Hybrid Genetic Algorithms for Two–Echelon Capacitated Vehicle Routing Problem for Evaluating City Logistics Systems

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This paper studies the Two-Echelon Capacitated Vehicle Routing Problem (2E-CVRP) in the distribution system. It consists of delivering goods from a main depot to the customers through intermediate depots, which are called the satellites. This problem is motivated by city logistics planning related to legal restriction, environmental impact, confined space, and congested network. Due to these policies, it becomes infeasible to use large vehicles and/or construct a depot facility inside the center of large cities. The proposed method is based on a modification of the Multi-Depots Vehicle Routing Problem (MDVRP) solved by using Hybrid Genetic Algorithms (HGAs) in order to enhance an initial solution. Results on 21 benchmark instances show that the algorithm performs effectively to solve 18 instances to the optimal solutions reported in previous studies using exact algorithms.

Key Words : *2E-CVRP, City Logistics, MDVRP, GA, HGAs*

1. INTRODUCTION

There are two main strategies of freight transportation: direct shipment system and multi-echelon distribution system[1)]. The single-echelon or direct shipment system operates only one layer of delivery activities meet the demands between a single depot and customers while the multi-echelon distribution system consists of delivering goods from one or more depots to the customers through intermediate depots, which are called satellites. Throughout decades, freight distribution and vehicle routing have been moved from a direct shipment in single layer delivery system to a multi-echelon distribution system[1)-12)].

Additionally, this approach can be integrated to city logistics systems for large cities, which usually are over-populated and have massive buildings for commercial, administrative, and cultural activities, served by a dense network of mostly narrow and generally congested streets[3),11)]. Also, in particular parking areas strict space regulations are implemented to limit the vehicle sizes. Under city logistics systems schematic, the controlled zones are relatively closed to the outskirts of the city where the depots are located. Therefore, it is more effective to arrange two-tier distribution network as in the 2E-CVRP where a depot is located at the outskirts of the city. **Fig. 1** illustrates an example of a 2E-CVRP distribution system with two satellites and nine customers. The customers are represented by circles, the satellites by triangles, and the depot by a square. First and second echelon vehicle routes are represented by bold lines and thin lines, respectively.

In this paper, the 2E-CVRP is studied that extend from the classical CVRP, and which has two layers of delivery systems. The problem consists of a depot, a set of satellites, and a set of customers with demand[4)]. A direct depot-to-satellites distribution mode operates for long distances, offering a large capacity vehicle type (first echelon vehicles). The distribution between satellite and customers is yielded for the city center traffic by using a small capacity vehicle type (second echelon vehicles).

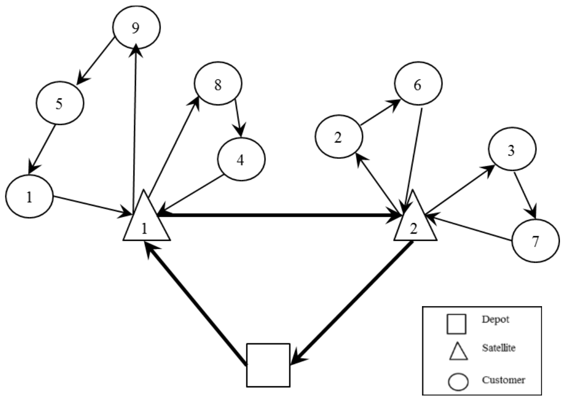

Fig.1 2E-CVRP distribution problem

The main algorithm used in this research is a hybrid genetic algorithm that works on relaxation for 2E-CVRP. The model is inspired by a hybrid genetic algorithm for the multi-depot vehicle routing problem (MDVRP)[12]. The GA has two phases; the first phase performs calculations for the second echelon. An hybrid algorithm consists of a genetic algorithm and *k*-means clustering is used to provide feasible solution for MDVRP. After that the second phase is solved for obtaining an optimal- feasible solution of the first echelon. The procedure starts after the best solution of the second echelon is imported. The objective is to minimize the total vehicle travel cost in both of the phases. Since the constraints on the maximum capacity of vehicles and the satellites are considered, this study, therefore, solves 2E-CVRP by using hybrid genetic algorithms method.

