



Research Article

Metaheuristic algorithms for multi objective vehicle routing problem

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ABSTRACT

Besides its economic purpose, the vehicle routing problem has also garnered attention due to its social and environmental objectives in recent years. In terms of ensuring sustainability, it is beneficial to consider these three objectives together. CO₂ emissions, which is one of the causes of global warming, which we have felt more prominently in the past few years, has also affected the policies of logistics companies. Organizing working hours and ensuring fairness among employees are also one of our motivations in this study. Financial objectives has always taken into account. Simulated annealing algorithm and adaptive large neighborhood search algorithm are developed for the solution of the multi-objective mix integer mathematical model, in which financial, environmental, and social objective functions, which include alternative ways with different properties between nodes and different speed options. Small problems can be solved with exact solution method in literature, but to solve medium and larger samples heuristic algorithms are needed. When comparing algorithms, Simulated Annealing also gives better results than Adaptive Large Neighborhood Search in a shorter time.

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INTRODUCTION

Although vehicle routing problem (VRP) is an old problem, it is still studied by researchers. VRP still has a wide range of applications in different industries. Reducing CO₂ emissions, one of the main factors of global warming, has also become an important issue for companies. In addition, transporters are bound by the legislation enforcing driver working hours. Also, unbalanced working hours might create problems among the workers and it may cause a trust problem towards the firm [1-3]. With the increasing sensitivity to environmental and social issues in recent years, these objectives are

considered together with financial objectives [4-6]. Motivated by these issues, vehicle routing problem considering financial, environmental, and social objectives are considered.

In general VRP studies in the literature, it is assumed that there is only one direct link between each pair of nodes in the network [7]. However, in reality, there may be more than one direct connection between two nodes. In Figure 1, the first value on each link denotes the length of the link (in km) and the two values inside the parentheses denote two different speed levels (in km/hour) that the vehicles can choose to go on that link. Besides, these alternative

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links might have different features as lengths, durations, and costs. For example, a short road might require a longer time due to traffic. Similarly, some roads require additional payments, leading to higher costs, or some roads may cause more CO₂ emissions due to speed limits.

In literature, even though the existence of alternative roads between different points is acknowledged, the shortest or the fastest of these roads is taken as a single link in the model, and the other alternatives are omitted, assuming that longer or slower roads will never be chosen based on the model objectives [8]. However, alternative links between nodes are studied by [9-11].

However, in real life, the shortest roads are not always the best ones due to speed limits, traffic jams, or toll roads. Depending on the objective function and constraints of the model, a faster but longer road might be chosen to go from

one node to another node, even if a shorter road may be in the same network.

As it is seen in Figure 2, 0 represents depot, 1 and 2 are customers. When there is no time window restriction in Figure 2 part of A, route is 0-1-2-0, and the length of selected alternative links are 20, 10 and 15, and selected speed levels are 50, 40, and 50. However, if there is time window restriction for node 1, the route is still the same, but, the selected alternative link is changed. In Figure 2 part of B, the selected length between the node of 0 and 1 is 50, and the selected speed level is 90. If the time window restriction is relaxed a little, the selected speed level between 0-1 could be 60 while the route and alternative links remain the same.

In the literature, according to the objective functions and constraints, different types of VRP are found. However, the mostly papers that are related to our study are analyzed [6,12,13] review different types of VRP literature [14-16]. Also review the literature about green vehicle routing problem (G-VRP).

The aim of G-VRP is minimizing CO₂ emissions or fuel consumption [17]. Solve multi-objective G-VRP with the iterated local search algorithm. Cost, fuel consumption, and distance equity are considered as an objectives [18] add different carbon emission policies into the inventory routing problem with minimizing inventory holding cost, transportation cost, and fuel consumption cost [19]. Minimize operational and environmental costs for the green capacitated location-routing problem [20]. Study the time-dependent vehicle routing and scheduling problem to minimize CO₂ emissions and develop an exact dynamic programming algorithm [21] are also interested in carbon emission. Speed of vehicle is separated into ranges, and so model linearized [22]. Compares metaheuristic algorithms for time window G-VRP. When looking the results, greedy randomized adaptive search procedure (GRASP) and ant colony optimization (ACO) gives better results than tabu search (TS) and variable neighborhood search (VNS) [23]

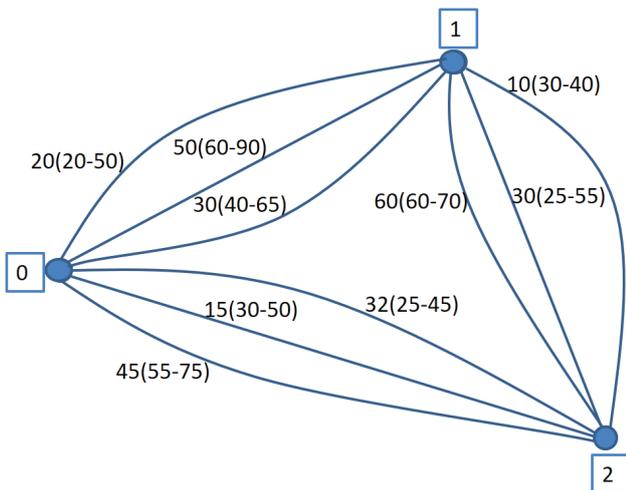


Figure 1. Sample of alternative links and speed choices between nodes.

