Measurement, Evaluation and minimization of CO₂, NO_x, and CO emissions in the open time dependent vehicle routing problem

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Abstract:

In this paper, a new comprehensive model has been presented for the measurement, evaluation and minimization of CO₂, NO_x and CO as three important emissions (emitted from vehicles) in the open time dependent vehicle routing problem (OTDVRP). In the OTDVRP, traffic properties of congested regions like city centers are considered. Travel time between two points depends on the time of departure, and the vehicles do not come back to the depot. In some distribution companies, vehicles are rental; therefore, they do not come back to the depot from the last customer. To solve the proposed problem, an improved Particle Swarm Optimization algorithm is developed. The results show good performance in computation experiments compared to original PSO algorithm. The results of the experiments show that considering minimization, the pollutants can reduce emissions by 16% on the average compared to the classical open TDVRP. Factors causing the variation in emissions are also identified and discussed in this study.

Keywords Air pollution, Transportation, Environmental emissions, Green open time dependent vehicle routing problem, Particle Swarm Optimization Algorithm.

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1. Introduction and Objectives

In recent years, much attention has been paid to minimize the pollutants' emission and fossil fuels consumption, also a significant part of regional air pollution originates in the transport sector (Kageson 1995). In the last decades, due to increasing demand and attempts for better service, distribution has become more complicated; therefore, more complicated variants of the Vehicle Routing Problem (VRP) have appeared in real life. There are different forms of VRP most of which minimize the total distance without considering environmental issues. Although pollutants' emission is largely determined by distance, other factors such as vehicle load, vehicle speed and road gradient, as we discuss in this paper, also have a considerable impact on the amount of pollutants' emission. All mentioned factors have an important impact on pollutants' emission. As shown in Fig. 1, if only distance and vehicle speed are the considerable factors, the amount of emissions and optimal speed (53 km/h) are different from the amount of emissions and optimal speed (39 km/h) when all the mentioned factors are considered for minimizing emissions, indicating the importance of other factors in addition to the vehicle speed.

Fig. 1 Diagram of factors efficiency on emissions

Rakha et al (2003) pointed out that there are many models for calculating emissions that are different in structure and modeling method. In this paper, we use MEET model (Hickman et al. 1999) for calculating CO₂, and CO as two important emissions that come out from vehicles (US Department Of Transportation 2008), and NO_x that is a primary pollutant mainly emitted by vehicle exhaust in the vicinity of arterial roads (Matsumoto et al. 2006).

Vehicle Routing Problem (VRP) was first discussed by Dantzig and Ramser (1959). Following them, Clarke and Wright (1964) suggested saving algorithm to solve VRP, which was considered as a basis for later researches. VRP can be defined as a complete graph $G = (N, A)$, N as a set of nodes and A as a set of arcs between two nodes, in which the nodes show customers and the arcs show the shortest path between the customers. Several vehicles with fixed capacity to service all customers start their trips from depot and return to the depot. Vehicle routing problem is categorized to the NP-hard type problems (Zhong and Cole 2005). Most articles regarding VRP assume that the travel speed (travel time) is constant and is not related to the departure time. In

more congested regions like city centers, with regard to the congestion during the rush hours, travel time during the day varies and is related to the departure time.

Vehicles in distribution companies have two states: those that the company purchases; therefore, drivers come back to the depot from last customer and those that are rental and drivers do not come back to the depot. In the literature, this kind of routing is named open vehicle routing problem. This article focuses on Measurement, Evaluation and Minimization of the CO₂, NO_x, and CO emissions in open time dependent vehicle routing problem. This problem applies to goods distribution in urban environments. Also, the “first- in- first- out” (FIFO) property, which does not allow for surpassing and few researches have considered, is satisfied in this paper. Then, because the proposed problem is NP-hard and in order to find routes with the least amount of pollutant's emission, an exact method for small size instances is proposed, and for large-scale instances, an improved metaheuristic method based on Particle Swarm Optimization algorithm has been presented. The innovations of this paper can be summarized as follows: a). Propose a new comprehensive model to Measurement and Evaluation of CO₂, NO_x and CO emissions in vehicle routing problem with respect to the MEET model and analysis of the effect of the proposed model on the reduction of pollutants' emission. b). Propose an enumeration method to solve the proposed problem exactly and an algorithm for calculating emissions with regard to the FIFO property and propose an improved metaheuristic algorithm base PSO algorithm to solve the large-size problems.

In the remainder of the paper and in section 2, the literature review is presented, and in section 3, the problem is defined and factors affecting pollutants' emission are investigated; furthermore, the FIFO property is described in this section. In section 4, the algorithm for calculating the amount of pollutants' emission is explained. In section 5, the solution methods are described; finally, in section 6, the results are analyzed.

