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Multi-Objective Vehicle Routing Problem for a Mixed Fleet of Electric and Conventional Vehicles with Time Windows and Recharging Stations

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ABSTRACT

The vehicle routing problem as a challenging decision problem has been studied extensively. More specifically, solving it for a mixed fleet requires realistic calculation of the performance of electric and combustion vehicles. This study addresses a new variant of the vehicle routing problem for a mixed fleet of electric and combustion vehicles under the presence of time windows and charging stations. A bi-objective mixed-integer programming model is developed which aims at minimizing cost and pollution level concurrently. To accurately quantify travel quantities, such as fuel consumption, emission, and battery charge level, a set of realistic mathematical formulas are used. The model is first converted to a single-objective counterpart using the epsilon-constraint method and a simulated annealing algorithm is tailored to obtain Pareto optimal solutions. A discussion is also made on how the final solution can be selected from the Pareto frontier according to the design objectives. The presented framework can find a set of Pareto optimal solutions as a trade-off between cost and pollution objectives by considering different combinations of electric and combustion vehicles. It was shown that those solutions that involve more electric fleet than combustion fleet, lead to higher total costs and smaller emissions and vice versa.

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Description	Notation	Description	Notation
0	Depot	q_i	Load of the vehicle at node i [kg]
u_0	Start depot node	e_i	The earliest beginning of service time in Node i [h]
u_{n+1}	End depot node	l_i	The latest beginning of service time in Node i [h]
C	Set of customers	s_i	Service time of each node [h]
F	Set of Recharging stations	τ_i	The actual start of service time for node i [h]
F'	Subset with repetition of recharging stations	u_i	Vehicle's current load when it enters node i [kg]
$N = C \cup F'$	Set of all nodes (customers+ recharging stations)	SOC_i	Vehicle SOC when it enters node i [kWh]
$N_0 = N \cup u_0$	Set of nodes with start depot	x_{ij}^k	the binary variable of a vehicle of type k that travel from node i to node j
$N_{n+1} = N \cup u_{n+1}$	Set of nodes with end depot	f_D	Driver wage [$/h]
V_E	Set of electric vehicles	f_Y	Battery recharging cost per energy [$/kWh]
V_{IC}	Set of internal combustion vehicles	f_L	Internal combustion fuel cost per liter of fuel [$/L]
$V = V_E \cup V_{IC}$	Set of all the vehicles	ΔE_{ij}^k	Battery discharge of a vehicle with type k when travels from node i to node j [kWh]
Q	Vehicle Load capacity [kg]	ΔL_{ij}^k	Fuel consumption of the vehicle with type k when travels from node i to node j [L]
k	Vehicle type	$f_{O,E}$	Operating cost of EVs per traveled distance [$/km]
t_{ij}	Travel time between two nodes i and j [hours]	$f_{O,IC}$	Operating cost of ICVs per traveled distance[$/km]
m_{ij}	Distance between two nodes i and j [km]	p_{ij}	The total emission of the vehicle when traveled from node i to node j [g]
g^k	Battery recharging time-rate [kWh/h=kW]	d_i	Node i demand [kg]
Y^k	battery capacity [kWh]	q_i	Load of the vehicle at node i [kg]
d_i	Node i demand [kg]		

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1. INTRODUCTION

Massive consumption of fossil fuels by conventional internal combustion engine vehicles has caused numerous environmental problems including global warming and the energy crisis [1]. In the European Union (EU-27) report, greenhouse gas (GHG) emissions have decreased rapidly in recent years, reaching 24 % below 1990 levels and 31 % below 2020 levels. As a result, the EU has met its 2020 GHG reduction target [2]. Numerous studies in the context of vehicle routing problems (VRP) have considered environmental aspects of transportation systems through solving green VRPs (GVRPs), in which a fleet of alternative fuel vehicles (AFVs), including homogeneous and heterogeneous fleets, are considered. Homogeneous fleets contain vehicles that are all the same. While heterogeneous fleets which have been addressed by fewer than 15% of the relevant studies include different types of vehicles with different quantities such as capacity, operating costs, environmental effects, charging systems, battery capacity, and energy consumption [3]. Schneider et al. [4], Erdoğan and Miller [5] proposed the formulation of electric VRPs (EVRP) with a fleet of electric vehicles while considering time windows and battery recharging stations. Romet et al. [6] addressed a homogeneous autonomous electric vehicle routing problem with the depth-of-discharge (DOD) method to improve battery life and reduce costs of battery replacement. The DOD method showed an 18 times longer battery lifespan even though it increased the initial cost and battery capacity. Hiermann et al. [7], Macrina et al. [8] have addressed a mixed heterogeneous fleet of conventional and electric vehicles. Minimization of air pollution is another objective considered in some other works in GVRP. Bektaş and Laporte [9] solved an emission routing problem by minimizing the travel distance and greenhouse emissions, fuel consumption, and travel times. Zhou et al. [10] presented a multi-depot heterogeneous vehicle routing problem in which average risk and costs were reduced by 3.99% and 2.01%, respectively, with an acceptable risk compared to a half-open multi-depot homogeneous vehicle routing problem.