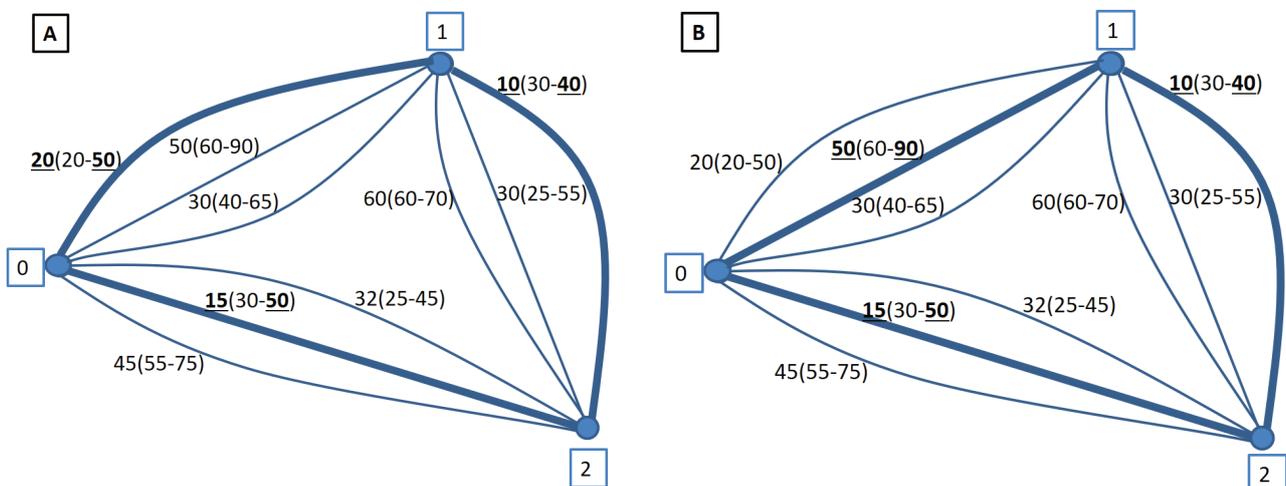


Figure 2. Selection of different links and speed levels.

measured releasing CO_2 , NO_x , CO with time-dependent Open-VRP [24]. Minimize total fuel cost and driver cost with a heterogeneous vehicle fleet [5] analyze the relationship between load and CO_2 emissions using a heterogeneous fleet of vehicles. They show that, the used vehicle type, curb weight, and carried weight affect the fuel consumption used genetic algorithm and weighted superposition attraction algorithm to solve green VRP [25,26]. State that the vehicle type, speed, and load capacity affect the objective functions composed of distribution cost, customer satisfaction, and environmental pollution with adding time windows and heterogeneous vehicle fleet [27]. Also analyze the effect of different speed choices on fuel consumption and route times [28]. Study the time-dependent pollution routing problem to minimize total fuel cost and driver wages. They attract attention to rising driver wages because of low speeds in congested traffic at certain hours consider the green open vehicle routing problem with time windows [29].

Since the classical VRP is NP-Hard, heuristic and meta-heuristic methods are generally used in the literature to solve these problems [30]. States that the optimal solution is difficult to find with more than 10 nodes and thus presents an approximation algorithm for the solution of his models [31]. Develop an adaptive large neighborhood search (ALNS) heuristic for the pollution routing problem, and they offer a speed optimization algorithm to minimize fuel and driver costs [32]. Also employ an ALNS algorithm to solve a bi-objective pollution routing model that minimizes fuel consumption and delivery time [33]. Consider fuel emission cost and driver cost as an objective function of (G-VRP) with stochastic demands [34]. Hybridized genetic algorithm (GA) and VNS to cope with time-dependent GVRP with multiple depots and time windows [35]. Solves multi-objective GVRP fuzzy distances and split-delivery by using GA [36]. Solved multi depot green VRP with using ALNS. Two speeding up methods are used, and results are better than classic algorithm. As different perspective, [37] used multiple-depot to decrease carbon emission [38]. Combined GVRP with disassembly line problem. Several multi criteria decision making methods are used to determine best pareto optimal solutions [39]. Minimizes total cost and fuel consumption, and problem solves with strength pareto evolutionary algorithm (SPEA2) and Non-dominated Sorting-based Genetic Algorithm (NSGA-II). When comparing results, NSGA-II gives better results. As a different perspective, [40] considered the cost of perishable products along with the financial cost. To solve time-dependent GVRP, VNS and GA is hybridized [41]. Considered energy consumption, partial re-charging policy and carbon emissions simultaneously for Electric VRP, and ALNS and Cplex are used to solve the problem [42]. Used two construction algorithm and SA algorithm to solve VRP with simultaneous linehauls and backhauls used GA and ACO to solve multi depot VRP [43].

In the literature, generally financial and environmental objectives are considered, and social considerations are studied less than others [44]. Considered economic,

environmental, and social objectives simultaneously in facility location problem focus on environmental and social issues in multi-objective VRP [4]. Present an integer linear program for the balanced VRP and a rank-based ant system algorithm for the solution of their model [45,46]. Analyze a multi-depot vehicle routing problem with simultaneous pickup and delivery with the aim to have a balanced distribution of travels. They include the total routing cost, penalty cost for overworking of drivers, and fix costs of drivers' employment in their objective function [47]. Study a bi-objective capacitated general routing problem solved VRP with using Particle Swarm Optimization (PSO) and ACO that takes into account route balancing handled fresh cut flowers delivering problem [48-50]. Initial solution is obtained with the path cheapest arc heuristic, after solution is improved with guided local earch algorithm. Different from classical algorithms, [50] used conditional neural heuristic algorithm to solve multi objective VRP. In addition, [51] used deep reinforcement learning based algorithm to solve green VRP.