2. Literature review

Most researches on VRP assume that travel speed is constant and not related to the time of the day. However, regarding traffic congestion, especially in rush hours, the travel speed undergoes changes during the day and the travel time changes accordingly. In the following, we first discuss the literature about TDVRP, and then literatures about open routing and emission of pollutants are presented. Malandraki and Daskin (1992) proposed a mixed integer programming formulation with time windows for the TDVRP. Their model does not satisfy the FIFO property. They suggested running away from congestion, permitting the vehicles to wait in a customer region. Hill and Benton (1992) suggested a model for time dependent travel speeds in time dependent vehicle routing problem. Their model does not satisfy FIFO property. Jung and Haghani (2001) studied TDVRP, and solved it with modified genetic algorithm. Ichoua et al. (2003) also investigated TDVRP. In their model, minimizing total time and lateness were considered. They partitioned the day into three-speed zones with different speed limitations. They used parallel tabu search algorithm to solve such problems. Van Woensel et al. (2003) developed queuing models to model congestion, where their model was set to different traffic flows and weather conditions. Chen et al. (2006) suggested a mixed integer-programming model for TDVRP, and used a heuristic algorithm to solve it. Van Woensel et al. (2008) solved TDVRP with tabu search algorithm. Donati et al. (2008) studied the optimization of starting time and routes in TDVRP. Results demonstrate that optimality and feasibility decrease when best solutions of constant speed are used at the time dependent context. Balseiro et al. (2011)

investigated time dependent vehicle routing problem with time windows using an ant colony system algorithm hybridized with an insertion heuristic method to solve the problem.

Brandao (2004) studied the OVRP with capacity constraints using a tabu search algorithm to solve it. Fu et al. (2005) solved the OVRP with the capacity constraints. They proposed a heuristic algorithm for generating initial solutions, and used tabu search heuristic method to solve their problem. Yanwei et al. (2008) used an algorithm for particle swarm optimization for open vehicle routing problem with time dependent travel time. Repoussis et al. (2010) proposed a hybrid evolution strategy (ES) to solve OVRP by considering minimization of the fleet size, and the distance traveled as their problem objective. Norouzi et al. (2012) proposed OVRP with competitive time windows (OVRPPCTW) considering the idea that the reaching time to customers affects the sales amount. In this paper, a new, multi-objective mathematical model of the homogeneous and competitive OVRP is presented in order to minimize the travel cost of routes and to maximize the obtained sales while concurrently balancing the goods distributed among vehicles. This model is solved by using a multi-objective particle swarm optimization algorithm (MOPSO). Li et al. (2012) addressed the heterogeneous fixed fleet open vehicle routing problem (HFFOVRP) in which the customers' demands were fulfilled by a fleet of fixed number of vehicles with various capacities and related costs. They proposed a multi start adaptive memory programming metaheuristic method with a modified tabu search algorithm to solve this new vehicle routing problem. Marinakis and Marinaki (2014) proposed an improved version of the Bumble Bees Mating Optimization (BBMO) algorithm to solve the open Vehicle Routing Problem. Erbao et al. (2014) investigated the open vehicle routing problem with uncertain demands by proposing the robust optimization model that aim at minimizing transportation costs and unsatisfied demands in the specific bounded uncertainty sets.

Few researches have been conducted on the VRP under minimizing emissions before 2006. Carins (1999) considered the environmental impact of grocery home delivery by converting distance into emissions without attention to speed changes. Van Woensel et al. (2001) demonstrated the importance of traffic flow information in emissions. Their results showed that calculating emissions under constant speed causes suboptimal routes up to 20% in emissions on the average for gasoline-consuming vehicles and about 11% for diesel-consuming ones, which increased by about 40% during congested periods. Sugawara and Niemeier (2002) proposed a model for emissions-based trip assignment optimization. Their results demonstrated potential emission reduction with the assumption that drivers pass emission-minimizing routes. Sbihi and Eglese (2007) discussed green logistic that deals with different strategies of distribution by measuring the environmental effects and decreasing emissions and fuel consumption. Kara et al. (2007) studied Energy Minimizing Vehicle Routing Problem (EMVRP), which considered CVRP with the objective of minimizing product of the total load and the length of the arc. Palmer (2008) considered vehicle routing problem with time windows by minimizing CO₂ emissions. Results showed that minimizing CO₂ emission instead of travel time causes about 5% reduction in CO₂ emission. He used real traffic data to estimate fuel consumption and emissions in studying emissions in the context of grocery home delivery vehicles. In another development, Kim et al. (2009) considered CO₂ emissions and freight transport costs by relating CO₂ emissions to speed and distance traveled. Maden et al. (2010) investigated TDVRP with time varying speeds. Their results demonstrated about 7% reduction in CO₂ emissions. Figliozzi (2010) studied the Emissions Vehicle Routing Problem (EVRP) whose objective is the minimization of emissions costs. In their model, emissions were related to the speed and distance traveled. They considered three traffic conditions: uncongested, somewhat congested and

congested. Urquhart et al. (2010) used evolutionary algorithms to solve VRPTW with CO₂ savings, distance and number of vehicles. Kuo (2010) proposed an algorithm for calculating traversed time and fuel consumption in TDVRP with regard to vehicle speed in his model. Bektas and Laporte (2011) presented the Pollution Routing Problem by offering a comprehensive model and considering the amount of greenhouse emissions, fuel, travel times and their costs. Demir et al. (2012) investigated optimum speed due to the speed limitation and traffic congestion. Jabali et al. (2012) used tabu search algorithm for TDVRP by considering the effect of limiting vehicle speed. They concluded that travelling in congested conditions causes emitting more CO₂ emission. Xiao et al. (2012) suggested a Fuel Consumption Rate (FCR), which is load dependent. They studied CVRP with minimizing fuel consumption as an objective. Kopfer et al. (2013) considered load for CO₂ emissions evaluations in the presence of heterogeneous vehicle types. A detailed presentation and description of studies, which consider the problem of vehicle routing as well as the problem of routing “green” vehicles can be found in Lin et al. (2014). Tajik et al. (2014) address a new time window pickup-delivery pollution routing problem (TWPDPRP) to deal with uncertain input; and a new mixed integer linear programming (MILP) approach is presented under uncertainty by considering greenhouse emissions. The objective of the model is to minimize fuel consumptions and greenhouse emissions along with their total costs in addition to travel distance and number of available vehicles.

