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An Electric Vehicle Routing Problem with Battery Swap and Battery Recharge Approach

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Abstract *–This study integrates the problem of locating and routing electric and conventional vehicles besides considering greenhouse gases emission. This problem is a subset of the problems of locating and routing and the green routing problem in which a combination of electric and conventional vehicles is used. The advantage of this model is the aid of the utilization of electric vehicle technology to reduce the elimination of greenhouse gases. This model can be used in the design of the transport and logistics system of organizations and companies. Many models have been developed and applied concerning electric vehicles. However, this type of composition and its use is subject to environmental requirements to reduce greenhouse gas emissions. We also assumed the capability of recharging and battery replacement in the model. The model for different samples was solved using GAMS software and a multi-objective particle swarm optimization (MOPSO) algorithm. Besides, the impact of increasing the tax on greenhouse gas (GHG) emissions was tested on electric vehicle usage, amount of GHG emissions, and system costs. The results show that the model can be used to design the transport and logistics systems of organizations to impose the least charges besides emitting the least greenhouse gases.*

Keywords*–Battery Swap in Electric VRP, Electric Vehicle Routing Problem (EVRP), Greenhouse Gas Emission Reduction, Location Routing, Two-Stage Stochastic Programing.*

I. INTRODUCTION

Currently, fossil fuels are considered the primary source of energy (Mouhrim et al.(2018)). Therefore, the continuous use of this kind of energy will produce greenhouse gases, which will cause global warming, reduce the concentration of oxygen, and create natural disasters. Since the transport sector is the main factor for producing carbon dioxide, a limitation for the total production of carbon dioxide is considered for transport companies. There are very restricted laws in this area. There are penalties and finings for emissions that increase gradually. Also, governments oblige car manufacturers to update themselves with the newest regulations related to environmental problems. Also, in some countries, there are incentive plans for companies that care about green transportation. The United States Environmental Protecting Agency (2020) and European Commission (2020) are two major legislator organizations in this area.

Because of these limitations, companies desire to utilize clean technology for their transport fleet. Therefore, electric vehicles are the solution to protect the planet against climate change. Electric Vehicles (EVs), such as cars, trucks,

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electric trains, airplanes, could be divided into several classes, including Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs), and Fuel-Cell Electric Vehicles (FCEVs). In this study, an EV is referred to as a hybrid truck. EVs could be utilized in several applications such as public transportation, commodity deliveries, or courier operations. The main advantage of EVs includes lower energy expense and less maintenance requirement (Mouhrim et al. (2018)). Also, electric vehicles are silent and could be easily recycled. Recently, governments have started projects to encourage companies to expand this technology on the market. However, several limitations exist on electric vehicles as follows:

I. Electric vehicles have a limited range. This issue imposes a construction charge of stations to the system.
II. The charging of electric vehicle batteries requires much more time than filling a fuel tank. Also, the time of charging depends on the amount of available charge of the battery.
III. The initial cost of the electric fleet is high due to the higher worth of electric vehicles.
IV. The battery is heavy and bulky, occupying much space.

All of these constraints have encountered difficulties in transporting electric vehicles in the transportation sector. So many companies have just partially replaced their fuel vehicles with electric vehicles.

The current study presents mixed-integer linear programming that desires to formulate a hybrid fleet that has a limited range besides conventional vehicles' greenhouse gas emission constraints. Time window and limited capacity constraints are evaluated too. The main goal is to present the best route that optimizes both incurred cost of the combined fleet and the incurred gas emission costs. The transport network consists of:

I. Several clients have to be visited. Each client possesses a positive demand with a specific visiting time.
II. Charging stations are set with the duty of charging the electric vehicles. These stations could be used by more than one electric vehicle.

This paper aims to optimize two different objectives. The first objective includes minimization of the energy expenses, cost of charging electric vehicles at stations, the cost of generating greenhouse gases produced by fuel vehicles, and finally, the cost of reducing the battery level of electric vehicles. The second objective includes minimization of the amount of carbon dioxide gas emissions. Both goals are prone to different scenarios. Paths are selected concerning constraints on the limitation of carbon dioxide emissions by vehicles, battery capacity, time window, and load capacity.

II. Literature review

the literature review is divided into several separate sections as follows to provide a comprehensive study:

A. The Vehicle Routing Problem (VRP)

The first study on the routing problem was conducted by Danzig, Fulkerson, and Johnson (1954) for a traveling salesman problem. The first paper published as a routing problem was Golden et al. (1977). The vehicle routing is divided into several categories, including Capacitated vehicle routing problem (Laporte (2009)), Periodic path problem (Campbell and Wilson (2014)), vehicle routing problem with time windows (Bräysy and Gendreau (2005a), (2005b) and Rabbani et al. (2018)), dynamic routing problem (Pillac et al. (2013)), pick-up and delivery (Berbeglia et al. (2007), Euchi (2017)), vehicle routing with multiple warehouses (Montoya-Torres et al.(2015)), routing problem with retransmissions (Archetti and Speranza (2012)) and the green routing problem. Since the routing problem is an NP-hard (Lenstra and Kan (1981)), exact algorithms are efficient only for small instances. Heuristic methods have been devised for large-scale problems.

B. Green Vehicle Routing Problem (GVRP)

The transportation sector is one of the biggest fuel consumers and has a large share of air pollution (Salimifard et al.

(2012)). Green routing problems are referred to as energy consumption issues. In Green routing problems, fuel prices constitute a large share of the transportation cost of the systems (Xiao et al.(2012)). Fuel consumption reduction and transportation efficiency improvement are critical solutions to reduce pollution. The reduction in fuel consumption will also reduce greenhouse gas emissions (Erdoğan and Miller-Hooks (2012), Kara et al. (2007), Li et al. (2019)). Therefore, fuel consumption is an essential factor for GVRP.

