A Two-Stage Hybrid Local Search for the Vehicle Routing Problem with Time Windows[1]

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Abstract

The vehicle routing problem with time windows is a hard combinatorial optimization problem which has received considerable attention in the last decades. This paper proposes a two-stage hybrid algorithm for this transportation problem. The algorithm first minimizes the number of vehicles using simulated annealing. It then minimizes travel cost using a large neighborhood search which may relocate a large number of customers. Experimental results demonstrate the effectiveness of the algorithm which has improved 13 (23%) of the 58 best published solutions to the Solomon benchmarks, while matching or improving the best solutions in 47 problems (84%). More important perhaps, the algorithm is shown to be very robust. With a fixed configuration of its parameters, it returns either the best published solutions (or improvements thereof) or solutions very close in quality on all Solomon benchmarks. Results on the extended Solomon benchmarks are also given.

1 Introduction

Vehicle routing problems are important components of many distribution and transportation systems, including such examples as bank deliveries, postal deliveries, school bus routing, and security patrol services. They have received considerable attention in the past decades. This paper considers the vehicle routing problem with time windows (VRPTW). Given a number of customers with known demands and a fleet of identical vehicles with known capacities, the problem consists of finding a set of routes originating and terminating at a central depot and servicing all the customers exactly once. The routes cannot violate the capacity constraints on the vehicles and, in addition, must meet the time windows of the customers, which specify the earliest and latest times for the start of service at a customer site. The standard objective of the VRPTW problem consists of minimizing the number of routes or vehicles (primary criterion) and the total travel cost (secondary criterion). The VRPTW problem is NP-complete [21] and instances involving 100 customers or more are very hard to solve optimally. Indeed, very few of the traditional benchmarks [29] involving 100 customers been solved optimally (See [9, 20] for some recent results). As a consequence, local search techniques are often used to find good solutions in reasonable time.

This paper presents a two-stage hybrid algorithm for the VRPTW problem. *The overall structure of the algorithm is motivated by the recognition that minimizing the objective function directly may not be the most effective way to decrease the number of routes.* Indeed, the objective function often drives the search toward solutions with low travel cost, which may make it difficult to reach solutions with fewer routes but higher travel cost. To overcome this limitation, our algorithm divides the search in two steps:

[1]Technical Report, CS-01-06, Department of Computer Science, Brown University, September 2001.

1. the minimization of the number of routes;

2. the minimization of travel cost.

This two-step approach makes it possible to design algorithms tailored to each sub-optimization. The only other two stage algorithm we are aware of is reference [15], where the same evolutionary metaheuristic is used with two distinct objective functions to approach the two subproblems. Our algorithm uses two distinct local search procedures to exploit the specificities of each subproblem. Indeed, the first step of our algorithm uses simulated annealing to minimize the number of routes. *One critical aspect of our simulated annealing algorithm is its lexicographic evaluation function which minimizes the number of routes (primary criterion), maximizes the sum of the squares of the route sizes (secondary criterion), and minimizes minimal delay [15] of the routing plan (third criterion).* The second criterion was also successfully used in other applications (e.g., graph coloring [17]). The second step of our algorithm uses a large neighborhood search (LNS) [28] to minimize total travel cost. *It is motivated by our belief that LNS is particularly effective in minimizing total travel cost when given a solution that minimizes the number of routes.* Note also that our implementation of LNS makes it very close to variable neighborhood search [13].

Experimental results demonstrate the effectiveness of the algorithm. On the standard Solomon benchmarks, the algorithm improved the best published solutions in 13 of the 56 problems (23%) and matches or improves the best published results in 47 problems (84%). More important perhaps, the experimental results highlight the robustness of the algorithm. With a standard configuration of its parameters, the algorithm consistently returns either the best published solutions (or improvements thereof) or solutions that are very close in quality.

The rest of this paper is organized as follows. Section 2 describes the problem formulation and specifies the notations used in the paper. Section 3 gives an overview of the overall algorithm. Section 4 presents the simulated annealing algorithm for minimizing routes, while Section 5 describes the LNS algorithm for minimizing travel costs. Section 6 presents the experimental results. Section 7 discusses related work and Section 8 concludes the paper. The appendix contains the improvements over the best solutions found during the course of this research.

2 Problem Formulation and Definitions

This section defines the vehicle routing problem with time windows (VRPTW) and the various concepts used in this paper.

Customers The problem is defined in terms of N customers who are represented by the numbers $1, \ldots, N$ and a depot represented by the number 0. The set $\{0, 1, \ldots, N\}$ thus represents all the sites considered in the problem. We also use *Customers* to represent the set of customers and *Sites* to represent the set of sites. The *travel cost* between sites i and j is denoted by c_{ij}. Travel costs satisfy the triangular inequality

$$c_{ij} + c_{jk} \geq c_{ik}.$$

The *normalized travel cost* c'_{ij} between sites i and j is defined as

$$c'_{ij} = c_{ij} \;/ \max_{i,j \in Sites} c_{ij}.$$

Every customer i has a *demand* $q_i \geq 0$ and a *service time* $s_i \geq 0$.

Vehicles The VRPTW problem is defined in terms of m identical vehicles. Each vehicle has a capacity Q.

Routes A vehicle route, or route for short, starts from the depot, visits a number of customers at most once, and returns to the depot. In other words, a route is a sequence $\langle 0, v_1, \ldots, v_n, 0\rangle$ or $\langle v_1, \ldots, v_n\rangle$ for short, where all v_i are different. The customers of a route $r = \langle v_1, \ldots, v_n\rangle$, denoted by *cust(r)*, is the set $\{v_1, \ldots, v_n\}$. The size of a route, denoted by $|r|$, is the number of customers $|cust(r)|$. The demand of a route, denoted by $q(r)$, is the sum of the demands of its customers, i.e.,

$$q(r) = \sum_{c \in cust(r)} q_c.$$

A route satisfies its capacity constraint if

$$q(r) \leq Q.$$

The travel cost of a route $r = \langle v_1, \ldots, v_n\rangle$, denoted by *t(r)*, is the cost of visiting all its customers, i.e.,

$$t(r) = c_{0v_1} + c_{v_1v_2} + \ldots + c_{v_{n-1}v_n} + c_{v_n0}.$$

if the route is not empty ($n \geq 1$) and is zero otherwise.

Routing Plan A routing plan is a set of routes $\{r_1, \ldots, r_m\}$ ($m \leq M$) visiting every customer exactly once, i.e.,

$$\begin{cases} \bigcup_{i=1}^{m} cust(r_i) \;=\; Customers \\ cust(r_i) \cap cust(r_j) = \emptyset \;\; (1 \leq i < j \leq m) \end{cases}$$

Observe that a routing plan assigns a unique successor and predecessor to every customer. These successors and predecessors are sites. The successor and predecessor of customer i in routing plan σ are denoted by $succ(i, \sigma)$ and $pred(i, \sigma)$. For simplicity, our definitions often assume an underlying routing plan σ and we use i^+ and i^- to denote the successor and predecessor of i in σ.

