Solving Multiple Vehicle Routing Problems with Time Constraints by Flower Pollination Algorithm Optimization

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Abstract: - The multiple vehicle routing problem (MVRP) with the time constraint is one of the most important real-world problems in industrial and logistic engineering. The MVRP problems can be considered as a class of the non-polynomial (NP) time-complete combinatorial optimization problem. Such the MVRP problems aim to find the set of routes with the shortest total distance for overall minimum route cost serving all the given demands by the fleet of vehicles. Based on modern optimization, the MVRP problems can be optimally solved by the potential metaheuristic optimization techniques. The flower pollination algorithm (FPA) is one of the most efficient metaheuristic optimizers proposed for solving the combinatorial optimization problems. With few searching parameters, the algorithm of the FPA is not complex and ease of use. In this paper, the FPA is applied to solve five selected benchmark MVRP problems with the time constraints consisting of 50-100 destinations. Results obtained by the FPA will be compared with those obtained by genetic algorithm (GA), tabu search (TS) and particle swarm optimization (PSO). From results, the FPA can provide optimal solutions of all five selected problems. Optimal results obtained by the FPA are superior to PSO, TS and GA, respectively, with shorter total distance and computational time consumed.

Key-Words: - Multiple Vehicle Routing Problem, Flower Pollination Algorithm, Time Constraint, Metaheuristic Optimizer

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1 Introduction

In the 1800s, the traveling salesman problem (TSP) was firstly lunched by Hamilton and Kirkman [1-7]. The TSP is the classic algorithmic problem in computer science, operations research and logistics engineering. Its objective is to seek for the optimal tour such that to visit *n* cities exactly once and then return to the home city. The optimal tour is defined as the tour having the minimum total distance. Mathematical speaking, the multiple traveling salesman problem (MTSP) is a generalization of the TSP [8] which is the distinctively non-polynomial (NP) time-complete problem [9],[10]. The MTSP is more difficult than TSP. In the MTSP, $m > 1$ salesmen are allowed. From a set of cities, the home city (or depot) are initially located. The pairwise distance matrix of *n* cities are performed. The objective of the MTSP is to find a route for each salesman for minimizing the total cost of the routes. In addition, each city is visited exactly once by any salesmen [8-12].

Several algorithms have been consecutively launched for solving the TSP, for example, branch-and-bound [13] and integer linear programming [14]. Metaheuristic optimizers have been accepted and applied for solving TSP, for example, simulated annealing (SA) [15], cutting planes [16], neural network (NN) [17], tabu search (TS) [18], genetic algorithms (GA) [19], particle swarm optimization (PSO) [20] and cuckoo search (CS) [21]. Many recent studies have been proposed by using metaheuristic optimizers to solve the MTSP. Some of the well-known optimizers are the GA [22], evolutionary algorithm (EA) [23], NN [24], TS [25] and ant colony optimization (ACO) [26].

The multiple vehicle routing problem (MVRP) expands the MTSP [11],[12] to include different service requirements at each node (city or destination), different capacities and time constraints of each vehicle in the fleet. The objective of MTSP problems is to minimize total cost (distance) across all routes. Based on graph theory, the MVRP consists of a fleet of vehicles leaving from the home city and returning to the home city. Each location will be visited exactly once by any vehicle in a fleet [11],[12],[27]. If the capacity limitations are neglected, the MTSP is assumed as a relaxation of the MVRP. This means that all formulations of the MVRP can be applied for MTSP for seeking a set of the optimal routes with the minimum cost serving all the given demands by the fleet of vehicles.

Following the literatures, the flower pollination algorithm (FPA) proposed by Yang in 2012 [28] is one of the most efficient metaheuristic optimizers. The FPA algorithm is based on the behaviour of pollination of flowering plant in nature. A random number with the Lévy flight distribution is applied in the FPA algorithm as the pollinators' movement to generate the elite solution within the defined search space. The performance tests of the FPA against several benchmark functions were reported [29],[30]. Also, the FPA was successfully conducted to optimize many real-world engineering problems including power system optimization (economic and emission dispatch [31],[32], reactive power dispatch [33], optimal power flow [34], solar photovoltaic (PV) parameter estimation [35] and load frequency control [36]), communication system optimization (wireless sensor networks [37] and linear antenna array optimization [38]), civil engineering system optimization (frames and truss systems [39] and structure engineering design [40]), image processing optimization [41], transportation optimization (TSP [42]), control system optimization (control system design [43-45] and model identification [46]) and hybrid renewable energy saving optimization [47]. Readers can find the state-of-the-art developments and significant applications of the FPA in [48],[49].