However, to the best of our knowledge, routing problems that desire to minimize fuel consumption are not extensively evaluated. Kara et al. (2007) considered a more realistic transportation cost based on the vehicle load and the length of the route it travels. Xiao et al. (2012) introduced a factor for fuel consumption, including traveled distance and the vehicle load. Kuo (2010) included the speed of the vehicle in the time-dependent routing problem. The other similar studies related to the routing problem to minimize fuel consumption can be mentioned by, Fagerholt (1999), Sambracos et al. (2004), Nanthavanij et al. (2008), Tavares et al.(2008), Apaydin and Gonullu (2008), and Glock and Kim (2015).

Pollution from greenhouse gases has direct and indirect impacts on humans and the ecosystem as a whole. Increasing concern and the negative environmental impact of transportation will encourage the evaluation of the rescheduling concept in the network by considering the production rate of greenhouse gases (Bektaş and Laporte (2011)). The problem of pollution routing is selecting vehicles with less pollution, especially prone to carbon gases (Lin et al. (2014a)). Palmer (2007) invented a routing model and carbon dioxide production, and along with travel time and distance, calculate the amount of carbon dioxide production. The reduction in carbon dioxide production is possible by broadening the objectives of the routing base for environmental impact (Bektaş and Laporte (2011), McKinnon (2007), Palmer (2007), Sbihi and Eglese (2007), Maden et al.(2010)).

Lin et al. (2014b) divided the Green VRP studies into several categories, including Green-VRP, VRP in reverse logistics (VRPRL), and Pollution Routing Problem (PRP). The first category optimizes energy consumption, while the other concentrates on gas emissions reduction and optimizing the distribution systems for reverse logistics (Govindan et al. (2015)). Tiwari and Chang (2015) presented a block recombination algorithm that desires to minimize the traveled distance and CO2 emission using a capacity-based allocation method. They generated different clusters for each visiting nodes by different vehicles.

Vincent et al.(2017) paid attention to vehicles with hybrid energy sources to minimize travel costs. They utilized simulated annealing to solve the model for two modes. The first mode adjusts the worst solution acceptance probability by the Boltzmann function, while the other uses the Cauchy function.

C. Electric vehicle routing problem (EVRP)

The routing problem for electric vehicles and charge stations has become more important by increasing the volume of environmental studies. According to Nakata (2000), the world will face a severe energy shortage in 2040. The main reason for this shortage is the continuous use of non-renewable energy resources. The basic segment of an electric vehicle is the battery, which constitutes the largest vehicle cost (Rahman et al. (2016)). Afroditi et al. (2014) presented a mathematical model for solving the routing problem of electric vehicles in the real world. The capacitance model included a time window and battery. Pourazarm and Cassandras (2015) presented a complex nonlinear model to solve the routing problem for electric and fuel vehicles. The purpose of the model is to minimize the total time, including travel time and charging of electric vehicles.

Liao et al. (2016) presented electric vehicle routing to reduce greenhouse gases and related global warming effects. Lin et al. (2016) presented an EVRP problem that would take time and minimize energy consumption charges. Keskin et al. (2018) evaluated the routing of electric vehicles with the time window wherein a fast-charging station, the battery is charged faster against higher energy charge. Schiffer and Walther (2017) added the time-window assumption to optimize distance, the number of charge stations, and the number of vehicles. Montoya et al. (2017) solved the problem concerning the nonlinearity of the battery charge consumption. To validate their model, they tested it with 120 case studies. Felipe et al. (2014a) developed constructive and local neighborhood search algorithms to solve the problem. A mathematical model was presented in which the results of the two methods were compared with experimental issues. Keskin and Çatay (2016) sought to solve the routing problem with the window when the battery was fully charged and semi-charged. They provided a neighborhood search algorithm similar to the Schneider et al. (2017a) and other metaheuristic methods to solve the model.

Keskin et al.(2018) introduced the time window concept and fast charging for electric vehicles and introduced a new destroy and repair mechanism associated with fast chargers. They considered electric vehicles as Battery Electric Vehicles (BEV). Furthermore, Li et al.(2020) presented a plug-in hybrid electric vehicle routing problem. They used a combined neighborhood search algorithm for solving their model. Shao et al. (2017) developed an electric vehicle routing problem with some uncertainty in charging time and travel time. The authors used a genetic algorithm to solve their model. Yang et al.(2015) presented a location and routing model for an electric fleet with limited capacity. Stations with battery swap capability were utilized instead of recharging stations. Hof et al. (2017b) conducted a study to minimize transport cost and the construction of stations with finding stations. Paz et al. (2018) also evaluated battery swap possibility in some locations.

Pelletier et al. (2017) optimized scheduling of battery charging at the depots besides insights on consumption, limitations on a grid, charging expenses, and charging schedules of the fleet. Finally, Pelletier et al.(2016) and Pelletier et al. (2018) provided a survey on goods distribution models with EVs.

D. Stochastic models

Stochastic vehicle routing problems (SVRPs) are being evaluated for more than 50 years (Tillman (1969)). Despite low attention in the 1980s, the 1990s contributed greater attention to this field. The new generation of processors and advances in software made it possible to solve SVRPs easier. Erera et al. (2010) presented a vehicle routing problem model with stochastic demand. They set a maximum duration for delivery time to enforce the vehicles to deliver goods in time. Chen et al. (2012) proposed a Self-Adaptive Memeplex Robust Search approach for SVRP. Their method reduced calculation time, and besides that, it produced robust and reliable solutions for the model.

In the green VRP research area, there are some new studies about stochastic models. For instance, Hsueh (2016) presented a green VRP with stochastic travel speeds. The author considered that the rate for fuel consumption depends on factors like the type of vehicle, roadway gradients, the average speed of travel, and vehicle load. Çimen et al. (2017) proposed a time-dependent GVRP where the travel speeds are stochastic and developed a dynamic programming-based heuristic. Zhang et al. (2019) evaluated stochastic demand for electric vehicle problems and presented a hybrid variable neighborhood search algorithm. Keskin et al. (2020) considered the time window in the EVRP model with stochastic waiting times at recharging stations. They developed a heuristic based on simulation to solve the model.