Time Windows The customers and the depot have time windows. The time window of a site i is specified by an interval $[e_i, l_i]$, where e_i represents the earliest and latest arrival times respectively. Vehicles must arrive at a site before the end of the time window l_i. They may arrive early but they have to wait until time e_i to be serviced. Observe that e_0 represents the time when all vehicles in the routing plan leave the depot and that l_0 represents the time when they must all return to the depot. The *departure time* of customer i, denoted by δ_i, is defined recursively as

$$\begin{cases} \delta_0 &= 0 \\ \delta_i &= \max(\delta_{i^-} + c_{i^- i}\ ,\ e_i) + s_i \quad (i \in \mathit{Customers}). \end{cases}$$

The earliest service time of customer i, denoted by a_i, is defined as

$$a_i = \max(\delta_{i^-} + c_{i^- i}\ ,\ e_i) \quad (i \in \mathit{Customers}).$$

The earliest arrival time of a route $r = \langle v_1, \ldots, v_n \rangle$, denoted by $a(r)$, is given by $\delta_{v_n} + c_{v_n 0}$ if the route is not empty and is e_0 otherwise. A routing plan satisfies the time window constraint for customer i if $a_i \leq l_i$. A routing plan σ satisfies the time window constraint for the depot if $\forall r \in \sigma\ :\ a(r) \leq l_0$. The latest arrival time for customer i which does not violate the time window constraints of i and the customers served after i on its route, denoted by z_i, is defined recursively as

$$\begin{cases} z_0 &= l_0 \\ z_i &= \min(z_{i^+} - c_{ii^+} - s_i\ ,\ l_i) \quad (i \in \mathit{Customers}). \end{cases}$$

The VRPTW Problem A solution to the VRPTW problem is a routing plan $\sigma = \{r_1, \ldots, r_m\}$ satisfying the capacity constraints and the time window constraints, i.e.,

$$\begin{cases} q(r_j) \leq Q & (1 \leq j \leq m) \\ a(r_j) \leq l_0 & (1 \leq j \leq m) \\ a_i \leq l_i & (i \in \mathit{Customers}) \end{cases}$$

The size of a routing plan σ, denoted by $|\sigma|$, is the number of non-empty routes in σ, i.e.,

$$|\{r \in \sigma \mid \mathit{cust}(r) \neq \emptyset\}.$$

The VRPTW problem consists of finding a solution σ which minimizes the number of vehicles and, in case of ties, the total travel cost, i.e., a solution σ minimizing the objective function specified by the lexicographic order

$$f(\sigma) = \langle |\sigma|, \sum_{r \in \sigma} t(r) \rangle.$$

3 Overview of the Algorithm

As mentioned in the introduction, our algorithm is motivated by the recognition that minimizing the objective function

$$\langle |\sigma|, \sum_{r \in \sigma} t(r) \rangle.$$

is not always the most effective way to approach the problem. Indeed, the objective function often drives the search towards solutions with low travel costs. The reduction in the number of routes

```
Function VRPTWOPTIMIZE

1.  σ := ROUTEMINIMIZE()
2.  return TRAVELCOSTMINIMIZE(σ);
```

Figure 1: The Two-Stage Hybrid Algorithm for Minimizing Routes and Travel Costs.

occurs more as a side-effect of the travel cost minimization than as a primary feature of the search. In addition, focusing on travel cost may make it extremely difficult to reach solutions with fewer routes since it may require considerable degradation of the travel cost component of the objective function. The situation is further exacerbated by the discovery of more effective algorithms for minimizing travel cost.

To overcome this limitation, our algorithm separates the optimization into two stages: the minimization of the number of routes and the minimization of travel costs. Each of these two stages is optimized by an algorithm exploiting the underlying structure of the subproblem. The overall algorithm is depicted in Figure 1. The next two sections discuss each suboptimization in detail. Observe also that [15] is the only paper we are aware of where a two-stage algorithm is proposed. Their algorithm uses different objective functions but the same search strategy based on evolutionary algorithms.

4 Minimizing the Number of Routes

As mentioned, the first stage of our algorithm consists of minimizing the number of routes or, equivalently, the number of vehicles used in the routing plan. It uses a simulated annealing algorithm [19] with a number of interesting features that are now reviewed.

4.1 The Neighborhood

The neighborhood of our simulated annealing algorithm is based on the traditional move operators described, for instance, in [6, 18]: 2-exchange, Or-exchange, relocation, crossover, and exchange. We describe these moves informally for completeness. See [18] for a comprehensive overview as well as as incremental data structures and algorithms to compute them efficiently.

2-exchange For two customers i and j on the same route where i is visited before j, remove arcs (i, i^+), $(j, j+)$, add arcs (i, j), (i^+, j^+), and reverse the orientation of the arcs between i^+ and j.

Or-exchange Remove a sequence of 1, 2, or 3 customers from a route and reinsert the sequence elsewhere on the same or on a different route.

Relocation For customers i and j, place i after j, i.e., remove arcs (i^-, i), (i, i^+), (j, j^+) and add arcs (i^-, i^+), (j, i), and (i, j^+).

Exchange Exchange the positions of customers i and j, i.e., remove (i^-, i), (i, i^+), (j^-, j), (j, j^+) and add (i^-, j), (j, i^+), (j^-, i), (i, j^+).

Crossover Exchange the successors of customers i and j, i.e., remove (i, i^+), (j, j^+) and add (i, j^+), (j, i^+).

Given a solution σ, $\mathcal{N}(\sigma)$ denotes the neighborhood of σ, i.e., the set of solutions that can be reached from σ by using one of these move operators. We also denote by *Operators* the set of move operators {2-exchange, Or-exchange, relocation, exchange, crossover}.

A Random Sub-Neighborhood One of the interesting features of our simulated annealing algorithm is how it explores the neighborhood. Indeed, each iteration of the algorithm focuses on a (random) sub-neighborhood of $\mathcal{N}$ obtained by randomly choosing a move operator o from *Operators* and a customer c from *Customers* and by constructing all the moves using operator o and customer c. The sub-neighborhood will be explored exhaustively to find whether it contains a solution improving the best available routing plan and to choose the next move. We denote by $\mathcal{N}(o, c, \sigma)$ the subset of $\mathcal{N}(\sigma)$ that can be reached by using move operator o and customer c.

4.2 The Evaluation Function

The evaluation function is another fundamental aspect of our simulated annealing algorithm. As mentioned earlier, the objective function

$$\langle |\sigma|, \sum_{r \in \sigma} t(r) \rangle.$$

is not always appropriate, since it may lead the search to solutions with a small travel cost and makes it impossible to remove routes. To overcome this limitation, our simulated algorithm uses a more complex lexicographic ordering

$$e(\sigma) = \langle |\sigma|, -\sum_{r \in \sigma} |r|^2, mdl(\sigma) \rangle.$$

especially tailored to minimize the number of routes. The first component is of course the number of routes. The second component maximizes

$$\sum_{r \in \sigma} |r|^2$$

which means that it favors solutions containing routes with many customers and routes with few customers over solutions where customers are distributed more evenly among the routes. The intuition is to guide the algorithm into removing customers from some small routes and adding them to larger routes. Components of this type are used in many algorithms, a typical example being graph coloring [17]. The third component minimizes the minimal delay of the routing plan. This concept was introduced by [15] in the context of evolutionary algorithms. It favors solutions where customers on the smallest route can be relocated on other routes with no constraint violations or with time window violations which are as small as possible. Minimizing minimal delay thus favors solutions where customers can be relocated more easily over solutions where relocation is hard. More precisely, the minimal delay is defined as follows:

Definition 1 [Minimal Delay] The minimal delay of a solution σ, denoted by $mdl(\sigma)$, is defined as

$$
\begin{array}{l}
mdl(\sigma) = mdl(r,\sigma) \text{ where } |r| = min_{r' \in \sigma}|r'|. \\
mdl(r,\sigma) = \sum_{i \in cust(r)} mdl(i,r,\sigma). \\
mdl(i,r,\sigma) = \begin{cases} 0 = \text{ if } \mathcal{N}(relocation, i, \sigma) \neq \emptyset \\ \infty = \text{ if } \forall r' \in r : r \neq r' : q(r') + q_i > Q. \\ \min_{j \in Customers \setminus cust(r)} mdl(i,j,r,\sigma) \text{ otherwise.} \end{cases} \\
mdl(i,j,r,\sigma) = max(\delta_j + c_{ji} - l_i, 0) + max(\delta_i + c_{ij^+} - z_{j^+}, 0).
\end{array}
$$

In other words, the minimal delay of a solution σ is the minimal delay of the route with the smallest number of customers. The delay of a route is the summation of the delay of its customers. The minimal delay of a customer i is 0 if i can be relocated on another route, ∞ if i cannot be relocated without violating the capacity constraints of the vehicle, or the minimal time window violations induced by relocating i after a customer j on another route. The time window violation is given by the summation of the violation of the time window of i and the violation of the time window of the successors of j.