The paper is organized as follows. The methodology of 2E-CVRP related to the relaxation of a transportation system in the city center problem is firstly introduced in Section 2. A HGAs application for MDVRP is presented in Section 3. Instance sets for evaluating model and computational results are reported in Section 4. Finally the conclusion follows in Section 5.

2. PROBLEM DESCRIPTION

In this paper, we decomposed 2E-CVRP into two phases. The first phase (the second echelon) is solved by using a classical MDVRP, in which a hybrid algorithms is used for preparing feasible solution. The second phase (the first echelon) is independently solved by using the similar procedure of the previous phase. Each satellite must be served by large vehicles based at the central depot.

The MDVRP approach is implemented at the second level routing as satellites represent multi-depots. The solutions of the multi-depot are initially compared with lower bounds in literature to ensure the accuracy before the next step. However, in order to solve the problem to the optimality, while the obtained results is still a local lower bound, it is important to determine a feasible solution for the second level shortly after the feasible solution of the first level can be generated. In this way, the feasible global solution can be considered as an upper bound[17].

As mentioned in the introduction, the delivery from the depot to customers, in multi-echelon VRP is allowed through different intermediated satellites. The process aims to ensure an effective and low-cost operation of the system, where the freight is delivered so that the travel cost on the whole transportation network is minimized. The focus of 2E-CVRP, in particular, is only one intermediate level of satellites connected with the depot and customers. The load must be delivered to customers, and meet customer's demand d_i. Each demand load cannot be split among different vehicles or multiple routes. We defined in the first echelon, a route that transports demands by a large vehicle $\bar{k}$ with capacity $Q_{\bar{k}}$ that starts from the depot, service one or more satellites and ends at the depot while in the second echelon, a route run by small vehicle k with capacity Q_k that starts from satellite, serves one or more customers, and ends at the same satellite.

The simplest version of 2E-CVRP is used with no time dependence[1)-11)]. At each level, all vehicles are in the service have fixed capacity. The fleet size of each level is fixed, while the number of vehicles assigned to each satellite is not known in advance and need to be optimized. The objective is to deliver loads to the customers by minimizing the total travel cost, satisfying the capacity constraints of the vehicles. There is a single depot and fixed number of capacitated satellites. All customer demands are fixed, known in advance, and must be compulsorily satisfied. The demand of both levels must less than vehicle's capacity.

3. HYBRID GENETIC ALGORITHMS

Genetic Algorithms (GA) was firstly developed as a stochastic optimization technique[12]. Likewise, the other artificial intelligence heuristics such as the Simulated Annealing (SA) and the Tabu Search (TS), GA can avoid getting trapped in a local optimum by the assistance of one of the genetic operations called mutation. The fundamental idea of GA is to preserve a population of candidate solutions that evolves under selection procedure and survival of the fittest. Hence, it can be illustrated as a class of local search algorithms based on a solution generation mechanism operating on characteristics of a set of solutions rather than of a single solution, which is commonly called the move-generation mechanism of the local search methods, such as SA and TS[18]. In recent years, GA has been adopted successfully to a wide variety of NP-hard optimization problems, such as the traveling salesman problem (TSP) and the quadratic assignment problem [19)-20)]. The success is principally due to its clarity, easy operation, and greater flexibility. These are the major reasons why GA is implemented as an optimization tool in this paper also.

This study applies the integration of three relatively hard optimization problems of grouping, routing, and scheduling problems. Each individual problem, mentioned-above, is already complex and difficult to solve. A simple GA may not perform well in the proposed MDVRP, which is a combination of the stated three hard optimization problems. The application of GA is therefore, hybridized to improve the solution further, and to deal with the problem effectively. Therefore, a Hybrid Genetic Algorithms (HGAs) is developed in this paper.