To calculate different quantities in GVRP (including but not limited to fuel consumption, emission, and battery energy consumption), different mathematical formulas have been utilized in the literature. Most of the works assumed that the energy consumption (i.e., fuel consumption of combustion fleet, and electrical energy of electric fleet) is a function of traveled distance [4, 5]. On the other hand, some other works are considered more realistic models. Davis and Figliozzi [11] assumed that energy consumption also depends on the average vehicle speed during the trip. Goeke and Schneider [12] and Perera [1] formulated a more complicated model of fuel consumption that considers speed, road gradient, and vehicle load in the model structure. Goeke and Schneider [12] used data from Global Positioning System (GPS) to predict energy consumption in simulation environments. Sivagnanam et al. [13] utilized real GPS data to predict electricity consumption based on several factors, including vehicle locations, traffic, elevation, and weather data.

Most studies in GRVP have considered a single objective including traveled distance [5], cost [7, 14], emission [9] and fuel consumption [15, 16]. Sivagnanam, et al. [13] considered an extra objective of emission as a constraint on the solution space. To allow the evaluation of possible trade-offs between multiple objectives, some other works have formulated multi-objective optimization models. Ghannadpour and Zarrabi [17] considered customers' requirements for servicing as an extra objective in a multi-objective problem. Abad et al. [18] proposed a bi-objective model to minimize cost and fuel consumption. Androutsopoulos and Zografos [19] formulated and solved a bi-objective path-dependent VRP to minimize time and load. Goeke and Schneider [12] considered three objectives including the traveled distance, energy consumed, and total costs.

Considering two objectives of cost and emission for a mixed fleet of electric and combustion engines requires multi-objective optimization programming to allow an evaluation of possible trade-offs between different objectives. On the other hand, quantifying each objective requires evaluating different travel quantities, such as fuel consumption and emission. The travel quantities are dependent on various vehicle parameters and states, including size, mass, engine characteristics, vehicle speed, battery state of the charge (SOC), etc. which may change by the vehicle type, assigned route, current load, environmental conditions, etc. Therefore, the calculation of the travel quantities requires using realistic mathematical models. In this work, a novel multi-objective VRP for a mixed fleet of combustion and electric vehicles with the presence of time windows and recharging stations is formulated and solved. The main contributions of this work are as follows:

(I) A new variant of bi-objective VRPs with a fleet of mixed electric and conventional vehicles under the presence of recharging stations and time windows is formulated.

(II) A set of realistic mathematical formulas are used to accurately quantify required travel-dependent quantities, including fuel consumption, electric energy consumption, and emission.

The rest of this paper is organized as follows. In section 2, a mixed-integer formulation is proposed for the problem. Section 3 presents the solution procedure and the developed general optimization framework. Section 4 presents the results and discussion for a set of benchmark instances. Finally, section 5 provides concluding remarks and future avenues for further research.

2. PROBLEM DESCRIPTION & FORMULATION

The targeted routing problem follows a classic VRP formulation with some additions including time windows and recharging stations. The problem is to start from a depot node u_0, serve a set of customers C once using a mixed fleet of vehicles with type K within acceptable time windows, and return to the node u_0, while a set of recharging stations F is available. The proposed Multi-Objective Vehicle Routing Problem for a Mixed Fleet of Electric and Conventional Vehicles with Time Windows and Recharging Stations (MF-EVRPTW) must satisfy the following additional conditions or assumptions:

- Each vehicle is fully recharged after visiting a recharging station.
- Every customer is visited exactly once
- Every route starts from and ends at the depot node u_0.

The goal of this paper is to propose and solve a multi-objective problem in which the two conflicting objectives of cost and emission are minimized.

The problem under study in this paper is an extension of work conducted by Schneider et al. [4], Hiermann et al. [20]. The proposed model seeks to find an optimal routing for a mixed fleet of EVs and ICVs under the minimization of cost and emission. The Nomenclature table summarizes different parameters and variables that are used in the model.

The optimization problem is formed as a mixed-integer program, which involves two objectives and multiple constraints. The first objective is to minimize the total cost as the summation of the driver cost, energy consumption cost, and operation cost, which is calculated as follows:

$$\text{minimize} \quad C = C_D + C_E + C_O = f_D \left\{ \sum_{i\in N_0} \sum_{j\in N_{n+1}, i\neq j} (t_{ij} + s_i) x_{ij}^k + \sum_{i\in F'} \sum_{j\in N_{n+1}, i\neq j} \left(\frac{(1-SOC_i^k)Y^k}{g^k} \right) x_{ij}^k \right\} + \sum_{k\in V_E} \sum_{i\in N_0, j\in N_{n+1}, i\neq j} (f_Y \Delta E_{ij} + f_{O,E} m_{ij}) x_{ij}^k + \sum_{k\in V_{IC}} \sum_{i\in N_0, j\in N_{n+1}, i\neq j} (f_L \Delta L_{ij} + f_{O,IC} m_{ij}) x_{ij}^k \tag{1}$$

The second objective is to minimize the total emission of the fleet, which is calculated as follows:

$$\text{minimize} \quad P = \sum_{k\in V_{IC}} \sum_{i\in N_0, j\in N_{n+1}, i\neq j} p_{ij}^k . x_{ij} \tag{1}$$

Additionally, to satisfy the problem requirements, multiple constraints are considered.

$$x_{ij}^k \epsilon \{0,1\} \quad \forall k\epsilon V \; i\epsilon N_0, j\epsilon N_{n+1}, i \neq j \tag{3}$$

First of all, constraints (3) define the binary decision variables.

