An Improved Differential Evolution Algorithm for Vehicle Routing Problem: An Application in Mobile Medical Equipment Maintenance Unit

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Abstract. This research aimed to solve a vehicle routing problem for mobile medical equipment maintenance unit which take a responsibilities of all equipments in 316 health promoting hospitals in Ubon Ratchathani by using a classical Differential Evolution algorithm (DE) and Improved Differential Evolution algorithm (IDE). In the IDE algorithm, we intend to find the best combinations of recombination formulas by comparing two different methods for DE algorithm. The first method applied the classical DE composes of 4 steps with are (1) generating initial solution, (2) performing mutation, (3) performing recombination, and (4) selection process. The second method used an IDE to find the best combinations of recombination formulas. After that, another step will be added before the selection process. Trial vector from step (3) creates the second trial vector is vector transition process, vector exchange process, vector insertion process and mix process. Finally, an IDE algorithm was applied to solve the vehicle routing problem in recombination. IDE algorithm can reduce transportation cost effectively compared with classical DE. The vector exchange process reduced overall annually maintenance cost 1.08%.

Keywords: Differential Evolution Algorithm, Vehicle Routing Problem, Mobile Medical Equipment Maintenance

1. INTRODUCTION

Nowadays, transportation cost was increased due to scarcity of fossil fuel. Therefore, logistics played an important role in both private and public sectors. If the firm could manage logistics activities effectively, they would have the competitive advantage among their rivalry.

Ministry of Public Health had a policy to develop the country and to improve more than 9,000 health promotion hospital focusing on health promotion, disease prevention and proactive services, flexible, and consistent with the community's potential. Personnel with the skills you have to offer health counseling.

Ubon Ratchathani Provincial Health Office (URPH O) had an objective to develop a standard for public health administration in the province. One of their activities was to take care and repair of medical equipments in 316 health promotion hospitals.

This research is aimed to solve a vehicle routing problem for medical equipment maintenance of 316

health promoting hospitals in Ubon Ratchathani which conducted by maintenance department of Ubon Ratchat hani Provincial Health Office by using a classical Differential Evolution algorithm (DE) and Improved Differential Evolution algorithm (IDE).

2. LITERRATER REVIEW

2.1 Vehicle Routing Problem

Many studies have been done to solve the vehicle routing problem. For surveys of both exact and heuristic methods for these VRPs up to 2002, the read er is referred to Toth and Vigo (2002) state that the use of computerized procedures in distribution planning results in 5% to 10% savings in transportation costs. Vidal *et al*. (2012) put forward a hybrid Genetic Algorithm (GA) originally designed to solve the VRP with Multiple Depots (MDVRP), Period VRP and the Multi-depot Period VRP, which also turned out to be highly efficient for the Capacitated VRP (CVRP). Prins (2009) proposed some heuristics based on Iterated Local Search (ILS), Evolutionary Strategies (ES) and Greedy Randomized Adaptive Search Procedure (GRAS P) that use some of the features previously adopted in 2004. Prins (2004) put forward a Memetic Algorithm (MA) whose main characteristics are: (1) TSP represen tation of chromosomes (giant tour), without tour delimiters, which can be directly converted to a VRP solution using a splitting procedure; and (2) first impro vement local search as mutation operator. Reimann *et al*. (2004) proposed an Ant Colony (AC) based heurist ic using a divide and conquer decomposition. Both the complete and partial problems are solved as follows: (1) a solution is generated employing a nearest neighbor heuristic; (2) local search is applied to the initial solution; (3) the pheromones are updated; and (4) information regarding the level of attractiveness between each pair of customers is augmented.

2.2 Differential Evolution

Differential Evolution (DE) algorithm is a branch of evolutionary programming developed by Rainer Storn and Kenneth Price (Price and Storn, 1997) for optimiz ation problems over continuous domains. In DE, each variable's value is represented by a real number. The advantages of DE are its simple structure, ease of use, speed and robustness. DE is one of the best genetic type algorithms for solving problems with the real val ued variables. DE is a population-based globally evolutionary algorithm, which uses a simple operator to create new candidate solutions and a one-to-one competitions scheme to select new candidate greedily. Due to its simple structure, easy implementation, quick convergence, and robustness, DE has been turned out to be one of the best evolutionary algorithms for solving continuous problems in a variety of fields. Nevertheless, due to DE's continuous nature, the research work on DE for combinatorial optimization is very limited. Obviously, it is difficult to apply DE to different are as of problem so there than continuous optimization hat inventors originally focused on. Recently, some researchers have used DE to design machine layout problem (Storn and Price,1995), and solved manufacturing problems with mixed integer discrete variables (Lampinen and Zelinka, 1999). But to the best of our knowledge, no work that uses differential evolution can be found for VRP.