Companies should regulate and comply with the laws of working and resting hours [52]. Notes that while regulations on drivers' working hours significantly affect total travel times, the vehicle routing literature has largely overlooked these restrictions. They describe the regulations for drivers' working hours in the European Union and present the vehicle routing problem considering these regulations [1]. Presents a model showing how driving periods, breaks, resting periods, and processing activities can be scheduled, and proposes a large neighbourhood search algorithm to create vehicle tours complying with the new regulations released by the European Union in 2007 [3]. And [2] also consider social legislations. [53] also study multi-objective GVRP as a financial, environmental and social objectives, and biased-randomized iterated greedy algorithm used to solve the problem. Financial cost consist of fixed vehicle costs, driver wages and fuel cost, the environmental cost is correlated with fuel consumption, and finally, social cost is accident risk cost.

In this study, like [10], and [11], minimizing the fuel cost, drivers cost, and fixed vehicle cost are considered as the financial objective for the company, minimizing the CO_2 emissions and oil usage are considered as the environmental objective, and the balancing drivers' working hours and adjusting route times are considered as the social objectives. Which routes, which alternative links, and which speed choices will be selected are determined by considering the financial, environmental, and social objectives. Although the problem is discussed in this study is the same as [11], unlikely, to solve middle and large data sets, and different scenarios, heuristic algorithms are used in this study.

In the next section, the problem is defined and model is explained. Then, in section 3, the Simulated Annealing (SA), and ALNS heuristic methods are presented to solve the problem. In section 4, numerical experiments with a discussion of the results are presented, and finally conclude our study in section 5.

PROBLEM DEFINITION AND MODEL

For a given set of n demand nodes and a depot, a directed graph is defined on these nodes. In the classical VRP problems, a single arc (i, j) is defined between a pair of nodes i and j . However, in our study, for more than one arc between each pair of nodes i and j is allowed, thus the notation (i, j, k) is used, where k denotes one of the alternative links between nodes i and j . Each link is assumed to have a distance denoted by d_{ijk} , and x_{ijk} denote the binary variable that is equal to 1 if a vehicle goes from i to j through link k . In addition, each vehicle can choose a different speed on each link and v_{ijkn} denotes the binary variable that is equal to 1 if a vehicle goes from i to j through link k at speed level n , and 0 otherwise. The possible speed levels that can be chosen at each arc are different from each other depending on the type of the arc. While vehicles can go at higher speeds on some arcs (i.e. highways), they need to choose slower speeds at others (i.e. inside the city). However, since faster roads might also be longer or more costly, the choice of the link depends on the parameters, constraints and the objectives of the problem. Even though different links have different characteristics, it is assumed that these characteristics are not time-dependent. Time-dependent speed choices and durations can be incorporated into the model, however since our focus is not on time-dependency, it is leaved for future studies as it makes the problem much more complicated and the solutions much harder to obtain.

In this model, each demand node i has a demand quantity, denoted by q_i , and if a demand node is visited, all of its demand needs to be delivered. In other words, partial delivery is not allowed. It is assumed a homogeneous fleet of vehicles and each vehicle is assumed to have a fixed capacity Q . In addition, time windows are considered in our problem, such that a delivery to a node i can only be made between times a_i and b_i , the earliest and latest service times for node i , respectively. If a truck arrives to a node before time a_i , it needs to wait there until time a_i , and it is not allowed to arrive a node i after time b_i . t_i is denoted the delivery service time at node i , such that each truck spends t_i time units at node i to make the deliveries. RT denotes the allowed regular time for a route and if the total duration of a route exceeds the value of RT , the drivers need to make overtime and an overtime cost is applied. The indices, parameters, decision variables of the model are defined in the [11] as follows:

Indices:

- i, j : Indices used for demand nodes
- k : Index used to denote alternative links between nodes
- n : Index used to denote the speed level

Clusters:

- $N = \{0, \dots, N\}$ Set of nodes, 0 denoting the depot
- $N0 = N \setminus \{0\}$ Set of customers
- Nh = Set of speed levels
- K = Set of arcs

$\mathcal{A} = \{(i, j) : i, j \in \mathbb{N} \text{ and } i \neq j\}$ Set of links between nodes

Parameters:

- q_i : Quantity of demand at node i
- a_i : the earliest service start time for node i
- b_i : the latest service start time for node i
- Q : Vehicle capacity
- t_i : Service time for node i
- m : Number of available vehicles
- M : A large number used in modeling
- f_v : Cost per vehicle used
- f_d : Cost of overtime for drivers on a route per unit time
- f_s : Cost of drivers/vehicles per unit time
- f_e : Social cost of unbalanced routes per unit difference
- f_a : Social cost of overtime per unit time
- f_b : CO_2 emission(kg/lt)
- d_{ijk} : Distance between node i and j through link k
- S_{ijkn} : Speed level n at link k between nodes i and j
- RT : Allowed regular time per route

Decision Variables:

- x_{ijk} : Binary variable equal to 1 if a vehicle goes from i to j through link k ; 0 otherwise
- v_{ijkn} : Binary variable equal to 1, if a vehicle goes from i to j through link k at speed level n ; 0 otherwise
- f_{ijk} : Flow carried from i to j through link k
- y_i : Start time of service at node i
- s_j : Total time of a route when j is the last node of the route
- o_j : Amount of overtime on a route
- e_{ij} : Difference between route times, when i and j are last nodes in two different routes
- Z : Objective function.