E. Solution approaches

In 2014, for the first time, the concept of electric vehicles was considered in the green routing issues (well Felipe et al.(2014b)). The core assumption was that battery capacity and its partial charge was limited. A local search algorithm and simulated annealing (SA) were used to find the best solution. The routing problem of electric vehicles with the time window was introduced by Schneider (2014). A hybrid algorithm was employed, and the algorithm was tested with different test problems to solve the model ((Erdoğan et al.(2012), Crevier et al.(2007), Tarantilis et al.(2008)). Goeke and Schneider (2015) presented the vehicle routing model considering the electric fleet alongside the conventional fleet. In the related model, energy consumption was a function of velocity, route slope, and load weight. They used a neighborhood search algorithm to solve the model. Desaulniers et al. (2016) considered four different modes for the electric vehicles routing problem: full charging for each route, partial charging per route, with one-time full charging, partial charging with full charging and just partial charging. Branch-cost and branch-price methods was utilized to find optimal solution. Hiermann et al. (2016) proposed the fleet size or the number of vehicles in the electric vehicle routing problem and constructed a combinatorial algorithm with neighborhood search and notation processes. Keskin et al. (2018) provided many efficient solutions to the electric vehicle routing problem by proposing fast-charging stations by implementing a Meta-heuristic algorithm.

In recent years, multi-objective models have been developed widely, and thus, using algorithms that have been constructed for solving multi-objective models have been raised (Coello et al.(2007)). There are various algorithms for solving these models, like Pareto Archive Evolutionary Strategy (Knowles and Corne (2000)) and NSGA-II (Deb et al.(2002)). The Particle Swarm Optimization algorithm (PSO) is based on bird flock movements that show remarkable performance in optimization problems Eberhart and Shi (2004). This algorithm has successful performance in nonlinear and integer models (Eberhart and Shi (2004)). Due to its fast convergence, it also could be used to solve multi-objective models. In several experiments, the algorithm performs better than the three applied algorithms in multi-objective models, including PAES, NSGA-II, and micro-genetic algorithms. (Coello and Pulido (2001)).

According to the studies in this area, the turning point of this study is considering both partial charge and battery swapping stations. Also, because of the dominance of the multi-objective particle swarm optimization algorithm (MOPSO) in the calculation time and reliability of solutions, this method has been used to solve the problem.

III. Problem model description

The presented model considers the distribution of a product from a manufacturer to a set of retailers via a set of warehouses that are set up in predefined areas. The model is constructed in a two-stage stochastic programming approach to manage uncertainty. At the first stage, charging station establishment decisions are made before complete information about uncertain parameters. At the second stage, the routing decisions are made to provide a route that optimizes the associated objective functions. Products are carried by conventional and electric vehicles. Each kind of vehicle has a certain capacity. The electric vehicle's battery capacity is limited. Therefore, during the distribution of goods, electric vehicles might need to visit charging stations. The energy usage and fuel usage are dependent on the amount of vehicles load.

A feasible route for electric vehicles starts from a warehouse, continues to a set of retailers and charging stations, and ends with the same warehouse. The capacity of vehicles exceeds the demand of retailers. Only one vehicle can travel at a specific time per route, and each vehicle can only distribute a load to retailers once. The objective of the model is to minimize the emission of greenhouse gases, and also minimizing costs including the costs of establishment and construction of stations, the cost of storing goods in retailers and the cost of transporting goods.

To make the model more transparent, the items that are used in the model are given as:

Sets

C	Set of Customers	$C = \{v_1, v_2, \dots, v_n\}$
F'	Set of charging stations	$F' = \{v_{n+2}, v_{n+3}, \dots, v_{n+s}\}$
F''	Set of swapping stations	$F'' = \{v_{n+s+1}, v_{n+s+2}, \dots, v_{n+s+p}\}$
V	Set of nodes	$V = F' \cup C \cup \{v_0\} \cup \{v_{n+1}\}$
E	Set of edges or routes	$E = \{(i,j) \in V \times V : i \neq j\}$
VC	Set of conventional vehicles	$VC = \{1, \dots, k\}$
VE	Set of electric vehicles	$VE = \{k+1, \dots, m\}$

K	Set of vehicles	$K = VC \cup VE$
S	Set of problem scenarios	$S = \{s_1, s_2, \dots, s_n\}$

Parameters

D_{is}	The demand of node i under scenario s
S_{is}	Service time in node i under scenario s
e_{is}	Earliest arriving time to node I under scenario s
l_{is}	Latest arriving time to node i under scenario s
d_{ij}	Distance between i and j nodes
tt_{ij}	Moving time between the nodes
CE	Cost of electricity consumption
CC	Cost of fuel consumption
CT	Tax on gas emissions
T	Full charging cost
CO	Cost of setting up a charging station
CS	Cost of swapping a battery
E_{max}	The maximum amount of gas emissions
V_k	If k is an electric car equals 1; otherwise, 0.
e_p	Amount of gas emitted by the filled vehicle
e_v	Amount of gas emitted by the empty vehicle
r	Battery charging coefficient
P_s	Probability of each scenario
O	Maximum number of charging stations
Q_1	Conventional vehicles capacity
Q_2	Electric vehicles capacity
α	Energy usage rate for empty vehicle
β	Energy usage rate for loaded vehicle
α'	Fuel usage rate for empty vehicle
β'	Fuel usage rate for loaded vehicle
$CMAX$	Electric vehicles battery capacity
$CMIN$	The minimum amount of battery charge to run a car

Variables

X_{ijks}	If vehicle k moves from node i to node j under scenario s, equals 1; otherwise, 0.
Y_i	If the charging station is built at node i, equals 1; otherwise, 0.
E_{iks}	The battery level of vehicle k when entering node i under scenario s
tc_{ik}	Charging time of vehicle k in station i
u_{iks}	The amount of cargo carried by vehicle k at node i under scenario s
ts_{iks}	Time to start serving vehicle k at node I under scenario s
bst_{ik}	Battery swapping time for vehicle k at node i