3. MATHEMATICS MODEL

A mathematical model was formulated from the vehicle routing problem model. The objective function was focus on the capacitated vehicle routing problem (CVRP) which was calculate from health promoting hospitals , time for maintenance, labor cost, fuel consu mption, maintenance costs and distance. The objective of CVRP is to minimize the travelling cost. The capacitated vehicle routing problem can be modeled as a mixed integer programming as follows:

$$\left[\left(\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N}\sum_{k=1}^{K}C_{ij}X_{ijk}\right)\times\left(C_f+C_m\right)\right]+\left[\left(\sum_{k=1}^{N}R_k\right)\times C_l\right]+\left[\left(\sum_{j=2}^{N}Y_{jk}\right)\times C_h\right] \quad (1)$$

Subject to

$$\sum_{i=1}^{N}\sum_{k=1}^{K}X_{ijk}=1 \qquad \forall_{j=(2,\ldots,N)\ and\ i\neq j} \quad (2)$$

$$\sum_{j=1}^{N}\sum_{k=1}^{K}X_{ijk}=1 \qquad \forall_{i=(2,\ldots,N)\ and\ i\neq j} \quad (3)$$

$$\sum_{i=1}^{N}X_{ipk}-\sum_{j=1}^{N}X_{pjk}=0 \qquad \forall_{k=(1,\ldots,K),p=(1,\ldots,N)} \quad (4)$$

$$\sum_{j=2}^{N}X_{1jk}\leq 1 \qquad \forall_{k=(1,\ldots,K)} \quad (5)$$

$$\sum_{i=2}^{N}X_{i1k}\leq 1 \qquad \forall_{k=(1,\ldots,K)} \quad (6)$$

$$U_i-U_j+N\sum_{k=1}^{K}X_{ijk}\leq N-1 \qquad \forall_{i,j=(2,\ldots,N)\ and\ i\neq j} \quad (7)$$

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$$\sum_{i=1}^{N}\sum_{j=2}^{N} X_{ijk}\,(t_{ij}+s_i) \le \sum_{j=2}^{N}(Y_{jk}+1)T_k \qquad \forall_{j=(2,\dots,N),i=(1,\dots,N),k=(1,\dots,K)} \quad (8)$$

$$\left(\sum_{i=1}^{N}\sum_{j=2}^{N} X_{ijk}(t_{ij}+s_i)\right)/T_k \le R_k \qquad \forall_{j=(2,\dots,N),i=(1,\dots,N),k=(1,\dots,K)} \quad (9)$$

$$X_{ijk} \le (1-Y_{jk}) \qquad \forall_{j=(2,\dots,N),i=(1,\dots,N),k=(1,\dots,K)} \quad (10)$$

$$Y_{ik} \epsilon \{0,1\} \qquad \forall_{i,j=(1,\dots,N),k=(1,\dots,K)} \quad (11)$$

$$X_{ijk} \epsilon \{0,1\} \qquad \forall_{i,j=(1,\dots,N),k=(1,\dots,K)} \quad (12)$$

Eq. (1) is the objective function. Eq. (2) and (3) is assigned to each client can receive the services from different transport only one vehicle or one route only. Eq. (4) shows continuity in each location connect ed together within each route. When a vehicle enters any point. And from that point on. Eq. (5) and (6) to verify the capability of the vehicle is available as sche duled. Eq. (7) to prevent sub-tours. Eq. (8), the maximum time required to travel. Eq. (9) conditions to stay overnight. Eq. (10) enforces that if there happens to be an overnight trip to the next town. Eq. (11) and (12) the means to make a decision variable is equal to 0 or 1 only

4. TEST PROBLEM

The test instance used in this research was formulated form a real case study of 316 health prom oting hospitals into 25 districts in Ubon Ratchathani shows in Figure 1

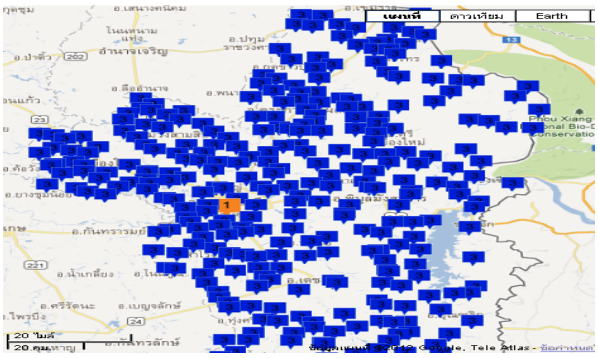

Figure 1: Map of 316 health promoting hospitals.

