A genetic algorithm for the vehicle routing optimization problem of logistics park distribution

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Abstract

The Vehicle Routing Problem of Logistics park distribution (VRPLPD) is an extension of the vehicle routing problem, which deals with simultaneous distribution of goods to customers. With the increasing importance of logistics activities, it is of great theoretical and practical significance to determine efficient and effective vehicle routes for simultaneous delivery activities. The study attempts to propose a genetic algorithm approach to tackle this problem. Numerical example is presented with parameter settings in order to demonstrate the applicability and feasibility of the proposed approach. The simulation is carried out in Simulink package of MATLAB. It is shown that Genetic Algorithms are highly effective in optimizing vehicle routing problem.

Keywords: Vehicle routing problem (VRP), Logistics park distribution, Genetic algorithms

1 Introduction

The Vehicle Routing Problem (VRP) can be described as the problem of designing optimal delivery routes from one or several depots to a number of geographically scattered customers within some constraints [1]. The VRP, the heart of distribution management, plays a pivotal role in the fields of physical distribution and logistics [2], which serves as an effective way to ascertain the optimal set of routes within specific constraints [3-4].

The VRP can be regarded as the travelling salesman problem (TSP). In order to solve the TSP, customers are partitioned into vehicles to minimize the required number of vehicles without violating the capacity constraint. For each vehicle, the VRP seeks to find out the lowest-cost (usually the shortest-distance) driving path, which is the same as what the TSP requires. The Vehicle Routing Problem with Time Window (VRPTW) is an extension of the VRP .In the VRPTW, customers have predefined time windows and a vehicle serves a customer within the time window [5]. The Vehicle Routing Problem of Logistics park distribution (VRPLPD) is typical of the VRPTW. In Logistics park distribution, the time window is a rigid constraint. If a Logistics park distribution vehicle arrives at the downstream distributors' location earlier, it must wait until the beginning of the time window; if a Logistics park distribution vehicle arrives at the downstream distributors' location later than the end of the time window, the solution is not acceptable [5]. Due to the complexity of the challenging problem, the VRPLPD is of great theoretical and practical significance in the fields of physical distribution and logistics research [5-6].

The VRPLPD is multi-objective, with minimization of the total travel distance as the most common one. The common way to achieve the objective is to minimize the total distance with a vehicle. This paper proposes a Genetic Algorithm (GA) to accomplish the objective. The remainder of this paper is organized as follows. Section 2 conducts an extensive and in-depth literature review. Section 3 defines the notation and problem formulation. The proposed approach is elaborated in Section 4, and numerical example in Section 5. Section 6 draws conclusion and provides future research directions. By looking into the trade-off between these solutions, scholars and practitioners in the sphere of vehicle routing can acquire more information and make more informed decisions.

2 Literature review

The literatures on vehicle routing problems are extensive and have been contributed by numerous scholars [7]. Hadjar et al (2009) adopted a pricing approach to solve the problem of multiple depot vehicle scheduling with time windows. They developed a dynamic time window reduction technique, which was used at every node of the price tree to tighten the time windows [8]. Chen Hsueh et al (2009) solved vehicle routing with time windows for perishable food products by utilizing a heuristic method [9]. Zachariadis et al (2009a) proposed a heuristic models methodology for the CVRP with two-dimensional loading constraints, the paper attempted to find the minimum cost routes that a vehicle started and terminated at a central depot [10]. Fleszar et al (2009) proposed a variable neighbourhood search heuristic for open vehicle problem. Proposed solution was based on reversing segments of sub-routes and exchanging segments between routes [11]. Li et al (2009) proposed a

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Lagrangian relaxation based-heuristic for the real-time vehicle rerouting problems with time windows. In real-time vehicle, rerouting problems there are service disruption because of vehicle breakdowns. Therefore, some vehicles must be rerouted [12]. Based on ant colony optimization, Fuellerer et al (2009) developed an effective heuristic algorithm for the two-dimensional loading vehicle routing problem. There is a combination of two problems: loading of the freight into the vehicles and routing the vehicles successfully [13].

