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Memetic Computing using Simulated Annealing for Dynamic Vehicle Routing Protocol

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ABSTRACT

This paper addresses the dynamic vehicle routing problem. The proposed work includes the optimization in path selection using simulated annealing and hybrid memetic-genetic algorithm. In this paper, first we apply simulated annealing approach to the input of VRP.We use standard SA method that includes various types of move including insertion move, swap move,2-opt move,3-opt move to solve VRP.Then the output of SA approach will be given as the input to hybrid memetic-genetic algorithm. In hybrid memetic-GA approach, there will be standard operation of GA and a local search method. The aim of the approach are to produce a better solution with a short time limit, to design an efficient and effective distribution network in order to deliver the produced goods to the customer with the lowest cost and in shortest possible time frame.

Keywords: Dynamic vehicle routing protocol, Simulated annealing, Genetic algorithm, Memetic optimization, local search, Annealing limit,Evolutionary Operator.

I. INTRODUCTION

Vehicle routing problem is first introduced by Dantzig and Ramser[10].The vehicle routing problem represents the cornerstone of optimization for distribution networks. VRP is considered as one of the most difficult problems due to its complex nature. It is the fusion of two NP-hard problems, Travelling salesman problem (TSP) and Bin packing problem(BPP)[13].In VRP,a set of N customers {e1,e2,…el,…En} is to be serviced by a fleet of K vehicles {v1,v2,…vi,…vk}.Each customer has demand el that must be serviced by vehicle vi.Each vehicle vi has a finite capacity denoted as Cv and travels a route Ti={ai1,ai2,…aij,…,aim} passing through the central depot e0,with aij representing the jth customer visited by vi.The objective of the VRP is to find the optimal routing solution s={T1,T2,…Ti,…Tk},that minimizes the overall distance travelled by all vehicles. The problem is widely applicable to real life tasks, such as taxi services, courier companies or other pickup and delivery businesses. There are two types of vehicle routing problem, static VRP and dynamic VRP [1].

A. Static VRP

Design least cost routes from a central depot to a set of geographically dispersed points with various demands using a fleet of vehicles. Each customer is to be serviced exactly once by only one vehicle. Each vehicle has a limited capacity. A service time representing the time required to service her/him is associated with each customer. But there are minimizations in static VRP due to following constraints: starting and finishing of each tour at same depot, each customer is visited exactly once, total demand of any route does not exceed capacity [8].

B. Dynamic VRP

New customer orders can continuously arrive over time, after a number of vehicles have been commissioned [14]. These new orders need to be incorporated into the existing vehicle tours or new tours created to handle them.Thus,at any moment in time,tm,there may exist customers already serviced and new customers which need to be serviced. If a working day is sub-divided into a number of discrete time periods, then the DVRP can be formulated as a sequence of digraphs, each one consisting of a static VRP.

II. LITERATURE SURVEY

Michal Okulewicz, Jacek Mandziuk proposes a hyperheuristic method based on two algorithms: Multi-Environmental Multi-swarm optimizer (MEMSO) and 2- Phase Multi-swarm particle swarm optimization (2MPSO). The hyper-heuristic uses the statistical data about the initially known set of requests in the given Dynamic vehicle routing problem [5]. Both, the MEMSO and the 2MPSO, use PSO as their base meta heuristic and 2-OPT as a route optimization heuristic. In both methods the working day is divided into discrete number of time slices, with the instance of the DVRP problem "frozen" within each time slice. Therefore, each method solves a series of dependent static VRP instances during the optimization process. Here PSO is an iterative population based continuous optimization meta-heuristic approach. During the optimization process PSO maintains a set of fitness function solutions called particles. Each particle has its own location, velocity, set of neighbours, memory of best observed solution, memory of best visited solution.2-opt.algorithm is a heuristic algorithm for solving the TSP.The algorithm operates by iterating over all the pairs of edges of a given route. The possibility of optimizing the length of route is checked by swapping the end of those edges. MEMSO uses PSO to optimize division of requests among the vehicles. The vehicles routes within those divided sets are created by a greedy insertion and optimized by the 2-OPT algorithm.The fitness function value is the total length of those routes. This algorithm includes discrete encoding of the requests division.The solution is an integer vector representing the requests and the values in the vector are the vehicles identifiers. Michal et al. [5] explored the use of choosing an optimization algorithm on the basis of characteristics of initial requests set to produce improvement of results. A limitation of this method is the economic cost for running the hyper-heuristic approach will be more. Franklin T. Hanshar, Beatrice M. Ombuki-Berman proposes a new effective chromosome representation scheme, and provides an efficient crossover operator for the DVRP [1]. In DVRP, customer requests/orders are revealed incrementally over time, although some requests may be known in advance at design time. Here some customer orders are known in advance and an initial route schedule is generated to service these customers. As time elapses new customer orders arrive, and this new addition requires the rescheduling of one or more of the routes. Genetic algorithms have become popular in a wide variety of combinatorial optimization problems. In a GA, a chromosome is used to define a candidate solution to a problem. In order to mimic natural selection, populations of candidate solutions (chromosomes) compete to be in the mating pool which is the subset of solutions which are allowed to produce offspring. The DVRP-GA system consists of two main components: Event scheduler and Genetic optimization algorithm. The event scheduler handles the commitment stage, manages customer orders, committing certain customers to vehicles, creates static problems, issuing new vehicles to be deployed or signalling them to return to the depot. Once a customer has been committed to a route, it cannot be changed. It serves as an interface between the arrival of new orders and the optimization procedure. The event scheduler is also responsible for receiving new orders and for constructing the static VRP like problem instances. The first static problem created for the first time slice consists of all orders left over from the previous working day. The genetic optimization stage handles the optimization of the static VRP instances using a GA approach [7]. It is called by the event scheduler and must run within an efficient amount of time. This optimization stage is run several times over a discrete number of time slices as delineated by the event scheduler. Each chromosome in the population pool represents a possible solution to a static VRP.The chromosomes are then subjected to an iterative evolutionary process until the termination condition is met. The evolutionary part is carried out as in ordinary GA's using selection, crossover and mutation operations on chromosomes.