$$\sum_{k\in V} \sum_{j\in N_{n+1}, i\neq j} x_{ij}^k = 1 \quad \forall i \in C \tag{4}$$

$$\sum_{k\in V} \sum_{j\in N_{n+1}, i\neq j} x_{ij}^k \leq 1 \quad \forall i \in F' \tag{5}$$

$$\sum_{i\in N_{n+1}, i\neq j} x_{ji}^k - \sum_{i\in N_0, i\neq j} x_{ij}^k = 0 \; ; \; \forall j \in N, \forall k \in V \tag{6}$$

There are multiple constraints regarding visiting the nodes; constraints (4) ensure that every customer is visited by one vehicle exactly once. Constraints (5) enforce that a recharge station does not necessarily need to be visited. Constraints (6) guarantee that the number of incoming arcs into a node is equal to the number of outgoing arcs from it.

$$e_i \leq \tau_i \leq l_i \quad \forall i \in N_{0,n+1} \tag{7}$$

$$\tau_i + (s_i + t_{ij}) x_{ij}^k - l_0 (1 - x_{ij}^k) \leq \tau_j \quad \forall k \in V, \forall i \in C, \forall j \in N_{n+1}, i \neq j \tag{8}$$

$$\tau_i + t_{ij} x_{ij}^k + \frac{(1-SOC_i^k)Y^k}{g^k} - \left(l_0 + \frac{Y^k}{g^k} \right) (1 - x_{ij}^k) \leq \tau_j \quad \forall k \in V_E, \forall i \in F, \forall j \in N_{n+1}, i \neq j \tag{9}$$

Additionally, constraints (7)-(9) enforce the timing to visit nodes; constraint (7) ensures that the start of service time τ_i must be within the time window $[e_i, l_i]$ of node i; constraints (8) guarantee that for the start of service time of customer node j who is visited after node i must be later than the start of service time plus the service time of customer node i plus the travel time from node i to node j. Constraints (9) are the same as constraints (8) but for recharging stations; they consider the recharging time of EVs as a function of the remaining battery SOC when it enters a charging station. Note that to maximize the range of electric vehicles and to simplify the problem, the battery is enforced to be fully charged at the exit of recharging stations.

$$q_j^k \leq q_i^k - d_i x_{ij}^k + Q^k (1 - x_{ij}^k) \quad \forall k \in V, \forall i \in N_0, \forall j \in N_{n+1}, i \neq j \tag{10}$$

$$0 \leq q_j^k \leq Q^k \quad \forall k \in V, \forall j \in N_{0,n+1} \tag{11}$$

There are some constraints regarding the load of the fleets. Constraints (10) ensure that a load of a vehicle in the node j depends on the initial load when visiting the previous node i plus the demand of node i. Constraints (11) enforce that a vehicle's load never exceeds the maximum capacity.

$$0 \leq SOC_j \leq SOC_i - \Delta SOC_{ij}^k . x_{ij}^k + (1 - x_{ij}^k) \quad \forall k \in V_E, \; \forall i \in N_0, \; \forall j \in N_{n+1}, i \neq j \tag{12}$$

$$SOC_0^k = 1 \quad \forall k \in V_E \tag{13}$$

According to the SOC of batteries, constraints (12) ensure that the battery SOC at the next node j depends on the SOC of node i plus battery discharge by traveling from node i to node j. Constraint (13) ensures that the battery is fully charged when exiting the depot.

3. SOLUTION PROCEDURE

According to the bi-objective constrained nature of the problem, we suggest a two-step solution method.

Step 1: Conversion to Single-objective Model
The epsilon-constraint method is used to obtain Pareto front solutions where the first objective function is considered as the main objective, and the second objective function is moved to the constraints of the problem:

$$\begin{aligned} &\min C \\ &\text{s.t.} \\ &\sum_{k\in V}\sum_{i\in N_0, j\in N_{n+1}, i\neq j} P_{ij}^k . x_{ij}^k \leq \varepsilon \\ &\text{Constraints in } (4)-(3) \end{aligned} \tag{14}$$

Step 2: Unconstrained Formulation
Many constraints exist in the model (14) which bound the solution space. By using the penalty function method, the constraints are treated as soft constraints for two reasons; First, it increases the chance of finding a significantly better routing solution with some extra cost on some penalties, such as being late for a customer or putting some extra load on a vehicle. This brings the opportunity to the user to deal with trade-offs between violating some of the constraints while decreasing the overall cost or emission significantly. Second, it lets the simulated annealing (SA) method keep answers that are almost optimal but slightly violate some of the constraints; therefore, a neighborhood solution that does not violate a constraint is likely to be selected in later iterations of the SA algorithm, which leads to finding a better solution at the end of the optimization iterations. SA is a common metaheuristic local search algorithm known as one of the most preferred methods applied for solving VRPs. In SA algorithm, the annealing process involves heating metal, glass, or crystal alloys above their melting points and cooling them slowly to achieve perfect crystal structures. In metaheuristics, SA can escape the local optimum by using hill-climbing moves to decrease the temperature parameter and the probability of acceptance of a worse objective function. There are some papers that describe more details of this method [21]. Accordingly, the penalty functions associated with the constraints (14) are as follows:

$$CV = \underset{k\epsilon V}{\text{mean}}\left\{\max\left(\frac{\sum_{i\epsilon c} q_i}{C_k} - 1\right)\right\} \tag{15}$$

$$TWV = \underset{i\in N_{n+1}}{\text{mean}}\left\{\max\left(0, 1-\frac{\tau_i}{e_i}, \frac{\tau_i}{l_i} - 1\right)\right\} \tag{16}$$