Minimizing the fuel consumption merely by considering load and distance can be insufficient since the travel speed plays a major role, and speed is directly affected by the road congestion. Paying attention to effective factors alone such as road gradient, distance, vehicle load and vehicle speed cannot minimize emissions well in vehicles due to the tradeoff between these factors. There are several emission models such as Macroscopic and Microscopic. We used emission function from MEET model, which is a kind of macroscopic model, to consider effective factors together to minimize emissions in vehicles.

The innovations of this paper can be summarized as follows:

- A comprehensive model based on MEET model is presented for measuring and evaluating the CO₂, NO_x, and CO emissions in open time dependent vehicle routing problem.
- The presence of several traffic patterns and the “first-in–first-out” (FIFO) property, which has been of little attention to researchers, are also considered in the presented model.
- Measuring and evaluating the performance of a particle swarm optimization algorithm for such a model
- The performance of the proposed method is measured using an exact algorithm in small size problems.
- Based on Particle swarm optimization, an Improved Meta heuristic algorithm has been presented and evaluated to solve the proposed problem in the large scale size by comparing results obtained from PSO (original PSO)

3. Problem definition

In this section, first, factors that influence vehicle emissions are discussed, then, the OTDVRP description is presented; and finally, the FIFO property is described.

3.1. Effective Factors in vehicle emissions

It is true that VRP with minimizing travelled distance has reduction emissions in its objective, but this issue must be studied more carefully. Models for calculating the amount of emissions are very complex and depend on factors such as travelled distance, vehicle load, vehicle speed and road gradient.

In this paper, we use MEET model to calculate emissions. MEET model was proposed by Hickman et al. (1999). Factors affecting emissions including vehicle speed, vehicle load and speed are fully considered in this model and we use this model for CO₂, NO_x and CO emissions. Eqs. (1), (2), and (3) express the relation between mentioned factors and CO₂, NO_x, and CO emissions respectively.

$$e = (110 + 0.000375v^3 + \frac{8702}{v}) \times GC \times LC \quad (1)$$

$$e = (0.508 + 3.87E - 6v^3 + \frac{92.5}{v} - \frac{77.3}{v^2}) \times GC \times LC \quad (2)$$

$$e = (1.5 - 0.0595v + 0.00119 - 6.16E - 6v^3 + \frac{58.8}{v}) \times GC \times LC \quad (3)$$

In these equations, e is the emission factor (gr/km), v is the vehicle speed (km/h), GC is the correction coefficient for the road gradient and LC is the correction coefficient for the vehicle load. Total emission (gr) is obtained with Eq. (4). In this equation, E is the emission (gr) produced and obtained according to the following equation. In this equation, D is the distance traversed (km).

$$E = e \times D \quad (4)$$

Finally, total emissions are obtained with the summation of CO₂, NO_x, and CO emissions.

3.1.1. Vehicle speed

Speed is the most important factor that affects emissions (Figliozzi 2011). Vehicle inertia, resistance of the wheels and air resistance are affected by vehicle speed (Hickman 1999). It is worth mentioning that in this paper, vehicles with GVWR 3.5 to 7.5 tons are studied. GVWR is maximum total weight permitted for the vehicle such as empty mass of the vehicle, equipment, driver, fuel and vehicle load (Bektas and Laporte 2011).

3.1.2. Road gradient

Resistance of the vehicle is affected by road gradient; therefore, it causes an increase in emissions. The data to estimate gradient influence coefficient exists in Hickman et al. (1999), and that gradient influence coefficient is presented within the limited range of speed and road gradient. In order to calculate this coefficient for a larger range of speed and road gradient, the regression estimate with an estimation correctness of about 95% is used. Eqs (5), (6) and (7) demonstrate road gradient coefficient for CO₂, NO_x and CO, respectively.

$$GC = \exp((0.0059v^2 - 0.0775v + 11.936)\gamma) \quad (5)$$

$$GC = \exp((0.0062v^2 - 0.0427v + 11.301)\gamma) \quad (6)$$

$$GC = \exp((0.001v^2 + 0.0442v + 6.1207)\gamma) \quad (7)$$

In these equations, GC is the road gradient influence coefficient, γ is the road gradient (%) and v is the vehicle speed (km/h).

3.1.3. Vehicle Load

Vehicle load affects vehicle inertia. Heavier load deduces more power from the engine and the emission is affected by the engine power proportionally; therefore, vehicle load affects emissions. In Hickman et al. (1999) the load influence coefficient is presented in two states of loaded and not loaded. In order to calculate the load influence coefficient in a wide range of loads, Eqs (8), (9), and (10) are proposed for CO₂, NO_x and CO, respectively.

$$LC = (0.27)x + 1 + 0.0614\gamma x - 0.0011\gamma^3 x - 0.00235vx - \left(\frac{1.33}{v}\right)x \quad (8)$$

$$LC = (0.26)x + 1 + 0.0672\gamma x - 0.00117\gamma^3 x - 1.90E - 5v^2 x - \left(\frac{1.6}{v}\right)x \quad (9)$$

$$LC = (0.09)x + 1 + 0.037\gamma x - 5.29E - 4\gamma^3 x - 1.52E - 7v^3 x \quad (10)$$

In these equations, LC is the vehicle load influence coefficient. γ is the road gradient (%), v is the speed (km/h) and x is the ratio of vehicle load to vehicle capacity ([0.1]).

