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A Green Competitive Vehicle Routing Problem under Uncertainty Solved by an Improved Differential Evolution Algorithm

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ABSTRACT

Regarding the development of distribution systems in the recent decades, fuel consumption of trucks has increased noticeably, which has a huge impact on greenhouse gas emissions. For this reason, the reduction of fuel consumption has been one of the most important research areas in the last decades. The aim of this paper is to propose a robust mathematical model for a variant of a vehicle routing problem (VRP) to optimize sales of distributers, in which the time of distributor service to customers is uncertain. To solve the model precisely, the improved differential evolution (IDE) algorithm is used and obtained results were compared with the result of a particle swarm optimization (PSO) algorithm. The results indicate that the IDE algorithm is able to obtain better solutions in solving large-sized problems; however, the computational time is worse than PSO.

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1. INTRODUCTION

In recent years, by increasing large-scale greenhouse gases (GHG) emissions, the social cost of the governments have considerably increased [1]. Increasing of fuel consumption creates significant negative impacts on greenhouse gas emissions.

Research has shown that in the real competitive world, the decrease of the distribution cost (especially in fuel consumption) has affected on the operation cost. The distribution cost depends on many criteria and can be separated into two broad categories. The first one includes the load, speed, road status, fuel consumption rate (in any distance), fuel price, etc. that are directly related to the scheduling issues. The second category includes vehicle depreciation, maintenance and repair costs, driver's wages, taxes, etc. [2–5].

Tavakkoli-Moghaddam et al. [6] considered a rival vehicle routing problem for the first time that maximizes the profit of earning liquidity and minimizes simultaneously the transportation costs. If competitors before drivers meet customers, the portion of income will be decreased. For this reason, distributors try to meet customers before their competitors to gain more profit. [7, 8]. However, in variant of a vehicle routing problem (VRP), parameters are considered deterministic. In order to use non-deterministic parameters, a stochastic approach has been used [9–11]. Mulvey et al. [12] presented stochastic robust optimization instead of a stochastic approach to estimate non-deterministic parameters. In this model, robustness considers robustness optimality and solution based on trade-off between cost and benefit. In addition, robust optimization model makes the structure to contribute robustness in the constraints and objective [13]. A VRP is classified as NP-Hard problem [14]. In recent years, different meta-heuristic methods were developed in order to solve a VRP, like tabu search [15], particle swarm optimization

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algorithm (PSO) and simulated annealing (SA) algorithm [16, 17].

Innovations of this research are as follows: the servicing time of rivals is considered under uncertainty and instead of an expected starting service time, a set of scenarios are considered in the proposed model, and a robust model is used to maximize the rate of sales and reduce the cost. In addition, reducing fuel consumption to reduce the operational cost and the harmful effects of greenhouse gases (especially, carbon and carbon dioxide) is also considered as bi-objectives. Moreover, a meta-heuristic based on IDE algorithm to find optimal solutions is another contribution used in this paper.

2. PROBLEM DEFINITION AND MODELING

2. 1. Collections And Indices

A VRP can be indicated by a graph G = (S, A), such that the points of nodes and $s = \{i | i = 0, \dots, n\}$ so that G is a set of the arrows and nodes; $A = \{(S_i, S_j): i \neq j\}$ that is a set of nodes joining the arrows, and S_0 represents the source. $D_{ij} \geq 0$, which is denoted arc (i, j), indicates the distance or cost of traveling among the two nodes i and j. The parameters used in this model are presented as follows:

N	Number of customers (i and j are the indices of customers)
yv	Number of vehicles
k_{yv}	The Capacity of vehicle v
T_v	Upper bound of the travel time of vehicle v.
T_v	Demand of the nodei.
t_{ij}^{v}	Time travel from node i to node j by vehicle v
M	large number
d_{tdi}	Time dependent demand of customeri
t_{uis}	In scenario s, an upper limit of rivals arrival time to node i
tl_{is}	In scenario s, a lower limit of rivals arrival time to node i
D_i	Total i-th customer demand so that $D_i = d_{tdi} + d_{ini}$
D_{tdi}	Demand of customer i (dependent to time)
D_{ini}	Demand of customer i (independent to time)
co_{rr}	Slip friction coefficient in each road
Ce_d	Air resistance coefficient
F_k	Front of the vehicle v
Ad	The density of air
GR	Earth's gravitational force
θg_{ij}	Average gradient of the road from node i to j
ac_k	Acceleration of vehicle v in meters per squared second
wv_k	Weight of vehicle v
Wl	Load unit weight
d_{ij}	Distance between customers i and j
v_k	Speed of vehicle v
l_i	Amount of time when vehicle reaches node i
D_i	Demand of customer i
x_{ij}^{v}	1, if vehicle v passes via route $[i, j]$
o_{is}	1, in scenario s, if the driver meets the customer more quickly than the lower bound of the rival
q_{is}	1, in scenario s, if the driver meets the customer during the rival time period
z_{is}	1, in scenario s, if the distributer begins customer service after the rival upper bound
y_{is}	1, in scenario s, if the driver meets customer before the rival upper bound.

2. 2. Mathematical Model

The proposed mathematical model is defined as follows:

$$\text{Max } Z_1 = \sum_{s\in\Omega} p_s \left[\sum_{i=1}^{n}\left(o_{is} d_{tdi} + q_{is}\left(\frac{t_{uis}-t_i}{t_{uis}-t_{lis}}\right) d_{tdi}\right)\right] + \lambda \sum_{s\in\Omega} p_s \left[\left(\sum_{i=1}^{n}\left(o_{is} d_{tdi} + q_{is}\left(\frac{t_{uis}-t_i}{t_{uis}-t_{lis}}\right) d_{tdi}\right) - \sum_{s'\in\Omega} p_{s'} \left[\sum_{i=1}^{n}\left(o_{is'} d_{tdi} + q_{is'}\left(\frac{t_{uis'}-t_i}{t_{uis'}-t_{lis'}}\right) d_{tdi}\right)\right]\right) + 2\theta_s\right] - \omega \sum_{s\in\Omega} p_s \delta_s \tag{1}$$

$$\text{Min } Z_2 = \sum_{v=1}^{yv}\sum_{j=0}^{n}\sum_{i=1}^{n}(f_k + g sin\theta g_{ij} + grco_{rr} cos\theta g_{ij})\left(wv_k + wl_j^v\right)\mathrm{d_{ij}} x_{ij}^{v} + \sum_{v=1}^{nv}\sum_{j=0}^{n}\sum_{i=1}^{n} 0.5\, ce_d\, Ac_k Ad v_k^2 \mathrm{d_{ij}} x_{ij}^{v}$$

$$\sum_{i=1}^{n}\sum_{v=1}^{yv} x_{ij}^{v} = 1, \qquad \forall\, j = 2, \dots, n \tag{2}$$

$$\sum_{j=1}^{n}\sum_{v=1}^{yv} x_{ij}^{v} = 1, \qquad \forall i = 2, \dots, n \tag{3}$$

$$\sum_{i=1}^{n} x_{ij}^{v} = \sum_{i=1}^{n} x_{ji}^{v}, \qquad \forall\, j = 1,2, \dots, n \quad v = 1, \dots, yv \tag{4}$$

$$(l_i^v - d_i - l_j^v) x_{ij}^{v} = 0 \qquad \forall i = 0,1, \dots, n \;\; j = 1, \dots, n \;\; v = 1, \dots, yv \tag{5}$$

$$\sum_{i=1}^{n} s_i \sum_{j=1}^{n} x_{ij}^{v} + \sum_{i=1}^{n}\sum_{j=1}^{n} \frac{d_{ij}}{v_k} x_{ij}^{v} \leq T_v \qquad \forall\, v = 1, \dots, yv \tag{6}$$

$$t_j = \sum_{i=1}^{n} t_i \sum_{v=1}^{yv} x_{ij}^{v} + \sum_{i=1}^{n}\sum_{v=1}^{yv}\left(\frac{d_{ij}}{v_k}\right) x_{ij}^{v} + s_j \qquad \forall\, j = 2, \dots, n \tag{7}$$