$$SOCV = \underset{i\in N_{n+1}}{\text{mean}}\{\max(0, -SOC_i, SOC_i - 1)\} \tag{17}$$

$$PV = \max\left(0, \left(\frac{p}{\varepsilon} - 1\right)\right) \tag{18}$$

in which CV, TWV, SOCV, and PV correspond to the constraints of the vehicle capacity, time windows, battery SOCs, and the epsilon, respectively. As a result, Equation (14) becomes an unconstrained problem with the following single objective function:

$$\begin{aligned} &minimize\ Z = C(1 + \beta_1 PV + \beta_2 CV + \beta_3 TWV + \\ &\beta_4 SOCV) = \Bigg(f_D\left\{\sum_{i\in N_0}\sum_{j\in N_{n+1}, i\neq j}(\Delta t_{ij} + s_i)x_{ij}^k + \right. \\ &\left.\sum_{i\in F'}\sum_{j\in N_{n+1}, i\neq j}\left(\frac{(1-SOC_i^k)Y^k}{g^k}\right)x_{ij}^k\right\} + \\ &\sum_{k\in V_E}\sum_{i\in N_0, j\in N_{n+1}, i\neq j}\left(f_Y \Delta E_{ij} + f_{O,E} m_{ij}\right)x_{ij}^k + \\ &\sum_{k\in V_{IC}}\sum_{i\in N_0, j\in N_{n+1}, i\neq j}\left(f_L \Delta L_{ij} + f_{O,IC} m_{ij}\right)x_{ij}^k\Bigg)\Bigg(1 + \\ &\beta_1 \max\left(0, \left(\frac{p}{\varepsilon} - 1\right)\right) + \beta_2 \underset{k\epsilon V}{\text{mean}}\left\{\max\left(\frac{\sum_{i\epsilon c} q_i}{C_k} - \right.\right. \\ &\left.\left.1, 0\right)\right\} + \beta_3 \underset{i\in N_{n+1}}{\text{mean}}\left\{\max\left(0, 1-\frac{\tau_i}{e_i}, \frac{\tau_i}{l_i} - 1\right)\right\} + \\ &\beta_4 \underset{i\in N_{n+1}}{\text{mean}}\{\max(0, -SOC_i, SOC_i - 1)\}\Bigg) \end{aligned} \tag{19}$$

where $\beta_1, \ldots, \beta_4$ denotes the weights associated with each penalty function. Note that all the penalty functions are designed to be between zero and one so all the weights can be chosen in the same order.

3. 1. Realistic Evaluation of Travel Information

To quantify the travel information, including fuel consumption, emission, and battery charge level, the models in ADVISOR are used [22]. ADVISOR contains realistic physics-based mathematical models for the vehicle's drivetrain components that can compute the performance of the vehicle in a driving scenario in the simulation environment accurately. Figure shows the ADVISOR model for the internal combustion engine drivetrain and electric drivetrains, respectively. Given the driving cycle as the input, ADVISOR estimates the fuel

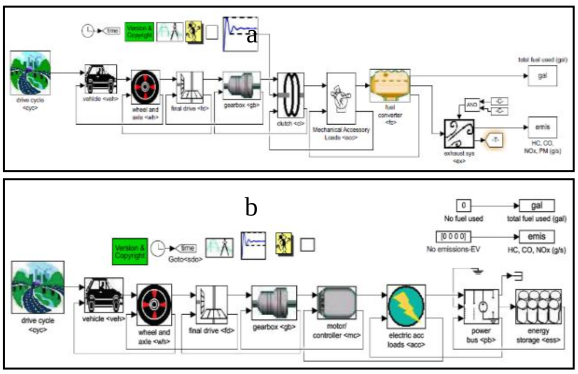

Figure 1. Drivetrain Model of combustion (a) and electric (b) vehicles in ADVISOR [22]. The models in the simulation environments provide vehicle performance such as fuel combustion, electrical energy consumption, and emission

consumption, change in the battery state of the charge, and amount of emission, which are needed to evaluate the cost function in Equation (19).

$$d_{ij} = \int_0^{t_f} V(t)dt, \quad (20)$$

where t_f is the duration of the trip which is determined by the driving cycle.

The fuel consumption, emission, and state of charge are functions of the vehicle's parameters, including the vehicle's mass, the type of the drivetrain and its components as well as the initial condition of the vehicle at the start of the trip. The vehicle's mass can vary not only from one trip to another but also during a single trip due to unloading at customer nodes along a single trip. The drivetrain of the vehicle contains various components, which all influence the overall fuel consumption, emission, and battery SOC change. Finally, the vehicle's initial condition affects the entire performance of the vehicle over the driving cycle since it changes the working points of the drivetrain's components which result in different efficiency of each component.

To address the variability of the vehicle's performance in different conditions, the vehicle's model is simulated in ADVISOR in offline mode for a discrete multidimensional grid of different driving cycles, vehicle types, vehicle loads, and initial conditions. The result is a 3D tensor for fuel consumption denoted by ΔL, a 3D tensor for the emission denoted by P, and a 4D tensor for SOC change denoted by ΔSOC:

$$\begin{aligned} &\Delta L = \Delta L(ij, K, L) \\ &P = P(ij, K, L) \\ &\Delta SOC = \Delta SOC(ij, K, SOC_0, L), \end{aligned} \quad (21)$$

where ij is the route path (which determines the driving cycle), K is the vehicle's type, L is the vehicle's load during the trip, and SOC_0 is the initial state of the charge of the battery at the start of the trip. Note that the amount of emission is nonzero for the combustion fleet and it is zero for the electric fleet while the SOC change is only applicable to the electric fleet.