It is known that the amount of fuel consumption depends on the speed of the vehicle, as well as the load of the vehicle, among others. Emissions and fuel consumption is computed using comprehensive modal emissions modeling (CMEM) developed by [54]. CMEM assumes that the vehicle is in a steady state between two consecutive locations and thus the vehicle's speed is assumed to be constant [55]. Examine the precision of carbon emission and fuel consumption calculations in green vehicle routing. Even though speed fluctuations and real life driving conditions are seen to have an impact on the results, CMEM computations are widely used in literature and generally thought to provide a good estimation of fuel consumption under realistic driving conditions. Thus, assuming that the vehicles maintain a constant speed between any two nodes, the average speed is used in our model as an approximation to the exact consumption values, which is a common approach in the literature [31]. Use CMEM and present the relationship between fuel consumption, speed and load. They calculate the amount of fuel consumption depending on the speed, load, and other factors as below:

$$f(v) = \lambda(kNV + w\gamma av + \gamma \alpha f v + \beta \gamma v^3) \frac{d}{v}$$

In the above relation, v denotes the speed, d denotes the distance, f denotes the load. In addition, $\lambda = \xi/\kappa\psi$, $\lambda = 1/1000 n_{tr}\eta$, $\alpha = \tau + g\sin\theta + gC_r \cos\theta$, $\beta = 0.5 C_d\rho A$ are the values calculated using the constants given in Table 1. Most of the data provided in Table 1 are obtained from [31]. It is assumed that the acceleration and the angle of the road denoted as τ and θ , respectively, are assumed to be 0.

Using the notation above and the decision variables in our model, the amount of fuel consumption is written as below:

$$\begin{aligned} \text{Fuel Consumption (FC)} = & \sum_{i,j,k,n} kNV d_{ijk} \frac{v_{ijkn}}{S_{ijkn}} \\ & + \sum_{ijk} w\gamma\alpha_{ijk} d_{ijk} x_{ijk} \\ & + \sum_{i,j,k} \gamma\lambda\alpha_{ijk} d_{ijk} f_{ijk} \\ & + \sum_{ijkn} \beta\gamma\lambda d_{ijk} v_{ijkn} (S_{ijkn})^2 \end{aligned} \tag{1}$$

For the objective functions, financial, environmental, and social costs are considered in our model. The economic cost of fuel consumption ($f_c FC$), the cost for regular time, and overtime costs of drivers/vehicles ($f_s \sum_j s_j + f_d \sum_j o_j$), and the fixed cost for the number of drivers/vehicles used ($f_v \sum_{j \in N_0} x_{0jk}$) are considered as the financial cost. Since the

amount of fuel consumption defines the CO₂ emissions, the environmental effect is calculated by multiplying FC with the emission factor, f_b . Thus, $f_b FC$ is considered as the environmental cost.

For the social cost, the overtime of drivers is considered firstly, which is socially undesirable. As the working hours of the drivers' increase, they become more tired on the road and this will increase the risk of accidents. In addition, driving hour regulations in some countries enforce certain constraints on the tour durations. Even though tour durations are not considered as hard constraints in our model, as soft constraints such that any additional time over the regular working hours is penalized in the objective function is used. Thus, have as little overtime for the drivers as possible is aimed firstly. In addition, balanced route times between different drivers are desired. Unbalanced working hours lead to discussions between drivers and the company, and result in an unpleasant working environment. Sometimes drivers are paid by the duration of their services and the drivers who are assigned fewer driving hours than others tend to complain about the fairness of the managers. On the other hand, sometimes drivers who are assigned more driving hours also complain about the long working hours, especially when the additional payments they get do

Table 1. Definition of parameters and their values from real life data

Notation	Definition	Value
W	Curb-Weight (kg)	6350
E	Fuel to air mass ratio	1
K	Engine friction factor (kilojoule/rev/litre)	0.2
N	Engine speed(rev/sn)	33
V	Engine displacement(liters)	5
G	Gravitational constant(meter/second ²)	9.81
C _d	Coefficient of aerodynamic drag	0.7
P	Air density (kg/m ³)	1.2041
A	Frontal surface area(m ²)	3.912
C _r	Coefficient of rolling distance	0.01
n _{tr}	Vehicle drive train efficiency	0.4
H	Efficiency parameter for diesel engines	0.9
f _b	CO ₂ emissions per liter fuel used (kg	2.67
f _c	Fuel emissions cost per liter(TL)	5.81
f _a	Social cost of overtime per unit time(per second)	0.025
f _d	Overtime cost for drivers (TL per second)	0.0124
f _s	Regular time driver cost (TL per second)	0.0062
f _v	Fixed Vehicle Cost (TL)	200
Q	Vehicle Capacity (kg)	5500
K	Heating value of a typical diesel fuel(kilojoule/gr)	44
Ψ	Conversion factor(gram/second to liter/second)	737
T	Acceleration	0
θ	Road angle	0

not justify the additional working hours. Thus, have balanced durations between routes are aimed. The differences between the durations of the routes, denoted as e_{ij} where i and j are the last two nodes in two different routes are calculated, and s_i and s_j are the total time of a route. Include these values as social cost factors in the objective function in order to obtain more balanced routes. As a result, the social cost of overtime for drivers with the social cost of unbalanced routes ($f_a \sum_j o_j + f_e \sum_{i,j} e_{i,j}$) are considered as the social objectives to be minimized. Thus, the model is developed in a multi-objective setting as follows.