Many researchers have worked with HGAs for solving hard optimization problem in last decade. The procedure of the proposed HGA is explained as follows: the GA parameters are decided first, including population size, the crossover rate, mutation rate and the iteration number. After that the initial chromosomes are generated. The initial solution is improved by grouping, based on *k*-means clustering heuristics, and with routing, based on Clark and Wright saving method [21)]. Finally, scheduling is improved with the Nearest Neighbor Heuristics (NNH)[25)]. The whole processes must satisfy the given constraints. The chromosomes contain nodes of customers, and link between them that can represent together the delivery sequences of the vehicles. The HGA iteration is started by randomly selecting some chromosomes for the genetic operations. It consists of uniform crossover and a single point mutation heuristics. All improved chromosomes are evaluated by the objective function. After all new chromosomes have been generated; each of them is assigned to the nearest depot. The iteration is repeated in order to improve predominated chromosomes, until the stopping criterion is met.

Above-mentioned process gives the solution procedure of the MDVRP that is generated in the second echelon. The first echelon is similarly solved by using the proposed HGA, on a network with depot and satellites. In section (3.1) we have further defined steps adopted for improved initial solution. The iterative HGA procedure, comprising of selection, crossover operator and mutation operator is described in section (3.2).

3.1. Improved Initialization solution

In the decision making procedure, at the grouping step, the initial solution is improved by the *k*-means algorithm. Briefly, the *k*-means clustering algorithm classifies or partitions off the customers into *k* clusters, in which each customer belong to the cluster with the nearest mean. The *k* is the number of available vehicles set in the second level, and it is set to a positive integer number. The Euclidean distance is used for checking the selection of the customers within cluster.

The grouping procedure is composed of the following steps: after the number of *k* has been decided, *k* clusters are randomly defined by the cluster centers. Then each customer is assign to the nearest cluster center, which is then recalculated to the new position of *k* centroids. This procedure is repeated until the convergence criterion is met, and the centroids are no longer moved. **Fig.2** illustrates the clustered customers after the *k*-means clustering has been applied.

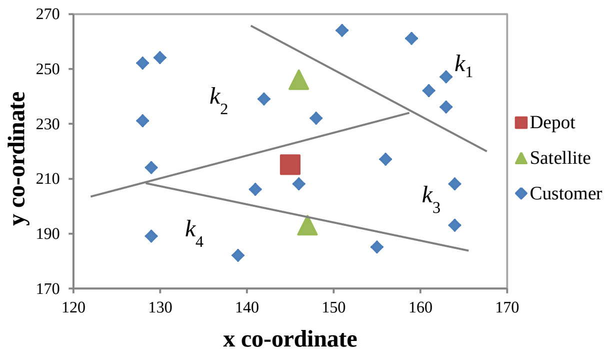

Fig 2 The clustered customers after *k*-means clustering

The routing procedure is then performed. The customers in the same cluster are assigned to a route that is to be served by the small vehicle. A saving matrix is constructed for every two customers in the same path based on Clark and Wright saving method[21)].

Finally, in the third step of improving procedure the scheduling problem is solved by NNH. There are two steps for scheduling; starting randomly with a customer in a path, obtained in the routing step. After that, the next nearest customer is selected from those unselected customers to the delivered sequence until all customers are selected.

From these three hard optimization processes, the initial solution is prepared to give the chromosomes of the initial population to be used in the next HGA procedure. Thus, to obtain the best solution, the initial solutions have been modified for GA, as compared to a random initialization.

3.2. Genetic algorithms

The GA gradually selects few parent chromosomes and generates children chromosomes until enough children chromosomes have been created to replace the old population. To breed, the programming begins with an empty population of children chromosomes. Then, two parent chromosomes are selected from the initial population. Copy and cross them over with one another, and finally mutate the results. This gives two children chromosomes, which are added to child population chromosomes. The process is repeated until the child population is entirely filled. The three steps of the algorithm are further defined as follow:

a) Selection

Two individuals of the initial population are selected randomly.

b) Crossover

The child chromosomes treat all genes fairly with respect to linkage by crossing over each point independently of one another, using Uniform crossover as shown in **Fig 3**. Each gene is defined by the randomly crossover rate. If that rate met the criterion of crossover, then they are able to swap independently to one another.