The objective of this paper is to apply the FPA for solving the MVRP problem with the time constraint. In order to perform its effectiveness, the FPA is applied against five selected benchmark MVRP problems from literatures. This paper consists of five sections. In the section 2, the problem formulation including VRP and MVRP models and details of selected benchmark problems are illustrated. Section 3 describes the FPA algorithm and the FPA-based MVRP optimization. In section 4, results obtained are discussed. Finally, section 5 gives the conclusions and future research.

2 Problem Formulation

2.1 VRP and MVRP Models

Mathematical speaking, the VRP problem is modelled by the graph theory [1-7]. Let $G = (V, E)$ be a complete undirected graph with vertices V, $|V| = n$, where n is the number of cities, m is the number of vehicles and edges E with edge length c_{ij} for the-ij city (i, j). This work focus on the symmetric VRP/TSP case in which $c_{ij} = c_{ji}$, for all cities (i, j), where c_{ij} is the cost associated to the distances between the i-th and j-th nodes, and c_m stands for the cost of the involvement of one vehicle.

As the constrained optimization problem regarding to modern optimization context, the VRP problem is defined for minimization as shown in (1)-(5). $f(\bullet)$ in (1) is the objective function as the total distant for traveling. The objective function $f(\bullet)$ will be minimized according to the constraint functions shown in (2) – (5). The constraint function in (2) is used for ensuring that each city will be entered from only one other city. The constraint function in (3) is conducted for ensuring that each city is only departed to on other city. The constraint function in (4) is utilized for eliminating the sub-tours. The constraint function in (5) is used for selecting the feasible solutions. If edge (i, j) is one of the feasible solutions, $x_{ij} = 1$. Otherwise, $x_{ij} = 0$.

$$\textbf{Min} \quad f(\cdot)\big|_{VRP} = \sum_{i\in V}^{n}\sum_{j\in V}^{n} c_{ij}x_{ij} + mc_m \tag{1}$$

$$\text{Subject to} \quad \sum_{j=2}^{n} x_{1j} = m, \quad j \in V \tag{2}$$

$$\sum_{j=2}^{n} x_{j1} = m, \quad j \in V \tag{3}$$

$$\sum_{i\in S}^{n}\sum_{j\in S}^{n} x_{ij} \le |S| - 1, \quad \forall S \subset V \tag{4}$$

$$\forall i, \forall j \in V : \; x_{ij} = \begin{cases} 0 \\ 1 \end{cases} \tag{5}$$

By literatures, there are several ways to generalize the MVRP problem. In case of the single depot [50-52], there are n cities, m vehicles and a distance metrix $d{:}n\times n\rightarrow\Re$ of all cities. All vehicles will start at the home city-1 (or depot). They will take a route such that each city is visited by exactly one vehicle ultil all vehicles in the fleet return to the depot at the end of the tour. If vehicle k travels from city i to city j, $\delta_{i,j,k} = 1$. Otherwise, $\delta_{i,j,k} = 0$. Also, let $T_{i,j,k}$ be the traveling time of the vehicle k from city i to city j. $T_{i,j,k}$ can be calculated by the relation between the average vehicle's speed and the its working time, and $T_{\max}$ is the maximum working time of each vehicle. The objective of the MVRP problem is to minimize the total traveling distances as stated in (6).