$$\sum_{i=1}^{n}(D_i - d_{tdi} z_{is}) \sum_{j=1}^{n} x_{ij}^{v} - \delta_s \leq k_{yv} \qquad \forall\, v = 1,2, \dots, yv \quad s\epsilon\Omega \tag{8}$$

$$(t_{uis} - t_i) - M(y_i) \leq 0 \qquad i = 1,2, \dots, n, s \in \Omega \tag{9}$$

$$(t_{uis} - t_i) - M(z_{is}) \geq 0 \qquad i = 1,2, \dots, n \quad s \in \Omega \tag{10}$$

$$z_{is} + y_{is} = 1 \quad i = 1,2, \dots, n \quad s \in \Omega \tag{11}$$

$$(t_{uis} - t_i) + M(1 - q_{is}) \geq 0 \quad i = 1,2, \dots, n \quad s \in \Omega \tag{12}$$

$$(t_{lis} - t_i) + M(1 - o_{is}) \geq 0 \quad i = 1,2, \dots, n \quad s \in \Omega \tag{13}$$

$$(t_{lis} - t_i) + M\varpi_{is} \leq 0 \quad i = 1,2, \dots, n \quad s \in \Omega \tag{14}$$

$$q_{is} + \varpi = 1 \quad i = 1,2, \dots, n \quad s \in \Omega \tag{15}$$

$$\sum_{i=1}^{n} \left(o_{is} d_{tdi} + q_{is} \left(\frac{t_{uis} - t_i}{t_{uis} - t_{lis}} \right) d_{tdi} \right) - \sum_{s \in \Omega} p_s \left(\sum_{i=1}^{n} \left(o_{is} d_{tdi} + q_{is} \left(\frac{t_{uis} - t_i}{t_{uis} - t_{lis}} \right) d_{tdi} \right) \right) + \theta_s \geq 0 \quad s \in \Omega \tag{16}$$

$$\sum_{v=1}^{nv} \sum_{j \in S} \sum_{j \notin S} x_{ij}^{v} \leq |s| - p(s) \quad \forall S \subseteq A - \{1\} \quad s \neq \phi \tag{17}$$

$$x_{ij}, o_{is}, y_{is}, z_{is}, q_{is}, \varpi_{is} \in [0,1] \quad t_i \geq 0 \quad t_1 = 0 \tag{18}$$

Equation (1) indicates the sales of distributer under uncertainty, and concerns reducing GHG emission and fuel consumption.

Restrictions (2) and (3) make it possible for each request to be served only from a distributor vehicle. Constraint (4) states that if a vehicle is to be inserted into a node, it must be removed, thus connecting the routes. Constraint (5) states that if $x_{ij}^{v} = 1$, the amount of goods carried to the *j*-th node is equal to the load transferred to the *i*-th node minus the *i*-th node's demand (i.e., the *i*-th node is served immediately by the *i*-th vehicle by the *v*-th vehicle immediately).

Constraint (6) indicates that the service time and route should be less than the specified value. Constraint (7) indicates the start time for serving customers. Constraints (8) to (11) indicates that if vehicle v starts to serve in the scenarios earlier t han t_{uis} to customer i then the i-th customer demand must be equal to D_i from the base station. This is because the distributor starts service faster than other competitors do and can take all profitable business out of it. If the start-of-service time to the i-th customer is after t_{uis}, then the profit previously earned will only be equal to the amount of independent demand. Constraints (12) to (15) relate to maximizing profits. Constraint (16) indicates the difference between the profits earned in the scenarios and expected value of earning profits for all scenarios. Constraint (17) is related to the elimination of subtractions, and the Constraint (18) relates to the model variables.

3. PROBLEM-SOLVING APPROACH

The differential evolution (DE) was first proposed by Storn and Price [18]. Due to considerable performance in discrete problems, DE has been used in solving problems in the past years [19]. The proposed algorithm is shown in Figure 1.

To define mutation operator in DE, trial vector, $v_i(\mathrm{l})$, for every individual of exciting population is generated by mutating. Off spring vector is produced trial vector, $v_i(\mathrm{l})$ by a crossover operator for parent $\mathrm{y_i}(\mathrm{l})$. The trial vector $v_i(\mathrm{l})$ is demonstrated in Figure 2.