Objective functions:

$$\text{Min } Z_f = f_c FC + f_s \sum_j s_j + f_d \sum_j o_j + f_v \sum_{j \in N0} x_{0jk} \quad (2)$$

$$\text{Min } Z_e = f_b FC \quad (3)$$

$$\text{Min } Z_s = f_a \sum_j o_j + f_e \sum_{i,j} e_{i,j} \quad (4)$$

Constraints:

$$\sum_{j \in N, k \in K} x_{0jk} \leq m \quad (5)$$

$$\sum_{j \in N, k \in K} x_{j0k} \leq m \quad (6)$$

$$\sum_{j \in N, k \in K} x_{ijk} = 1, \forall i \in N0 \quad (7)$$

$$\sum_{i \in N, k \in K} x_{ijk} = 1, \forall j \in N0 \quad (8)$$

$$\sum_{j \in N, k \in K} f_{jik} - \sum_{j \in N, k \in K} f_{ijk} = q_i, \forall i \in N0 \quad (9)$$

$$q_j x_{ijk} \leq f_{ijk} \leq (Q - q_i) x_{ijk}, \forall (i, j) \in \mathcal{A}, k \in K \quad (10)$$

$$y_i - y_j + t_i + \sum_{n \in N_h} d_{ijn} v_{ijn} / S_{ijn} \leq M(1 - x_{ijk}), \forall i \in N, \forall j \in N0, i \neq j \quad (11)$$

$$y_j + t_j - s_j + \sum_{n \in N_h} d_{j0n} v_{j0n} / S_{j0n} \leq M(1 - x_{j0k}), \forall j \in N0 \quad (12)$$

$$a_i \leq y_i \leq b_i, \forall i \in N0 \quad (13)$$

$$\sum_{n \in N_h} v_{ijn} = x_{ijk}, \forall (i, j) \in \mathcal{A} \quad (14)$$

$$o_j \geq (s_j - RT), \forall j \in N \quad (15)$$

$$s_i - s_j \leq e_{i,j} + M(1 - \sum_k x_{j0k}), \forall (i, j) \in N0 \quad (16)$$

$$s_j - s_i \leq e_{i,j} + M(1 - \sum_k x_{i0k}), \forall (i, j) \in N0 \quad (17)$$

$$f_{ijk} \geq 0, \forall (i, j) \in \mathcal{A}, k \in K \quad (18)$$

$$y_i \geq 0, \forall i \in N \quad (19)$$

$$o_j \geq 0, \forall j \in N0 \quad (20)$$

The objective function contains financial, environmental and social objectives. (2) represents the fuel cost, regular and overtime costs for routes and fixed vehicle costs as the financial cost, (3) represents emissions associated with the fuel consumption amount as the environmental cost, and (4) represents the overtime cost of drivers, and the penalty cost for imbalances between route times as the social cost.

Constraints (5-7) and (8) ensure that all vehicles leave from and return back to the depot, visiting each customer only once. (9) and (10) calculate the carried load at each node and make sure that each customer's demand is satisfied. They also eliminate sub-tour formations in the solution. (11) and (12) calculate the service time and total route time, respectively. (13) ensures time window constraints. (14) guarantees that one-speed level is selected for each arc. (15) calculates the overtime for each route. (16) and (17) calculate the differences between route times. Finally, (18-20) are nonnegativity constraints.

METAHEURISTIC ALGORITHM FOR VRP WITH ALTERNATIVE LINKS

Showed that middle VRP can not be solved for exact methods. Because of that, it is needed to heuristic methods. In literature, there are many heuristic methods for VRP [56-63], used SA for different kind of routing problems [36,41,64-66], used ALNS algorithm to solve VRP. In this study, because of giving good solution for combinatorial optimization problems, and remarkable success of ALNS and SA algorithms in routing problems, both of them are used to solve the problems. SA is a stochastic search method. It is inspired by the annealing process of solids. Solids heat until a definite temperature, it is kept this temperature for a while, and it cools slowly. Different temperatures and cooling rate can be used. SA is introduced by [67,68] modified LNS by using different searching methods, and named ALNS. In ALNS algorithm, probability of selecting a neighborhood changes according to past performance in the searching process. The detailed structure of ALNS is explained in the algorithm.

A mathematical model is used to solve this problem. For 20, 50, 75 and 100 nodes, and different scenarios are tried to

solve. But, the best solution can not be found within a time limit (3 hours). In our study, SA, and ALNS does not have start with a feasible solution. If a solution does not ensure constraints, penalty cost is incorporated into the objective function for each instance of infeasibility. Therefore, with every iteration, the result is close to a feasible solution. Initial solutions are generated using the Cheapest Insertion algorithm.

The Cheapest Insertion Algorithm

To find initial solution The Cheapest Insertion Algorithm (TCIA) is used. When starting with a better solution than a random solution, a better solution can be obtained with fewer iteration numbers. In addition, in most of the scenarios covered in this problem, there are time window constraints. In addition, a good solution based on a fit-only objective function may be far from a solution with time window constraints. With TCIA, compliance with time window constraints is also ensured. Initially, the vehicle starts the route from depot, and ends at the depot. Randomly a node is selected, and inserted to the route, and the best alternative link and speed is selected in accordance with the objective function. Until all nodes are inserted to the routes, every node is inserted between node *i* and *j*, and the objective function is calculated for every *i-j* position, and the best position is selected. This obtained solution is the initial solution of SA and ALNS.

Simulated Annealing Algorithm

Input: Demand, speed, distance, time windows, service time, initial temperature (T), cooling rate (t), iteration number (Y), and initial route values.

```

 $X_{best} \leftarrow X_{now} \leftarrow X_{initial};$ 
 $T = T;$ 
While  $T < 1$ 
 $y = 1;$ 
for  $y = 1$  to  $Y$ 
Generate  $X_{new}$ 
    If  $X_{new} < X_{now};$ 
         $X_{now} \leftarrow X_{new};$ 
    Else if
         $v = e^{-(X_{new} - X_{now})/T};$ 
        Generate a random value(a)  $a \in [0, 1];$ 
        If  $a < v;$ 
             $X_{now} \leftarrow X_{new};$ 
        End If
    End If;
    If  $X_{now} < X_{best};$ 
         $X_{best} \leftarrow X_{now};$ 
    End If
 $y = y + 1;$ 
 $T = T * t;$ 
Output:  $X_{best}$ 
    
```

Adaptive Large Neighborhood Search

The ALNS algorithm has four main components in [69,70] and same format is followed.