A. Mathematical Model

The objectives and constraints of the problem are presented as follows:

$$\begin{aligned} Z_1 = \sum_{i\in F'} CO.Y_i + CS\sum_{k\in VE}\sum_{i\in F''} bst_{ik} + \sum_{s\in S} P_s\,(T \\ + \sum_{i\in V}\sum_{j\in V}\sum_{k\in VE} CEd_{ij}\left(\alpha X_{ijks} + \frac{\beta-\alpha}{Q_2}u_{iks}\right) \\ + \sum_{i\in V}\sum_{j\in V}\sum_{k\in VC} CCd_{ij}\left(\alpha' X_{ijks} + \frac{\beta'-\alpha'}{Q_1}u_{iks}\right) \end{aligned} \tag{1}$$

$$Z_2 = \sum_{s\in S} P_s\,(CT\sum_{k\in VC}\sum_{i\in C}\sum_{j\in C} d_{ij}\left(\left(\frac{e_p-e_v}{Q_2}(u_{iks}-D_{is})\right)+e_v\right)X_{ijks}) \tag{2}$$

Subject to.

$$\sum_{i\neq j, j\in V/\{0\}} X_{ijks} \le V_k \qquad \forall i\in V \quad \forall k\in K \quad \forall s\in S \tag{3}$$

$$\sum_{i\in V/\{0\}} X_{ijks} \le \sum_{i\in V/\{n+1\}} X_{ijks} \qquad \forall j\in V \quad \forall k\in K \quad \forall s\in S \tag{4}$$

$$\sum_{i\in V}\sum_{k\in K} X_{ijks} = 1 \qquad \forall j\in C \quad \forall s\in S \tag{5}$$

$$\sum_{i\in V} X_{ijks} \le 1 \qquad \forall j\in F' \quad \forall k\in VE \quad \forall s\in S \tag{6}$$

$$\sum_{i\in V} Y_i \le O \tag{7}$$

$$E_{jks} \le E_{iks} - C_{ij}D_{ij}X_{ijks} \qquad \forall i\in C \;\; \forall j\in V \quad \forall k\in VE \quad \forall s\in S \tag{8}$$

$$E_{jks} \le E_{iks} + rtc_{iks} - C_{ij}D_{ij}X_{ijks} \qquad \forall i\in F' \;\; \forall j\in V \quad \forall k\in VE \;\; \forall s\in S \tag{9}$$

$$E_{jks} \leq CMAX - C_{ij}D_{ij}X_{ijks} \quad \forall i \in F'' \ \ \forall j \in V \ \ \forall k \in VE \ \ \forall s \in S \tag{10}$$

$$E_{0ks} = CMAX \quad \forall k \in VE \ \ \forall s \in S \tag{11}$$

$$CMIN \leq E_{iks} \leq CMAX \quad \forall i \in V \ \ \forall k \in VE \ \ \forall s \in S \tag{12}$$

$$E_{iks} + rtc_{iks} \leq CMAX \quad \forall i \in F' \ \ \forall k \in VE \ \ \forall s \in S \tag{13}$$

$$ts_{jk} \leq ts_{ik} + \left(S_{is} + tt_{ij}\right) X_{ijks} \quad \forall i \in C \ \ \forall j \in V \ \forall k \in K \ \ \forall s \in S \tag{14}$$

$$ts_{jk} \leq ts_{ik} + \left(tc_{ik} + tt_{ij}\right) X_{ijks} \quad \forall i \in F' \ \forall j \in V \ \forall k \in VE \ \ \forall s \in S \tag{15}$$

$$ts_{jk} \leq ts_{ik} + \left(bst_{ik} + tt_{ij}\right) X_{ijks} \quad \forall i \in F'' \ \forall j \in V \ \forall k \in VE \ \ \forall s \in S \tag{16}$$

$$e_{is} \leq ts_{ik} \leq l_{is} \quad \forall i \in C \ \ \forall k \in K \ \ \forall s \in S \tag{17}$$

$$u_{jks} \leq u_{iks} - D_{is} X_{ijks} \quad \forall i, j \in V \ \ \forall k \in K \ \ \forall s \in S \tag{18}$$

$$D_{js} X_{ijks} \leq (u_{iks} - D_{is}) X_{ijks} \quad \forall i, j \in V \ \ \forall k \in K \ \ \forall s \in S \tag{19}$$

$$u_{0ks} = Q_1 \quad \forall k \in VC \ \ \forall s \in S \tag{20}$$

$$u_{0ks} = Q_2 \quad \forall k \in VE \ \ \forall s \in S \tag{21}$$

$$u_{iks} \leq Q_1 \quad \forall j \in V \ \ \forall k \in VC \ \ \forall s \in S \tag{22}$$

$$u_{iks} \leq Q_2 \quad \forall j \in V \ \ \forall k \in VE \ \ \forall s \in S \tag{23}$$

$$\sum_{k \in VC} \sum_{i \in C} \sum_{j \in C} d_{ij} \left(\left(\frac{e_p - e_v}{Q_2} (u_{iks} - D_{is}) \right) + e_v \right) X_{ijks} \leq E_{max} \quad \forall s \in S \tag{24}$$

$$E_{ik}, tc_{ik}, u_{iks}, ts_{ik}, bst_{ik} \in R^{+} \quad \forall i, j \in V \ \ \forall k \in K \ \ \forall s \in S \tag{25}$$

$$X_{ijks}, Y_i \in \{0,1\} \quad \forall i, j \in V \ \ \forall k \in K \ \ \forall s \in S \tag{26}$$

The first objective aims to minimize the total costs of the charging station and the cost of fuel/energy consumption. The second objective minimizes the cost of producing carbon dioxide produced through fuel vehicle utilization.