Jacek Ma´ndziuka and Adam Zychowskiaa propose an effective algorithm for solving vehicle routing problem with dynamic requests based on memetic algorithms [5]. It includes investigation into the importance of the so-called starting delay parameter, whose appropriate selection has a crucial,impact on the quality of results. Another key factor is proposed effective mechanism of knowledge transfer between partial solutions developed in consecutive time slices. Novelty of their work lies in their innovative combination into one synergetic system as well as their application to a different. version of DVPR in which some of the customer's location will be unknown at the starting stage and it arrives gradually as time passes. At the end of time slices route optimization procedure will be executed. This system composed of two main components.The first module is responsible for receiving new orders, dividing working day into some pre-defined number of timeslices and creating static instances of the VRP for each of them.The second component is responsible for optimizing the routes by means of solving a (static) VRP instance in each time slice. A working day is split into nts equal-length time slices and in each time slice a static version of the problem (VRP) is solved for the set of currently known customers (requests).New requests arriving during the cur-rent time slice are postponed to its end and optimized in the next algorithm's run (in the next time slice).Once the calculations allotted for a given time slice are completed the best-fitted chromosome is selected, decoded and the vehicle routes it represents are examined .Starting delay (Sd, $0 \leq Sd \leq 1$) is defined as a fraction of a working day time (tc− to) in which the planned route must be completed. The remaining time, i.e. (1 − Sd)(tc− to), serves as a time reserve for the future route modifications which may possibly be required.The customers already visited and the ones to whom the vehicle is already dispatched are removed from the chromosome and called committed.

Here the proposed approach is based on memetic computing which enhances population based Evolutionary algorithms by means of adding a distinctive local optimization phase [12]. This is an effective and reliable method. It prevents the system from premature convergence or stagnation. But this is an ineffective error correction method in GA.

Xianshun Chen, Yew Soon Ong and Meng Hiot Lim proposes a memetic algorithm for capacitated vehicle routing problems (CVRP), which is specially designed for applying intense local search methods or memes [3]. The main contribution of this work is a VRP domain-specific cooperating multi-strategy individual learning procedure. The MA finds high quality solutions by using memes, each having different roles. Experiments on several sets of benchmarks showed that the algorithms are better when compared to other algorithms. Unlike adaptive memetic algorithm it is VRP domain specific thus making it less useful when used for another problem such as arc routing problem.

Tsung-che Chiang And Wei-huai Hsu proposes a knowledge-based evolutionary algorithm for the multiobjective vehicle routing problem with time windows[16].The objectives are to minimize the number of vehicles and the total distance simultaneously. This approach is based on an evolutionary algorithm and aims to find the set of Pareto optimal solutions.It incorporate problem-specific knowledge into the genetic operators. The crossover operator exchanges one of the best routes, which has the shortest average distance.The relocation mutation operator relocates a large number of customers in non-decreasing order of the length of the time window. The split mutation operator breaks the longest-distance link in the routes.

