Brock University

Department of Computer Science

WASTE COLLECTION VEHICLE ROUTING PROBLEM WITH TIME WINDOWS USING MULTI-OBJECTIVE GENETIC ALGORITHMS

Beatrice M. Ombuki-Berman, Andrew Runka, FranklinT.Hanshar
Technical Report # CS-07-04
May 2007

Brock University
Department of Computer Science
St. Catharines, Ontario
Canada L2S 3A1
www.cosc.brocku.ca

To be presented at Computational Intelligence 2007,
Banff, AB, Canada, July 2-4, 2007

WASTE COLLECTION VEHICLE ROUTING PROBLEM WITH TIME WINDOWS USING MULTI-OBJECTIVE GENETIC ALGORITHMS

Beatrice M. Ombuki-Berman
Dept. of Computer Science
Brock University
St. Catharines, ON, Canada L2S 3A1
bombuki@brocku.ca

Andrew Runka
Dept. of Computer Science
Brock University
St. Catharines, ON, Canada L2S 3A1
ar03gg@brocku.ca

Franklin T. Hanshar
Computing and Information Science
University of Guelph
Guelph, Ontario N1G 2W1
fhanshar@uoguelph.ca

ABSTRACT
We study a waste collection vehicle routing problem with time windows (VRPTW) complicated by multiple disposal trips and driver's lunch breaks. Recently Kim et al. [1] introduced and addressed this problem using an extension of the well-known Solomon's insertion approach, and a clustering-based algorithm. We propose and present the results of an initial study of a multi-objective genetic algorithm for the waste collection VRPTW using a set of benchmark data from real-world problems obtained by Kim et al.

KEY WORDS
waste collection, vehicle routing problem with time windows, genetic algorithms, multi-objective optimization, Pareto ranking

1 Introduction

We address a waste collection VRPTW with consideration of multiple disposal trips and driver's lunch breaks. Vehicle Routing Problems (VRPs) are well known combinatorial optimization problems arising in transportation logistics that usually involve scheduling in constrained environments. VRPs have received much attention in recent years due to their wide applicability and economic importance in determining efficient distribution strategies to reduce operational costs in distribution systems. As a result, variants have been studied extensively in literature (for a detailed reviews, see [2-5]).

The classic VRP can be stated as follows: design least-cost routes from a central depot to a set of geographically dispersed points (customers, stores, schools, cities, warehouses, etc.) with various demands. Each customer is to be serviced exactly once by only one vehicle, and each vehicle has a limited capacity. The problem can be further characterized by type of fleets, number of depots, and types of operations (pick-ups, deliveries, and mixed). The VRPTW is an extension of the VRP; here a *time window* is associated with each customer. That is, in addition to vehicle capacity constraints, each customer provides a time frame within which a particular service must be completed. The objective of the VRPTW is to minimize the number of vehicles and total distance traveled to service the customers without violating the capacity and time window constraints. The VRPTW has received much attention due to applicability of time window constraints in real-world situations [1], such as the waste collection problem studied in this paper.

There are three major areas in the waste collection industry: commercial waste collection, residential waste collection, and roll-on-roll-off. Although waste collection problems are presented as arc routing problems without time windows in various literature, that view is mainly skewed towards residential waste collection. Recently Kim et al. [1] studied the waste collection problem as a variant of VRPTW, since commercial waste collection stops may have time windows. The constraints specific to landfills are a major component of the routing model for waste collection companies. When a vehicle fills up its load capacity, it must make a trip to the closest available disposal location before proceeding on its route. Each vehicle can, and usually does make multiple disposal trips per day. In addition, unlike the standard VRPTW, each driver is assumed to take a one-hour lunch break beginning between 11a.m. and 1p.m.