3.2. Necessity of using OTDVRP in green routing

In traditional VRP, it is assumed that travel time is constant and is not related to the time of the day when travelling occurs. With regard to the fact that travel time is related to the departure time, time dependent vehicle routing problem occurs.

In the OVRP, vehicles do not return necessarily to the depot after the last customer, meaning that routes start at the depot and end at one of the nodes, and each route is a Hamiltonian path instead of a Hamiltonian cycle in VRP (Repoussis et al. 2007). In this paper, we assume that vehicles do not come back to the depot resulting in an open route in which each vehicle starts its travel at the depot and ends at the last customer it serves. Vehicle speed is one of the parameters considered in TDVRP, and because vehicle speed is one of the important factors in emissions, considering environmental issues in TDVRP is effective in emissions.

3.3. FIFO property

FIFO property in TDVRP assures that if a vehicle starts travelling earlier from customer i to customer j , it arrives earlier compared to another vehicle that starts travelling later. When the speed in period $k+1$ is more than that in K , it is possible that the FIFO property is not satisfied. In this paper, to satisfy FIFO property, an algorithm based on the algorithm proposed by Kuo (2010) is employed. Therefore, we propose open time dependent vehicle routing problem that assumes no vehicles come back to the depot after last customer and FIFO property is satisfied.

4. Calculation of the amount of emissions

In this section an algorithm for calculating emission with regard to the FIFO property is proposed and as shown in pseudo code, travel time and emission can calculate.

The notation employed in the pseudo code for the calculation of emission between customer i and j are as follows.

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T_{ij}^0	Starting time travel from customer i to customer j
D_{ij}	Distance traversed between customer i & customer j
T_{ij}'	Arrival time to customer j from customer i
u_k	Upper limit of the k^{th} period

v_{ij}^k	Optimal speed between customer i & customer j in k^{th} period
t	Current time
e_{ij}^k	Emission factor in k^{th} period between customer i & customer j
E_{ij}	Emission produced between customer i & customer j

Pseudo code of calculating emission with regard to the FIFO property algorithm is as follows:

```

K=1, Eij=0
IF  $T_{ij}^0 \leq u_k$ 
    Calculate  $v_{ij}^k$  &  $e_{ij}^k$  according to the road gradient
    and vehicle load ratio with Eq. (11)
     $d = D_{ij}$ ,  $t = T_{ij}^0$ 
     $T_{ij}' = t + \frac{d}{V_{ij}^k}$ 
     $E_{ij} = e_{ij}^k \times d$ 
Else
     $k = k + 1$ 
End
If  $T_{ij}' > u_k$ 
    Calculate  $v_{ij}^{k+1}$  &  $e_{ij}^{k+1}$  according to the road
    gradient and vehicle load ratio with Eq. (11)
     $d = d - v_{ij}^k(u_k - t)$ 
     $t = u_k$ 
     $T_{ij}' = t + \frac{d}{v_{ij}^{k+1}}$ 
     $E_{ij} = E_{ij} + (e_{ij}^{k+1} - e_{ij}^k) \times d$ 
     $k = k + 1$ 
    Go to step 10
End

```

4.1. Optimal Speed

In this article, the objective is to minimize total travel time and emissions. To have an objective by minimizing costs, we multiply these terms by w_1 and w_2 , sequentially in which w_1 is driver wage is assumed to be \$3 in one hour and w_2 is the cost of one gram emission assumed to be \$0.000027 (Bektas and Laporte 2011). With regard to this objective and Eq. (11), the related function depends on three variables: vehicle speed, vehicle load ratio and road gradient, for different values of road gradient and vehicle load ratio, the presented function become a uni-variable function. Therefore, optimal speed is obtained by MAPLE software.

$$\begin{aligned}
obj = & w_1 \times \left(\frac{D}{v}\right) + w_2 \times D \times \left[\left(110 + 0.000375v^3 + \frac{8702}{v}\right) \times \exp((0.0059v^2 - 0.0775v + 11.936)\gamma) \right. \\
& \times \left(1 + (0.27 + 0.0614\gamma - 0.0011\gamma^3 - 0.00235v - \frac{1.33}{v})x\right) + [(0.508 + 3.87E \\
& - 6v^3 + \frac{92.5}{v} - \frac{77.3}{v^2}) \times (\exp(0.0062v^2 - 0.0427v + 11.301)\gamma) \times (1 + (0.26 + \\
& 0.0672\gamma - 0.00117\gamma^3 - 1.90E - 5v^2 - \frac{1.6}{v})x) + [(1.5 - 0.0595v + 0.00119v^2 \\
& - 6.16E - 6v^3 + \frac{58.8}{v}) \times (\exp(0.001v^2 + 0.0442v + 6.1207)\gamma) \times (1 + (0.09 + 0.037\gamma \\
& - 5.29E - 4\gamma^3 - 1.52E - 7v^3)x)] \left. \right]
\end{aligned} \tag{11}$$

In Eq. (11), the first term is driver cost and the second term is emissions cost. The first bracket is emission factor for CO₂, the second and third brackets are emission factors for NO_x, and CO, respectively.