III. SYSTEM MODEL

Figure1 depicts the system model for dynamic vehicle routing problem. Here we use three optimization techniques.

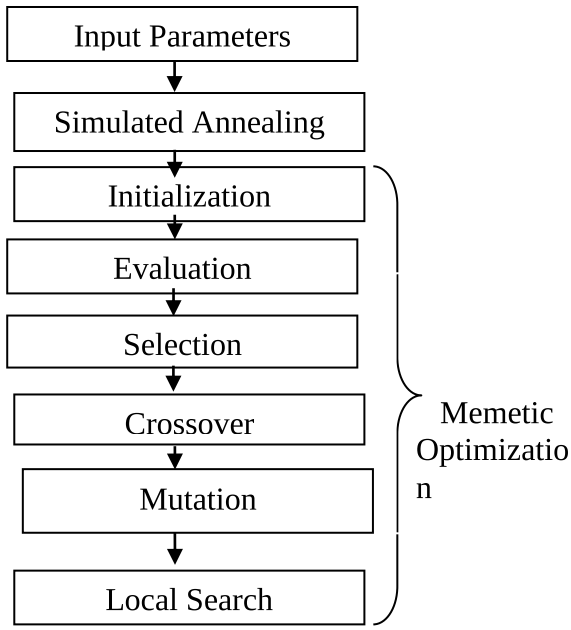

Figure1. System Model

At first, simulated annealing will be performed on the input of VRP.The output obtained will be given as input to hybrid memetic-genetic algorithm. In genetic algorithm, we perform four standard operations.

A. Initialization

This is a repeatable step of the program, until it does not reach a maximum value of failed initialization. It chooses a random, on repeating permutation of the customers, which of course might not be valid. If the truck reaches the customer after the closing time, the chromosome is invalid. Then a new chromosome has to be generated until the loop does not reach the allowed tries to generate chromosomes. Once a chromosome is valid, it is returned with its calculated fitness.

B. Evaluation

The fitness is the total length of the chromosome, so as it becomes larger, the solution becomes worse. One chromosome is visited by one vehicle.

C. Selection

The selection ends, when the given number of individuals is reached.

D. Crossover

It is hard to create new individuals with crossover, which are not invalid, so no duplicate customers appear. The method uses two parents for a new individual and goes though I gene by gene. For the children it selects the gene from the parent, where the distance of the current gene and the previous gene is less. In the n-th step it means the comparison of:

Distance (parent1.gene (n), parent1.gene (n-1)) and
Distance (parent2.gene (n), parent2.gene (n-1))

The child inherits the value, which is less. After the inheritance, the gene which the children inherited have to be found and replaced by the non-inherited one in the parent from the children does not inherited. It then avoids us from having duplicates, because it is not going to be selected later again.

E. Mutation

Mutation selects a random parent and swaps one of its genes, and recomposes and revalidates the fitness value of it. This might be then a new child.

The Figure.2 below shows simulated annealing (SA) procedure.SA is a stochastic gradient method for the global optimization problem. It is a local search procedure that is capable of exploring the solution space stochastically and effectively trying to escape from being trapped in local optima. To escape local optima, SA accepts worse solutions during its search with a probability which is monotonically decreasing by temperature. We use a standard SA procedure which includes various types of move such as insertion, swap, 2-opt and 3-opt.Dummy zeroes are treated as customers when performing these moves.

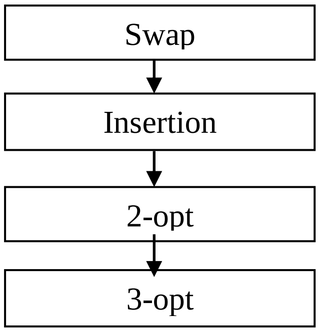

Figure 2. Simulated Annealing

F. Insertion

It is carried out by randomly selecting the ith number of X and inserting it into the position immediately before another randomly selected jth number of X.

G. Swap

It is performed by randomly selecting the ith and jth numbers of X and then exchanging the position of these two numbers.

H. 2-opt

This is implemented by randomly selecting two customers that are assigned to the same depot and then reversing the substring in the solution representation between them.

I. 3-opt

This is implemented by randomly selecting two customers that are assigned to the same depot and then shifting the substring backwards along the solution representation [9].

J. Local search

Memetic algorithm represents a subfield of memetic computing that is widely established as the synergy of population based approaches with separate local search or individual learning process [11]. The algorithm starts with the initialization of population of candidate solutions. At each generation, a population of offspring is generated using evolutionary search through reproduction operators such as crossover and mutation. The population of offspring subsequently undergoes lifetime learning and fitness evaluation, and updates the global best solution. Memetic search proceeds until some stopping conditions are reached.