Genetic algorithms (GAs) were put forward by John Holland in the 1960s and were further developed by Holland, his students and colleagues at the University of Michigan in the 1960s and the 1970s [14-15].Genetic Algorithms have been extensively studied, experimented and applied in many fields in engineering world. GAs not only provide an alternative method to solve problem but also consistently outperform other traditional methods in most of the problems link [16].Genetic algorithms have shown great advantages in solving the combinatorial optimization problem, including certain types of vehicle routing problem [17]. Numerous researchers have conducted studies to solve VRP using GAs. Baker et al (2003) considered the application of GAs to solve the VRP, in which customers of unknown demands were supplied from a single depot [18]. Wang et al (2009) primarily focused on solving a capacitated vehicle routing problem by applying a novel hybrid genetic algorithm [19]. Chan et al (2004) considered the problem of scheduling a single production plant in order to satisfy delivery time constraints. They proposed two approaches, an exact method suitable only for very simple cases, and a GA for instances of more realistic size. The paper did not address a realistic application scenario, as it considered only a single depot, ignored limited resources for transportation [20]. In another recent research work, Feng et al. (2004) focused on scheduling for a single depot, equipped with a fleet of vehicles with identical capacity and a fixed (customer and depot independent) loading/unloading times [21].

3 Notation and problem formulation

The vehicle routing problem of logistics park distribution (VRPLPD) can be viewed as a vehicle routing optimization problem of single distribution centre within time windows. This problem can be described as: the goods are delivered with more than one vehicle to multiple customers from a logistics park, each vehicle departures from park and returns to the park after the completion of delivery. Each customer's location and demand is changeless, the time to send the goods is set within a certain window, and each vehicle load is fixed.

A feasible solution to the VRPLPD must satisfy the following constraints:

1) Each customer must be served by one vehicle exactly one time along the designated route;
2) The route of each vehicle must start from and end at the depot;
3) The total demand of the customers served by each vehicle shouldn't exceed the maximum capacity;
4) A vehicle must arrive at customer no later than the end of the time window;
5) The service shouldn't start before the beginning of the time window;
6) The length of each route is no more than maximum mileage of a vehicle.

The parameters of Vehicle Routing Problem of Logistics Park Distribution (VRPLPD) are defined as follows:

1) The VRPLPD involves two types of objects: locations and vehicles. A special location 0 represents the depot. The remaining N locations correspond to N customers. The centre of Logistics park distribution has k vehicles. The maximum capacity of vehicle k is Q_k, the maximum mileage is D_k, The fixed cost of vehicle k is C_k, the average cost is M_k $(k=1\sim K)$, the dispatching cost for all vehicles is Z;
2) Each customer i has a fixed demand A_i and a time window $[E_i, L_i]$;
3) The distance from customers i to j is d_{ij}, the distance from logistics centre to each customer is d_{0i};
4) Arrival time of vehicle at customer i is t_i, the time of vehicle arrival at customer i from the customer j is t_{ij}, unloading per ton cargo needs time t_i. The serve time is S;
5) $$y_{ik} = \begin{cases} 1, if\ vehicle\ k\ delivers\ goods \\ to\ Customer\ i \\ 0, else \end{cases}$$
6) $$X_{ijk} = \begin{cases} 1, if\ vehicle\ k\ arrives\ loaction \\ of\ customer\ j\ \ from\ customer\ i \\ 0, else \end{cases}$$

The model, which is shown as below:

$$\begin{aligned} \min Z &= M_k \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{K} d_{ij} X_{ijk} + \sum_{k=1}^{K} c_k, \\ \min S &= \sum_{i=1}^{N}\sum_{j=1}^{N}\left\{\left[t_j - (t_i + t_{ij})\right] X_{ijk}\right\}. \end{aligned} \quad (1)$$

Subject to

$$\begin{aligned} &\sum_{i=1}^{N} A_i y_{ik} \le Q_k, \\ &\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{K} d_{ij} X_{ijk} \le D_k, \\ &\sum_{k=1}^{M} y_{ik} = \begin{cases} 1, i = 1\sim N \\ 0, i = 0 \end{cases} \\ &E_i \le t_i \le L_i. \end{aligned} \quad (2)$$

4 Genetic Algorithms

Genetic Algorithms (GAs) are adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetic. The basic concept of GAs is designed to simulate processes in natural system, which is necessary for evolution, specifically for those principles, which are firstly laid down by Charles Darwin of survival of the fittest. As such, they represent an intelligent exploitation of a random search within a defined search space to solve a problem [22].