After constructing the multidimensional grid of Equation (21) offline, it is then used as the database during the vehicle routing optimization process. This is very beneficial since there is no need to run an ADVISOR simulation during the optimization loop of solving the routing problem, which can significantly reduce the computational load of the optimization problem.

Given the fact that the multidimensional grid in Equation (21) is discrete if a load of vehicles or state of charge of a vehicle is between two discrete values of the grid, a linear interpolation approach is used over the multidimensional grid to calculate the fuel consumption, emission and the SOC change of a trip from one node to another.

3. 2. SA Algorithm The SA algorithm is tailored to find an optimal or near-optimal solution to the proposed VRP problem. The main advantage of SA is using exchange methods to produce new neighbors stochastically and search in a wider domain for better solutions to avoid being trapped in local extremums. The SA algorithm involves an outer loop for increasing initial temperature and an inner optimization loop. The iterative process continues until reaching the lowest limit of temperature or realizing the predetermined number of iterations.

3. 2. 1. Solution Vector Definition The solution vector is defined as a vector of an ordered sequence of customers' ids. A delimiter technique is used within the solution vector to create the distinction between customers that are allocated to different vehicles. In addition to the customers, recharging stations need to be added to the solution vector. However, the required number of recharging stations is not known initially since they are not all mandatory to be visited according to the assumption of the problem. To select and place recharging stations along the customer route, a subset of stations is randomly placed along the customers' routes. Afterward, in each iteration, the number of recharging stations is reduced to avoid unnecessary visits to redundant recharging stations, until the best and most feasible solution vector is obtained.

3. 2. 2. SA Exchange Methods In the SA process, the current solution vector needs to be replaced by its neighboring stochastically. Several different exchange methods can be implemented to generate neighborhoods. In this paper, four exchange methods, including swapping, insertion, reversion, and elimination, are used, where two index positions i, and j (i.e. two distinct numbers smaller than the length of the solution vector n where $i_1 < i_2 < n$) are randomly selected as the place in the solution vector to change the current solution vector under these four methods [23]. The swap operator is almost similarly to insertion whereas two distinct numbers change their position in the string vector. Inversion acts similar to the swap operator, except that in addition to swapping, it also puts the numbers between the two numbers reversely on the string vector. Due to the presence of a random insertion operator, the number of recharging stations added in each iteration of the algorithm may be surplus. For this reason, the removal operator was used such that with a low probability in each iteration of the algorithm, the number of recharging stations was reduced to end up with a lower cost while the solution remains feasible.

3. 2. 3. Overall Framework Figure 2 illustrates the proposed framework to solve the VRPs. According to this figure, the framework consists of three main layers; an offline layer (denoted in red) which calculates the required tensors of travel information by ADVISOR which are needed for the other layers; an outer optimization layer (denoted in yellow) that uses the ε-constraint approach to find the Pareto optimal solution; an inner optimization layer based on SA to find the optimal solution for each given $\boldsymbol{\varepsilon}$. After reaching the SA stop condition for all values of epsilon, the Pareto frontier will be obtained as the final answer.

4. RESULTS AND DISCUSSION

In this section, the results of the proposed framework for solving the routing problem of a set of benchmark instances are presented. The benchmark instances are based on the Solomon modified data [4], which extends 56 VRPTW instances with a mixed fleet and recharging stations. To evaluate the solution method presented in this research, a sample problem of the transportation system has been set up. Table 1 summarizes the instances of the problem.

Accordingly, there are 15 customers with a time window between 0 to 8, 5 charging stations, and a fleet of 6 vehicles including 3 conventional and 3 electric vehicles. The algorithm was programmed in MATLAB and executed with the hardware of Intel(R) Core (TM) i7-3770K CPU, 3.5 GHz with 8 GB of RAM.

The mixed fleet contains two types of conventional and electric vehicles, including Navistar eStar Electric

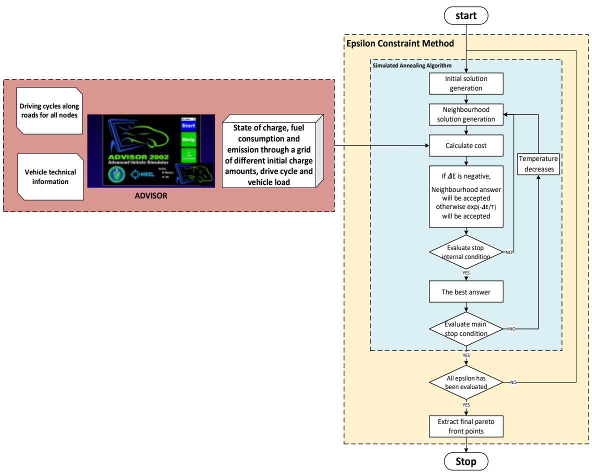

Figure 2. The schematic diagram of the proposed optimization framework to solve the VRPs. There are three main layers; an offline layer (red) containing travel information provided by the advisor. An outer optimization layer (yellow) illustrated a Pareto optimal solution using an Epsilon constraint. An inner layer (blue) demonstrates the simulated annealing process

TABLE 1. The details of the problem instances, including customers and recharging stations

Code	Type	Demand (kg)	Earliest starting	Latest starting	Service
			Time (hours)		
C01	Customers	100	0	8	0.25
C02		100	0	8	0.25
C03		200	0	8	0.5
C04		100	0	8	0.25
C05		100	0	8	0.25
C06		300	0	8	0.75
C07		100	0	8	0.25
C08		100	0	8	0.25
C09		100	0	8	0.25
C10		300	0	8	0.75
C11		200	0	8	0.5
C12		400	0	8	1
C13		300	0	8	0.75
C14		100	0	8	0.25
C15		100	0	8	0.25
S16	Recharging stations	0	0	8	0
S17		0	0	8	0
S18		0	0	8	0
S19		0	0	8	0
S20		0	0	8	0

Truck and ISUZU NKR 77- 5.2 Ton, whose specifications are summarized in Tables 2 and 3, respectively.