4.3 The Simulated Annealing Algorithm

Figure 2 depicts the simulated annealling algorithm. The algorithm consists of a number of local searches (lines 3-23), each of which starts from the best solution found so far and from the starting temperature. Each local search performs a number of iterations (lines 6-21) and decreases the temperature (line 22). These two steps are repeated until the time limit is exhausted or the temperature has reached its lower bound. Lines 7-20 describe one iteration and are most interesting. Lines 7-9 compute the sub-neighborhood

$$\mathcal{N}(o,c,\sigma) = \langle \sigma_1, \ldots, \sigma_s \rangle \text{ where } e(\sigma_i) \leq e(\sigma_j) \ (i < j)$$

for a random move operator and a random customer. Lines 10-12 select the solution σ_1 minimizing f in $\mathcal{N}(o,c,\sigma)$ if it improves the best solution found so far. These lines introduce an aspiration criterion [12] in the simulated annealing algorithm. Lines 14-19 are the core of the algorithm. Line 14 chooses a random element $\sigma_r \in \mathcal{N}(o,c,\sigma)$ and σ_r is selected as the nest routing plan if it does not degrade the current solution (line 16) or with the traditional probability of simulated annlealing otherwise (line 18). Observe also line 14

14. r := $\lfloor \text{RANDOM}([0,1])^{\beta} \times s \rfloor$;

which biases the search towards "good" moves in $\mathcal{N}(o,c,\sigma)$ when $\beta > 1$.

```
Function RouteMinimize

σ_b := getInitialSolution();
while (time < timeLimit) {
    σ := σ_b;
    t := startingTemperature;
    while (time < timeLimit & t > temperatureLimit) {
        for( i := 1; i ≤ maxIterations; i++) {
            o := random(Operators);
            c := random(Customers);
            ⟨σ_1, ..., σ_s⟩ := 𝒩(o,c,σ) where e(σ_i) ≤ e(σ_j) (i < j);
            if e(σ_1) < e(σ_b) then {
                σ_b := σ_1;
                σ := σ_1;
            } else {
                r := ⌊random([0,1])^β × s⌋;
                Δ := e(σ) − e(σ_r);
                if Δ ≥ 0 then
                    σ := σ_r;
                else if random([0,1]) ≤ e^(Δ/t) then
                    σ := σ_r;
            }
        }
        t := α × t;
    }
}
return σ_b;
```

Figure 2: The Simulated Annealing Algorithm to Minimize the Number of Routes

5 Minimizing the Travel Cost

Our algorithm uses a large neighborhood search (LNS) to minimize travel cost. LNS was proposed in [28] for vehicle routing problems. It was shown particularly effective on the class 1 problems from the Solomon benchmarks, producing several improvements over the then best published solutions. However, the algorithm performs poorly on the class 2 benchmarks where it could not reduce the number of routes satisfactorily [28] (page 426).[2] By separating the overall optimization in two stages, our algorithm directly addresses this LNS weakness and exploits its strength in minimizing travel cost. The rest of this section describes the LNS algorithm in detail. In general, the algorithm follows the heuristics and strategies described in [28], although it departs on a number of issues that seem important experimentally.

5.1 The Neighborhood and the Evaluation Function

Given a solution σ, the neighborhood of the LNS algorithm, denoted by $\mathcal{N}_R(\sigma)$, is the set of solutions that can be reached from σ by relocating at most p customers (where p is a parameter of the implementation). Since the LNS algorithm also uses subneighborhoods and explores the neighborhood in specific order, we use additional notations. In particular, $\mathcal{N}_R(\sigma, S)$ denotes the set of solutions that can be reached from σ by relocating the customers in S. Also, given a partial solution σ with customers $Customers \setminus S$, $\mathcal{N}_I(\sigma, S)$ denotes the solutions that can be obtained by inserting the customers S in σ. Finally, the LNS algorithm uses the original objective function

$$\langle |\sigma|, \sum_{r \in \sigma} t(r) \rangle$$

as evaluation function. Observe that the evaluation function still involves the number of routes. This is important since, in some cases, minimizing travel costs makes it possible to decrease the number of routes.

5.2 The Algorithm

At a high level, the LNS algorithm can be seen as a local search where each iteration selects a neighbor σ_c in $\mathcal{N}_R(\sigma_b)$ and accepts the move if $f(\sigma_c) < f(\sigma_b)$. It can be formalized as follows:

```
for(i := 1;i ≤ maxIterations; i++) {
    SELECT σ_c ∈ N_R(σ_b);
    if f(σ_c) < f(σ_b) then
        σ_b := σ_c;
}
```

In practice, it is important to refine and extend the above algorithm in three ways. The first modification consists of exploring the neighborhood by increasing number of allowed relocations. The second change generalizes the algorithm to a sequence of local searches. At this stage, the overall algorithm becomes

[2] Our own experimental results in fact confirm the findings in [28].

```
    Function TravelCostMinimize(σ_b)

1.  for(l := 1; l ≤ maxSearches; l++)
2.     for(n := 1; n ≤ p; n++)
3.        for(i := 1; i ≤ maxIterations; i++) {
4.           S := SelectCustomers(σ_b, n);
5.           SELECT σ_c ∈ N_R(σ_b, S) SUCH THAT f(σ_c) = min_{σ ∈ N_R(σ_b, S)} f(σ);
6.           if f(σ_c) < f(σ_b) then {
7.              σ_b := σ_c;
8.              i := 1;
9.           }
```

Figure 3: The LNS Algorithm to Minimize Travel Cost

```
1.  for(l := 1; l ≤ maxSearches; l++)
2.     for(n := 1; n ≤ p; n++)
3.        for(i := 1; i ≤ maxIterations; i++) {
4.           S := SelectCustomers(σ_b, n);
5.           SELECT σ_c ∈ N_R(σ_b, S);
6.           if f(σ_c) < f(σ_b) then {
7.              σ_b := σ_c;
8.              i := 1;
9.           }
```

Observe line 2 which adds another loop, line 4 which selects a set of customers S of size n, line 5 which selects a neighbor in $\mathcal{N}_R(\sigma_b, S)$, and line 8 which reinitializes the number of allowed iterations. In fact, the algorithm is now very close to variable neighborhood search [13]. The third modification consists of exploring the subneighborhood $\mathcal{N}_R(\sigma_b, S)$ more exhaustively to find its best solution. More precisely, the idea is to replace line 5 in the above algorithm by

```
5.           SELECT σ_c ∈ N_R(σ_b, S) SUCH THAT f(σ_c) = min_{σ ∈ N_R(σ_b, S)} f(σ);
```

The overall algorithm is depicted in Figure 3. It remains to describe how to select customers and how to implement line 5 in the above algorithm.