5. Solution Methods

Since the standard mathematical modeling for solving proposed problem cannot be used, first we propose an enumeration technique to find the optimal solutions (enumeration technique specifies all possible solutions and always finds the optimal solution).

5.1. Enumeration method

The proposed enumeration method considers all states that vehicles can visit customers. Therefore, all partitions of number n (number of customers) with size m (number of vehicles) are determined, then, for every permutation that access from set with size n, all partitions are considered. Pseudo codes of partitioning algorithm and pseudo code of permutation algorithm are presented respectively as follows: In these pseudo codes, m is the number of vehicles and n is the number of customers.

Pseudo code of the permutation algorithm is presented as follows:

```

Set a[i]=i for i=1, 2,..., n (first permutation)
  i=n
  While (i> 0)
    x=a[i]+1
    P=false
    While p=false
      If x≤ n
        for all j=1,..., n a[j]≠ x
          a[i]=x
          Recognize numbers
          between 1 to n that are not in vector a,
          Assign them to vector a
          non-Descending, from
          a[i+1] to a[n]
          Save new permutation
          i=n
          P=true
        Else

```

```

        x=x+1
    End
Else
    a[i]=0
    i=i-1
    If i> 0
        x=a[i]+1
    Else
        Break
    End
End
End
End
End

```

Also, Pseudo code of the partitioning algorithm is as follows:

```

Set b[i]=1, for i=1, 2,..., m-1 and b[m]=n-sum(b)
While b[1] < n-m+1
    b[m]=b[m]-1
    If b[m] ≥ 1
        b[m-1]=b[m-1]+1
        b (new partition)
    Else
        For j= m-1,...,1
            If b[j] ≠ 1
                Break
            End
        End
        b[j-1]=b[j-1]+1
        For i=j,..., m-1
            b[i]=1
        End
        b[m]=n-sum(b)
        b (new partition)
    End
End
End

```

For example, if 3 vehicles and 4 customers exist, all partitions of number 4 with size 3 with respect to the proposed algorithm are as follows: 1-1-2, 1-2-1, 2-1-1.

Then, for every permutation access from set with size 4 that are 4!, considering all partitions. For example, for the first permutation with respect to the proposed algorithm: 1-2-3-4 by first partition: 1-1-2, it means the first customer is visited by the first vehicle, the second customer is visited by the second vehicle and the third and fourth customers are visited by the third vehicle. It is worth mentioning that the proposed exact method computes all possible routes for assignment and sequence of customers to vehicles and the time complexity of this method is $O(m^n n!)$.

5.2. Particle Swarm Optimization Algorithm (PSO)

PSO includes some multidimensional particles. Each particle has a position and velocity to move. When each particle moves, its own best position, global best position and its neighborhood's best position are updated.

In the original PSO, three-dimensional particles are used. In this PSO, it is possible that the algorithm traps into local optimum because if the global optimum does not lie on between original particle positions and local optimum, it may cause many particles are to waste computational efforts; however, if various particles explore other possible search directions, better results may be obtained (Ai and Kachitvichyanukul 2009). The original PSO does not consider this issue and does not include a neighbour particle (nbest), while Veeramachaneni et al. (2003) introduced another dimension in which the particles are influenced by other particles, while in the original PSO, particles move towards the best position found so far. Therefore, they used Fitness Distance Ratio (FDR) to add a new dimension to this moving due to natural observations of animal behavior:

1. An organism is most likely to be influenced by others in its neighborhood.
2. Among the neighbors, those that have been more successful (than it) are likely to affect its behavior.

The mentioned PSO steps are as follows:

- 1) Initialize a population of M particles (number of particles) (X_k , $k=1,2,\dots, M$) and objective function $f(X)$ using FIFO algorithm, $X=(X_1, X_2, \dots, X_d)^T$
- 2) Set velocity $q_{ks}(1)=0$ and personal best $Xpbest_k=X_k$ ($k=1,2,\dots, M$) and set iteration $t=1$.
- 3) Update pbest: if $f(X_k) < f(Xpbest_k)$, $Xpbest_k=X_k$ ($k=1,2,\dots, M$).
- 4) Update gbest: if $f(Xpbest_k) < f(Xgbest)$, $Xgbest=Xpbest_k$ ($k=1,2,\dots, M$)
- 5) Update lbest: among all the kth particle's neighboring pbests, set particle with least objective $Xlbest_k$ ($k=1,2,\dots, M$)
- 6) Generate nbest: the sth dimension of the kth particle's velocity updates with a particle called nbest, whose dimension update with particle j that maximizes following ratio.

$$FDR = \frac{f(X_k) - f(Xpbest_j)}{|X_{ks} - Xpbest_{js}|} \quad j=1, 2, \dots, M, j \neq K \quad (12)$$

Eq. (12) shows the ratio of fitness difference to the one-dimensional distance.