Large neighborhoods: The current solution is changed by using seven neighborhood search procedures. These procedures are given in section 3.1. After modifying, the best link and speed levels are identified according to multi-objective functions. If there is any infeasibility due to capacity or time constraints, penalty cost is added to the objective function.

Adaptive search engine: In each iteration of the algorithm, the neighborhood search procedure is chosen using a roulette-wheel mechanism. Each neighborhood is assigned a weight, determining its probability of selection. After a certain iteration, the weight of neighborhood is changed according to past performance of the neighborhoods in selecting new current solutions. Let w_v be the weight of neighborhood v depending on its past performance. The neighborhood is selected with probability $w_v / \sum_{k=1}^{NoN} w_k$ (NoN: Number of Neighborhoods defined in algorithm).

Adaptive weight adjustment: Initially, each neighborhood has equal weight, and same probability of being selected. The iteration number of algorithm is divided into several phases that contains the same number of iterations named Ω . After finishing each phase, the weights of the neighborhoods w_v are updated as reported by their performance of the current phase. The performance of each neighborhood is represented by π_v for neighborhood v . After finishing each iteration, the mark of the neighborhood selected at that iteration is updated as below, where $\alpha_1, \alpha_2, \alpha_3$ are integer numbers that $\alpha_1 > \alpha_2 > \alpha_3$, x_{new} is the new solution, x_{best} is the best solution, x_{now} is the current solution, and z is the objective function to be minimized. Generally ALNS is used SA based algorithm.

```

if  $z_{new} < z_{best};$ 
     $\pi_v : \pi_v + \alpha_1$ 
else if  $z_{new} < z_{now};$ 
     $\pi_v : \pi_v + \alpha_2$ 
else if  $z_{new}$  is accepted as the next current solution by the SA criterion:
     $\pi_v : \pi_v + \alpha_3$ 
else:
     $\pi_v : \pi_v$ 
end if
    
```

The aim of this process is enhancing probability of selecting the neighborhood v with better solution. After finishing each phase the weights are updated as follows:

$$w_{v+1} = \begin{cases} w_{vj} & \text{if } o_{vj} = 0 \\ (1 - \eta)w_{vj} + \frac{\eta\pi v}{o_{vj}} & \text{otherwise} \end{cases}$$

o_{vj} is the number of times neighborhood v is selected in the current phase j , and η is a controlling factor that affects the current weights. In our algorithm, the length of phase is 200, 300, 400 and 500 for 20, 50, 75 and 100 nodes respectively. The update score $\alpha_1, \alpha_2, \alpha_3$ is 6, 4 and 2 respectively. The controlling factor η is 0.3. When η is greater than 0.3,

results are not of good quality. If η is less than 0.3, there will not be much difference between SA and ALNS.

Stopping criteria: Stopping criteria is defined as an cooling temperature.

Neighborhood Search Procedures

Different neighborhood structures are used in VRP to enhance the quality of the solution, [70] are used some destroy and repair procedures. Some of them are used in accordance with the problem.

Link-Speed Change: One route is selected, and one node is selected in that route. The best links and speed levels according to objective function between previous and next nodes are found and selected.

Interoute 1-0 move: As seen in Figure 3-A, different two routes are chosen, and two nodes are chosen each selected route. A node at the first route is taken out, and this node is added at the second route after the selected node.

Interoute 1-1 exchange: As seen in Figure 3-B, different two routes are chosen, and two nodes are chosen for each selected route. These nodes are swapped.

Interoute 1-1-1 rotation: As seen in Figure 3-C, different three routes are chosen, and three nodes are chosen for each selected route. These nodes are swapped.

Swap: As seen in Figure 3-D, one route is selected, and one node is selected in that route. Swap two nodes (before and after node of the selected node).

Interoute 2-opt move: Two different routes are selected, and two nodes are chosen from each route. All the nodes following the chosen nodes are then swapped between the routes. A new objective function (X_{new}) value is calculated. For example, routes are: 0-1-2-3-4-0, and, 0-5-6-7-8-0, after procedure new routes are: 0-1-2-7-8-0, 0-5-6-3-4-0.

Intraroute 2-Opt: As seen in Figure 3-E, one route is selected, and two-node is selected in that route. Those nodes between two nodes are reversed, and connected again. For example, the route is: 0-1-2-3-4-5-6-0. 2 and 5 are selected.

2-3-4-5 is reversed, turned to 5-4-3-2, and connected again. Finally, route is 0-1-5-4-3-2-6-0.

After implied neighborhood searching procedures, at new routes, the best link and speed levels between previous and next nodes are calculated and selected according to the multi-objective functions. According to link and speed values, the earliest starting service time is specified. If the starting service time exceeds the latest starting service time, the penalty cost is added to the objective function. Also, the new total demand of routes is calculated. If total demand exceeds the vehicle capacity the penalty cost is added to the objective function.