IV. PSEUDO CODE

Procedure 1 Simulated Annealing

```
Procedure Neighbourhood ()
        Swap two random genes in the route ()
        Store the new route ()
End
Procedure simulated annealing ()
        Initial variables ()
        While the annealing limit is not zero do
                Create a new route with the
        neighbourhood
                function ()
                For all of the genes in the route step by
        step
                If it's a depot, try to move the truck
                        there, and start the next one
                                Bvalidroute=check
                        MCOP
                If it's not, try to move there
                                Bvalidroute=check
                        MCOP
                If bvalidroute=true
                        Calculate fitness ()
                        If better or equal than before,
                        store as current generation
                                If best store as current
                        and
                                best generation
                If worse, check annealing limit
        If limit is ok, store as current generation
                Else, mark as invalid generation
        Bvalidroute=false
                                End
                        End
        If bvalidroute=false
Restore last generation and do not store new one
Decrease annealing limit, increase generations
Calculate time and necessary data, output
                data
        End
End
```

Procedure 1 outlines schematic workflow of Simulated Annealing. The algorithm starts with procedure neighbourhood.After the first generation is evaluated it is very easy to create further generations. The loop runs until the annealing is decreased to zero or the given number of generations is reached. In each loop, the neighborhood function replaces two customers in the current generations and then it tries to validate the new string. If the new route is invalid, the generation is immediately dropped and marked as unsuccessful and the last generation is used again for further annealing.

Procedure 2 Genetic Algorithm

Begin PATHSELECTION_GA
Create initial population of n nodes randomly.
While generation_count < k **do**
/*k=max.no.of generations.*/
Begin
Selection
Fitness function
Modified crossover
Mutation
Increment generation_count.
End;
Output the optimal path by selecting the highest probability value chromosome on which data can be sent.
End PATHSELECTION_GA.

Procedure 3 Memetic Algorithm

Begin
    Create an initial population of solutions
    Pop (gen) =0= {s1, s2,……., sm}
    While (stopping conditions are not satisfied)
    gen=gen+1
    Perform evolutionary operators to generate.
    Pop (gen) from pop (gen-1) based on f (s1):
    Evaluate f (s1), ¥s1 € pop (gen)
    Perform lifetime learning
    Update global best solution sg
    End while
End;

V. RESULTS AND DISCUSSIONS

The proposed model has been run and the corresponding screenshot has been taken. Based on the experiment, analysis has been performed.

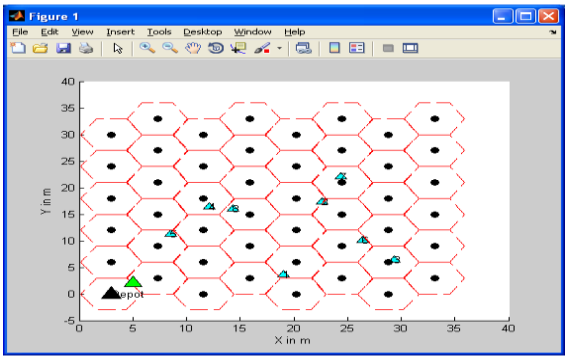

Figure 3. Routing Model

Figure 3 shows the corresponding routing model with cyan triangle indicates deliver Point. Black color triangle indicates Depot point and Green color triangle indicate vehicle. Here the virtual hexagon is to indicate the coverage of deliver point and black dot indicate junction.

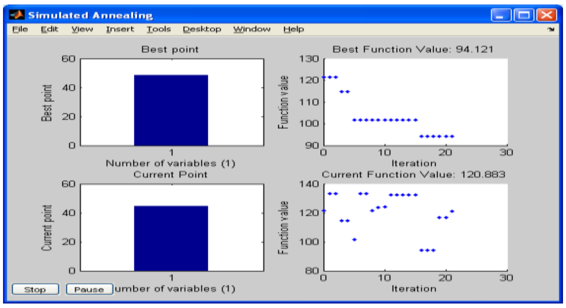

Figure 4. Simulated Annealing function

Figure 4 shows simulated annealing function. It is used to find optimal route globally. Each and every iteration assigns random permutation and finds routing distance. Simulated annealing is used to find minimum routing distance.