- 7) Update velocity of the kth particle:

$$q_{ks}(t+1) = w(t)q_{ks}(t) + c_p u_1 (Xpbest_{ks} - X_{ks}(t)) + c_g u_2 (Xgbest_s - X_{ks}(t)) + c_k u_3 (Xlbest_{ks} - X_{ks}(t)) + c_n u_4 (Xnbest_{ks} - X_{ks}(t)) \quad (13)$$

In Eq. (13), $q_{ks}(t)$ is the sth dimension of the velocity of the kth particle, c_p is personal best solution acceleration constant, c_g is global best solution acceleration constant and c_k and c_n are local best solution and near neighbor best solution acceleration constants. As shown in Eq. (13), velocity of the kth particle updates with the previous iteration velocity, local best position, global best position, neighborhood best position, $w(t)$ is the inertia weight in the tth iteration that is calculated with the following equation:

$$w(t) = w(T) + \frac{t-T}{1-T} [w(1) - w(T)] \quad (14)$$

In Eq. (14), T is max iteration, $w(1)$ and $w(T)$ are input parameters, ($w(1) > w(T)$) and $w(t)$ decrease with an increase in the number of iterations.

- 8) Update position of the kth particle and calculate its objective function, using FIFO algorithm.

$$X_{ks}(t+1) = X_{ks}(t) + q_{ks}(t+1) \quad (15)$$

9) Apply local search algorithms to predetermined number of particles randomly selected (local search algorithms are described in subsection 5.4). If objective function of a particle is improved, accept changes on it; otherwise, go to the next step without applying changes.

10) If stop criterion is met ($t=T$), stop. Otherwise, go to further iteration and go to step 3.

The following flowchart presents steps of algorithm:

Fig 2. IPSO Flowchart

5.3. Solution encoding

In order to present particles in the PSO algorithm and because that particle moves in a continuous space; it must create a relation between the space created by algorithm and the space for the problem. Therefore, we use $3n$ string permutation where n is the number of customers. The created numbers in the permutation are randomly in the range of $[0,100]$. This permutation includes 3 parts: the first part is related to the sequence of vehicles and the second and third parts are related to allocation of customers to vehicles. From the second and third parts, one of these parts is selected randomly. The distance between the maximum and the minimum value of the selected part is divided by the number of vehicles (m). Then, if the e^{th} room of the selected part is located within the m^{th} range, the e^{th} customer is allocated to the m^{th} vehicle. Then, with regard to the first part, the customer with the larger number has priority in servicing (Farhang Moghaddam et al. 2012).

In the presented PSO algorithm, if each of dimensions exceeds $[0,100]$, the same value exceeding the limit is returned. It is worth mentioning that for initial population, the position of

particles is produced randomly. For better illustration, an example with three vehicles and seven customers is shown in Fig. 3. In this example it is supposed that the second part is selected for allocating customers to vehicles, and considering that the larger the number allocated to a customer, the higher the priority assigned to him, three tours 0-7-6-2-0, 0-5-1-0 and 0-3-4-0 are generated.

First part							Second part							Third part						
1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
2	1	8	5	5	3	8	5	3	8	7	4	2	1	2	1	8	5	5	3	8
4	7	2	3	4	2	9	4	2	9	4	7	2	4	4	7	2	3	4	2	9

customers	1	2	3	4	5	6	7
Assigned Vehicles	2	1	3	3	2	1	1

Routes	Vehicle one			Vehicle two			Vehicle three		
	7	6	2	5	1		3	4	
	8	3	1	5	2		8	5	
	9	2	7	4	4		2	3	

Fig.3 An example for solution representation

5.4. Local search

In this section, some local searches explain what we use in algorithm to increase convergence speed to better solution.

5.4.1. 2-OPT

The 2-opt local search is one of the λ -opt local searches in which the two arcs (i, i+1) and (j, j+1) are deleted from a route and two new arcs (i, j) and (i+1, j+1) are added (Fallahi et al. 2008). For example, if two arcs (2-4) and (6-3) are deleted from 0-2-4-8-5-7-6-3-0 route, the new route will be 0-2-6-7-5-8-4-3-0.

5.4.2. Exchange

In the Exchange local search, places of two customers in a route change (Balseiro et al. 2011). For example, if two customers 3 and 1 are selected from route 0-2-1-5-8-3-0, the new route becomes 0-2-3-5-8-1-0.

5.4.3. Exchange in two routes

Exchange in two routes is done as follows: Two customers from two routes are selected and places of these customers change; therefore, vehicles that serve these customers change (Balseiro et al. 2011).

6. Computational experiments

In the following experiments, the proposed PSO (IPSO) algorithm is tested by GOTDVRP instances including CVRP instances from Augerat et al.[†] for equal vehicles. For using the instances for proposed problem, the following changes are considered.

6.1. Test problem generation

Within the scheduling horizon, assume that the number of periods between every two successive customers is considered to be 4. It is assumed that there are 2 different types of scenarios. Hence, scenario 1 is the one with the highest degree of time-dependency, while scenario 2 is the one with the lowest, and each scenario has one constant traffic pattern. In scenario 2, less traffic is considered (the speed changes are less dependent on the changes of periods and can be called a low-traffic scenario) and the speed is higher. The traffic periods considered for two scenarios are presented in Fig. 4. To determine the limit of the periods, it is assumed that the periods between every two successive customers are equal. It is worth mentioning that the time limit of each of the periods depends on the intended problem. Therefore, with regard to the answer in the basic problem (VRP), the longest tour obtained is divided into three parts so as to obtain the limit of the first three periods. The upper limit of the last period (the fourth period) is considered to be 100 (the great number) so that if a vehicle's travel time is not finished in the first three periods, it is finished in the last period. The traffic periods considered in the problem for the two scenarios are presented in Fig. 4.

