic operators such as crossover and mutation are tuned for limited</td>
</tr>
<tr>
<td>(Surekha, et al., 2011)</td>
<td></td>
<td>generations</td>
</tr>
<tr>
<td>Cellular Genetic Algorithm (Nebro et al.,</td>
<td>To solve VRP’s</td>
<td>Each node is interacting with the overlapped neighbour nodes and the routes</td>
</tr>
<tr>
<td>2009; Alba et al., 2004)</td>
<td></td>
<td>are constructed</td>
</tr>
<tr>
<td>Machine Scheduling and</td>
<td>To solve integrated problems</td>
<td>The problem is divided into sub problems and the solutions of the sub</td>
</tr>
<tr>
<td>Vehicle Routing with Time Windows (Christian</td>
<td>using Genetic Algorithm</td>
<td>problem have been merged to produce the feasible solution</td>
</tr>
<tr>
<td>et al., 2013)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PSO multi-depot vehicle routing problem with</td>
<td>To find the suitable mapping</td>
<td>The initial population or the routes are generated randomly and then based</td>
</tr>
<tr>
<td>simultaneous pickup and delivery and time</td>
<td>between the VRPs with</td>
<td>on the fitness function the routes are ranked</td>
</tr>
<tr>
<td>window (Sombuntham et al., 2010)</td>
<td>stochastic demands</td>
<td></td>
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<td></td>
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<tr>
<td>Method</td>
<td>Description</td>
<td>Additional Information</td>
</tr>
<tr>
<td>----------------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>----------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>ACO with semi-greedy state transition rule (Chen et al., 2012)</td>
<td>The first phase is to find and assign the best customer to the vehicle; the second phase is making span minimization in which the shortest routing distance is solved using NEH heuristic approach</td>
<td>The size of RCL is very high and hence computing the state transition rule is more complex and results in high computational complexity</td>
</tr>
<tr>
<td>Hybrid Ant Colony Optimization in VRPTW (Sedighpour et al., 2014)</td>
<td>To avoid the local optima struck</td>
<td>λ interchange mechanism improvise the computational speed.</td>
</tr>
<tr>
<td>ACO with hybrid meta-heuristic for close-open vehicle routing problems with time windows (J.Britoa et al., 2015)</td>
<td>Vehicles which are used in goods delivery system are not necessary to reach the depot.</td>
<td>The cost of returning to the depot need not to be considered, this in turn reduces the problem solving constraints to some extent</td>
</tr>
<tr>
<td>Hybrid particle swarm optimization and ant colony optimization (Ai et al., 2009)</td>
<td>To solve a joint order batching and picker routing problem</td>
<td>It is used to concentrate on pick-up the delivery since it is a repetitive process and the vehicle has a maximum capacity limit to load, limited vehicles for pickup.</td>
</tr>
<tr>
<td>Multi-objective VRP with time windows (Qi et al., 2015)</td>
<td>To enhance the performance of memetic algorithm using local search methods</td>
<td>Proposed memetic algorithm obtains more diverse set of non-dominated solutions than other algorithms for the instances which hold long time windows.</td>
</tr>
<tr>
<td>Multi-objective VRP</td>
<td>To solve this VRP with time</td>
<td>This algorithm has been</td>
</tr>
</tbody>
</table>
with Soft Time Windows using Bees (Iqba la et al., 2015) & windows balancing between exploration and exploitation & applied for Solomon’s problem in order to find the efficiency of algorithm

Random Population seeding Technique (Ho et al., 2009) & To generate initial population using random technique & a lack of prior information about the problem to be solved

Gene Bank seeding Technique (Yingzi et al., 2007) & To generate the initial population of solutions with better quality and diversity & Individuals in the population that is generated from the GB are of above-average fitness and short defining length

Nearest Neighbor seeding Technique (Yingzi et al., 2007) & To construct the initial population of solutions for solving TSP with Gas & Lacks in terms of randomness and individual diversity

Sorted Population technique (Olga et al., 2008) & To generate the initial population and then sorted based on their fitness values and individuals with lower fitness are removed & The opportunity of having good fitness individuals in the large initial population may have a high probability of having good solutions in the population.

Table 2.1 Comparative study of existing approaches

Objectives and Research Contribution

The table 2.1 provides the comparison of existing approaches and methods to determine the research position. The traditional GA with Random population seeding technique is simple, but poor individuals’ causes long time to converge with optimal solutions. The other popular hybrid population seeding techniques such as NN and GB techniques lacks in terms of randomness and individual diversity. To improve the better quality solution, an efficient seeding technique is needed to solve the VRP problems. The major contribution of this research work to achieve the objective of providing a solution model to solve the different variants of Vehicle Routing Problems (VRP’s). In this
research work an enhanced Genetic Algorithm is designed which uses the proposed Ordered Distance Vector (ODV) based Equi-begin with Variable-diversity (EV) population seeding technique to solve VRP problems. To achieve the derived objectives, this research work provides different solution models for Vehicle Routing Problems using an Enhanced Genetic Algorithm.

2.10 SUMMARY

There are numerous approaches proposed in view of solving VRPs, particularly in the class of evolutionary algorithms. Some of the evolutionary algorithms are used to solve vehicular routing problems including Genetic Algorithm, Ant Colony Optimization, Particle Swarm Optimization, Memetic Algorithm, Shuffled Frog Leading, Bacterial Foraging Optimization, Harmony Search, Artificial Bee Colony, etc., These algorithms works in Vehicular routing problem both in standalone and could be fused with other algorithms in order to produce optimized results. Genetic Algorithm is the first evolved in the class of evolutionary optimization algorithms in which it acts as a better and widespread model in that class. Genetic algorithm is considered to be a heuristic approach. It is based on natural reproduction behaviour; works in a guided random manner. It uses its historical performance for exploitation of search space; it directs the search towards optimal solution with the help of two operators. GA will be applicable for both continuous and discrete problems. These algorithms are still improvised by either hybridized or modified fashions in order to obtain better results. In this perspective, the work reported in this thesis contains a set of enhanced GA models for solving a class of VRPs in competent models. The objectives and research contributions are also determined.