The VRPTW, without considering multiple disposal trips and the lunch break itself, is NP-hard, and finding a feasible solution with a fixed fleet size is an NP-complete problem (see [6-7]). Given this, and the large problem sizes, the combinatorial explosion is obvious; finding exact optimal solutions for the waste collection VRPTW within reasonable time is computationally intractable [1,6]. Hence, heuristic approaches to this kind of problem is a natural choice. Since the waste collection VRPTW is inherently a multi-objective optimization problem [8], in minimizing the expected transportation costs in terms of travel distance and the number of vehicles deployed (besides the other objectives expounded in Section 2.1), an algorithm for this problem must also account for the feasibility of implementation of the solution by considering route and vehicle capacity and time windows. As our main contribution we propose the first multi-objective genetic algo-

rithm approach for the waste collection VRPTW problem as introduced in [1]. Research on combinatorial optimization based on meta-heuristics such as genetic algorithms, has gained popularity especially since the 90s. These approaches seek approximate solutions in polynomial time instead of exact solutions which would be at intolerably high cost.

Kim et al. [1] present a set of benchmark problems for the WCVRPTW that are used in this paper, as well as a cluster-based algorithm. The work they developed, as well as the savings they have effected for Waste Management Inc., are described in [1,9]. Tung et al. [10] address a real world application of waste collection with time windows in Hanoi, with an insertion heuristic. Nuortio et al. [11] apply a meta-heuristic to optimize waste collection routes in Eastern Finland.

The remainder of this paper is constructed as follows. Section 2 describes the problem definition and introduces the pareto ranking method. In Section 3, our proposed GA is presented. Our experimental results are discussed in Section 4, and the concluding remarks are given in Section 5.

2 Background

2.1 The Waste Collection Vehicle Routing Problem with Time Windows

We adopt the problem definition given by Kim et al. [1]. Similar to a standard single depot VRPTW, it is assumed that there is an operational area (such as a city or county), a set of homogeneous vehicles, which service a set of geographically dispersed stops including dump sites (transfer stations or landfill facilities). For each stop, the waste removal service must be provided within a given time window. Each stop is also associated with a load value, which is the amount of waste to be removed. Drivers depart from the depot at an opening time, service a number of stops within each stop's respective time window, and then return to the depot before its close time.

Because the waste management problem is a variant of the VRPTW with extra constraints specific to landfills and drivers's lunch, when a vehicle fills up its load capacity, it must make a trip to the closest available disposal location before proceeding on its route. Each vehicle can, and usually makes multiple disposal trips per day. In addition, unlike the standard VRPTW, each driver is assumed to take a one-hour lunch break between 11a.m. and 1p.m.

Two main capacity constraints are considered: vehicle capacity and route capacity. Vehicle capacity dictates the maximum volume and weight that each vehicle can hold at any given time. Route capacity provides the daily capacity for each driver: maximum number of stops, maximum number of lifts, maximum volume and weight handled per driver per any given day. The vehicle capacity dictates when and whether a disposal trip should be made. Each vehicle is expected to depart and return to the depot with zero volume.

Although minimizing the number of vehicles used and total distance/travel time is the main objectives of VRPTW in the literature, consideration to route compactness and route balancing are also important objectives in practical operations [1]. Route compactness depicts how the stops are grouped into a route, where no/less route overlap is considered more compact and favourable. Figure 1 shows a route sequence without considering dump operations; whereas Figure 2 shows the route sequence with one dump site.

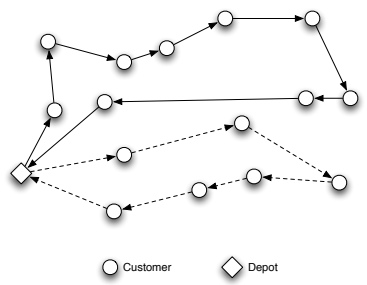

Figure 1. Standard VRPTW, no dump facility

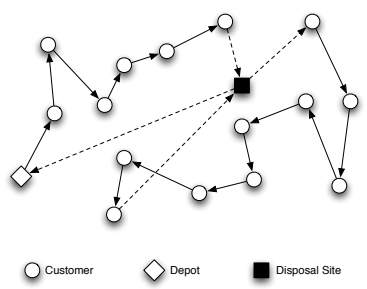

Figure 2. Waste collection VRPTW with one dump facility

Following the reference [1]'s model, the waste management VRPTW can be summarized as follows:
Objectives:

- Minimize the total number of vehicles used to service the customers.
- Minimize the distance traveled by the vehicles.
- Maximize route compactness.
- Balance workload among the vehicles.