The mathematical model consists of series of constraints that control the time window, the limitation of batteries, and load capacity of transport and greenhouse gas production. Constraint (3) prevents the arrival of conventional vehicles into the charging stations. Constraint (4) ensures that each node, except the warehouse, is closely associated with two nodes. Constraint (5) shows that each client receives the service exactly once. Also, constraint (6) determines that the electric vehicles go to the charge at most once. Constraint (7) limits the number of charging stations. Constraints (8),(9), and (10) show vehicles' battery levels after visiting customers, charging stations, and battery swapping stations. Constraint (11) states that electric vehicles start their route with a fully charged battery. Constraints (12) and (13) control the amount of energy in the battery. Constraint (13) ensures that the charging level of the vehicle does not exceed the battery capacity. Constraints (14), (15), and (16) update the arrival time of the vehicle at node j exactly after meeting the customers, charging stations, and battery swapping stations. Constraint (17) states limitations related to the time window. Constraint (18) indicates that the difference between the load entering node i and the load entering node j is equal to the customer i's demand. Constraint (19) ensures that a vehicle does not meet a customer unless it meets the customer demand. Constraints (20) and (21) define the initial load of the vehicle in the warehouse. Constraints (22) and (23) restrict the load carried by vehicles. Constraint (24) controls the number of greenhouse gases produced by vehicles. Constraints (25) and (26) show the type of decision variables of the model.

B. Multi-objective particle swarm optimization (MOPSO)

Comparing the PSO method with other meta-heuristic methods shows that using a Pareto classification method effectively solves multi-objective problems (Goldberg 1989). Such efficiency incoherence arises due to using social intelligence processes alongside the archive of superior solutions. The steps of the MOPSO algorithm are as follows:

1. Make the first pop-up.
    1. For *i* = 0 to *NP*. *NP* is the number of particles.
    2. Make Pop (i). Pop.
2. Determine the velocity of each particle.
    1. For *i*=0 to NP.
    2. $V(i) = 0$
3. Examine every particle of Pop members.
4. Add the location of the superior particles in the repository archive.
5. Divide the solution space into several parts and determine the location of the particles by using their spatial coordinates, formed from the values of the objective functions.
6. Update the memory of each particle.
    1. For *i*=0 to NP.
    2. $Pop.best(i) = Pop(i)$
7. Repeat the following steps until you reach the maximum number of repetitions:
    1. Calculate the velocity of each particle using the following equation:
    $$V(i) = w \times V(i) + C1 \times \left(Pop.Best(i) - Pop(i)\right) + C2 \times (Rep(j) - Pop(i))$$
    2. Calculate the new location of each particle using the following equation.
    $$Pop(i) = Pop(i) + V(i)$$

In the equations mentioned above, *w* is called the inertia weight, which takes a value of 0.4 in this study. *C1* and *C2* are the random numbers between zero and one. *Pop.Best (i)* is the best place that has a particle *i*. *Rep (j)* is the amount that is extracted from the archive. *J* is concerned with parts of the solution space where there is more than one particle. A test problem is devised to implement the presented algorithm. A problem solves the algorithm with a 2.00 GHz processor and 4GB RAM.

C. Solution Representation

A Multi-Objective Particle Swarm Optimization (MOPSO) approach has been adopted to solve the proposed multi-objective model. For using MOPSO, constituting the particles has a substantial influence on the efficacy of the algorithm. Each particle has two sections. The first section size corresponds to the number of customers and charge/battery swap stations (m dimensions) and is called customers and charge/battery swap priority matrix. Each dimension includes a real number between 0 and 3. The second section corresponds to the coordinates for each vehicle ($2v$ dimensions). Each particle has $m+2v$ dimensions. A schematic view of the particle for 6 customers and 2 vehicles is depicted as follows:

Customers and charge/battery swap stations priority matrix						Vehicle coordinate section			
0.3	0.5	1.9	0.8	0.9	2.7	1.1	1.8	0.6	1.5

The following procedure is required to decode a particle:

- Step 1: Building customers and charge/battery swap stations visit priority
- Step 2: Building the priority matrix of vehicles
- Step 3: Building the route for vehicles

The steps mentioned above are presented as follows:

Step 1: Building customers and charge/battery swap stations visit priority

The algorithm is proposed to determine the priorities of visiting customers and charge/battery swap stations. Each dimension contains a real number between 0 and 3. The integer part of the number shows the type of location. (0 for the customers, 1 for the charge station, and 2 for the battery-swapping station). The decimal part of the number shows the priority of each dimension. The dimensions with lower decimal values should be met sooner.

Step 2: Building the priority matrix of vehicles

It describes how customers and stations are allocated to vehicles. In this procedure, distance is calculated as direct Euclidean distance. The nearest vehicles to each customer or charge/battery swap station are allocated it.

Step 3: Building the route for vehicles

At this step, each vehicle will visit the allocated customers, and charge/battery swap stations based on customers and charge/battery swap stations visit priority which is attained at step 1.

The representation of a particle is shown schematically in Figure 1.

IV. Computational results and analysis

According to the model, we first produced several samples. Then, the sample problems are solved using GAMS software and MOPSO algorithm. Results are presented in table 1. Cases included in this table are the number of warehouses used, the number of vehicles used, the number of charge stations, total cost, total greenhouse gas emissions, and computation time.

Since the problem mentioned in the study is multi-objective, the LP metric method is used for solving in the GAMS. (Asadi-Gangraj et al. (2018))

$$Z_3 = \left[\frac{Z_1 - Z_1^*}{Z_1^*} + \frac{Z_2 - Z_2^*}{Z_2^*}\right] \quad (27)$$

By using the LP metric, objective function, and the initial constraints, multi-objective optimization is converted to a single-objective problem which can easily be solved by solving linear programming.