Offspring vector, $y_i'(t)$, is generated by:

$$y_{ik}'(t) = \begin{cases} v_{ik}(l) & \text{if } j \in \delta \\ y_{ik}(l) & \text{otherwise} \end{cases} \tag{19}$$

where $y_{ik}(g)$ presents to the k-th $(k \in \{1, \dots, n_x\})$ particle of vector, $y_i\,(g)$, and a set of crossover points are represented as δ. The DE binomial crossover operator is shown in Figure 3.

Experimental studies show that model $DE/rand/1/bin$, in which a target vector is chosen randomly, provides a good variety in answers and is capable of converging the answers. On the other hand, strategy $current - to\ best/2/bin$ will result in convergence in answers, which is shown in the following equation:

$$v_i(g) = y_{i_1}(g) + \beta\big(\hat{y}(g) - y_i(g)\big) + \beta\big(y_{i_2}(g) - y_{i_3}(g)\big) \tag{20}$$

where a differential vector is first calculated from the difference between best available vector $\hat{y}(g)$ with parent vector $y_i\,(g)$ and the second differential vector is calculated by the difference between $y_{i_2}(g), y_{i_3}\,(g)$ vectors which are chosen randomly to achieve the best results in DE, strategies are used dynamically based on

```
l is a generation and set  l = 0
c(l) is indicated as a member of generation G
the control parameters are λ and k_r ;
For, y_i(g)ϵC(l) do
Calculate, f (x_i(l))
Use the mutation operator to calculate trial vector, v_i(l);
Use the crossover operator to calculate an child, y_i'(l) ;
If f(y_i(t))  is less than f(y_i'(l))
then y_i'(l) ∈ c(l + 1);
Else y_i(l) ∈ c(l + 1)
End.
```

Figure 1. Pseudo code of the proposed algorithm

```
For each individual, y_{i_i}(l)ϵC(l)  and   i_i~U(1,n_s) do
Select target vector, such that i_i and i_1 not equal.
Select y_{i_2}(l) and y_{i_3}(l) randomly, t  i ≠ i_1 ≠ i_2 ≠ i_3.
 Calculate trial vector ass following equation:
v_i(l) = y_{i_1}(t) + λ(y_{i_2}(g) − y_{i_2}(g))
End.
```

Figure 2. Selecting trial vector by the mutation

```
Select δ~U(1, n_s) and p_r randomly.
  For each j, y_i(l)
      If k_r > U(0,1) then δ ← δ ∪ {j}
  End
```

Figure 3. DE binomial crossover operator

probability. $d_{s,1}$ and $d_{s,2} = 1 - d_{s,1}$ are assumed as the probable selection of strategy $\mathrm{DE/rand/1/bin}$ and $\mathrm{DE/current-to\ best/2/bin}$, respectively as the following equation:

$$d_{s,1} = \frac{q_{s,1}(q_{s,2}+q_{f,2})}{q(q_{s,2}+q_{f,2})+q_{s,2}(q_{s,1}+q_{f,1})} \quad (21)$$

where $q_{s,1}$ and $q_{s,2}$ in next repetition $c(g+1)$, indicates children number $y_i'(g)$ which are considered according to $\mathrm{DE/rand/1/bin}$ and $\mathrm{DE/current-to\ best/2/bin}$ respectively. Also, $q_{f,1}$ and $q_{f,2}$ are the number of children which are not converted to the next repetition.

4. COMPUTATIONAL RESULTS

In this paper, standard samples of the PVRPTW considered by Cordeau et al. [20] are used. For each scenario, lower and upper bound of time windows are considered as upper and lower reaching times of vehicles. That is the upper limit of reaching time to customers is considered in all scenarios t_{uis} in a uniform distribution in interval [15, 60] and the lower limit of the distributors' reaching time to customers in all scenarios tl_{is} in a uniform distribution in interval [10, 40].