5.3 Selecting Customers to Relocate

The LNS algorithm uses the same strategy as in [28] to select the customers to relocate. The implementation is depicted in Figure 4. It first selects a customer randomly (line 1) and iterates lines 3-6 to remove the $n - 1$ remaining customers. Each such iteration selects a customer from

```
     Function SELECTCUSTOMERS(σ,n)

1.   S := { RANDOM(Customers) };
2.   for(i := 2;i ≤ n; i++) {
3.      c := RANDOM(S);
4.      ⟨c_0,...,c_{N−i}⟩ := Customers \ S SUCH THAT relateness(c,c_i) ≤ relateness(c,c_j) (i ≤ j);
5.      r := := ⌊RANDOM([0,1])^β × |Customers \ S|⌋;
6.      S := S ∪ {c_r};
7.   }
```

Figure 4: Selecting Customers in the LNS Algorithm

S (the already selected customers) and ranks the remaining customers according to a relateness criterion (lines 3-4). The new customer to insert is selected in line 5 and, once again, the algorithm biases the selection toward related neighbors. The relateness measure is defined as in [28]:

$$relateness(i,j) = \frac{1}{c'_{ij} + v_{ij}}$$

where $v_{ij} = 0$ if customers i and j are on the same route and is one otherwise.

5.4 The Exploration Algorithm

Our LNS algorithm uses a branch and bound algorithm to explore the selected subneighborhood. The algorithm is depicted in Figure 5. If the set of customers to insert is empty, the algorithm checks whether the current solution improves the best solution found so far. Otherwise, it selects the customer whose best insertion degrades the objective function the most (this heuristic is also used in [28]). The algorithm then explores all the partial solutions obtained by inserting c by increasing order of their travel costs. Also, observe that only the partial solutions whose lower bounds are better than the best solution found so far are explored by the algorithm. The lower bound satisfies the inequality

$$\textsc{Bound}(\sigma, S) \leq \min_{\sigma' \in \mathcal{N}_I(\sigma,S)} f(\sigma').$$

It remains to discuss the lower bound and how to keep the computation times reasonable.

Bounding The bounding function used in the LNS algorithm returns the cost of a minimum spanning k-tree [8] on the insertion graph with the depot as distinguished vertex, generalizing the well-known 1-tree bound of the travelling salesman problem. The insertion graph vertices are the

Function $\text{DFS}\textsc{Explore}(\sigma_c, S, \sigma_b)$

if $S = \emptyset$ **then** {
    if $f(\sigma_c) < f(\sigma_b)$ **then** $\sigma_b := \sigma_c$;
} **else** {
    c := arg-$\max_{c \in S} \min_{\sigma \in \mathcal{N}_I(\sigma,\{c\})} f(\sigma)$;
    S_c := $S \setminus \{c\}$;
    $\langle \sigma_0, \ldots, \sigma_k \rangle$:= $\mathcal{N}_I(\sigma, \{c\})$ WHERE $f(\sigma_i) \leq f(\sigma_j)$ $(i \leq j)$;
    for(i := 1; $i \leq k$; i++)
        if $\textsc{Bound}(\sigma_i, S_c) < f(\sigma_b)$ **then**
            $\text{DFS}\textsc{Explore}(\sigma_i, S_c, \sigma_b)$;
}

Figure 5: The Branch and Bound Algorithm for the Neighborhood Exploration

customers. Given a solution σ over customers $C = \cup_{r \in \sigma} cust(r)$ and a set S of vertices to insert, the insertion graph edges come from three different sets:

1. the edges already in σ;
2. all the edges between customers in S;
3. all the feasible edges connecting a customer from C and a customer from S.

More precisely, the insertion graph is defined as follows.

Definition 2 [Insertion Graph] Let σ be a partial solution over customers C and S be the set of customers to insert ($Customers = C \cup S$). The insertion graph is the graph $G(Customers, E)$ where

$$\begin{array}{lcl} E & = & E_\sigma \cup E_S \cup E_c; \\ E_\sigma & = & \{(i, i^+) \mid i \in C\}; \\ E_S & = & \{(i,j) \mid i,j \in S\}; \\ E_c & = & \{(pred(j,\sigma'), j) \mid \ j \in S \ \& \ pred(j,\sigma') \in C \ \& \ \sigma' \in \mathcal{N}_I(\sigma,\{j\})\} \ \cup \\ & & \{(j, succ(j,\sigma')) \mid \ j \in S \ \& \ succ(j,\sigma') \in C \ \& \ \sigma' \in \mathcal{N}_I(\sigma,\{j\})\}; \end{array}$$

Incomplete Search For large number of customers, finding the best reinsertion may be too time-consuming. Our algorithm uses limited discrepancy search to explore only a small part of the search tree. Limited Discrepancy Search (LDS) [14] is a search strategy relying on a good heuristic for the problem at hand. Its basic idea is to explore the search tree in waves and each successive wave allows the heuristic to make more mistakes. Wave 0 simply follows the heuristic. Wave 1

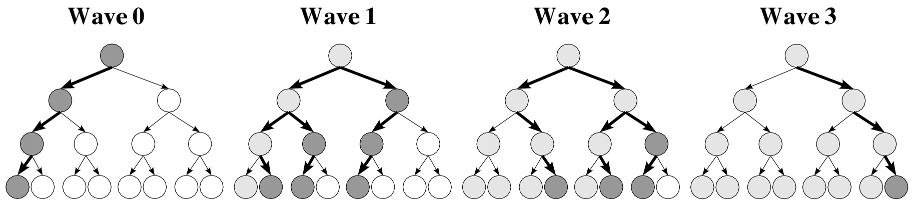

Figure 6: The Successive Waves of LDS.

explores the solutions which can be reached by assuming that the heuristic made one mistake. More generally, wave i explores the solutions which can be reached by assuming that the heuristic makes i mistakes.

Figure 6 illustrates these waves graphically on a binary tree. By exploring the search tree according to the heuristic, LDS may reach good solutions (and thus an optimal solution) much faster than depth-first and best-first search for some applications. Its strength is its ability to explore diverse parts of the search tree containing good solutions which are only reached much later by depth-first search. Our implementation uses one phase of limited discrepancy search which allows up to d discrepancies. Figure 7 depicts the algorithm. Observe that, in the LNS algorithm, the tree is not binary and the heuristic selects the insertion points by increasing lower bounds.

6 Experimental Results

This section describes experimental results on our algorithm. The algorithm was implemented in C++ and the entire code is less than 4500 lines. The core of the algorithm is about 2,000 lines. They include about 350 lines for the simulated annealing algorithm, 300 lines for the LNS algorithm, and about 1300 lines for the data structures. All results are given on a Sun Ultra 10, 440 MHZ, 256 MB RAM using Sun C++ compiler. All numbers used were double precision floating points. Our experimental results use the standard Solomon benchmarks available at *http://www.cba.neu.edu/~solomon/problems.html*. See [29] for their descriptions.

The rest of this section is organized as follows. Section 6.1 compares our best solutions with the best published solutions. Section 6.2 report the best results for minimizing routes and compares them with other approaches. Section 6.3 gives the robustness results. Section 6.4 reports results on the extended Solomon benchmarks. In reporting the results, we use the following abbreviations to denote existing algorithms: S = [28], RT = [26], DDS = [7], HG = [15], RGP = [27], TOS = [31], CLM = [4], CR = [2], GTA = [10], DFS = [6], TBG = [30], PB = [24], IKP = [16].