$$\textbf{Min} \quad f(\cdot)\Big|_{MVRP} = \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{m}\delta_{i,j,k}d(i,j) \quad (6)$$

$$\text{Subject to} \quad \sum_{j=2}^{n}\delta_{1,j,k} = 1, \quad \forall 1 \le k \le m \quad (7)$$

$$\sum_{i=2}^{n}\delta_{i,1,k} = 1, \quad \forall 1 \le k \le m \quad (8)$$

$$\sum_{j=1}^{n}\sum_{k=1}^{m}\delta_{i,j,k} = 1, \quad \forall 2 \le i \le n \quad (9)$$

$$\sum_{i=1}^{n}\sum_{k=1}^{m}\delta_{i,j,k} = 1, \quad \forall 2 \le j \le n \quad (10)$$

$$\sum_{i=1}^{n}\delta_{i,r,k} = \sum_{j=1}^{n}\delta_{r,j,k}, \forall 2 \le r \le n, \forall 1 \le k \le m \quad (11)$$

$$u_i - u_j + (n-m)\cdot\sum_{k=1}^{m}\delta_{i,r,k} \le n-m-1, \quad \forall 2 \le i \ne j \le n \quad (12)$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n}T_{i,j,k} \le T_{\max}, \quad 1 \le k \le m \quad (13)$$

The constraint function in (7) ensures that every vehicle leaves the depot exactly once. The constraint function in (8) guarantees that every vehicle returns to the depot exactly once. The constraint function in (9) ensures that every non-depot city is left exactly once. The constraint function in (10) guarantees that all vehicle combined return only once to each non-depot city. The constraint function in (11) ensures that the number of times a vehicle visits a non-depot city equals the number of times that city is left. The constraint function in (12) ensures that no subtours exist (degenerate routes that do not include the depot), using $n - 1$ as dummy variables of $u_2,...,u_n$. Finally, the constraint function in (13) is the time constraint ensuring that each vehicle works within its maximum working time.

2.2 Selected VRP Problems

In this work, five benchmark problems consisting of 50-100 destinations from literatures are selected [53],[54]. Deatials of five benchmark problems including prppblem names, numbers of destinations (or city) and their optimal solutions are summarized in Table 1. The destination (or city) locations and distance matrix of Entry#1 (Eil51) are plotted in Fig. 1 and Fig. 2 to desplay their locations as an example. From the distance matrix in Fig. 2, it can be observed that the Entry#1 (Eil51) possesss the symmetric distance between city *i* and *j*.

Table 1 Selected Problems for MVRP optimization.

Entries	Names	Number of Cities	Optimal Solutions (Km.)
Entry#1	Eil51	51	426
Entry#2	Birlin52	52	7,542
Entry#3	St70	70	675
Entry#4	Rat99	99	1,211
Entry#5	Rd100	100	7,910

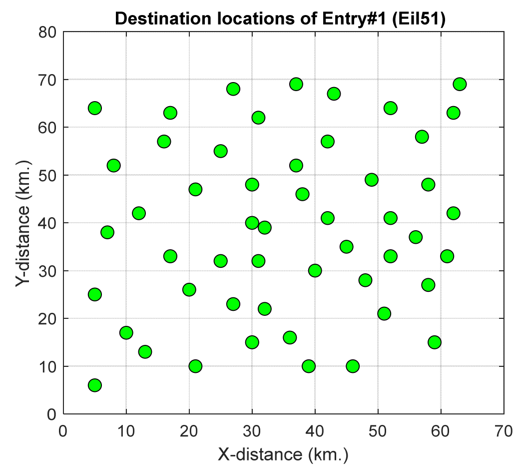


Fig. 1 Destination locations of Entry#1 (Eil51).

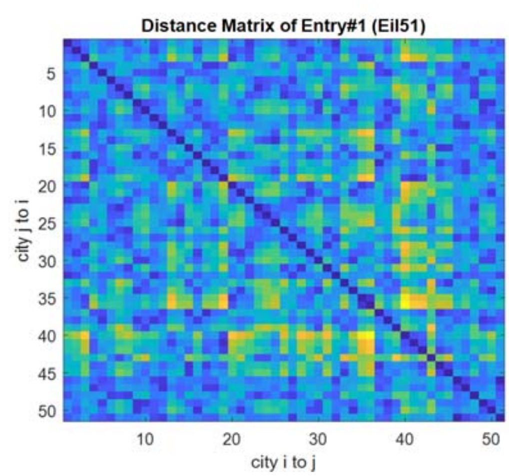


Fig. 2 Distance matrix of Entry#1 (Eil51).