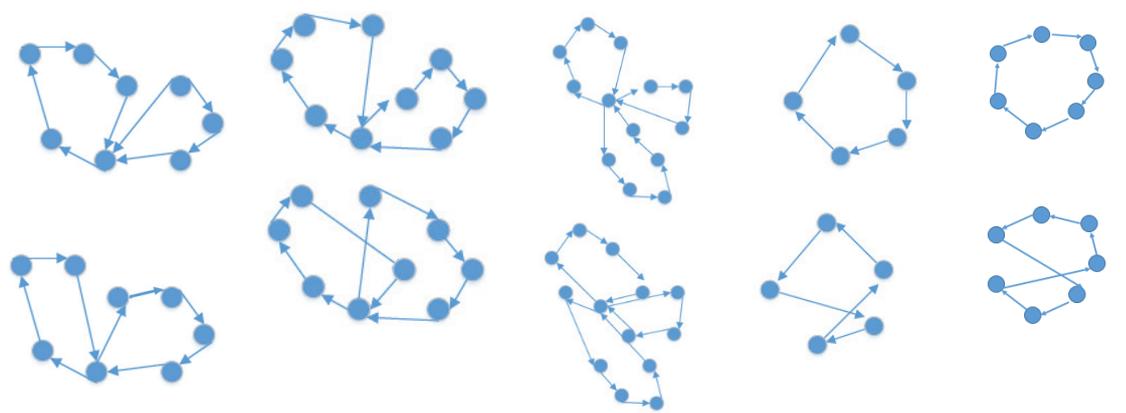
NUMERICAL RESULTS AND DISCUSSION

In this section, the computational results of the models are presented and explained above under different parameter settings. All the results in this section are obtained by solving the models using GAMS with the solver Cplex on a workstation with an Intel(R) Xeon(R) CPU E5-1650 v2 @ 3.50GHz, and 16 GB of RAM.

[11], find optimal solution of 10 nodes. But, for larger problems, optimal solutions can not be found within a reasonable time limit by using GAMS, Cplex solver. Because of that, in this study, 20, 50, 75 and 100 nodes are tried to solve using SA and ALNS.

In this case studies, a logistics company that serves different customers in Turkey at various locations and needs to deliver the products in the required time windows is considered. In all of models in this study, the same parameters are used as in the previous section and the data given in Table 1.

In addition to the real-life data given in Table 1, it is assumed that $RT=9$ hours, $t_i=20$ minutes for all nodes i , and $f_a=1.5$ Turkish Lira (TL) per minute. Different scenarios are considered as explained below and the results of each



A. 1-0 Move

B. Interoute 1-1 exchange

C. Interoute 1-1-1 rotation

D. Swap

E. Intraroute 2-Opt move

Figure 3. Neighborhood structures.

scenario for 20, 50, 75 and 100 nodes respectively are presented in Table 2, Table 3, Table 4 and Table 5.

The flexible time window is between 0 and 10 hours for all customers. For base case time windows there are 3-4 hours between early and late starting service times for these customers. In strict time windows, there are 2-3 hours between early and late starting time windows.

For SA, T is used as a 300, t is 0.9, and y depends on the customer dimension, 1200, 1400, 1500 and 1800, is used for 20, 50, 75 and 100 nodes respectively. For each sample, SA was run 10 times and the best result is given. One cycle for 20 nodes is completed in an average of 180 seconds. For 50,75 and 100 nodes, this time averages 310, 500, and 620 seconds, respectively.

For ALNS algorithm, T is used 900, t is 0.98, and y 200, 300, 400 and 500 for 20, 50, 75 and 100 nodes respectively. Since the weights of the neighborhood structures change after each phase, the number of iterations at each temperature is not increased much, the starting temperature of the algorithm is increased when comparing SA. When ALNS and SA are runned at the same iteration ALNS does not give close results to SA. Therefore, cooling temperature to stop is decreased, and iteration number is increased. When results does not change, it is stopped. Solution times of

ALNS are 200, 320, 600, 800 seconds for 20, 50, 75 and 100 nodes respectively.

When number of nodes increases, problem can not be solved with exact methods, and GAP becomes so large. In addition, increasing the cost multiplier greatly increases the value of GAP. For exact method, 3 hours time limit is used. GAP values obtained with GAMS-Cplex solver are 12.8%, 17.5%, 7.36%, 15.8%, 32%, 94.6%, 97%, 90% for scenarios of 20 nodes respectively. As the number of nodes increases, larger GAP values appear. In this situation, the quality of metaheuristic algorithms are not compared with these GAP values. All of the samples the best results are obtained with SA. Therefore, Relative GAP is calculated, and results are compared according to SA. Result of SA is expressed by z_1 , and to calculate relative gap of ALNS z_2 is expressed the result of ALNS, and to calculate GAP of CPLEX, z_2 is expressed the result of CPLEX. Relative GAP is given in equation 4.1.

$$Relative\ gap = \frac{z_2 - z_1}{z_1} \cdot 100 \tag{4.1}$$

A larger number of customers and present the results for N=20, N=50, N=75, and N=100 customers, results of SA, relative gap of SA, results of ALNS, relative gap of ALNS, results of Cplex, and relative gap of Cplex are given in Table 2, respectively.