6.1 Best Published Results

Tables 1 and 2 report our best results and compare them to the best published results. Column *data* gives the names of the benchmark, column *best* gives the best published solutions, column *SA+LNS* describes the best solution found by our algorithm, and the last two columns report the

```
Function LDSExplore($\sigma_c$,$S$,$\sigma_b$,$d$)

if $d \geq 0$ then {
    if $S = \emptyset$ then {
        if $f(\sigma_c) < f(\sigma_b)$ then $\sigma_b := \sigma_c$;
    } else {
        $c$ := arg-$\max_{c \in S}$ $\min_{\sigma \in \mathcal{N}_I(\sigma,\{c\})}$ $f(\sigma)$;
        $S_c$ := $S \setminus \{c\}$;
        $\langle \sigma_0, \ldots, \sigma_k \rangle$ := $\mathcal{N}_I(\sigma, \{c\})$ WHERE $f(\sigma_i) \leq f(\sigma_j)$ $(i \leq j)$;
        for($i$ := 1; $i \leq k$; $i$++) {
            if Bound($\sigma_i, S_c$) $< f(\sigma_b)$ then {
                LDSExplore($\sigma_i, S_c, \sigma_b$,d);
                $d$ := $d + 1$;
            }
        }
    }
}
```

Figure 7: The Branch and Bound Algorithm with a Limited Discrepancy Strategy.

Data	Best	Ref	Trun. Best	Ref	SA+LNS	Compare	
c101	828.94 10	RT	827.3 10	DDS	**828.937 10**	0	0%
c102	828.94 10	RT	827.3 10	DDS	**828.937 10**	0	0%
c103	828.06 10	RT			**828.065 10**	0	0%
c104	824.78 10	RT			**824.777 10**	0	0%
c105	828.94 10	PB			**828.94 10**	0	0%
c106	828.94 10	RT	827.3 10	DDS	**828.937 10**	0	0%
c107	828.94 10	RT	827.3 10	DDS	**828.937 10**	0	0%
c108	828.94 10	RT	827.3 10	DDS	**828.937 10**	0	0%
c109	828.94 10	PB			**828.937 10**	0	0%
r101	1650.8 19	RT	1607.7 18	DDS	**1650.8 19**	0	0%
r102	1486.12 17	RT	1434 17	DDS	**1486.12 17**	0	0%
r103	1292.68 13	S	1207 13	TOS	**1292.68 13**	0	0%
r104	1007.31 9	S			**1007.31 9**	0	0%
r105	1377.11 14	RT			**1377.11 14**	0	0%
r106	1252.03 12	RT			**1252.03 12**	0	0%
r107	1104.66 10	S			**1104.66 10**	0	0%
r108	963.99 9	S			*960.876 9**	-3.1	-0.3%
r109	1194.73 11	HG			**1194.73 11**	0	0%
r110	1124.4 10	RGP			*1118.84 10**	-5.56	-0.5%
r111	1096.72 10	RGP			1096.73 **10**	0.01	0%
r112	982.14 9	GTA			991.245 **9**	9.1	0.9%
rc101	1696.94 14	TBG	1669 14	TOS	1696.95 **14**	0.01	0%
rc102	1554.75 12	TBG			**1554.75 12**	0	0%
rc103	1261.67 11	S	1110 11	TOS	**1261.67 11**	0	0%
rc104	1135.48 10	S			**1135.48 10**	0	0%
rc105	1633.72 13	RGP			*1629.44 13**	-4.3	-0.3%
rc106	1427.13 11	CLM			*1424.73 11**	-2.4	-0.2%
rc107	1230.48 11	S			**1230.48 11**	0	0%
rc108	1139.82 10	TBG			**1139.82 10**	0	0%

Table 1: Solomon Benchmarks Class 1: Comparison with Best Published Results

Data	Best	Ref	Trun. Best	Ref	SA+LNS	Compare	
c201	591.56 3	PB			**591.557 3**	0	0%
c202	591.56 3	PB			**591.557 3**	0	0%
c203	591.17 3	RT			**591.173 3**	0	0%
c204	590.60 3	PB			**590.599 3**	0	0%
c205	588.88 3	PB			**588.876 3**	0	0%
c206	588.49 3	PB			**588.493 3**	0	0%
c207	588.29 3	RT			**588.286 3**	0	0%
c208	588.32 3	RT			**588.324 3**	0	0%
r201	1252.37 4	HG			**1252.37 4**	0	0%
r202	1191.7 3	RGP			1195.3 **3**	3.6	0.3%
r203	942.64 3	HG			*941.408 3**	-1.2	−0.1%
r204	849.62 2	CLM			*825.519 2**	-24.1	−2.8%
r205	994.42 3	RGP			**994.42 3**	0	0%
r206	912.97 3	RT	833 3	TOS	914.627 **3**	1.7	0.2%
r207	914.39 2	CR			*893.328 2**	-21.1	−2.3%
r208	726.823 2	GTA			**726.823 2**	0	0%
r209	909.86 3	RGP	855 3	TOS	*909.163 3**	-0.7	0%
r210	939.37 3	DFS			951.294 **3**	11.9	1.3%
r211	910.09 2	HG			*892.713 2**	-17.4	−1.9%
rc201	1406.94 4	CLM	1249 4	TOS	1412.45 **4**	5.5	0.4%
rc202	1377.089 3	GTA			1387.38 **3**	10.3	0.7%
rc203	1060.45 3	HG			1064.14 **3**	3.7	0.3%
rc204	798.464 3	GTA			**798.464 3**	0	0%
rc205	1302.42 4	HG			*1297.65 4**	-4.8	−0.4%
rc206	1153.93 3	RGP			*1146.32 3**	-7.6	−0.7%
rc207	1062.05 3	CLM			*1061.14 3**	-0.9	−0.1%
rc208	829.69 3	RGP			*828.141 3**	-1.5	−0.2%

Table 2: Solomon Benchmarks Class 2: Comparison with Best Published Results

Data	RT	TBG	CR	CLM	HG	DFS	GTA	S	SA+LNS
c1	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**
c2	**3**	**3**	**3**	**3**	**3**	**3**	**3**	-	**3**
r1	12.25	12.17	12.17	12.08	**11.92**	12.5	12	12	**11.92**
r2	2.91	2.82	**2.73**	**2.73**	**2.73**	3	**2.73**	-	**2.73**
rc1	11.88	**11.5**	11.88	**11.5**	**11.5**	12	11.63	11.75	**11.5**
rc2	3.38	3.38	**3.25**	**3.25**	**3.25**	3.38	**3.25**	-	**3.25**

Table 3: Comparison of the Number of Routes on the Solomon Benchmarks.

distances with respect to the best solutions, both in absolute terms and in percentage. We also include results from papers using integers or one decimal point of precision if they are better than the double precision floating point results. These results can be infeasible using double floating point precision [30]. Columns labeled *Ref* gives references where the best published solutions can be found. Finally, bold faced values indicate achievement of best published solutions, italicized/starred results indicate an improvement on the best published results we know of.