An initial population of individuals (chromosomes) evolves through generations until reaching the satisfactory quality criteria, and a maximum number of iterations or time limits are reached. New individuals (children) are generated from individuals forming the current generation (parents) by means of genetic operators (crossover and mutation). GAs simulate the survival of the fittest among individuals over consecutive generation for solving a problem. Each generation consists of a population of character strings that are analogous to the chromosome that we see in our DNA. Each individual represents a point and a possible solution in a search space. The individuals in the population are then made to go through a process of evolution [23-24].

Algorithmically, the basic genetic algorithm is outlined as below:

Step I [Start] Generate random population of chromosomes, that is, suitable solutions for the problem.

Step II [Fitness] Evaluate the fitness of each chromosome in the population.

Step III [New population] Create a new population by repeating following steps until the new population is completed:

a) [Selection] Select two parent chromosomes from a population according to their fitness.
b) [Crossover] With a crossover probability, cross over the parents to form new offspring, that is, children. If no crossover is performed, offspring is the exact copy of parents.
c) [Mutation] With a mutation probability, mutate new offspring at each locus.
d) [Accepting] Place new offspring in the new population.

Step IV [Replace] Use new generated population for a further run of the algorithm.

Step V [Test] If the end condition is satisfied, stop, and return the best solution in current population.

Step VI [Loop] Go to step II.

The framework of the proposed genetic algorithm is shown in Figure1.

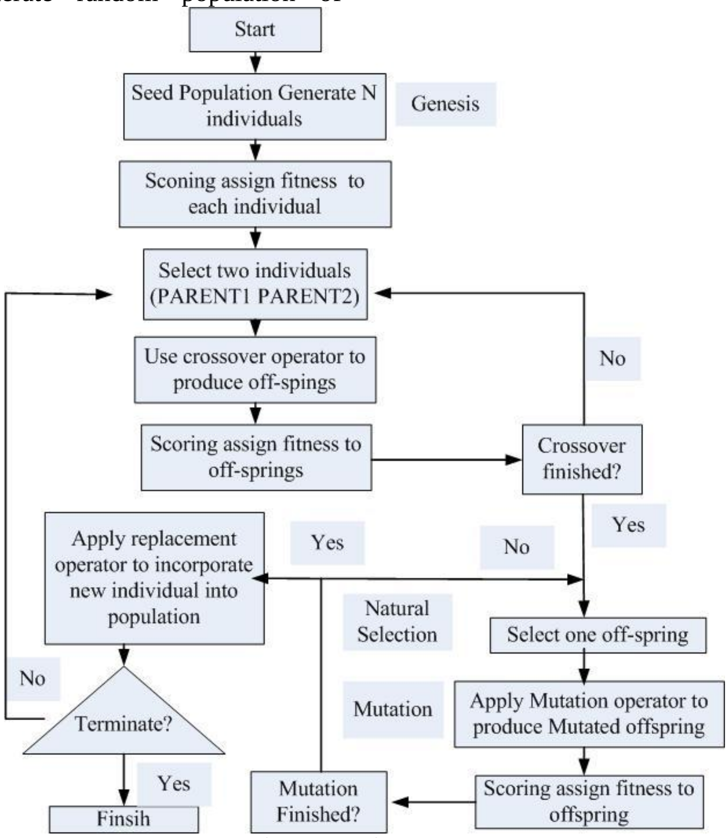

FIGURE 1 The framework of the proposed genetic algorithm

5 Numerical example

In this numerical example, there are 39 customer nodes, the customer nodes coordinates are shown in table 1. The depot 0 coordinates are (41, 43). A vehicle capacity is 30 units, each customer has the same demands.

Initially, a pilot study is conducted to determine the appropriate population size and number of generations for GA. The proposed approach is applied with combinations of population sizes M = {50,100,150}, and number of generations T= {2000, 3000, 4000}. The other parameters used in GA are crossover rate 0.75 and mutation rate 0.1.