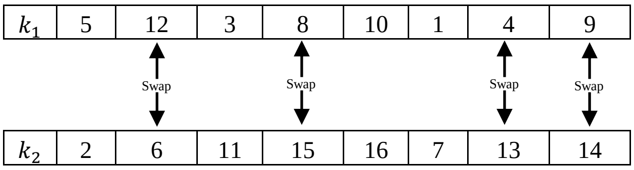

Fig.3 Uniform Crossover

However, all child chromosomes that are generated must satisfy the demand constraints. They will have an opportunity to be breeded further by mutation.

c) Mutation

The mutation operation is performed with one chromosome only. The gene is selected in order to mutate by using the mutation operation rate. **Fig 4** illustrates the gens 3 and 15 which are exchanged together. The advantage of mutation operator is to preferable increase in the diversity of population than the quality of the population.

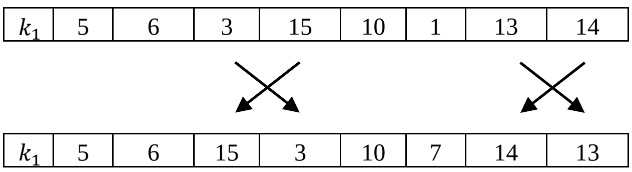

Fig.4 Mutation

Each path obtained in the child population is assigned to the nearest satellites. The calculation is based on the travel cost matrix between the satellites node and the customers nodes. After the path is assigned to the nearest satellite, it is evaluated for the travel cost. The worst solution path is replaced in the new population. The whole process of HGA is repeated until the stopping criterion of iteration is satisfied. Implementation of the algorithm steps is outlined in **Fig. 3**.

```
BEGIN
Import: number of customers, vehicles and satellites
        : location of customers, satellites, and the depot
Step of 2nd layer
  {
  Initialize population by using Improved Initialization solution
     Set parameters by user
           Set parameter "population size"
           Set parameter "crossover rate"
           Set parameter "mutation rate"
           Set parameter "generation"
     repeat
       {
        Evaluate chromosomes
        Perform the selection operator to two chromosomes
           Perform "the randomly selection operator"
        Perform the crossover operator
           Perform "the uniform crossover operator"
           if
              {
                 satisfied demand constraints
              }
           end if
        Perform the mutation operator
           Perform "the mutation operator"
           For
           Each path are assigned to the nearest satellites
           end for
           if
              {
                 The path is better than the worst path
                 Then
                 Replace the worst path
              }
           end if
Step of 1st layer
        repeat
           the step of 2nd layer
        generation = generation + 1
        }
     until
        the process reaches the criterion of generation
  Select the best path as a result
END
```

Fig 3 The pseudo-code of the algorithm

5. COMPUTATIONAL RESULTS

In this section, the computational results of the proposed algorithm are shown in term of effectiveness and efficiency comparing it with exact solution method in the litterers[1), 4)].

5.1. Instance sets

The performance is evaluated by using instances sets for the 2E-CVRP. These have been modified from the existing instances for CVRP by Christofides and Eilon namely E-n13-k4, E-n22-k4, E-n33-k4, and E-n51-k5[22)]. All instances can be downloaded at the OR-Library website[23)]. In this paper we define some benchmark to test and verify the effectiveness of the algorithm. Through a large number of experiments, the genetic parameters are set as iteration = 10,000, crossover rate = 0.8 and mutation rate = 0.15. All of instance tests were performed on a 2.21 GhZ AMD Athlon ™ 64 X2 Dual Core Processor 4200 PC with 2 Gb of Ram. The codes of the model were implemented in MATLAB (R2012a version) programming.