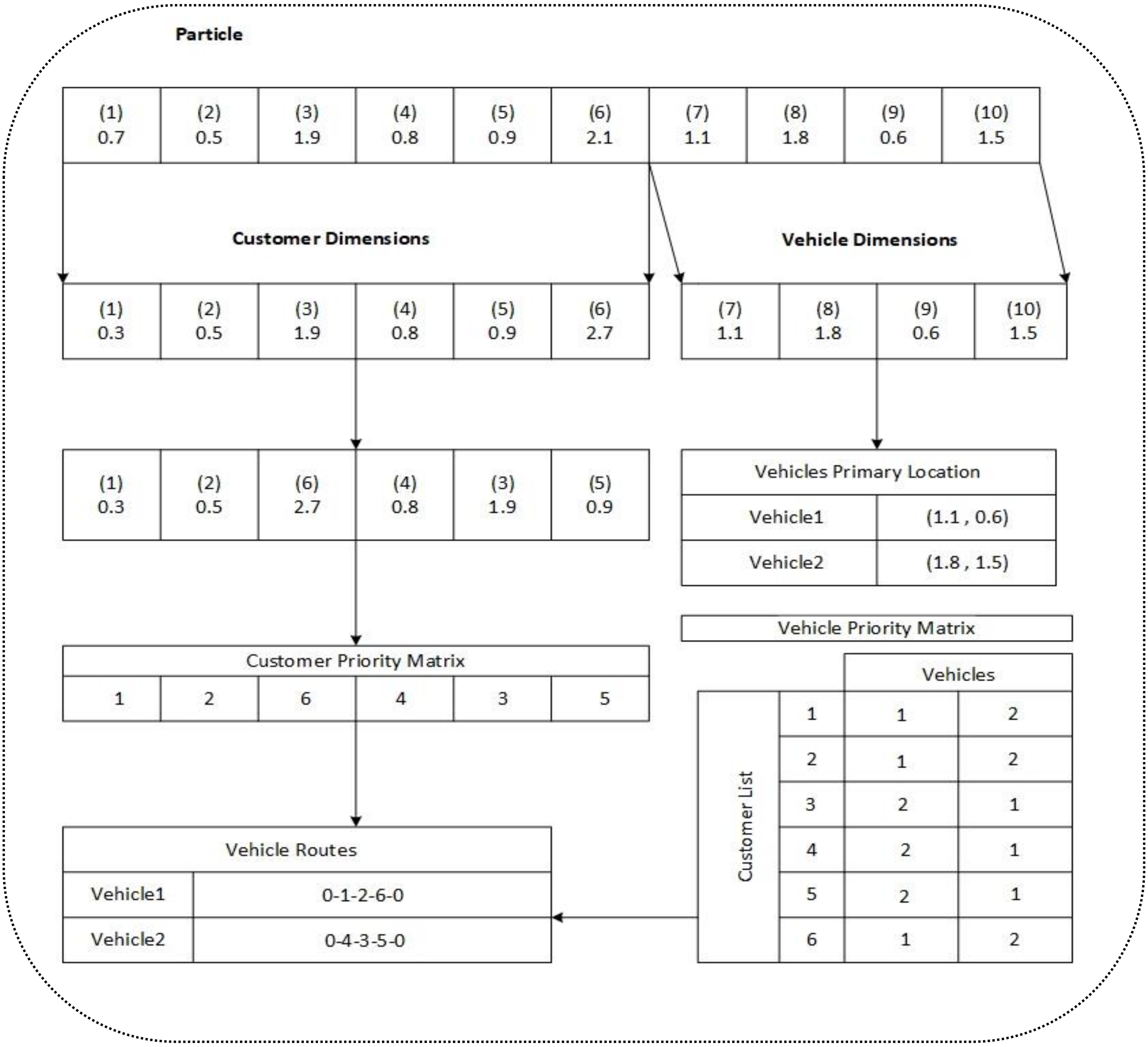

Fig. 1. Schematic view of a particle

In Table 1, results of LP metric method and MOPSO algorithm are depicted. In MOPSO columns, results are related to the optimum Pareto front. Each member of the front placed in Z_3 and member which minimized the function was chosen in respected columns.

According to table 1, it can be found that the total cost of the system depends on many factors such as the number of warehouses, number of vehicles, and the number of charging stations. The increasing number of warehouses causes the shortening of the route for the distribution of goods. Therefore, the costs should be reduced, but the other factors do not let this reduction be tangible. Increasing the number of vehicles increases the total cost due to increasing fueling cost, charging, and producing greenhouse gas. Increasing the number of stations has a fixed cost to build the station, which increases the cost linearly.

Also, it can be seen that the MOPSO algorithm has better performance in computation time.

Table 1. The results are obtained by GAMS software for sample problems

Problem Description				*GAMS Software*			*MOPSO Method*		
instance	***Depots***	***Vehicles***	***Stations***	***Total Cost***	***Emissions***	***Time (s)***	***Total Cost***	***Emissions***	***Time (s)***
Ins1	1	1	2	2794.5	1.11	22.87	2795.4	1.53	0.212
Ins2	1	1	3	2916	0.74	91.17	2916.1	1.02	25.60
Ins3	1	1	3	2943.4	0.555	4.42	2943.9	0.613	0.230
Ins4	1	2	1	2146.5	2.96	2.61	2146.5	3.85	0.135
Ins5	1	3	0	2754.2	4.254	1.31	2754.4	4.315	0.158
Ins6	1	4	4	4266.4	2.964	25998.97	4266.5	2.991	120.93
Ins7	2	2	1	1606.5	2.59	1.46	1605.4	2.78	0.145
Ins8	2	2	1	1971.6	2.405	0.44	1972.4	2.498	0.324
Ins9	2	2	2	2362.5	2.412	16.95	2363.4	2.428	1.16
Ins10	2	2	2	2443.5	1.854	1.52	2443.7	1.894	0.265
Ins11	2	2	3	3199.5	1.738	100.34	3200.1	1.751	3.67
Ins12	2	3	1	3766.5	4.441	3.92	3767.4	4.504	0.220
Ins13	2	3	1	3807.8	3.871	1.58	3808.4	3.899	0.184
Ins14	2	3	2	4198.5	4.055	65.6	4199.2	4.061	19.04
Ins15	2	3	2	4131.3	4.248	23291.8	4132	4.331	665.20
Ins16	2	3	2	4387.5	4.175	38.39	4387.9	4.253	8.76
Ins17	2	3	3	4482.4	3.668	68.3	4482.8	3.687	6.40
Ins18	2	4	1	4792.5	3.866	0.72	4792.7	3.906	0.082
Ins19	2	4	1	4698.4	4.634	5.12	4698.4	4.648	1.441
Ins20	4	10	5	9561.3	3.745	651.7	9564.5	3.254	146.96
Ins21	5	15	5	74460.1	3.83	3760	74155.1	4.068	20.4
Ins22	10	15	10	275851	3.464	3654	275851.7	4.21	85.2
Ins23	10	20	10	326186.8	4.609	6720	326187.2	4.445	193.7
Ins24	15	20	10	485680	4.893	9273	485483.6	4.79	197.28
Ins25	15	25	15	652822	5.79	9648	672545.8	6.671	258.64