TABLE 1 Customer's coordinates (unit: km)

Customer ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14
X	25	8	50	41	62	18	19	38	52	42	29	9	24	51
Y	52	62	37	30	36	40	54	17	44	13	44	48	43	32
Customer ID	15	16	17	18	19	20	21	22	23	24	25	26	27	28
X	11	19	31	29	57	36	44	24	33	40	51	59	34	61
y	40	60	58	64	28	64	51	27	16	41	59	44	22	64
Customer ID	29	30	31	32	33	34	35	36	37	38	39			
X	61	31	45	54	18	59	24	15	13	7	60			
y	18	25	14	24	22	52	13	15	27	27	58			

Using Matlab to solve the problem, results of several iterations are summarized in Table 2. For each combination, the best objective function value (column I), the average of the best values obtained through several runs (column II), the worst of the best values obtained through several runs (column III), the average objective function value of the population (column IV) are given.

TABLE 2 Computational results for the parameter settings

Popsize	Number of generations	I	II	III	IV
50	2000	405	435	489	503
100	2000	348	426	456	489
150	2000	326	450	437	514
50	3000	356	435	478	524
100	3000	378	406	436	536
150	3000	406	408	490	513
50	4000	379	456	431	543
100	4000	396	425	434	510
150	4000	356	411	453	514

In this example, the best objective function values and the corresponding distribution path through the evolution process are given in Figs.2 and Figs.3 respectively.

From these results, it can be concluded that population size 150 combined with number of generations 2096 results in good solutions considering the best objective function values. Total travelled distance by the vehicle is 326.The vehicle served 39 customer nodes through:

$$0 \to 4 \to 8 \to 14 \to 19 \to 32 \to 29 \to 31 \to 13 \to 8 \to 33 \to 27 \to 31 \to 35 \to 40 \to 33 \to 36 \to 38 \to 15 \to 6 \to 22 \to 11 \to 14 \to 1 \to 7 \to 12 \to 2 \to 16 \to 18 \to 17 \to 20 \to 25 \to 28 \to 39 \to 34 \to 26 \to 5 \to 3 \to 9 \to 21 \to 24 \to 0$$