In this paper, test results are presented for set 2 and set 3 of benchmark 2E-CVRP instances[1)]. The study used class of instance E-n22-k4 in both set 2 and set 3, which have different location of satellites. For instances E-n22-k4 and E-n33-k4, 2 satellites have been adapted. For instances E-n51-k5, 4 satellites are selected. **Table 1** summarizes of number of solved instances.

Table 1 Summary of instances tests

Instance set	Class	Satellites	No. of instances
Set 2	E-n22-k4	2	6
	E-n33-k4	2	6
	E-n51-k5	4	3
Set 3	E-n22-k4	2	6

5.2. Comparison and discussion

The performance of the algorithm is compared with other literatures using an exact solution method. The proposed heuristics algorithm gives 18 out of the best solutions and three close to optimal solutions for E-n51-k5, while computational time is less than 1000 second as shown in **Table 2.** The first column reports name of the class instances, while the name of satellites node is shown in Column 2. Column 3 and 4 contain the previous best solution from literature and our best solution, respectively. The last column shows percent gap of that solution.

Table 2 Results on tested instances.

Instance	Satellites	Literature[1),4)]	Tested Results	Gap (%)
		Best bound		
E-n22-k4	6, 17	417.07	417.07	0.00
	8, 14	384.96	384.96	0.00
	9, 19	470.60	470.60	0.00
	10, 14	371.50	371.50	0.00
	11, 12	427.22	427.22	0.00
	12, 16	392.78	392.78	0.00
E-n22-k4	13, 14	526.15	526.15	0.00
	13, 16	521.09	521.09	0.00
	13, 17	496.38	496.38	0.00
	14, 19	498.80	498.80	0.00
	17, 19	512.80	512.80	0.00
	21, 19	520.42	520.42	0.00
E-n33-k4	1, 9	730.16	730.16	0.00
	2, 13	714.63	714.63	0.00
	3, 17	707.48	707.48	0.00
	4, 5	778.74	778.74	0.00
	7, 25	756.85	756.85	0.00
	14, 22	779.05	779.05	0.00
E-n51-k5	2, 4, 17, 46	530.76	548.41	3.33
	6, 12, 32, 37	531.92	546.33	2.71
	11, 19, 27, 47	527.63	577.25	9.40

6. CONCLUSIONS

The 2E-CVRP associated with the application of city logistics schemes, is a challenging problem and only few researches have been developed in this topic. The uniqueness of this 2E-CVRP is two layers of delivery system; a direct depot-to-satellites and a satellite-to-customers. Both stages must be optimized to satisfy transportation choice.

The 2E-CVRP model is solved using the developed HGA. The grouping procedure of initial solution of the HGAs is developed on an optimization technique in order to efficiently solve the MDVRP problem in the second echelon. The algorithm shows the effectiveness and efficiency, as based on the 21 instances tested in this study, it seems that the algorithm is working efficiently and it can be implemented to large-scale real word problems.

Future research will concentrate on real-world situation of the city network. It deals with an evaluation of environmental impact and delivery on congested network.