The results indicate that our algorithm improved 13 (23%) of the best published solutions to the Solomon benchmarks, while matching or improving the best solutions in 47 benchmarks (84%). The algorithm was able to obtain the minimum number of vehicles published on all instances. In addition, on all benchmarks but one, the algorithm produced solutions which are less than 1% from the best published solutions and, in a couple cases, it improved the best published solutions by more than 2%. *These results seem to indicate the benefits of decomposing the optimization in two stages, the effectiveness of simulated annealing to minimize routes, and the benefits of LNS to minimize travel cost.*

6.2 Minimizing Routes

Table 3 compares our algorithm to other metaheuristics with respect to the number of routes. It gives the average number of vehicles for the best solution in each class of Solomon's problems. The best results are marked in bold. The results shows that our algorithm, together with HG, always produces the best results. *Observe that our algorithm and HG use fundamentally different local search techniques and yet they both produce the best results. Hence these results seem to indicate the benefits of using a separate stage to minimize the number of our routes.*

6.3 Robustness

Robustness is a fundamental and desirable property of local search algorithms. An algorithm is robust if it performs well on large classes of problems with the same parameter configurations. This section studies the robustness of our algorithm.

Tables 4 and 5 depict the results for a specific configuration of our algorithm. The results correspond to five runs of our algorithm. For simulated annealing, the parameters are 2000 for

Data	Veh	30 CPU Minutes					120 CPU Minutes				
		Best	Cmp	Avg	Comp	Worst	Best	Cmp	Avg	cmp	Worst
c101	**10**	**828.937**	0.0%	**828.937**	0.0%	**828.937**	**828.937**	0.0%	**828.937**	0.0%	**828.937**
c102	**10**	**828.937**	0.0%	**828.937**	0.0%	**828.937**	**828.937**	0.0%	**828.937**	0.0%	**828.937**
c103	**10**	**828.065**	0.0%	**828.065**	0.0%	**828.065**	**828.065**	0.0%	**828.065**	0.0%	**828.065**
c104	**10**	**824.777**	0.0%	**824.777**	0.0%	**824.777**	**824.777**	0.0%	**824.777**	0.0%	**824.777**
c105	**10**	**828.937**	0.0%	**828.937**	0.0%	**828.937**	**828.937**	0.0%	**828.937**	0.0%	**828.937**
c106	**10**	**828.937**	0.0%	**828.937**	0.0%	**828.937**	**828.937**	0.0%	**828.937**	0.0%	**828.937**
c107	**10**	**822.937**	0.0%	**828.937**	0.0%	**828.937**	**828.937**	0.0%	**828.937**	0.0%	**828.937**
c108	**10**	**828.937**	0.0%	**828.937**	0.0%	**828.937**	**828.937**	0.0%	**828.937**	0.0%	**828.937**
c109	**10**	**828.937**	0.0%	**828.937**	0.0%	**828.937**	**828.937**	0.0%	**828.937**	0.0%	**828.937**
r101	**19**	**1650.8**	0.0%	**1650.8**	0.0%	**1650.8**	**1650.8**	0.0%	**1650.8**	0.0%	**1650.8**
r102	**17**	**1486.12**	0.0%	**1486.12**	0.0%	**1486.12**	**1486.12**	0.0%	**1486.12**	0.0%	**1486.12**
r103	**13**						**1292.68**	0.0%	1296.17	0.3%	1297.62
	14	1213.62		1214.48		1217.92					
r104	**9**						1017.52	1.0%	1017.52 1	1.0%	
	10	981.232		984.13		989.803			987.38 4		989.056
r105	**14**	1387.14	0.7%	1401.83	1.8%	1426.17	**1377.11**	0.0%	1380.85	0.3%	1387.14
r106	**12**	1257.96	0.4%	1270.19	1.5%	1292.16	1257.96	0.5%	1258.31	0.5%	1259.71
r107	**10**	1114.78	0.9%	1119.28 4	1.3%		**1104.66**	0.0%	1111.39	0.6%	1114.29
	11			1072.12 1		1072.12					
r108	**9**	966.86	0.3%	979.75 4	1.6%		966.118	0.2%	968.04	0.4%	973.424
	10			961.359 1		961.359					
r109	**11**	1197.42	0.2%	1219.9 4	2.1%		1197.42	0.2%	1218.54 4	2.0%	
	12			1166.24 1		1166.24			1153.89 1		1153.89
r110	**10**	1126.63	0.2%	1130.76 4	0.6%		*1119.14*	−0.5%	1125.66	0.1%	1127.94
	11			1114.28 1		1114.28					
r111	**10**	1096.74	0.0%	1107.78 4	1.0%		1096.73	0.0%	1097.49	0.0%	1100.55
	11			1063.3 1		1063.3					
r112	**9**						992.754	1.1%	1001.54 3		
	10	966.793		971.79		986.753			967.95 2		968.94
rc101	**14**	1697.43	0.1%	1697.43 1	0.1%		1296.95	0.0%	1697.21 4	0.0%	
	15			1624.51 4		1627.29			1623.58 1		1623.58
rc102	**12**	**1554.75**	0.0%	**1554.75**	0.0%	**1554.75**	**1554.75**	0.0%	**1554.75** 4	0.0%	
	13								1477.54 1		1477.54
rc103	**11**	**1261.67**	0.0%	1267.47	0.5%	1278.55	**1261.67**	0.0%	1267.17	0.4%	1270.72
rc104	**10**	**1135.48**	0.0%	1144.97	0.8%	1156.05	**1135.48**	0.0%	1141.15	0.5%	1159.43
rc105	**13**	1635.9	0.1%	1638.24 2	0.3%		_1629.44*_	−0.3%	1636.86 3	0.2%	
	14			1553.03 3		1563.76			1541.23 2		1542.27
rc106	**11**						_1424.73*_	−0.2%	1435.82 4	0.6 %	
	12	1376.26		1378.52		1387.57			1376.25 1		1376.25
rc107	**11**	1230.95	0.0%	1231.85	0.1%	1232.26	1230.95	0.0%	1231.84	0.1%	1232.26
rc108	**10**	**1139.82**	0.0%	1162.00	1.9%	1193.45	**1139.82**	0.0%	1156.04	1.4%	1187.76

Table 4: Solomon Benchmarks Class 1: Robustness Results.