3 FPA-Based VRP Optimization

3.1 FPA Algorithms

The pollination of flowering plants in nature is for survival and reproduction. Flower pollination in nature can be classified as the self-pollination and cross-pollination. The flower pollination process can be done by both of biotic and abiotic pollinators. There is about 80-90% of flower pollination using biotic pollinators for long-distant pollination from a particular plant to other plants called the cross-pollination [55]. Therefore, the cross-pollination using biotic pollinators is regarded as the global pollination. On the other hand, there is about 10-20% of flower pollination using abiotic pollinators for short-distant pollination in a same flower or from a particular flower to other flowers in the same plant called the self-pollination [55]. Therefore, the self-pollination using abiotic pollinators is regarded as the local pollination [55-57]. The FPA algorithm, firstly proposed by Yang in 2012 [28], mimics the flower pollination in nature by using four rules as follows.

Rule-1: For global pollination (cross-pollination with biotic pollinators), a random with the Lévy-flight distribution is utilized for generating new solutions.

Rule-2: For local pollination (self-pollination with abiotic pollinators), a random with the uniform distribution is conducted utilized for generating new solutions.

Rule-3: Flower constancy, which is equivalent to the reproduction probability, can be developed by pollinators. All flower constancy is assumed to similarity.

Rule-4: Switching between local and global pollinations is controlled by a switch probability $p \in [0, 1]$.

For the FPA algorithm proposed by Yang [28], a solution $\boldsymbol{x}_i$ is any flower (or pollen gamete). Regarding to the global pollination in Rule-1, biotic pollinators are used with Lévy-flight random for long-distant pollination. With Rule-1 and Rule-3, new solutions can be formulated as stated in (14), where $\boldsymbol{g}^*$ is the current best solution at the current generation/iteration t. L is a random with the Lévy-flight distribution which can be calculated by (15), where $\Gamma(\lambda)$ is the standard Gamma function.

Regarding to the local pollination in Rule-2, abiotic pollinators are used with uniformly random for short-distant pollination. With Rule-2 and Rule-3, new solutions can be formulated as stated in (16), where $\boldsymbol{x}_j$ and $\boldsymbol{x}_k$ are selected solution at the current generation/iteration t. ε is a random with the uniform distribution which can be calculated by (17), where a and b are boundaries of random. Regarding to Rule-4, selecting between local and global pollinations can be controlled by a switch probability p.

Fig. 3 shows the flow diagram of the FPA algorithm. From Yang's recommendation [28-30], the number of flowers n = 25-50 and the switching probability p = 0.15-0.25 are suitable for most applications.

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + L(\boldsymbol{x}_i^t - \boldsymbol{g}^*) \tag{14}$$

$$L \approx \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{s^{1+\lambda}}, \quad (s >> s_0 > 0) \tag{15}$$

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + \varepsilon(\boldsymbol{x}_j^t - \boldsymbol{x}_k^t) \tag{16}$$

$$\varepsilon(\rho) = \begin{cases} 1/(b-a), & a \le \rho \le b \\ 0, & \rho < a \text{ or } \rho > b \end{cases} \tag{17}$$

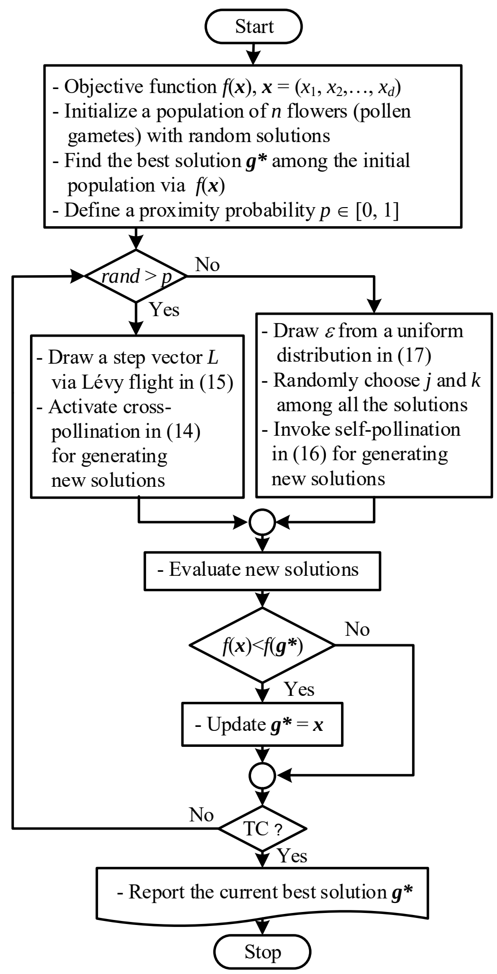


Fig. 3 Flow diagram of FPA algorithm.