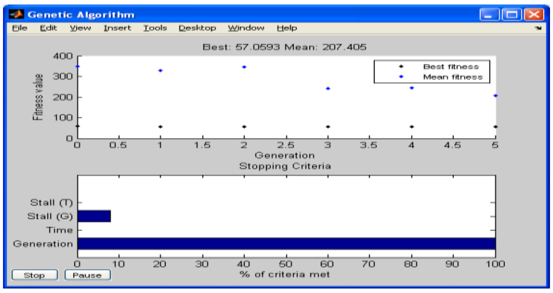

Figure 5. Genetic Algorithm

Figure 5 shows Genetic algorithm function. It is used as a local search method and identifies the minimum routing cost in local search. It also includes traffic information.

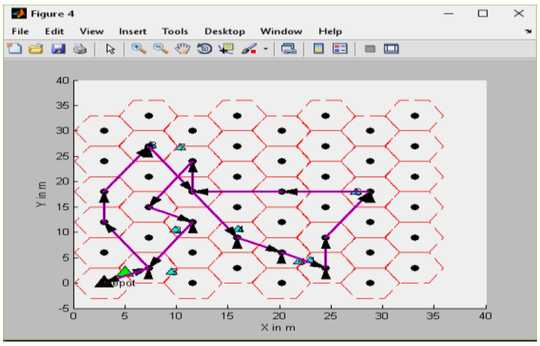

Figure 6. Proposed Routing path for test case 1

Figure 6 shows proposed routing path for test case1.Here the starting and ending point are depot itself.

VI. EXPERIMENTAL ANALYSIS

The proposed model reduces the complexity, ie; in existing method both the global search and local search are performed in genetic algorithm. But in case of proposed model global search is performed in simulated annealing and local search in genetic algorithm. Hence complexity gets reduced.

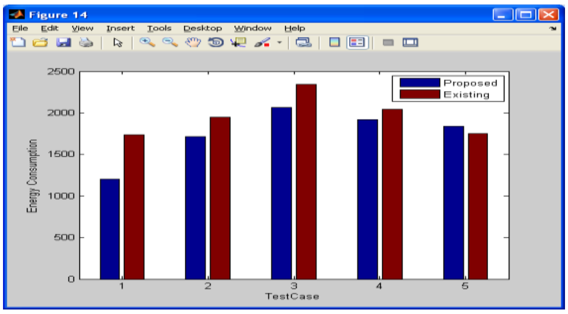

Figure 7. Energy consumption

Bar chart shows energy consumption or fuel cost. Compared to existing method proposed has better performance.

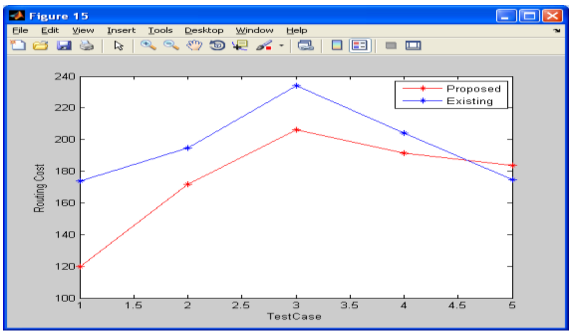

Figure 8. Routing distance

Figure 8 shows routing distance with different test cases. Compared to existing method proposed have better performance.

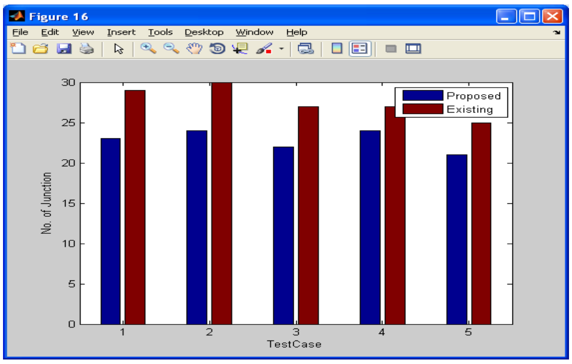

Figure 9. Number of Junctions

Figure 9 shows Number of junctions to meet vehicle. Minimum junction in proposed method.

VII. CONCLUSION

In this article optimization in path selection using simulated annealing and hybrid memetic –genetic algorithm has been introduced. The simulated annealing approach includes various types of moves including insertion, swap, 2-opt, 3-opt to solve VRP.It can be easily obtained that all models are starting with nearly a same fitness and at the end the models have nearly the same improvement after the same time. This means that the initial population doesn't really influence the efficiency of the simulated annealing. After that by applying genetic algorithm, the first population takes a very long time to be generated. As the number of customers in a file grows, this time becomes also larger, because the number of genes increased, so the possibility of invalidation is also larger. The aim of the approach are to produce a better solution with a short time limit, to design an efficient and effective distribution network in order to deliver the produced goods to the customer with the lowest cost and in shortest possible time frame.

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