Table 2. Results of 20 nodes

Scenarios	Results of SA	Relative Gap of SA (%)	Results of ALNS	Relative Gap of ALNS (%)	Results of Cplex	Relative Gap of Cplex (%)
Base case	2135	0%	2143	0.37%	2140	0.23%
Flexible time windows	1937	0%	1940	0.15%	1945	0.41%
Strict Time windows (STW)	2281	0%	2351	3.05%	2287	0.26%
Base case, and RT=8	2145	0%	2152	0.32%	2153	0.37%
Base case, and RT=6	2650	0%	2698	1.81%	2704	2.03%
Base case, RT=6 and $f_d=3$	33404	0%	34057	1.95%	33460	0.16%
Base case, RT=6 and $f_d=6$	63967	0%	65562	2.49%	63987	0.03%
Base case, RT=6, $f_d=6$ and $f_s=0.744$	118910	0%	119180	0.22%	127843	7.51%

Table 3. Results of 50 nodes

Scenarios	Results of SA	Relative Gap of SA (%)	Results of ALNS	Relative Gap of ALNS (%)	Results of Cplex	Relative Gap of Cplex (%)
Base Case	4065	0%	4642	14.2%	4170	2.58%
Flexible time windows	3616	0%	3765	4.13%	3675	1.62%
Strict time windows	4492	0%	4953	10.26%	4515	0.51%
Base case, and RT=8	4316	0%	4844	12.21%	4585	6.23%
Base case, and RT=6	5582	0%	6387	14.42%	5673	1.63%
Base case, RT=6 and $f_d=3$	107997	0%	118556	9.77%	118209	9.45%
Base case, RT=6 and $f_d=6$	202765	0%	222827	9.89%	211385	4.25%
Base case, RT=6, $f_d=6$ and $f_s=0.744$	329996	0%	355591	7.75%	390714	18.39%

Table 4. Results of 75 nodes

Scenarios	Results of SA	Relative Gap of SA (%)	Results of ALNS	Relative Gap of ALNS (%)	Results of Cplex	Relative Gap of Cplex (%)
Base case	5288	0%	5827	10.2%	5937	12.28%
Flexible time windows	5336	0%	5776	8.22%	5510	3.24%
Strict time windows	5993	0%	7040	17.4%	6088	1.58%
Base case, and RT=8	5896	0%	6692	13.4%	5989	1.57%
Base case, and RT=6	7002	0%	8542	21.9%	8701	24.2%
Base case, RT=6 and $f_d=3$	60462	0%	78181	29.3%	93449	54.5%
Base case, RT=6 and $f_d=6$	108752	0%	142316	30.8%	151305	39.1%
Base case, RT=6, $f_d=6$ and $f_s=0.744$	274577	0%	360975	31.1%	347961	26.7%

Table 5. Results of 100 nodes

Scenarios	Results of SA	Relative Gap of SA (%)	Results of ALNS	Relative Gap of ALNS (%)	Results of Cplex	Relative Gap of Cplex (%)
Base case	7450	0%	8599	15.42%	10285	38.05%
Flexible time windows	6982	0%	7797	11.6%	7859	12.56%
Strict time windows	7706	0%	9291	20.57%	10608	37.65%
Base case, and RT=8	7488	0%	8901	18.86%	9080	21.25%
Base case, and RT=6	8719	0%	11203	28.48%	12172	39.59%
Base case, RT=6 and $f_d=3$	80447	0%	107086	33.11%	182031	126.44%
Base case, RT=6 and $f_d=6$	132517	0%	191183	44.26%	343189	158.97%
Base case, RT=6, $f_d=6$ and $f_s=0.744$	329535	0%	425075	28.99%	601155	82.42%

When the exact solution method is compared with the heuristic methods, it is seen that the heuristic methods achieve better results in a shorter time than the exact solution method in every sample and scenario. In addition, all of the samples SA gives better results than ALNS. Solution time of ALNS and SA are close to each other. As seen in Table 2, relative gap of ALNS are close to results of SA. When looking at the results obtained with ALNS and Cplex for larger samples, it is seen that the relative gap value increases. Looking at the results in Tables 2-5, it is observed that the gap value obtained in scenarios with flexible time windows is lower than in other scenarios. The increase in cost parameters also increased the gap value. Generally, the best solutions found are obtained by SA. When the results obtained with ALNS and the exact solution method are compared, in some examples the ALNS, and in some examples the exact solution method give better results than other.

CONCLUSION

The vehicle routing problem on a network with multiple alternative links between nodes, considering the three main pillars of sustainability; financial, environmental and social

are analyzed. The optimal routes are determined to deliver the goods to a set of customers in order to minimize the delivery cost for the company, minimize the gas emissions to decrease environmental effects and improve the working conditions for drivers. A multi objective mixed integer linear model for this problem is solved with simulated annealing and adaptive large neighborhood solutions algorithms.

The shortest path or the fastest path may not always be chosen according to the objective functions and constraints discussed in the problem. When the financial, environmental and social objectives are considered together, it is seen that alternative links and speed levels are also chosen. Even though the optimal solution is obtained for small sized problems, as the problem size increases, the optimal solution could not be obtained in a reasonable time limit. Therefore, heuristic methods are used to solve problem in reasonable time limit. Simulated annealing is easily implemented, and in a short time, good solution can be attained. To compare quality of results, adaptive large neighborhood solutions is used to solve same problem. Examples of 20, 50, 75 and 100 node sizes are prepared and 8 scenarios are created using different parameters for each size. Different problem sizes and scenarios are solved, and for all of the samples, Simualted Annealing gives better results in a

shorter time than adaptive large neighborhood solutions. It is seen that as the problem size increases, the gap values increase in the results obtained with the exact solution method.

Time-dependent speed choices and durations can be incorporated into the model in the future. In addition, stochastic versions of this problem in which the durations or speeds are random due to unknown traffic conditions, can be analyzed. In recent years, algorithms using artificial intelligence have begun to be used to solve vehicle routing problems. Algorithms using artificial intelligence can also be used to solve this problem. The production and use of electric vehicles has increased in recent years. The energy consumption of these vehicles can be handled with the same objectives and constraints. Finally, several extensions of this vehicle routing problem such as using heterogeneous fleet of vehicles, multiple depots etc. can be analyzed in future studies.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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