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REFERENCES

1) G. Perboli, R. Tadei, and D. Vigo. J. W. : The two-echelon capacitated vehicle routing problem: Models and Math-Based Heuristics, *Transportation Science*., Vol. 45, No. 3, pp. 364-380, 2011.
2) G. Perboli, F. Pezzella, and R. Tadei. : An hybrid algorithm for the capability vehicle routing problem, *Math. Methods Oper. Res.*, Vol. 68, pp. 361-382, 2008.
3) T. G. Crainic, N. Ricciardi, and G. Storchi. : Modees for Evaluating and planning city logistics, *Transportation Science*., Vol. 43, pp. 432-454, 2009.
4) M. Jepsen, S. Spoorendonk, and S. Ropke. : A branch-and-cut algorithm for the symmetric two-echelon capacitated vehicle routing problem, *Transportation Scienc*., pp. 1-15, 2012.
5) Nguyen, V., C. Prins, C. Prodhon. : A multi-start evolutionary local search for the two-echelon location routing problem, *Lecture Notes in Computer Science*, Vol. 6373, 2010.
6) Perboli, G., R. Tadei, F. Masoero. : New family of valid inequalities for the two-echelon vehicle routing problem, *Electronic Notes in Discrete Math*., pp. 639–646, 2010.
7) Gonzáles-Feliu, J., G. Perboli, R. Tadei, D. Vigo. : The two-echelon capacitated vehicle routing problem, *Technical report DEIS OR.INGCE*, 2007.
8) Crainic, T. G., S. Mancini, G. Perboli, R. Tadei. : Two-echelon vehicle routing problem: A satellite location analysis., *Procedia Soc.—Behaivioral Stud*, pp. 5944–5955, 2010.
9) Crainic, T. G., S. Mancini, G. Perboli, R. Tadei. : Clustering based heuristics for the two-echelon vehicle routing problem, *Technical report CIRRELT*-46, 2008.
10) W. Meihua, T. Xuhong, C. Shan, W. Shumin. : Hybrid ant colony optimization algorithm for two echelon vehicle routing problem, *Procedia Engineering: Advanced in Control Engineering and Information Science*, pp. 3361-3365, 2011.
11) Crainic, N. Ricciardi, G. Storchi : Advanced freight transportation systems for congested urban areas, *Transportation Research Past C*, pp. 119-137, 2004.
12) W. Ho, G. T.S. Ho, .and H.C.W.Lau. : A hybrid genetic algorithm for the multi-depot vehicle routing problem, *Engineering Application of Artificial Intelligence*., pp. 548-557, 2008.
13) P. Chen and X. Xu. : A hybrid algorithm for multi-depot vehicle routing problem, *IEEE International conference on Service Operations and Logistics, and Informatics*., pp. 2031-2034, 2008.
14) G. Jeon, H. R. Leep, and J. Y. Shim. : A vehicle routing problem solved by using a hybrid genetic algorithm, *Coputers and Industrial Engineering*, Vol. 53, pp. 680-692, 2007.
15) B. Creviera, J.-F. Cordeaua, and G. Laporte. : The multi-depot vehicle routing problem with inter-depot routes, *European Journal of Operational Research*, Vol. 176, pp. 756-773, 2007.
16) B. Ombuki-Berman and F. Hanshar. : Using genetic algorithms for multi-depot vehicle routing," in bio-inspired algorithms for the vehicle routing problem, *Computational Intelligence*, Vol.161, pp. 77-99, 2009.
17) C Contardo, J.F. Cordeau, and B. Gendron. : A branch-and-cut algorithm for the capacitated location routing problem, *Optimization Days*, 2008.
18) Osman, I.H., Kelly, J.P.: Meta-heuristics: Theory and Applications, *Kluwer Academic Publishers*, 1996.
19) Gen, M., Cheng, R. : Genetic Algorithms and Engineering Design, *Wiley*, 1997.
20) Goldberg, D.E. : Genetic Algorithms in Search, Optimization and Machine, *Learning. Addison-Wesley*, 1989.
21) Clarke, G., Wright, J.W. : Scheduling of vehicles from a central depot to a number of delivery points, *Operations Research 12*, pp. 568–581, 1964.
22) Christifides, N., S. Eilon. : An algorithm for the vehicle dispatching problem, *Operation Research* 20, pp. 309-318, 1969.
23) Beasley, J. E. : OR-Library: Distribution test problems by electronic mail. J., *Operation Research 41*, pp. 1069-1072, 1990.
24) L. Hubert, H. F. Kohn, and D. Steinley. : Cluster analysis: a toolbox for MATLAB., *The SAGE Handbook of Quantitative Method in Psychology*, pp. 444-513, 2009
25) Reinelt, G. : The Traveling Salesman: Computational Solutions for TSP, *Applications. Springer*, 1994.

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