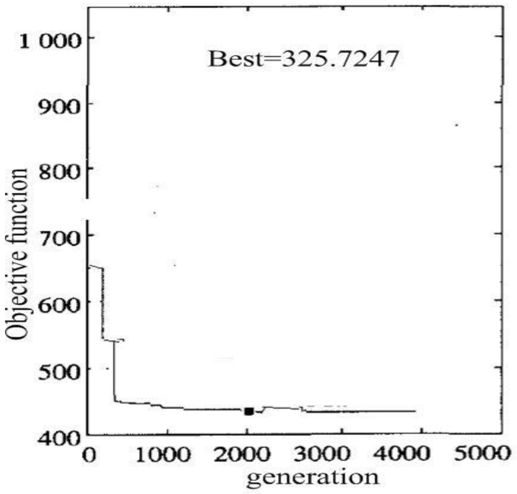

FIGURE 2 Best objective function value through the evolution process

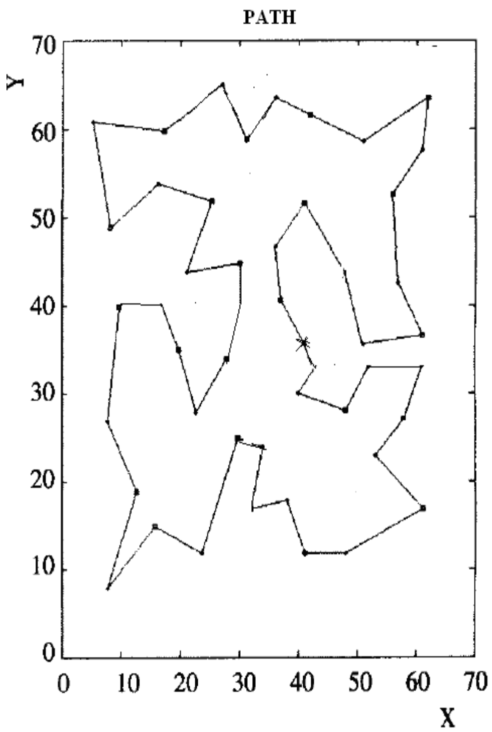

FIGURE 3 The optimal distribution path

6 Conclusion

The VRP is a well known combinatorial optimization problem. The Vehicle Routing Problem of Logistics Park Distribution (VRPLPD) is an extension of the VRP and considers simultaneous distribution of goods to customers. The VRPLPD has been getting more and more attention due to the increasing importance of logistics activities. In the same vein, VRPLPD has a combinatorial nature. Due to GAs' effectiveness in solving complex optimization problems, an improved GA approach for solving VRPLPD is proposed in this study.

This study sheds light on the VRP field by providing an efficient and effective GA approach that produces highly feasible routes for VRPLPD. Details of the proposed approach are presented in the previous sections after introducing VRPLPD and its mathematical formulation. In the following section, a numerical example is provided.

According to the results of numerical example, the proposed GA approach is proved to be effective and superior to other existent methods. Also, genetic algorithms can be applicable to other combinatorial optimization problems, but for different optimization problem, need to adopt different ways of encoding and different operation of genetic operators. Therefore, blending with other algorithms is highly advisable with the aim of gaining the most favourable solutions.

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References

[1] Pisinger D, Ropke S 2007 *Computers and Operations Research* **34**(8) 2403–35
[2] Laporte G 1992 *European Journal of Operational Research* **59**(3) 345-58
[3] Bräysy O, Gendreau M 2005 *Transport Sci* **39**(1) 119–39
[4] Rabinovich E, Windle R, Dresner M, Corsi T 1999 *International Journal of Physical Distribution and Logistics Management* **29**(6) 353-74
[5] Tsung Che Chiang, Wei Huai Hsu 2014 *Computers&Operations Research* **45**(5) 4525-37
[6] Tasan A S, Gen Mitsuo 2012 **62**(3) 755-61
[7] Ligil H B, Kara S S, Alcan P, Ozkan B, Caglar E G 2011 *Expert Systems with Applications* **38**(10),12730-38
[8] Hadjar A, Soumis F 2009 *Computers & Operations Research* **36**(7) 2160-72
[9] Chen H, HsuehC, Chang M 2009 *Computers & Operations Research* **36**(7) 2311-19
[10] Zachariadis E E, Tarantilis C D, Kiranoudis C T 2009 *European Journal of Operational Research* **195**(3) 729-43
[11] Fleszar K, Osman I H, Hindi K S 2009 *European Journal of Operational Research* **195**(3) 803-09
[12] Li J, Mirchandani P B, Borenstein D 2009 *European Journal of Operational Research* **194**(3) 711-27
[13] Fuellerer G, Doerner K F, Hartl R F, Lori M 2009 *Computers & Operations Research* **36**(3), 655-73
[14] Holland J H 1992 *Adaptation in Natural and Artificial Systems* CambridgeMIT Press
[15] Holland J H 1986 *Escaping brittleness: The possibilities of general−purpose learning algorithms applied to parallel rule−based systems* Boca Raton Florida: CRC Press
[16] Pisinger D, Ropke S 2007 *Computers and Operations Research* **34**(8) 2403–35
[17] Neri F, Cotta C 2012 *Swarm and Evolutionary Computation* **2**1-14
[18] Wang C H, Lu J Z 2009 *Expert Systems with Applications* **36**(2) 2921-36
[19] Baker B M, Ayechew M A 2003 *Computers & Operations Research* **30**(5) 787-800
[20] Chan F T S, Chung S H, Wadhwa S 2004 *International Journal of Production Research* **42** (1) 1–19
[21] Feng C W, Cheng T M, Wu H T 2004 *Automation in Construction* **13** (3) 327-40
[22] Schmitt L M, Nehaniv C L, Fujii R H 1998 *Theoretical Computer Science* **200**(1-2) 101-34
[23] *Genetic Algorithms in Engineering and Computer Science* 1995 New Jersey: John Wiley & Sons Ltd
[24] Mitchell M 1998 *An Introduction to Genetic Algorithms* Cambridge, Massachusetts London, England: MIT Press

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