Table 4 includes all values of different cost parameters which are based on the research performed by Lin et al. [24], Feng and Figliozz [25]. Table 5 summarizes the economic data and assumptions of electric and conventional vehicles based on the work of [24], Feng and Figliozz [25].

TABLE 2. Specification of Navistar eStar- Electric Truck [26]

Parameters	Amount
Net weight (kg)	3185
Load capacity (kg)	2313
Battery capacity (kWh)	80
Battery voltage (V)	300
Electric motor max power (kW)	70
Max range (km)	160
Air Drag Coefficient	0.5

TABLE 3. Specifications of Isuzu ELF truck N [27]

Parameters	Amount
Net weight (kg)	3185
Load capacity (kg)	2313
Engine capacity (CC)	3000
Max speed (km/h)	102
Tank capacity (L)	75
Air Drag Coefficient	0.7

TABLE 4. Considered cost parameters

Cost parameter	Description	Amount	Reference
f_D	Driver wage during working hours ($\$/h$)	16.43	
f_Y	Battery charging cost ($\$/kWh$)	0.12	[24]
f_L	Combustion fuel cost ($\$/L$)	1.03	
$f_{O,E}$	Electric vehicle operating cost ($\$/km$)	0.40	[25]
$f_{O,IC}$	Combustion vehicle operating cost ($\$/km$)	0.14	

TABLE 5. Economic data and assumptions of vehicles (maximal age=10 years, rate of interest=6.5%) [25]

Vehicle	Acquisition Cost ($)	Utilization (km/year)	Salvage value ($)
Navistar	149000	41840	58451
Isuzu	50000	41840	12803

In a real simulation, the real values can be taken into account, and the preferred output can be obtained using navigational and surveying equipment such as a Global Positioning System (GPS) to predict energy consumption and provide data based on the route of the vehicles in the simulation environments. Among 20 standard drive cycles that are selected as the benchmark, one is assigned randomly to every possible route between all the binary combinations of nodes. It is also assumed that the two types of vehicles in the fleet follow the same driving cycles between two nodes since the selected vehicle types fall in the same vehicle class with comparable specifications. The speed profiles of the selected driving cycles are presented in the appendix in Figure A1.

Table 6 summarizes the optimal hyperparameters of the SA method obtained by the Taguchi L16 method.

To obtain the Pareto front, the epsilon changes from 1500 to 0 with the step of 75. The obtained Pareto frontier points are shown in Figure 3. In this figure, the highest amount of costs and emissions belong to the lowest value of emissions (point 1) and costs (point 13), respectively. In fact, it depicts the effectiveness of using a mixed fleet of electric and conventional vehicles. The routing associated with the Pareto frontier points is summarized in Table 7. According to this table, among the points that are in the Pareto frontier, the solution points that have less emission correspond to the routings in which more nodes are assigned to the electric vehicles.

On the other hand, the points that have more emissions correspond to the routings which involve using more combustion vehicles. To investigate the cost of the Pareto points in detail, Table 7 and Figure 4 summarize the break-down of the total cost, in terms of fuel consumption cost, the annual operating cost, driver of fuel consumption has increased with the increase in wages, the recharging cost, the cost of a battery kilowatt-hour, and the amount of emission. Accordingly, the cost number of combustion vehicles. The operating cost of the first Pareto point is higher than others, which means that more use of the electric fleet would result in more operational costs.

According to the priority of the design objectives, one can choose the final solution among the Pareto front points. If the cost is of the highest priority, using more combustion vehicles is more cost-effective compared to the electric fleet. On the other hand, with more priority on reducing the total emission, allocation of fewer combustion vehicles to customers is desirable.

According to the results, using more electric vehicles results in far less emissions, despite the total costs increase. The increase in the total costs is due to the increase in operating costs and the driver's wage. There is an increase in the total costs because the electric vehicle has traveled along the route for a longer period of

TABLE 6. Simulated Annealing hyper-parameters obtained by Taguchi L16 method

SA parameters	Amount
Initial temperature	100
Iteration of each temperature	100
Temperature decrease factor	0.1

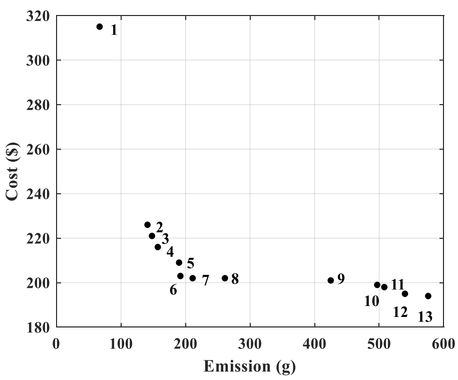

Figure 3. Pareto frontier solutions of the bi-objective routing problem

TABLE 1. Details of the Pareto frontier points. For each solution, combustion and electric fleets are assigned to different customers which results in different emissions and total costs