Constraints:

- Vehicle capacity constraints.
- Route capacity constraints.

- Time windows of stops and depot constraints.
- Routing time limit per vehicle.
- Disposal trips.
- Driver's lunch break.
- Each stop is serviced exactly once.

2.2 Multi-Objective Optimization and Pareto Ranking

A multi-objective optimization problem (MOP) is one in which two or more objectives or parameters contribute to the overall result. These objectives often affect one another in complex, nonlinear ways. The challenge is to find a set of values for them which yield an optimization of the problem at hand. Evolutionary computation has been widely applied to MOP's [8,12-14]. Their success resides in the general applicability of evolutionary algorithms to finding good solutions to problems with appropriate structure, and the adaptability of genetic representation and fitness evaluation towards problems in the MOP field.

While various approaches exist for handling multiple-objectivity into evolutionary algorithms, we employ the Pareto ranking scheme [8,12,13]. It is easily incorporated into the fitness evaluation process within a genetic algorithm, by replacing the raw fitness scores with Pareto ranks. The underlying idea behind Pareto ranking is to preserve the independence of individual objectives. This is accomplished by stratifying the current candidate solutions into ranks, whereby lower ranks store the more desirable solutions. In order for a solution to occupy a lower rank, it must be clearly superior (i.e., non-dominated) to the others in all objectives of the problem. Solutions that occupy the same rank are considered indistinguishable from each other. This contrasts with a pure GA's attempt to assign a single fitness score to a MOP, perhaps as a weighted sum, hence reducing the MOP to a single-objective problem [8]. The difficulty with this is that the weighted sum necessitates the introduction of bias into both search performance and quality of solutions obtained. For many MOP's, finding an effective weighting for the multiple dimensions is difficult and *ad hoc*.

The following is based on a discussion in [14]. We assume that the MOP is a minimization problem, in which lower scores are preferred.

Definition: Given a problem defined by a vector of objectives $\vec{f} = (f_1, ..., f_k)$ subject to appropriate problem constraints. Then vector $\vec{u}$ **dominates** $\vec{v}$ iff

$$\forall i \in (1, ..., k) : u_i \leq v_i \wedge \exists i \in (1, ..., k) : u_i < v_i$$

This is denoted as $\vec{u} \preceq \vec{v}$.

The above definition says that a vector is dominated if and only if another vector exists which is better in at least 1 objective, and at least as good in the remaining objectives.

Definition: A solution $\vec{v}$ is **Pareto optimal** if there is no other vector $\vec{u}$ in the search space that dominates $\vec{v}$.

Definition: For a given MOP, the **Pareto optimal set** $\mathcal{P}^*$ is the set of vectors $\vec{v}_i$ such that $\forall v_i : \neg\exists \vec{u} : \vec{u} \preceq \vec{v}_i$.

Definition: For a given MOP, the **Pareto front** is a subset of the Pareto optimal set.

Many MOP's will have a multitude of solutions in its Pareto optimal set. Therefore, in a successful run of a genetic algorithm, the Pareto front will be the set of solutions obtained.