The performance of algorithms is demonstrated in Table 1. In terms of the quality, IDE algorithm's solution could improve an average of more than 1% of the solutions. The mean error for the IDE and PSO algorithms is 0.36 and 1.1%, respectively. The greatest improvement in IDE solution algorithm occurred in problem 9, and a 3.66% improvement in response has occurred. The average run time for PSO is lower than the IDE. On average, the PSO algorithm has a run time of PSO algorithm 1,233 seconds, which is about 10% less than the IDE resolution time.

5. CONCLUSION AND FUTURE RESEARCH

This paper has presented a robust mathematical model for a variant of a vehicle routing problem (VRP), in which a competition exists among distributors in order to increase their sales under uncertainty of customers by rivals. In addition, optimization of fuel consumption is related to decline of the effects of CO_2. A set of scenarios for service time of distributers has been defined and optimized the objective function. Because of the computational complexity of the problem considered in this paper, two meta-heuristic algorithms (i.e., IDE and PSO) have been used and their performances were evaluated. The results indicate that IDE has better performance in terms of the results than PSO with more computational time in solving large-sized problems. For further studies, the demand for customers in an uncertain condition is proposed. Considering a competitive environment in other modes of the VRP may be an innovative topic for future research. Finally, implementation of the presented model, taking into account the actual data from a case study can be considered as one of the future studies.

TABLE 1. Comparison of the performance of the proposed algorithms

No. problems	PSO			IDE		
	Best Solution	**Run Time (s)**	**Gap%**	**Best Solution**	**Run Time (s)**	**Gap %**
1	1,239.60	780.60	0.00%	1,209.60	536.90	2.48%
2	2,459.70	962.30	0.00%	2,442.60	763.50	0.70%
3	4,125.90	905.30	1.55%	4,189.70	987.30	0.00%
4	4,258.80	1,236.30	0.00%	4,258.60	1,356.60	0.00%
5	5,347.60	1,456.60	0.73%	5,386.40	1,305.60	0.00%
6	7,108.80	1,950.30	0.00%	7,005.60	1,769.30	1.47%
7	5,795.60	953.60	0.00%	5,705.60	967.60	1.58%
8	4,879.60	1,500.60	0.96%	4,926.60	1,259.60	0.00%
9	6,971.60	1,763.60	0.00%	6,725.60	1,537.90	3.66%
10	8,039.70	2,100.30	0.00%	7,865.60	1,853.30	2.21%
Mean	5,022.69	1,360.95	0.36%	4,971.59	1,233.76	1.10%

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چکیده

در طول سال‌های گذشته، همزمان با افزایش میزان تقاضا، سیستم‌های توزیع کالا تغییرات اساسی داشته‌اند، لذا میزان مصرف سوخت وسایط نقلیه توزیع کننده نیز به طور قابل توجهی افزایش یافته است که دارای تاثیر زیادی بر آلودگی هوا و انتشار گازهای گلخانه‌ای دارد. هدف از ارائه این مقاله، ارائه یک مدل ریاضی جدید از مساله مسیریابی وسایط نقلیه به منظورکمینه‌سازی مصرف سوخت و بیشینه‌سازی سود قابل کسب در شرابط رقابتی در میان توزیع‌کنندگان تحت شرایط عدم قطعیت شروع سرویس‌دهی توزیع‌کنندگان به مشتریان با استفاده از رویکرد بهینه‌سازی استوار تحت سناریو است. از سوی دیگر کاهش مصرف سوخت منجر به کاهش هزینه‌های جاری وسایط نقلیه می‌شود و کاهش زمان شروع سرویس‌دهی به مشتریان باعث افزایش نرخ فروش در مقایسه با سایر توزیع‌کنندگان در محیط رقابتی می‌شود. به منظور ارزیابی کارایی مدل ارائه شده از الگوریتم تکامل تفاضلی بهبود یافته استفاده شد و به منظور ارزیابی عملکرد الگوریتم‌های پیشنهادی، تعدادی مساله نمونه در ابعاد بزرگ ایجاد و با نتایج حل مساله توسط الگوریتم انبوه ذرات مقایسه و بررسی شد. نتایج محاسباتی نشان می‌دهد که الگوریتم تکامل تفاضل دارای عملکردی محاسباتی بهتری می‌باشد، اما الگوریتم انبوه ذرات دارای زمان محاسباتی بهتری می‌باشد.

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