	Z_2	Z_1	Allocated customers					
Pareto Point	**Emission (g)**	**Cost ($)**	**Combustion Fleet**			**Electric Fleet**		
1	66.8	315	-	-	1	8-11-5-9-7-15-13-2-4	6-3-14	12-10
2	141	226	-	1	11-8	4-5-13-9-10-15-3-7	14-12-6-2	-
3	148	221	-	1	11	4-5-7-3-15-10-9-13-8	4-12-6-2	-
4	157	216	-	4	11-8	2	7-15-3-6-1-12-14-10-9-13-5	-
5	190	209	-	5-4	8	2-6-1-12-10-13-9-15-3-7	11-14	-
6	192	203	-	4	8	2-6-1-3-15-7-5-13-9-10-12-14	11	-
7	211	202	-	7	11	2-6-5-4	14-10-12-1-3-15-9-13-8	-
8	261	202	-	2	2-5-7	14-10-12-1-6-3-15-9-13-8	11	-
9	425	201	-	11	3-15-9-13-8	14-10-12-1-6-2	4-5-7	-
10	497	199	-	4-5-7-15-3	8-13-9	11	14-10-12-1-6-2	-
11	508	198	-	7	4-5-13-9-8	14-12-10-15-3-1-6-2	11	-
12	540	195	-	8-13-9-15-3	4-5-7	14-10-12-1-6-2	11	-
13	576	194	-	4-5-13-9-15-3-7	8	11	14-10-12-1-6-2	-

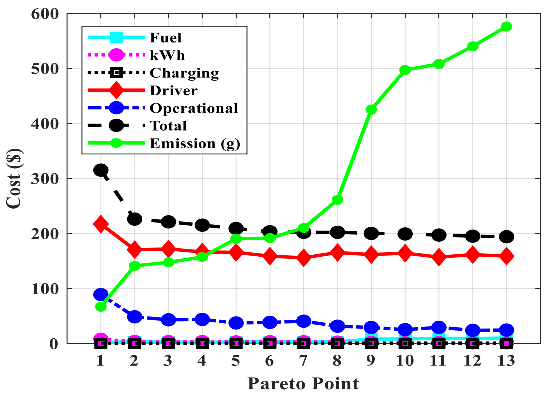

Figure 4. The breakdown of cost for the Pareto frontier points along with the emission

time (using the charging stations). Despite a decrease in the total cost, the number of conventional vehicles and emission increase along the route. A combination of the conventional and electric fleet can provide a solution that is balanced in terms of cost and emission. This can be achieved by selecting a middle point of the Pareto frontier, such as point 7 or point 8. In terms of cost, there is a small difference between these two points. This is because the operational cost of point 8 is less than point 7 while the driver cost is more (Figure 4 and Table 8).

The main difference between them is the amount of emission, which is due to the larger number of allocated combustion vehicles for point 8. Accordingly, one can select point 7 as the balanced final solution of the Pareto frontier.

TABLE 8. The cost breakdown and the emission values of the Pareto frontier solutions

Pareto Point	**Fuel Cost ($)**	**Battery kWh Cost ($)**	**Charging Cost ($)**	**Driver wage ($)**	**Annual Operational Cost ($)**	**Total Cost ($)**	**Emission (g)**
1	1.990	7.60	0	217	88.8	315	66.8
2	2.93	3.70	0	170.5	48.5	226	141.0
3	2.50	3.44	0	171.7	43.0	221	147.5
4	1.940	3.50	0	166.4	43.7	215	157.2
5	2.96	2.88	0	165.6	37.3	209	190.3
6	2.74	3.23	0	158.7	38.3	203	191.5
7	2.82	3.18	0	155.7	40.5	202	210
8	2.99	2.44	0	165.3	31.4	202	261
9	8.10	1.850	0	161.5	29.1	200	425
10	8.19	1.210	0	164.2	25.1	199	497
11	9.66	1.670	0	156.9	29.3	197	508
12	8.86	1.210	0	161.5	23.9	195	540
13	10.04	1.210	0	158.7	24.4	194	576

5. CONCLUSION

In this research, a new variant of the VRPs is formulated for a mixed fleet of vehicles to optimize cost and emission. Additionally, time windows and recharging stations were considered in the presented framework. In addition to considering the multi-objective nature of the routing problem, the proposed framework uses a set of realistic mathematical models to evaluate different travel quantities, including fuel consumption, change in the state of charge, and emission. To solve the resulting optimization model, the epsilon-constraint and simulated annealing methods were used. It was shown that those solutions that involve more electric fleet than combustion fleet, lead to higher total costs and smaller emissions and vice versa. Finally, a discussion was made on how the final solution can be selected from the Pareto frontier according to the design objectives.

Some improvements can be considered for future research. First, the electric fleet was always fully charged in this study. Therefore, taking partial charging into account can improve the results of this problem. This modified way may decrease the total cost of the electric fleet by lowering the charging cost and the driver cost. Second, based on the SA limitations, results may be improved using other well-known metaheuristic methods such as adaptive large neighborhood search. Furthermore, the proposed framework can be tested for a set of real instances to further investigate the effectiveness of the framework in practice.