3 Multi-objective GA System for Waste collection VRPTW

This section provides the details of our implementations of the GA approach. In the GA, each chromosome in the population pool is transformed into a cluster of routes. The chromosomes are then subjected to an iterative evolutionary process until a minimum possible number of clusters is obtained or the termination condition is met. The transformation process is achieved by our routing scheme; whereas the evolutionary part is carried out like in ordinary GAs, that is, in each generation, genetic operations, crossover and selection are applied upon chromosomes. We adapt the crossover operator which we devised for the standard VRPTW in [15] for this paper. No mutation operator was employed in our GA.

```
initialise population
do {
    evaluate route network
    Selection
    Crossover
} while (stopping condition not met);

return best individual;
```

Figure 3. Pseudo code for genetic routing system

3.1 Chromosome Encoding and Initial populations

Each individual in the population represents a possible route schedule. A chromosome representing a network configuration is given by an integer string of length N, where N is the number of stops in a particular problem instance. A gene in a given chromosome indicates the original node number assigned to a stop, while the sequence of genes in the chromosome string dictates the order of visitation of stops.

A chromosome string contains a sequence of routes, but no delimiter is used to indicate the beginning or end of a respective route in a given chromosome. The correspondence between a chromosome and the routes is further explained in Section 3.5. An initial population is generated by random permutations of N stop nodes.

3.2 Fitness evaluation

We employed both the weighted sum and Pareto ranking approaches to determine the fitness of a chromosome, after building the best possible cluster of routes from it.

3.2.1 Weighted sum method

In this method, the problem objective functions are added together using weighted coefficients for each individual objective. Hence, the multi-objective waste collection VRPTW is transformed into a single-objective optimization problem where the fitness of an individual returned as:

$$\begin{aligned} Fitness &= \alpha \cdot \mid V \mid + \beta \cdot \sum_{k \in V} D_k \\ D_k &= \sum_{i \in N} \sum_{j \in N} t_{ij} x_{ijk} \end{aligned}$$

α and β are weight parameters associated with the number of vehicles and the total distance traveled by vehicles, respectively. The weight values of the parameters used in this function were established empirically and set at $\alpha = 100$ and $\beta = 0.001$.

3.2.2 Pareto Ranking procedure

A straight-forward MOP interpretation of the waste collection VRPTW is adopted. The problem objectives under consideration are the number of vehicles and the total cost. They define two independent dimensions in a multi-objective fitness space. Thus, using the characterization of Section 2.2, each candidate waste collection VRPTW solution in the population has associated with it a vector $\vec{v} = (n, c)$, where n is the number of vehicles for that candidate solution, and c is the total cost. Unlike the weighted sum above, these two dimensions are retained as independent values, eventually to be used by the Pareto ranking procedure.

Figure 4 shows how the Pareto ranking scheme is incorporated with the genetic algorithm. Pareto ranking is applied to the (n, c) vectors of the population, essentially creating for the population a set of integral ranks ≥ 1. These ranks are then used by the GA as fitnesses for generating the next population. Note , the ranks themselves do not convey the quality of solutions, nor whether an optimal solution has been discovered. Each population, including the randomized initial population, is guaranteed to have a rank 1 set. This is not a disadvantage for general instances of the waste collection VRPTW, since there is no efficient means of knowing whether a candidate waste collection VRPTW solution is truly optimal.

```
initialise population
Repeat until max. generation reached {
    For each chromosome i in population:
        Evaluate route network
          ⇒ (n_i, c_i)
        Determine Pareto rank.
          ⇒ rank_i
        Apply GA to population, using rank_i as fitness value.
          ⇒ new population
}
```

Figure 4. Pseudo code for genetic routing system with Pareto ranking

3.3 Fitness-based selection

The tournament selection strategy with elite retaining model [16] is used to generate a new population. A tournament set of K individuals are randomly selected from the population. We also select a random number $r \in (0, 1)$. If r is less than 0.8 (set empirically), the fittest individual in the tournament set is then chosen as the one to be used for reproduction. Otherwise, any chromosome is chosen for reproduction from the tournament set. The elite model is incorporated to ensure that the best solution produced by the overall best chromosome can never deteriorate from one generation to the next.