Data	Veh	30 CPU Minutes					120 CPU Minutes				
		Best	Cmp	Avg	Cmp	Worst	Best	Cmp	Avg	Cmp	Worst
c201	**3**	**591.557**	0.0%	**591.557**	0.0%	**591.557**	**591.557**	0.0%	**591.557**	0.0%	**591.557**
c202	**3**	**591.557**	0.0%	614.04	3.8%	703.993	**591.557**	0.0%	**591.557**	0.0%	**591.557**
c203	**3**	**591.173**	0.0%	656.844	11.1%	753.137	**591.173**	0.0%	607.11	2.7%	670.834
c204	**3**	**590.599**	0.0%	619.72	4.9%	672.158	**590.599**	0.0%	**590.599**	0.0%	**590.599**
c205	**3**	**588.876**	0.0%	**588.876**	0.0%	**588.876**	**588.876**	0.0%	**588.876**	0.0%	**588.876**
c206	**3**	**588.493**	0.0%	607.99	3.2%	685.964	**588.493**	0.0%	**588.493**	0.0%	**588.493**
c207	**3**	**588.286**	0.0%	607.78	3.3%	685.758	**588.286**	0.0%	**588.286**	0.0%	**588.286**
c208	**3**	**588.324**	0.0%	**588.324**	0.0%	**588.324**	**588.324**	0.0%	**588.324**	0.0%	**588.324**
r201	**4**	1287.67	2.8%	1300.26	3.8%	1317.98	1254.72	0.2%	1271.48	1.5%	1284.68
r202	**3** 4	1237.04	3.8%	1261.89 2 1135.3 3	5.9%	 1166.0	1199.17	0.6%	1228.12	3.1%	1245.4
r203	**3**	967.822	2.7%	985.32	4.5%	1026.83	963.66	2.2%	972.94	3.2%	995.084
r204	**2** 3	*833.883*	−1.8%	860.03 3 793.73 2	1.2%	 798.701	*838.06*	−1.4%	857.11	0.9%	871.655
r205	**3**	1036.83	4.3%	1050.06	5.6%	1061.8	1008.55	1.4%	1041.31	4.7%	1070.27
r206	**3**	956.289	4.7%	981.85	7.5%	1018.26	927.724	1.6%	955.70	4.7%	977.019
r207	**2** 3	*901.091*	−1.5%	923.73 4 866.577 1	1.0%	 866.577	*893.328**	−2.3%	*908.51*	−0.6%	920.876
r208	**2**	737.369	1.5%	758.773	4.4%	773.315	**726.823**	0.0%	749.17	3.1%	773.681
r209	**3**	943.709	3.7%	955.90	5.1%	980.098	941.318	3.5%	955.30	5.0%	970.167
r210	**3**	967.996	3.0%	982.66	4.6%	1006.61	968.661	3.1%	975.75	3.9%	979.958
r211	**2** 3	913.752	0.4%	934.30 4 809.538 1	2.6%	 809.538	*908.062*	−0.2%	923.53	1.5%	943.14
rc201	**4**	1466.02	4.2%	1481.45	5.1%	1519.08	1426	1.4%	1438.44	2.2%	1459.07
rc202	**3** 4	1387.38	0.7%	1424.73 2 1238.38 3	3.5 %	 1301.23	1387.38	0.7%	1411.00 4 1162.8 1	2.5%	 1162.8
rc203	**3**	1097.31	3.4%	1109.04	4.6%	1125.8	1068.08	0.7%	1078.96	1.7%	1099.70
rc204	**3**	841.282	5.4%	850.46	6.4%	865.928	818.208	2.5%	833.82	4.4%	851.993
rc205	**4**	1322.64	1.6%	1353.91	4.0%	1395.88	1312.9	0.8%	1325.77	1.8%	1347.59
rc206	**3**	1187.28	2.9%	1217.93	5.5%	1239.49	1170.52	1.4%	1215.85	5.4%	1242.71
rc207	**3**	1093.75	2.9%	1111.6	4.7%	1130.36	1070.85	0.8%	1096.06	3.2%	1115.05
rc208	**3**	875.605	5.5%	900.61	8.5%	914.755	875.977	5.6%	900.85	8.6%	942.997

Table 5: Solomon Benchmarks Class 2: Robustness Results.

Data	RT	TBG	GTA 1800	S 3600	SA+LNS 1800	SA+LNS 3600	SA+LNS 5400	SA+LNS 7200	Best Possible
c1	**10** 540	**10** 2926	**10**	-	**10**	**10**	**10**	**10**	10
c2	**3** 1200	**3** 3275	**3**	-	**3**	**3**	**3**	**3**	3
r1	12.58 1300	12.33 13774	12.38	12.33	12.25	12.2	12.07	**12.03**	11.92
r2	3.09 4900	3.00 3372	3.00	-	2.85	2.76	2.75	**2.73**	2.73
rc1	12.38 2600	11.9 11264	11.92	11.95	11.8	11.7	11.65	**11.63**	11.5
rc2	3.62 1300	3.38 1933	3.33	-	3.3	3.35	3.33	**3.28**	3.25

Table 6: Solomon Benchmarks: Robustness of the Route Minimization.

starting temperature, .95 for cooling factor α, 2500 iterations per each temperature, .01 minimum temperature, 10 for the simulated annealing determinism factor β. For LNS, the parameters are 35 for the maximum customers to remove p, 1000 iterations w/o improvement before removing one more customers, 15 for the determinism factor β and 4 discrepancies. The allowed time is split $\frac{1}{3}$ for SA and $\frac{2}{3}$ for LNS. Bold-faced numbers indicate matches with the best published results. Italicized numbers indicate results better than the best published solutions. Italicized and starred numbers indicate results better than the best published solutions and equal to best results we found. Where different numbers of vehicles were discovered, the number of times each vehicle result is obtained is indicated next to the average results. There are a number of interesting observations to be drawn from these results.

Best Results The algorithm finds the best published result (or an improvement thereof) **in all 5 runs** in 15 problems (27%) after 30 minutes and in 18 problems (32%) after 120 minutes. Furthermore, the best published result (or an improvement thereof) is achieved at least once in 24 problems (43%) after 30 minutes and in 33 problems after 120 minutes (59%). In the 30 minutes runs, the algorithm improves the best published results in two cases with the standard configuration and it is almost always within 5% of the best published solutions. In the 120 minutes runs, the algorithm improves the best published results in six cases with the standard configuration and is always within 3.5% of the best published solutions except in one case (5.6%). In general, giving more time to the algorithm helps produce better solutions, although this is not always true (since simulated annealing gives extremely random starting solutions).

Average Results The average results are harder to compare systematically since all five runs do not always produce the best number of routes. However, it can be seen that they are never very far from the best solutions. For the 30 minutes runs, they are in general within 2% of the best solutions on class 1 and within 6% on class 2. For the 120 minutes runs, they are always within 2% and almost always within 1% on class 1 and almost always within 5% on class 2. It is also interesting to compare the average results in 120 minutes and the best results in 30 minutes. These results are in fact quite similar in quality, which is a good indication of the robustness of the algorithm.

Route Minimization Table 6 reports the average number of vehicles required over 5 runs and compares these results with other approaches where the papers gave averages across independent runs of their programs. The results are clustered by problem classes. The best results are in bold. CPU time is given in the column headers or underneath the results. Note, however, that comparing times is misleading as prior results were achieved on less powerful machines. The final column gives the best possible value for each class, i.e., the average number of vehicles for the class if the best published number of vehicles is achieved for each benchmark.

Observe that, after 30 minutes, our algorithm beats the average number of vehicles of any published results using this metric. On the non-trivial r2 class, our algorithm achieves the best possible value inferred from the published results. Once again, the results indicate the robustness of our algorithm.

Summary Overall, the algorithm appears to be very robust, performing well on all instances of the benchmarks. The algorithm is robust both with respect to route minimization and travel cost minimization on these benchmarks. This is one of the strengths of the algorithm, together with its ability to produce excellent solutions on all benchmarks.

6.4 Extended Solomon Benchmarks

Table 7 and 8 contain our best results for the extended solomon benchmark problems. To the best of our knowledge, there are no results to compare our algorithm to, except for some minimum number of vehicle results. Results are rounded to 6 significant digits. The only results we know on these problems are from [16] and concern only the number of vehicles. They are given in the column labeled IKP.

7 Discussion and Related Work

This paper presented a two stage hybrid local search algorithm for the vehicle routing problem with time windows. To our knowledge, reference [15] is the only other paper presenting a two stage algorithm for vehicle routing. Their algorithm is not hybrid however and uses the same evolutionary metaheuristic with two evaluation functions. Their evolutionary metaheuristic uses the uniform order-based crossover of [5] and their mutation operators are or-opt from [22] (generalized so that sequences of customers can be moved to other vehicles), λ-interchange [23], and 2-opt* from [25].