3.2 FPA-Based MVRP Optimization

The FPA algorithm was applied to solve the MVRP problems with the time constraint as follows.

Step-0 Define the objective function $f(\cdot)$ in (6) with constraint functions in (7)-(13). Generate n flowers randomly and evaluate them via $f(\cdot)$. Select the best solution $\boldsymbol{g^*}$ among initial flowers giving the least value of $f(\cdot)$. Define a switch probability p = 0.2 (or 20%). Set the maximum generation (MaxGen) as the termination criteria (TC) and a generation counter (Gen = 1).

Step-1 If Gen ≤ MaxGen, go to Step-2. Otherwise, go to Step-4.

Step-2 If `rand` > p, calculate L as a random with Lévy-flight distribution in (15) and employ the global pollination in (14) to create a new solution $\boldsymbol{x}$. Otherwise, calculate ε as a random with uniform distribution within [0, 1] in (17). Select $\boldsymbol{x}_j$ and $\boldsymbol{x}_k$ randomly among all current solutions. Activate the local pollination in (16) to create a new solution $\boldsymbol{x}$.

Step-3 Update solution. If $f(\boldsymbol{x}) < f(\boldsymbol{g^*})$, set $\boldsymbol{g^*} = \boldsymbol{x}$ and update Gen = Gen+1. Otherwise, unchanged $\boldsymbol{g^*}$ and update Gen = Gen+1. After that, go back to Step-1 for next generation.

Step-4 Report the best solution found and terminate the search process.

4 Results and Discussions

To solve the MVRP problems with the time constraint, the FPA algorithms were coded by MATLAB version 2017b run on Intel(R) Core(TM) i5-3470 CPU@3.60GHz. For the time constraint in (13), T_{max} = 8 hr. is assumed as the working time a day of all vehicles. With the average vehicles' speed of 80 Km/hr., this means that the overall distance of each vehicle cannot be longer than 640 Km/day. 50 trial-runs are executed to search for the best solution. For a fair comparison, in each iteration a number of solution population of GA, TS and PSO is set as a same number of solution population of FPA. Setting parameters of GA, TS, PSO and FPA for comparison is detailed as follows.

For GA:
- No. of offspring (population) = 50
- Crossover = 0.8 (80%)
- Mutation = 0.2 (20%)
- TC : MaxGen = 10,000

For TS:
- No. of neighborhoods (population) = 50
- Search radius = 20%
- TC : MaxIter = 10,000

For PSO:
- No. of particles (population) = 50
- Cognitive learning rate = 2.0
- Social learning rate = 2.0
- Inertia weight θ_{min} = 0.4 and θ_{max} = 0.9
- TC : MaxGen = 10,000

For FPA [28-30]:
- No. of flowers n = 50
- Switching probability p = 0.2 (20%)
- TC : MaxGen = 10,000

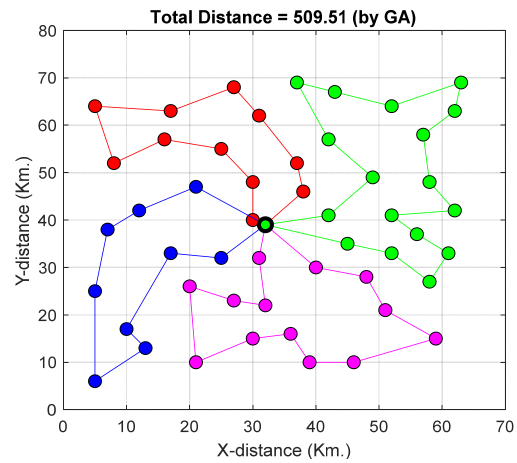


Fig. 4 Optimal tour of Entry#1 (Eil51) by GA.