We develop a heuristic for the continuous routing, which allows continuous transportation without limitation of truck operation hours and returning locations. In this system, drivers are allowed to take routine breaks at designated rest areas without having to return back to the hub shows in Figure 2

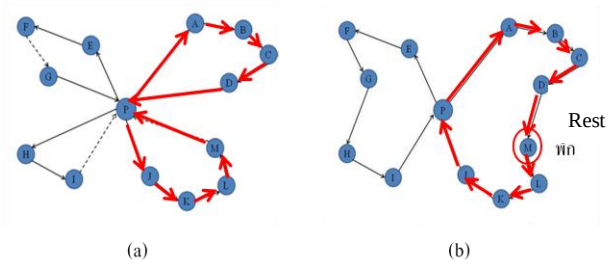

Figure 2: (a) Traditional VRP, (b) Continuous routing

5. PROPOSED HEURISTICS

Classic differential evolution algorithm composes of 4 steps with are (1) generating initial solution, (2) performing mutation, (3) performing recombination, and (4) selection process. In our algorithm, one other step will be added before the selection process. Trial vector from step (3) creates the second trial vector and performs the selection process between the old and new generated trial vectors before the selection process between target and selected trial vectors and will be add one move and two-opt (step (4)) will perform.

5.1 Generate an initial set of target vector

NP target vectors have to be randomly generated. Each vector has dimension *D*, when *D* is number of health promoting hospitals. If *NP* is set to 10 then 10 vectors that has dimension of 316 will be generated as shown in table 1.

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Table 1: Trial Vector NP#1- NP#10

NP	Target Vector						
Trial Vector	2	3	4	…	314	315	316
1	0.89	0.96	0.45	…	0.56	0.30	0.43
2	0.90	0.69	0.21	…	0.74	0.80	0.56
3	0.38	0.14	0.44	…	0.26	0.30	0.46
4	0.37	0.80	0.09	…	0.21	0.43	0.96
5	0.46	0.58	0.93	…	0.21	0.56	0.80
6	0.39	0.61	0.53	…	0.13	0.46	0.58
7	0.56	0.96	0.90	…	0.95	0.99	0.61
8	0.74	0.79	0.38	…	0.52	0.85	0.96
9	0.26	0.37	0.37	…	0.50	0.30	0.79
10	0.28	0.10	0.46	…	0.55	0.80	0.37

The row represents position of the health promoting hospitals while the column represents value of randomly generated number.

5.2 Perform mutation process

In mutation process, mutant vector ($V_{i,j,G}$) will be calculated from some randomly selected target vectors ($X_{i,j,G}$). This process is performed using formula (13) which are taken from Qin et al. (2009).

$$V_{i,G+1} = X_{r1,G} + F(X_{r2,G} - X_{r3,G}) \quad (13)$$

Let X_{r1}, X_{r2}, X_{r3} be the vectors which are randomly selected from a set of target vectors *j* represents the best vector found so far in the algorithm. *F* is the scaling factor, in the proposed heuristics *F* is set equals to 0.5 (Zou *et al.* 2011). *i* is the vector number which starts from 1 to *NP* and *j* is position of the vector which run from 1 to *D*.

5.3 Perform recombination process

5.3.1 Traditional recombination process.

The mutant vectors will apply recombination formula (14) – (15)

$$V_{ji,G+1} \quad \text{if (randb (j)} \leq \text{CR) or j = rnbr(i)} \quad (14)$$
$$X_{ji,G+1} \quad \text{if (randb(j) > CR or j} \neq \text{rnbr(i)} \quad (15)$$

Let *randb (j)* be random number between 0 to 1 and *CR* be recombination probability which is the predefined parameter. *rnbr(i)* is random integer number. Denote *randb (j)* and . *rnbr(i)* as random integer numbers which are used to represent the position of the vector and these random numbers rest from 1 to *D*. Compare the value of the Trial Vector with the CR by comparing the position of the Target Vector of the value of NP. If compared to the value of the Trial. Vector is less than or equal to the value of CR to make a selection in that position as the Mutant Vector as a condition of equation (14) if it is worth more than the value of the CR to use the Target Vector the original equation. (15).