Fig. 4- a Speed changes for the first scenario

b Speed changes for the second scenario

In this figure, it is assumed that the second and third periods are rush hours while in the first and last periods, traffic density is lower. To specify road gradient, the uniform distribution with the parameters of -10% to 10% is considered.

6.2. Tuning of the parameters

In order to specify parameters value of PSO algorithm, the Taguchi method is considered. In this method, a ratio named signal to noise (S/N) is used, where S is the amount of desirability and N is the value for undesirability (standard deviation of the answers), and Taguchi method attempts to increase this ratio. According to the proposed objective function, the pattern of “smaller is better” is used to minimize the objective. Eq. (16) shows formula for calculating S/N for these problems (Montgomery 2001):

[†] www.bernabe.dorronsoro.es/vrp

$$\frac{S}{N} = -10 \log \left(\frac{1}{n'} \sum_{i=1}^{n'} y_i^2 \right) \quad (16)$$

In equation (16), y_i is answer values (answer values, $i=1, \dots, n'$) of the objective functions. With regard to the results, $M=30$, $w(1)=0.9$, $w(T)=0.4$, $c_p=0.6$, $c_g=0.2$, $c_k=1.5$ are obtained which are considered identical between PSO and IPSO algorithms. The original PSO does not include a neighbour particle (nbest), so $c_n=1.5$ is only obtained for IPSO. To determine the maximum number of iterations in both algorithms, the trial and error method is used, and according to the results obtained, the value is considered to be 100.

6.3. Results

In this section, results from the proposed algorithms are studied. The algorithms are coded by MATLAB 2012 and are performed on a computer equipped with CPU Core i3 and 4 GB Ram. First, for instances for up to 10 customers (limited to 30 hours), we use the enumeration technique to check the efficiency of the original PSO algorithm and Improved PSO algorithm (IPSO). The results of small size problem are shown in table 1.

Table 1 Comparison of PSO and IPSO with exact solution

#	Enumeration method		PSO			IPSO		
	Obj ^a (\$)	ST	Obj (\$)	ST	EP (%)	Obj (\$)	ST	EP (%)
1/5/2 ^b	30.73	0.3	30.73	2	0	30.73	3	0
2/6/2	25.21	4	25.21	5	0	25.21	6	0
3/7/3	30.00	48	30.00	6	0	30.00	6	0
4/8/3	31.52	461	31.52	7	0	31.52	8	0
5/9/2	23.96	4229	23.96	11	0	23.96	13	0
6/9/3	29.92	4875	29.92	12	0	29.92	12	0
7/10/2	26.18	49783	26.21	21	0.11	26.18	22	0
8/10/3	32.91	91945	32.91	12	0	32.91	14	0
9/10/4	40.66	101023	40.73	16	0.16	40.66	17	0
10/10/5	48.96	193465	49.05	8	0.18	48.96	9	0
average	32.01	44583	32.02	10	0.046	32.01	11	0

^aTotal driver cost and emissions cost

^bNo./number of customers/number of vehicles

In tables 1 and 2, Obj is the amount of objective function, ST is the solving time (second), and EP is the error percentage calculated with Eq. (17).

$$\frac{\text{obtained solution} - \text{optimal solution}}{\text{optimal solution}} \times 100 \quad (17)$$

As shown in table 1, in all small instances, IPSO reaches the best solution, but in 3 instances, original PSO does not reach the optimal value, and percentage error for PSO is 0.046%, while for IPSO, it is 0%; showing that IPSO has appropriate performance compared to original PSO and exact method.

To investigate the efficiency of IPSO and PSO, in large scaled problems, 27 large scaled problems are solved with algorithms. The results have been shown in Table 2. In this table, Error percentage is calculated using eq.(18). In this equation, problem solution is the solution obtained by algorithm and best solution is the best solution obtained by all considered algorithms.

$$\frac{\text{problem solution} - \text{best solution}}{\text{best solution}} \times 100$$

(18)

Table 2 Comparison of PSO with IPSO in large-scale instances

#	PSO			IPSO		
	Obj (\$)	ST (Second)	EP (%)	Obj (\$)	ST (second)	EP (%)
1/31/5	72.07	54	4.0	69.30	55	0
2/32/5	57.83	73	2.7	56.31	74	0
3/32/6	62.89	63	6.0	59.33	63	0
4/33/5	63.37	88	6.0	59.78	90	0
5/35/5	63.75	93	0	63.75	95	0
6/36/5	61.32	117	5.5	58.12	118	0
7/36/6	76.36	107	0.3	76.14	109	0
8/37/5	70.02	124	5.1	66.56	127	0
9/38/5	74.75	144	6.1	70.46	146	0
10/38/6	74.32	133	0	74.32	135	0
11/43/6	76.74	201	0.1	76.66	204	0
12/44/6	90.17	221	0	90.17	224	0
13/44/7	89.69	207	1.7	88.19	210	0
14/45/7	86.58	244	0.3	86.32	247	0
15/47/7	97.01	285	4	93.28	289	0
16/52/7	93.06	290	0.1	92.97	294	0
17/53/7	98.10	321	3.8	94.51	324	0
18/54/9	86.08	342	0	86.08	345	0
19/59/9	125.47	374	5.6	118.82	379	0
20/60/9	100.65	386	5.3	95.58	386	0
21/61/8	114.39	398	0	114.39	401	0
22/62/9	143.66	425	2.0	140.85	431	0
23/62/10	121.88	417	4.9	116.19	422	0
24/63/9	115.88	456	3.6	111.85	461	0
25/64/9	117.95	472	4.8	112.54	480	0
26/68/9	107.27	515	3.3	103.84	523	0
27/79/10	154.91	617	3.4	149.82	622	0
average	92.45	265	2.9	89.86	269	0