3.4 Crossover

Recombination is an important aspect of a genetic algorithm: it allows good traits from individuals (parents) to be transferred to new individuals (children). In this work, we extended a crossover operator for the waste collection problem, based primarily on the Best-Cost Route Crossover (BCRC) which was introduced in [15]. The BCRC was developed for the VRPTW, and so we modify it slightly and extend it to the waste collection VRPTW. The BCRC employs the idea of a customer (i.e., a stop) reinsertion, using information from two parents. The crossover works on the phenotypic or routed chromosome representation, which means a chromosome decoding must take place before the crossover is applied. The crossover operator produces two children, which are feasible chromosomes (i.e., a repair function is not needed).

This crossover operator uses an insertion strategy that has some aspects of local search incorporated. Two alternative insertion methods were considered. One involved the exhaustive insertion method used in BCRC, that is, an exhaustive search of all possible feasible locations to find

the very best one. The second idea uses a tournament style insertion technique similar to the tournament selection. In this method, k feasible insertion locations are selected at random throughout the chromosome, and the customer is inserted at the best of these insertion points. Further details for the BCRC are given in [15].

3.5 Routing Scheme

We employ two simple routing decoding schemes that transform each of the chromosomes into a cluster of routes. In the route-based decoder a vehicle must depart from the depot, and the first gene of a chromosome indicates the first customer stop the vehicle is to service. A stop is appended to the current route in the order that it appears on the chromosome. The routing procedure avoids violating the constraints of the vehicle capacity, route capacity and time window constraints before adding a stop to the current route. If a vehicle reaches its vehicle capacity, then a landfill trip is inserted. Lunch breaks are handled similarly. A new route is initiated every time a vehicle reaches its route-capacity. This process is continued until each stop has been assigned to exactly one route.

The vehicle-based decoder inspired by Kim et al. [1] uses vehicle estimates. Initially number of vehicles needed is estimated, based on the total number of customers and total load vs. the respective route capacities. Then each chromosome is decoded into routes by iteratively adding one stop to each of the estimated number of vehicles until all of the stops are assigned. If all vehicles reach their route capacities before all stops are assigned, then a new vehicle is added to the list and its route is constructed as in the route-based decoder. A comparison between the performances of these two decoders is presented in section 4.

4 Experimental evaluation of the GA

The GA system described in Section 3 was implemented and applied to the benchmark data from [1], which were obtained from real world problems. All experiments were coded in Java v1.5.0 and run on a Beowulf cluster with Intel 3.0GHz P4 machines with 1GB of RAM each.

Unless otherwise stated, the results presented below are based on the following set of GA parameters:

- population size = 100
- generation span = 200
- crossover rate = 0.90
- Tournament size = 3

These experimental results aim at showing three sets of simulations: E1 uses the vehicle-based decoder and tournament insertion, E2 uses the vehicle-based decoder with exhaustive insertion, and E3 uses the route-based decoder

Table 1. Weighted sum experimental results

Instance data	E1	E2	E3
102	3 140.3	**3 135.3**	3 135.7
277	5 379.8	**3 358.6**	**3 358.6**
335	6 190.3	**6 165.9**	**6 165.5**
444	11 67.2	**11 63.4**	**11 63.4**
804	14 615.5	**6 502.4**	6 508.8
1051	24 2239.6	**17 1991.6**	18 2084.6
1599	26 1363.6	**15 1146.4**	**15 1146.4**
1932	28 1393.0	**20 1141.8**	**20 1141.8**
2100	23 1892.1	**19 1588.0**	**19 1588.0**

Table 2. Weighted-sum Vs Pareto rank-based results

Instance data	E2	E3	pE2	pE3
102	**3 135.3**	3 135.7	3 135.4	**3 135.3**
277	3 358.6	3 358.6	**3 357.9**	**3 357.9**
335	6 165.9	6 165.5	6 165.3	**6 164.4**
444	**11 63.4**	**11 63.4**	**10 81.9**, 11 63.7	10 85.1, 11 63.8
804	6 502.4	6 508.8	**4 548.3**, 10 511.3	5 502.6, **12 501.8**
1051	17 1991.6	18 2084.6	16 2142.6, 23 1983.9	**16 2055.3**, **18 1933.3**
1599	**15 1146.4**	**15 1146.4**	**14 1446.9**, 22 1219.6	**14 1446.9**, 22 1219.6
1932	20 1141.8	20 1141.8	18 1354.8, 28 1143.4	**17 1165.7**, **20 1101.9**
2100	**19 1588.0**	**19 1588.0**	**17 2137.5**, 20 1648.5	**17 2137.5**, 20 1648.5