5.3.2 Modified recombination process

We design three types of vector creation process in order to generate an accompany trial vector which is following:

5.3.2.1 Vector transition process

The vector transition process started from, this number lies between 1 to *D* then positions in the vector will be randomly picked. Number of positions that will be picked equals to number of transition points. The selected positions have to randomly generate new values in each position. Figure 3 shows the vector transition process. Position 3,6 and 8 are selected as the transition points (the pre-selected number of the transition points is 3). Values in position 3,6 and 8 will be randomly generated while other positions' value remain unchanged

Original vector

1	2	3	4	5	6	7	8
0.75	0.54	0.63	0.32	0.91	0.46	0.98	0.67

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New vector

1	2	3	4	5	6	7	8
0.75	0.54	0.44	0.32	0.91	0.79	0.98	0.82

Figure 3: Example of Vector transition

5.3.2.2. Vector exchange process.

The vector exchange process will start from composes of two steps which are (1) random selection of two exchange points in a trial vector (2) value exchange in selected positions. From figure 4, the selected exchange points are 3 and 7. Value in position 3 (0.63) is exchanged with value in position 7 (0.98) thus new value in position 3 is 0.98 and new value in position 7 is 0.63.

Original vector

1	2	3	4	5	6	7	8
0.75	0.54	0.63	0.32	0.91	0.46	0.98	0.67

New vector

1	2	3	4	5	6	7	8
0.75	0.54	0.98	0.32	0.91	0.46	0.63	0.67

Figure 4: Example of Vector exchange

5.3.2.3 Vector insertion process.

The vector insertion process starts from randomly selecting one insertion point and one moving point then inserting value from the moving point to the insertion point. All values after the insertion point will move backward. Figure 5 shows, position 3 is selected to be the insertion point and position 7 is selected to be the moving point. Value in position 7 (0.98) will be inserted into position 3 thus values in position 3, 4, 5, 6 and 7 are changed from 0.63, 0.32, 0.91, 0.46 and 0.98 to 0.98, 0.63, 0.32,0.91 and 0.46 respectively.

Original vector

1	2	3	4	5	6	7	8
0.75	0.54	0.63	0.32	0.91	0.46	0.98	0.67

New vector

1	2	3	4	5	6	7	8
0.75	0.54	0.98	0.63	0.32	0.91	0.46	0.67

Figure 5: Example of vector insertion

5.3.2.3 Vector Mix process

The vector mix process is the combination of all three methods of the past.

5.4 Perform selection process

A result of selection process will be a target vector in next generation which will be used as a starting point of mutation process of next iteration. The selection process is applied using formula (16)

$$X_{i,j,G} = \begin{cases} U_{i,j,G} \; if \; f(U_{i,j,G}) \leq f(X_{i,j,G}) \\ X_{i,j,G} \qquad\qquad Otherwise \end{cases} \qquad (16)$$

Let $f(U_{i,j,G})$ and $(X_{i,j,G})$ be objective functions of the trial vectors $(U_{i,j,G})$ and target vector $(X_{i,j,G})$.

6. COMPUTATION FRAMEWORK AND RESULT

This session will discover benefits of the proposed heuristics (IDE). We also compare algorithm with Classic DE that is developed by us. IDE is differential evolution algorithm with new vector creation using different creation processes. All experiments are performed on Desktop computer, Inter (R) Core (TM) i3-3240 CPU 3.40 GHz.

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Table 2: Compare algorithm with Classic DE and IDE

Case	Total Cost (F=0.5 CR=0.85)				
	DE classic	IDE			
		transition	exchange	insertion	Mix
1	233,398	231,098	225,309	231,260	232,411
2	229,197	230,883	226,748	227,641	228,715
3	231,037	229,278	233,429	229,740	228,133
4	228,481	228,213	229,304	232,285	235,557
5	229,959	230,063	224,840	228,464	228,909
Avg.	230,414	229,907	227,926	229,878	230,745
%Gap		0.22	1.08	0.23	0.14

Figure 6: Compare algorithm with Classic DE and IDE

7. CONCLUSION

In this research, we present the traditional and modified differential evolution algorithm (DE and IDE) to solve continuous routing, which allows continuous transportation without limitation of truck operation hours and returning locations. In this system, drivers are allowed to take routine breaks at designated rest areas without having to return back to the hub. We compared between DE and IDE, we find that DE and IDE generate the same excellent solution quality but IDE algorithm can reduce transportation cost effectively compared with classical DE. The vector exchange process reduced overall annually maintenance cost 1.08%.

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