As shown in table 2, in all instances, IPSO performs better results compared to PSO. Error percentage for PSO is 2.9%, showing appropriate improvement in IPSO compared to the PSO. It could be the result of adding neighbour particle (nbest) to IPSO algorithm. while solution time of IPSO is a little longer than PSO, 265 (Sec) and 269 (Sec) on the average for PSO and IPSO, respectively. Therefore, the results of algorithms show better solution quality of IPSO compared to the PSO.

In order to show convergence process trend of PSO and IPSO in optimizing, one case of the test problems with 64 customers and 9 vehicles is considered.

Fig.5 : the convergence trend of PSO and IPSO algorithms

As can be seen in the Fig. 5, original PSO algorithm in the initial iterations has a better performance comparing with IPSO algorithm, but after about 20 iterations the algorithm falls in to the trap of local optimal solution and improvement trend is reduced. The convergence trend of IPSO algorithm in the initial iterations is slow but gradually driven toward better solutions. The deference between two algorithms may be related to the neighbour particle (nbest).

In order to study the ability of proposed model, reduction of the amount of emissions problem by only minimizing driver cost as an objective (model 1) is compared with the model by minimizing driver cost and emissions cost as an objective (model 2). Results are shown in table 3. In this table, Tt is travel time (hour), PU is percentage of the amount of delivered load in 40% of the first stops and E is the amount of emissions generated.

Table 3. Compared of problems with different objectives

#	Model 1			Model 2		
	E (gr)	Tt	PU	E (gr)	Tt	PU
1/5/2	113124	7.91	33.1	97259	8.43	55.1
2/6/2	84703	6.31	39.4	75840	6.95	38.3
3/7/3	126169	7.59	41.9	103691	8.16	41.3
4/8/3	81642	7.94	26.1	72382	8.87	30.6
5/9/2	25148	6.79	26.9	20654	7.02	29.3
6/9/3	76346	7.81	36.8	65000	8.45	35.5
7/10/2	47208	6.99	28.2	42395	7.51	36.8
8/10/3	137385	8.35	26.8	116420	8.93	33.1
9/10/4	159639	10.61	32.7	136914	11.09	41.1
10/10/5	244475	12.22	32.5	193728	13.12	43.2
11/31/5	257009	18.18	35.1	220864	19.00	55.9
12/32/6	284019	14.01	29.4	235679	15.89	59.1
Average	136406	9.56	32.4	115069	10.29	41.6

As shown in table 3, in model 2, the average amount of emissions is 115069 (gr) while for model 1 it is 136406 (gr), showing about 16% reduction in emission generation, and 7% increase in travel time. The highest improvement occurs in problem 10 that is 21% reduction in emission generation and 7% increase in travel time. Also, percentage of the amount of delivered load in the 40% of the first stops is 32.4% and 41.6%, on the average for model 1 and 2, respectively, showing that the amount of emissions is reduced by delivering the heavier loads in first steps in

model 2. In addition, in model 2, the vehicles travel at optimum speed as much as possible with regard to the factors which affect the amount of emissions such as the road gradient and vehicle load in addition to the vehicle speed unless the traffic zone prevents driving at the optimal speed, in which case the permitted speed nearest to the optimal speed is used. As a result, the amount of emissions is reduced but in model 1, the vehicles use max speed that causes increases in emissions to minimize the deriver cost. These results are shown in Fig. 6 as follows:

Fig. 6.a Diagram of emissions in model 1 and 2

b Diagram of travel time in model 1 and 2

As shown in Fig. 6, emissions in model 2 are remarkably less than model 1, while travel time does not notably increase.

7. Conclusion

In this paper, Measurement, Evaluation and Minimization of CO_2 , NO_x , and CO as three important emissions (that come out from vehicles) in the open time dependent vehicle routing problem (OTDVRP) were investigated using MEET model. This issue can be useful for distribution managers to minimize emissions and fuel consumption in vehicles. To solve the proposed problem, an improved Particle Swarm Optimization algorithm was presented. Computational results confirm appropriate performance of IPSO compared to the original PSO. We also showed that the proposed model causes remarkable reduction in emissions while it causes 16% reduction in emission generation on the average. With regard to the proposed problem, when vehicles first serve customers with larger demands, the pollutant emissions are reduced. In addition, in the proposed problem, vehicles travel at optimum speed resulting in reduction in emissions.

There are several emission models such as Macroscopic and Microscopic and in this paper the meet model, one of the Macroscopic models, are used to estimate the emission factors, Future work will include comparing these models deciding which one has more accuracy in real world at distribution area. Another activity can be considering environmental issues in other logistic issues.

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Fig. 3.a Diagram of emissions in model 1 and 2

b Diagram of travel time in model 1 and 2