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Appendix A:

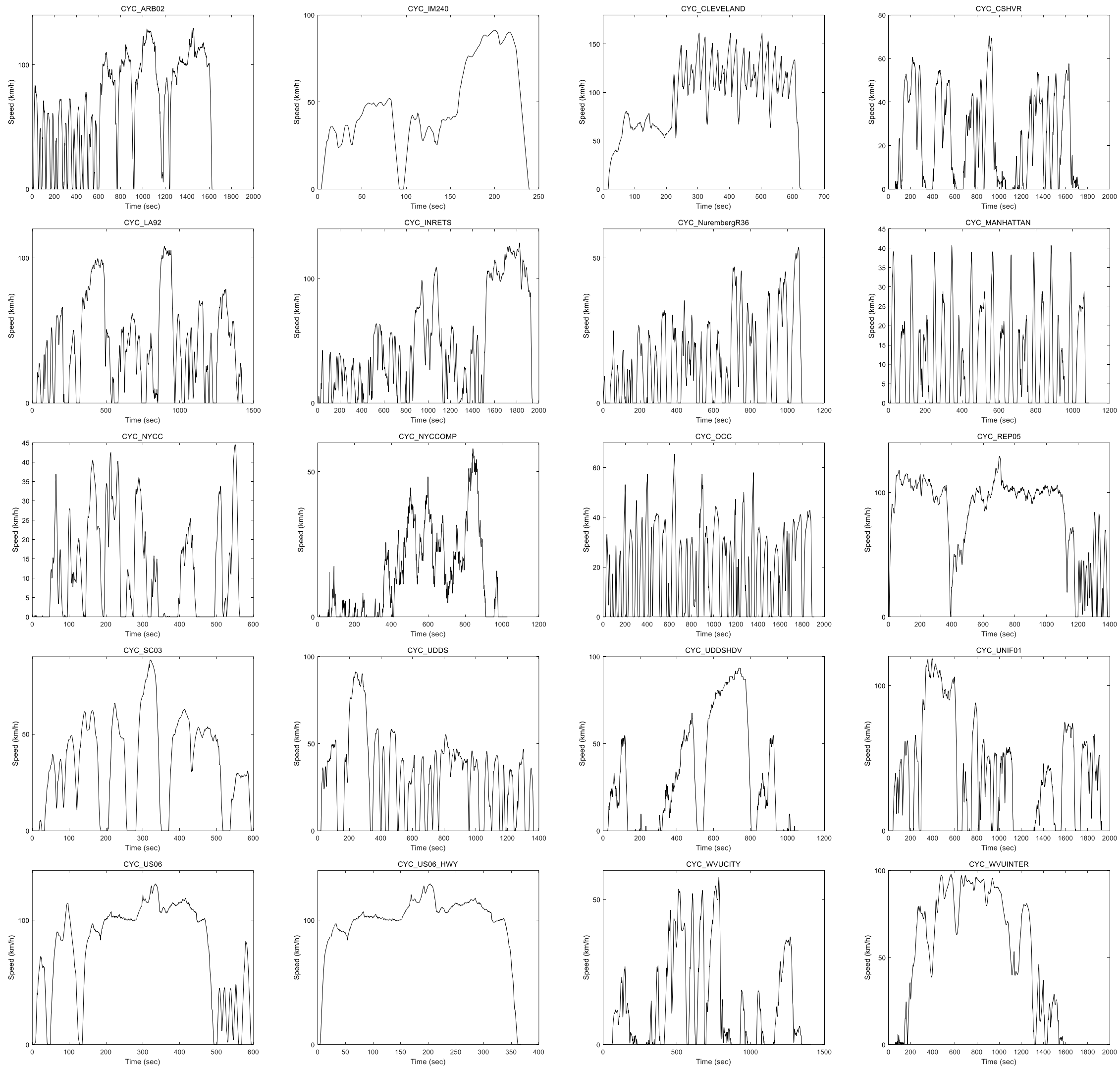

Figure A1. Speed profile of the driving cycles used for the problem instances

Persian Abstract

چکیده

حل مساله مسیریابی وسیله نقلیه، همچنان یک موضوع چالشی مورد مطالعه می باشد. به طور دقیقتر، حل مساله مسیریابی وسیله نقلیه تلفیقی نیازمند محاسبه واقع بینانه عملکرد ناوگان الکتریکی و احتراقی است. در این پژوهش مسئله مسیریابی وسیله نقلیه تلفیقی الکتریکی و احتراقی با در نظر گرفتن پنجره های زمانی و ایستگاه های شارژ بررسی شده است. مدل مسئله از نوع برنامه ریزی عدد صحیح مختلط دو هدفه با اهداف کمینه سازی مقدار هزینه و آلایندگی می باشد. مدل مسئله ابتدا با استفاده از روش محدودیت اپسیلون به مدل تک هدفه تبدیل شده و سپس، از یک الگوریتم شبیه سازی تبرید برای به دست آوردن نقاط بهینه پارتو استفاده شده است. به منظور تعیین دقیق کمیت مقادیر مرتبط با سفر مانند مصرف سوخت، آلایندگی و میزان شارژ باتری از مجموعه‌ای از فرمول‌های ریاضی استاندارد استفاده شده است. نتایج نشان می‌دهد چارچوب ارائه‌شده توانایی دستیابی به مجموعه‌ای از نقاط بهینه پارتو به عنوان تعادلی میان توابع هدف هزینه و آلایندگی با در نظر داشتن ناوگان ترکیبی الکتریکی و احتراقی را دارا می باشد.