with exhaustive insertion. First, we established the performance of the GA based on the two routing schemes provided in Section 3.5. Tables 1 presents a summary of these results based on averages of five runs for the weighted sum fitness approach. Each table entry shows two numbers representing the number of vehicles and route costs respectivefully. Route costs are measured by average Euclidian distance. The bolded numbers show the best solutions in each case. The instance data name in Tables 1-3 is the number of stops in the problem.

As depicted by the E2, E3 columns in Table 1, we concluded that both the route-based scheme (as proposed in Section 3.5) and the vehicle-based routing inspired by [1] performed fairly the same, hence either is suitable for our purposes. This was further confirmed by Pareto results depicted in columns pE2 and pE3 in Table 2. Since the experiments with exhaustive insertion outperformed those with tournament insertion in terms of solution quality (as shown in Table 1), we only consider the exhaustive approach in Table 2. Table 2 shows a comparison between the weighted sum and Pareto rank based fitness evaluations. The advantages of the efforts of interpreting the waste collection VRPTW as a MOP using Pareto ranking, as opposed to the single objective using weighted sum, can be established from the solution quality.

When using the Pareto ranking, one has a choice of two (or more) solutions, depending on whether the user wants the best number of vehicles or best travel costs solutions. In some experiments, for example data instances 102, 277 and 335 in Table 2, there is a single Pareto solution that is optimal to the best known in both vehicle and distance objectives. With a weighted sum approach, there is only one solution which does not necessarily effectively serve the purpose of both objectives. Furthermore, in the weighted sum approach, one has to use a trial and error approach in finding the right weighted coefficients. In many cases one is forced to assume (unless stated by the user) that one objective has more weight than the other(s) in applying weighted sum. The Pareto approach as indicated by pE2 and pE3 columns of Table 2 indicates a wider selection of potential good solutions.

Tables 3 give comparisons of our results with published results [1] using non-GA approach. Recall that in the interpretation of Pareto result, user has a choice between a solution with the least distance or one with the least number of vehicles. Table 3 shows that our GA competes well with the published results found in [1]. It should however be noted that in [1] compactness is also explicitly taken into account. However, our approach does not explicitly consider route compactness or workload balancing as noted in the weighted sum function and Pareto ranking strategy. Nonetheless , this study gives us an encouraging outcome in our initial employment of multi-objective GA for this difficult, NP-hard problem and other researchers can have a basis in comparing their GA or related approaches to this problem.

Table 3. Pareto rank-based GA to Ref. [1] results

Instance data	**pE2**	**pE3**	**ref.[1]**
102	3 135.4	**3 135.3**	3 205.1
277	**3 357.9**	**3 357.9**	3 527.3
335	6 165.3	**6 164.4**	6 205.0
444	**10 81.9**, **11 63.7**	10 85.1, 11 63.8	11 87.3
804	**4 548.3**, 10 511.3	5 502.6, **12 501.8**	5 769.5
1051	16 2142.6, 23 1983.9	**16 2055.3**, **18 1933.3**	18 2370.4
1599	14 1446.9, 22 1219.6	14 1446.9, 22 1219.6	**13 1166.6**
1932	18 1354.8, 28 1143.4	**17 1165.7**, **20 1101.9**	17 1395.3
2100	17 2137.5, **20 1648.5**	17 2137.5, **20 1648.5**	**16 1833.8**

5 Concluding Remarks

This paper introduced a multi-objective genetic algorithm approach for the waste collection vehicle routing with time windows. To the best of our knowledge, this is the first GA approach for the particular waste collection problem. The Pareto ranking procedure precludes the need to experiment with weights as required in a weighted-sum approach. Poorly chosen weights can result in unsatisfactory solutions, and only after considerable experimentation can effective weights be obtained for a specific instance of a waste collection VRPTW. Our initial comparison of the GA with other published work shows potential in using GA for this large scale practical problem. As a next step, we will further develop our GA to take care of the issue of solution compactness and load balancing as discussed in Section 2.1 and further design our crossover operator to reduce computational time.