A. Impact of taxes on the transport fleet

Taxing is one of the tools for controlling GHG emissions. In the context of gas emissions in 2018, it was established in the Treaty of Paris to pay $ 25 for each ton of greenhouse gas and an annual increase of one to 5 percent per ton (Ramseur and Leggett (2019)). In the sample of Ins8, which has two warehouses, one electric vehicle, and one conventional vehicle with one charging station, we examine the impact of the tax and its increase on the variables of the problem. It is necessary to mention that the results shown in Table 2 and figures 2 to 4 are related to MOPSO algorithm results.

Table 2. The changes of model variables by increasing the tax on gas emissions

Tax	*Percent of increase*	*Percent of EV usage*	*GHG Emissions*	*Total Cost*
25	0	32.31	2.021	2167.04
26.25	5	34.75	1.921	2058.7
27.5	10	37.17	1.819	1950.34
28.75	15	39.6	1.732	1857.7
30	20	42.03	1.659	1779.69
31.25	25	44.4	1.599	1714.68
32.5	30	46.72	1.548	1661.3
33.75	35	48.93	1.508	1618.43
35	40	51.27	1.478	1585.18
36.25	45	52.97	1.454	1560.92
37.5	50	54.53	1.439	1545.06
38.75	55	55.85	1.427	1531
40	60	57.21	1.416	1518.65
41.25	65	58.32	1.408	1507.92
42.5	70	59.19	1.398	1498.8
43.75	75	59.78	1.39	1491.26
45	80	60.32	1.383	1485.27
46.25	85	60.8	1.379	1480.81
47.5	90	61.21	1.376	1477.83
48.75	95	61.57	1.376	1476.34
50	100	61.87	1.376	1475.61

As seen in Table 2, the tax rate on gas production increased by 5 %, and the percentage of the electric fleet usage, amount of gas emissions, and the total cost of the system were calculated. The table shows that the electric transport fleet usage has increased as tax increases. However, factors such as battery capacity constraints and the limited range that they can travel do not let it exceed a certain limit (Figure 2).

Increasing the electric fleet usage, the use of fuel, and the amount of greenhouse gas emissions are reduced by greenhouse gases. However, due to the constraints involved in the electric transport fleet usage, it cannot be expected that GHG emissions reach zero, but they can be reduced significantly (Figure 3).