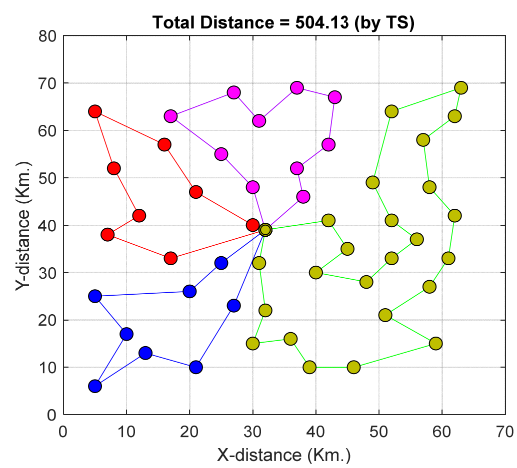


Fig. 5 Optimal tour of Entry#1 (Eil51) by TS.

The optimal solutions of the Entry#1 (Eil51) obtained by the GA, TS, PSO and FPA are depicted in Fig. 4 - 7, where ● stands for the common depot. Results of the MVRP optimization obtained by GA, TS, PSO and FPA including the optimal solutions, the search times consumed and numbers of vehicles are summarized in Table 2 and Fig. 8. From results, the FPA can yield the optimal solutions for all MVRP problems according to the time constraint.

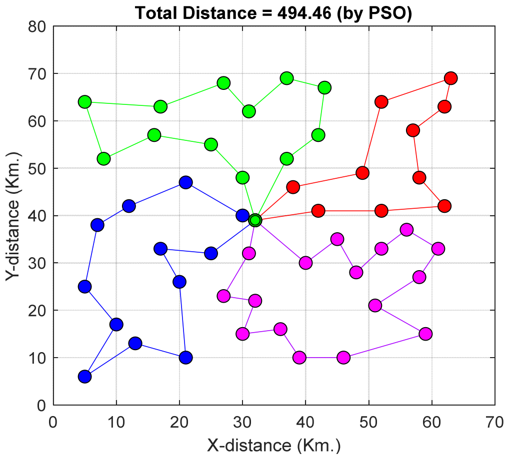


Fig. 6 Optimal tour of Entry#1 (Eil51) by PSO.

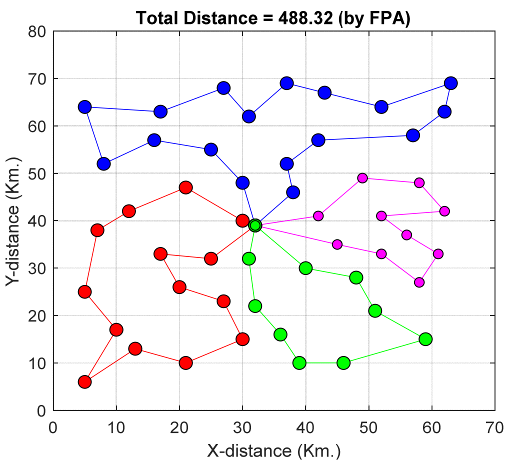


Fig. 7 Optimal tour of Entry#1 (Eil51) by FPA.

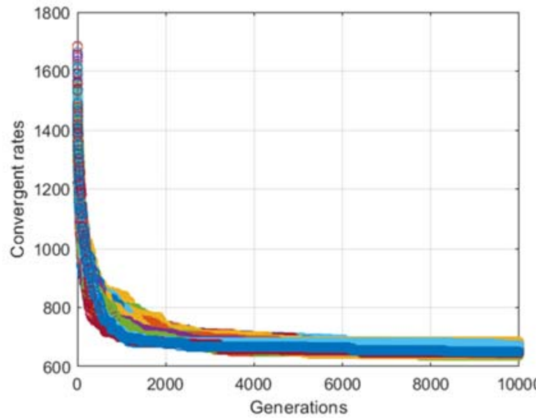


Fig. 9 Convergent rates of Entry#1 (Eil51) by FPA.