Acknowledgement: This research is supported through the Natural Sciences and Engineering Council of Canada, NSERC Operating Grant. This support is gratefully acknowledged. The authors wish to thank Dr. Michael Berman for his valuable comments.

References

[1] B.-I. Kim, S. Kim, and S. Sahoo, "Waste collection vehicle routing problem with time windows, " *Computers Operations Research*, 33(2006): 3624-3642.

[2] J. Desrosier, Y. Dumas, M. M. Solomon and F. Soumis, "Time constraint routing and scheduling," In *Handbooks in Operations Research and Management Science*, Vol. 8: Network Routing, M.O. Ball, T/L Magnanti, C.L Monma, G.L. Nemhauser (eds.). Elsevier Science Publishers, Amsterdam, pp. 35-139, 1995.

[3] J.F. Cordeau, G. Desaulniers, J. Desrosiers, M.M. Solomon, and F. Soumis, "The VRP with Time Windows. To Appear in The Vehicle Routing Problem,"

Chapter 7, P. Toth and D. Vigo (eds), *SIAM Monographs on Discrete Mathematics and Applications*, 2001.

[4] O. Braysy, and M. Gendreau, "Vehicle Routing Problem with Time Windows, Part 1: Route Construction and Local Search Algorithms," *SINTEF Applied Mathematics Report, Department of Optimization*, Norway, 2001.

[5] O. Braysy and M. Gendreau, "Vehicle Routing Problem with Time Windows, Part II: Metaheuristics," *SINTEF Applied Mathematics Report, Department of Optimization*, Norway, 2001.

[6] M. R. Garey, and D. S. Johnson, *Computers and Intractability, A Guide to The Theory of NP-Completeness*, W. H. Freeman and Company, 1979.

[7] J. K. Lenstra and A. H. G. Rinnooy Kan, "Complexity of Vehicle Routing Problem with Time Windows," *Networks*, 11:221-227, 1981.

[8] K. Deb, *Multi-objective Optimization using Evolutionary Algorithms*, John Wiley, 2001.

[9] S. Sahoo, S. Kim, and B.-I. Kim. "Routing Optimization for Waste Management." Interfaces 35(2005): 24-36.

[10] D.V. Tung, and A. Pinnoi. "Vehicle routing-scheduling for waste collection in Hanoi." European Journal of Operational Research 125(2000): 449-468.

[11] T. Nuortio, J. Kytojoki, H. Niska, and O. Braysy. "Improved route planning and scheduling of waste collection and transport." Expert Systems with Applications 30(2006): 223-232.

[12] C. A. Coello Coello, D. A Van Veldhuizen, and G.B Lamont. *Evolutionary Algorithms for Solving Multi-Objective Problems*, Kluwer Academic Publishers, 2002.

[13] C. M. Fonseca and P.J. Fleming. "An Overview of Evolutionary Algorithms in Multiobjective Optimization," *Evolutionary Computation*, 3(1):1-16, 1995.

[14] D. A Van Veldhuizen and G.B Lamont. "Multiobjective Evolutionary Algorithms: Analyzing the State-of-the-Art," *Evolutionary Computation*, 8(2):125-147, 2000.

[15] Beatrice Ombuki, Brian J. Ross and Franklin Hanshar. "Multi-Objective Genetic Algorithms for Vehicle Routing Problems with Time Windows", *Applied Intelligence*, 24(1):17-30, 2006.

[16] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison Wesley, 1989.