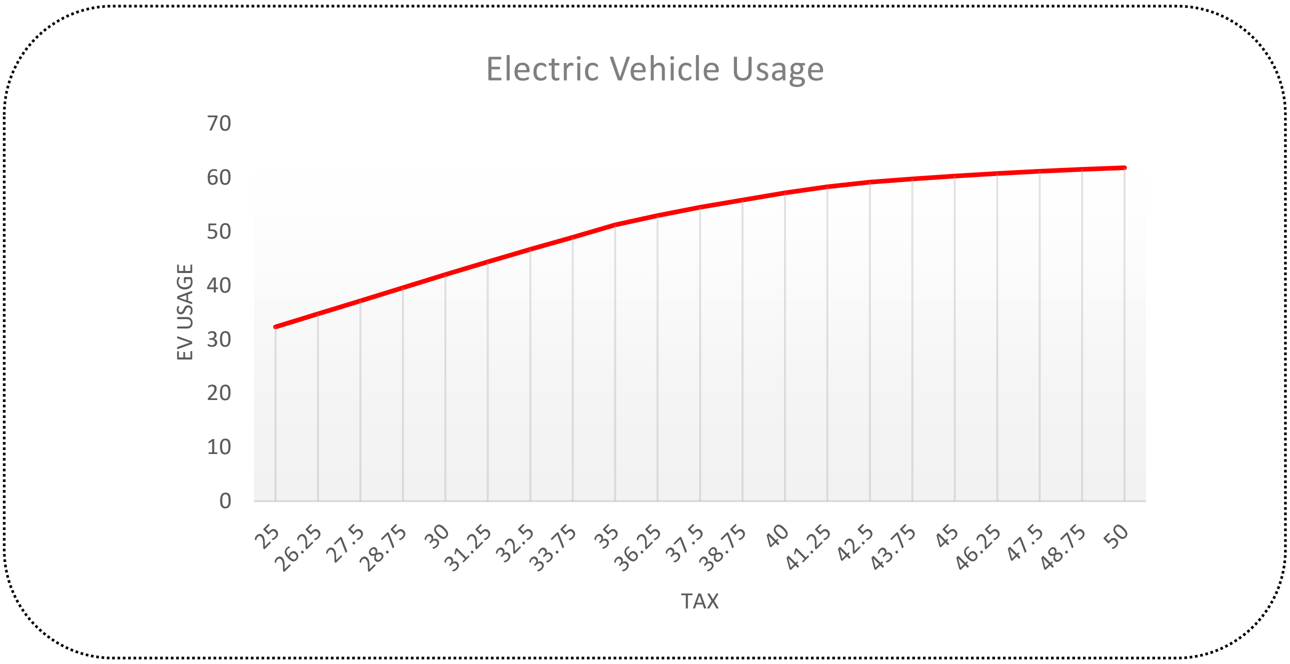

Fig. 2. Changes in the use of electric transport fleet to increase gas emissions

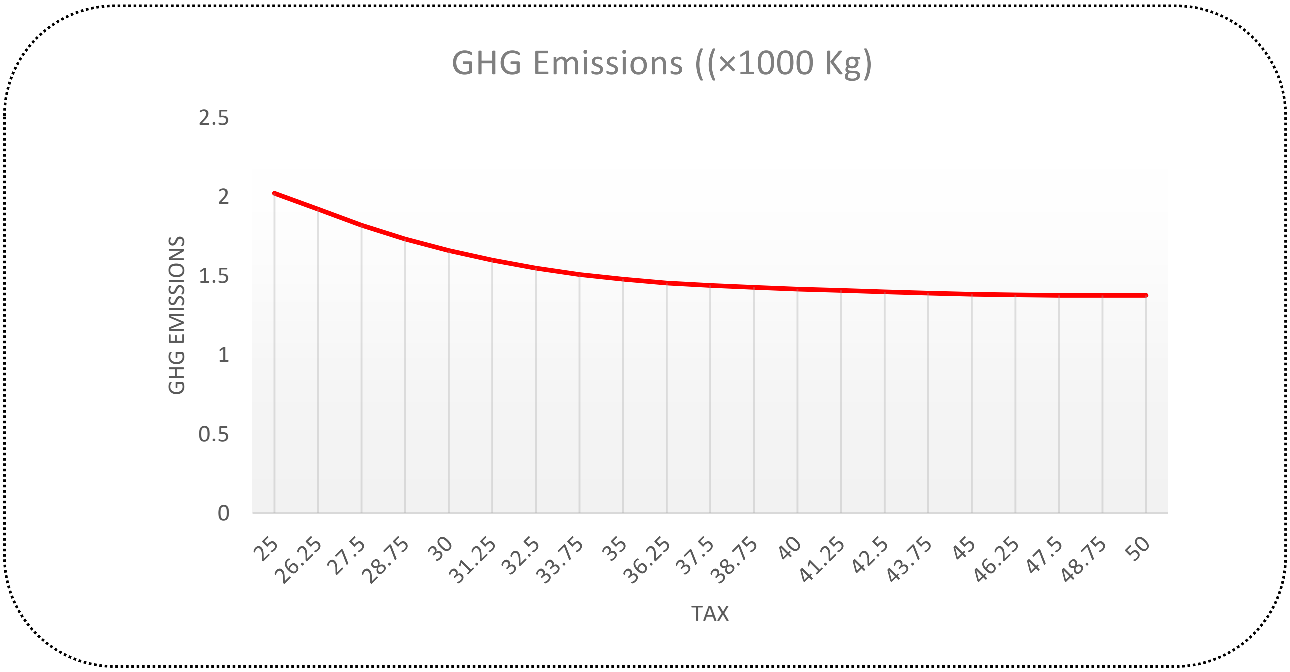

Fig. 3. Changes in greenhouse gas emissions by increasing gas emissions

Although this part of the costs increases by increasing the tax on greenhouse gas emissions, the conventional vehicle's usage and fuel consumption which is one of the most important parts of system costs will decrease, and subsequently, the total cost of the system will decrease too. But due to the limited number of electric vehicles, this falling trend is not continuous, and according to Figure 4, there are no tangible changes in the total cost, almost after raising taxes to fifty percent and above.

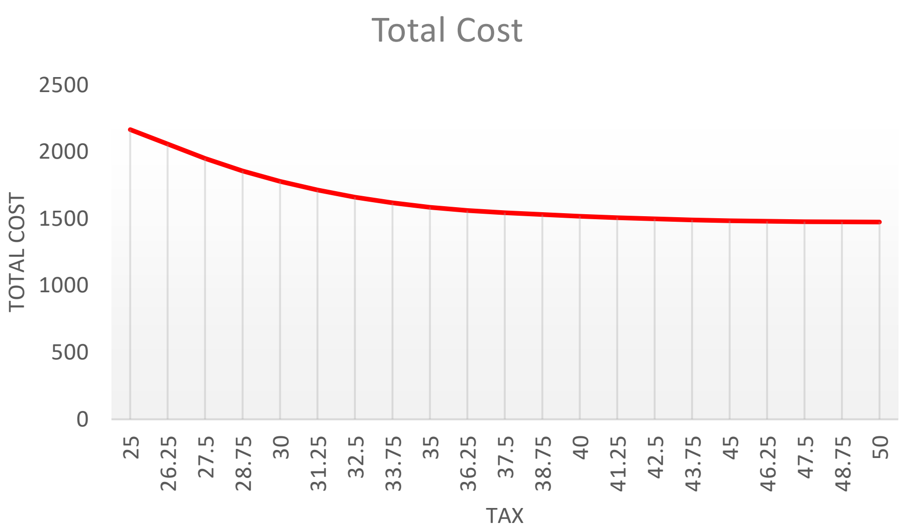

Fig. 4. The total cost variation caused by the increase in gas emissions.

According to the mentioned studies, it can be found that applying a tax on gas emissions can limit the amount of gas released and also reduce the total cost of the system. However, it is not sufficient and should consider other methods as complements to this method to reduce GHG emissions and system total cost.

V. Conclusion

We presented a mathematical model for calculating the cost of the transportation system and limiting the production of greenhouse gases for a combination of electric and conventional vehicles and a multi-objective particle swarm optimization algorithm was presented to solve the model. A mathematical model of the problem with two objective functions was presented. A number of samples were produced. Examples were solved by LP metric method and MOPSO algorithm, and their best results were mentioned. Total cost and the amount of GHG emissions were calculated together with the solution time. Then, the impact of increasing taxes on system total cost and the amount of GHG emissions were investigated. For future research, new objective functions can be added to the model. For example, timing and customer satisfaction are interesting topics that can be added to the model. Customers can be clustered by their specifications, such as demand. Authors can use clustering methods like K-means. Furthermore, other metaheuristic methods like Genetic algorithms, Ant colony, and searching algorithms like neighborhood search can solve the model.

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