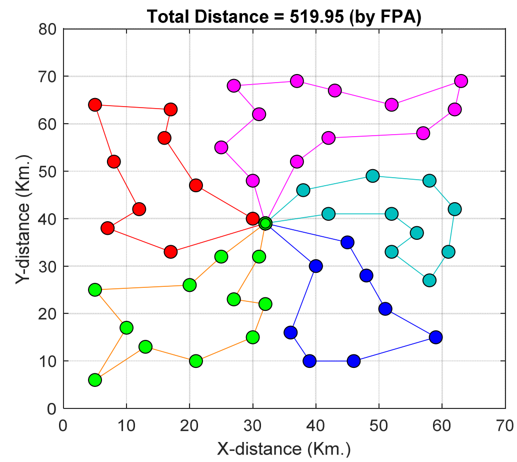
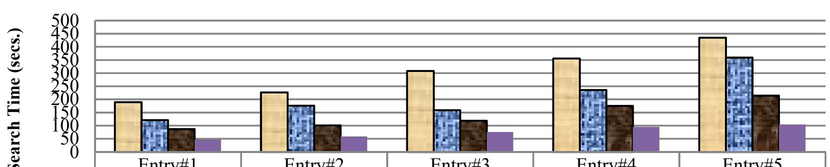


Fig. 10 Optimal tour of Entry#1 (Eil51) by FPA (5 vehicles).

Table 2 Optimal solutions of MVRP problems obtained by GA, TS, PSO and FPA.

Entries	Names	Optimal Solutions (Km.)	No. of Vehicle *m*	GA (Km.)	TS (Km.)	PSO (Km.)	FPA (Km.)
Entry#1	Eil51	426	4	476.43	471.59	468.27	**462.29**
Entry#2	Birlin52	7,542	12	7,683.62	7,604.34	7,585.41	**7,552.01**
Entry#3	St70	675	5	696.27	688.33	682.14	**678.42**
Entry#4	Rat99	1,211	8	1,401.24	1,356.17	1,264.93	**1,221.45**
Entry#5	Rd100	7,910	14	8,105.78	8,017.96	7,998.38	**7,936.53**



	Entry#1	Entry#2	Entry#3	Entry#4	Entry#5
GA	189.48	226.64	308.07	355.63	434.81
TS	121.15	176.58	159.32	236.02	359.47
PSO	87.14	101.57	118.86	175.31	214.47
FPA	47.24	58.36	75.54	95.18	104.47

Fig. 8 Search time consumed of MVRP problems by GA, TS, PSO and FPA.

In average, the FPA gives the superior solutions to PSO, TS and GA, respectively. Moreover, it can be observed that the FPA spend less time consumed than the PSO, TS and GA, respectively, as can be seen in Fig. 8.

The convergent rates of the global minimum finding of the Entry#1 (Eil51) problem optimized by the FPA are depicted in Fig. 9. Those of other problems are omitted because they have a similar form to that of Entry#1 in Figure 9. From Fig. 9, it can be visualized that the FPA has the strong robustness for the global minimum finding with the different randomly initial solutions over 50 trial-runs. In addition, to demonstrate the effectiveness of the FPA for solving MVRP with 5 vehicles (m = 5) over the Entry#1 (Eil51) problem as an example, the additional result is depicted in Fig. 10.

5 Conclusions

In this paper, the application of the FPA to solve the MVRP problem with the time constraint based on the modern optimization has been proposed. The MVRP problem could be modeled by the general MTSP. In this work, the FPA has been applied to solve the MVRP problem consisting of 50-100 destinations with the time constraints. The FPA has been tested against five selected benchmark MVRP problems. Results obtained by the FPA have been compared with those obtained by GA, TS and PSO. As results, the FPA can yield optimal solutions for all five selected MVRP problems superior to PSO, TS and GA, respectively, with shorter total distance and computational time consumed. This can be noticed that the FPA is one of the most powerful metaheuristic optimizers that can be alternatively used to solve the MVRP problems with the time constraints. For future research, vehicle routing balancing problems (VRBP) will be investigated in order to balance the work load of each vehicle in the fleet with non-uniform capacity. Multiple-depots multiple-vehicle routing problems (MD-MVRP) will be studied by novel metaheuristic optimizers.

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