Data	Customers									
	200		400		600		800		1000	
	IKP		IKP		IKP		IKP		IKP	
c1-1		2704.57 20		7152.06 40		14095.6 60		25184.4 80		42479.0 100
c1-2		2917.89 18		7435.84 37		15266.1 56		25947.4 75		42920.7 92
c1-3		2719.62 18		7291.45 36		14414.5 56		25438.6 72		42571.6 90
c1-4		2651.98 18		7231.07 36		14454.2 56		25076.7 72		42678.1 90
c1-5		2702.05 20		7152.06 40		14085.7 60		25166.3 80		42469.2 100
c1-6		2701.04 20		7153.45 40		14089.7 60		25160.9 80		42471.3 100
c1-7		2701.04 20		7149.43 40		14085.7 60		25287.9 80		42486.8 100
c1-8		2781.09 19		7302.24 38		14346.8 58		25437.0 76		42564.8 96
c1-9		2716.42 18		7173.37 37		14180.6 56		25655.6 73		42428.0 92
c1-10		2670.63 18		7168.62 36		14552.2 56		25561.9 73		41984.0 91
r1-1	21	4785.96 20	41	10536.5 40	62	22393.8 59	81	39612.2 79	101	58169.5 100
r1-2	18	4102.03 18	36	9308.53 36	55	19319.6 55	72	34610.9 72	92	53167.5 92
r1-3	18	3473.53 18	36	8119.22 36	54	18812.8 54	72	31534.8 72	91	47668.2 92
r1-4		3096.91 18		7674.75 36		16854.8 54		29481.7 72		46203.0 92
r1-5		4173.93 18		9722.66 36		20550.9 55		36139.4 72		55531.4 92
r1-6		3634.81 18		8594.27 36		18798.0 55		32975.7 72		50778. 3 92
r1-7		3211,78 18		8026.80 36		21868.5 54		31009.1 72		48037.7 92
r1-8		3032.12 18		7517.22 36		16488.1 54		29268.8 72		45355.1 92
r1-9		3874.04 18		9078.99 36		19242.0 55		34824.7 72		54239.3 92
r1-10		3394.44 18		8554.75 36		18757.7 55		33921.8 72		52784.7 92
rc1-1		3748.24 18		8834.4 37		17682.0 56		32003.5 73		49658.9 91
rc1-2		3382.34 18		8294.59 36		16963.2 55		30421.1 73		48537.1 90
rc1-3		3066.08 18		7800.79 36		16008.7 55		29305.0 73		46760.4 90
rc1-4		2939.02 18		7711.69 36		15455.0 55		28035.1 73		44330.0 90
rc1-5		3489.6 18		8805.42 36		18021.0 55		31484.0 73		49398.2 91
rc1-6		3465.55 18		8705.25 36		17812.9 55		31579.5 73		51296.2 90
rc1-7		3292.33 18		8572.14 36		17444.3 55		30676.9 73		50995.0 90
rc1-8		3151.62 18		8369.29 36		17364.5 55		31081.1 73		48380.5 90
rc1-9		3181.94 18		8317.05 36		16815.9 55		30333.0 73		48717.4 90
rc1-10		3083.21 18		7899.18 36		16791.6 55		30082.3 73		48267.8 90

Table 7: Best Results on Extended Solomon Benchmarks (Class 1).

Data	Customers				
	200	400	600	800	1000
c2-1	1931.44 6	4136.57 12	7935.53 18	12215.2 25	18210.9 32
c2-2	1881.67 6	4101.33 12	8427.13 18	13578.1 24	19074.3 30
c2-3	1839.39 6	4239.28 12	8105.29 17	13180.0 24	19092.6 30
c2-4	1835.66 6	3955.63 12	8081.06 17	13497.4 23	18404.4 29
c2-5	1878.85 6	4120.15 12	8536.4 18	12547.8 25	18586.4 31
c2-6	1884.06 6	4031.08 12	8405.48 18	25858.7 25	18149.7 30
c2-7	1861.58 6	4388.98 12	8482.08 18	13345.3 25	18808.0 31
c2-8	1823.88 6	4277.57 12	8139.01 18	12547.6 24	18886.4 30
c2-9	1843.49 6	4282.59 12	8316.23 18	13054.2 25	18987.7 30
c2-10	1821.65 6	4010.86 12	8162.16 18	12714.0 24	17260.9 30
r2-1	4172.92 5	10086.0 8	21154.6 11	33051.1 15	50359.2 19
r2-2	3691.67 4	8130.93 8	17549.5 11	26930.0 15	42951.6 19
r2-3	3060.13 4	6759.18 8	14111.9 11	24460.6 15	33188.5 19
r2-4	2119.99 4	5325.8 8	10840.3 11	18234.6 15	24795.1 19
r2-5	3477.5 4	7711.95 8	16829.9 11	28309.2 15	44361.5 19
r2-6	3183.23 4	6871.34 8	15333.7 11	24694.7 15	36936.3 19
r2-7	2564.58 4	6072.80 8	12610.1 11	21413.3 15	31261.4 19
r2-8	2002.80 4	4937.13 8	9837.03 11	17518.4 15	25600.2 19
r2-9	3185.23 4	7123.09 8	15939.0 11	26785.3 15	40106.5 19
r2-10	2778.13 4	6579.24 8	14348.3 11	24149.1 15	37809.4 19
rc2-1	3149.88 6	6752.19 12	13886.4 16	21807.8 20	34133.8 23
rc2-2	2941.43 5	6270.38 10	12456.2 14	20022.5 19	29322.2 22
rc2-3	2697.49 4	5531.38 8	11561.1 12	17287.7 17	25199.2 19
rc2-4	2201.31 4	4680.07 8	9786.24 11	15973.7 15	23639.3 18
rc2-5	2796.98 5	6139.65 10	12257.7 14	20028.1 18	31171.8 20
rc2-6	2657.67 5	5947.63 9	12817.1 12	20329.3 16	31530.1 19
rc2-7	2650.75 4	5841.3 8	12046.5 12	19867.4 16	28461.6 19
rc2-8	2441.02 4	5237.78 8	12168.5 11	18105.2 15	30556.4 18
rc2-9	2337.28 4	5085.48 8	11685.6 11	18557.3 15	28879.5 18
rc2-10	2156.95 4	4831.14 8	11213.6 11	17429.4 15	27903.9 18

Table 8: Best Results on Extended Solomon Benchmarks (Class 2).

Their evaluation function to minimize routes is a lexicographic function with three components. Their second component is the size of the smallest route, while ours is the sum of the squares of the route sizes. Their third component is the minimal delay of the routing plan. Their motivation for using a two-stage algorithm is similar to ours: the recognition that minimizing travel costs may not always be most effective for minimizing the number of routes. *One of the contributions of this paper is to provide evidence of the benefits of a two-stage approach for vehicle routing with time windows. Indeed, the fundamentally different nature of these two two-stage algorithms, together with their effectiveness, seem to indicate that the two-stage approach has benefits across metaheuristics.*

The first stage of our algorithm uses a novel simulated annealing algorithm. The algorithm uses traditional moves operators described in [6, 18]: 2-exchange, Or-exchange, relocation, crossover, and exchange. A critical aspect of the simulated annealing is the lexicographic evaluation function. Its second component, maximizing the sum of the squares of route sizes, was inspired by some graph-coloring algorithms [17]. Its third component is the minimal delay of [15]. Our simulated annealing algorithm also includes some greedy components typical of tabu search [12], including an aspiration criterion and a bias towards good solutions in the random process. These greedy aspects were shown to be beneficial experimentally. Of course, simulated annealing was used for solving vehicle routing problems in the past. In particular, reference [1] describes a simulated annealing where the neighborhood is defined by the λ-interchange mechanism of [23] and the k-node interchange mechanism of [3]. The algorithm in [1] makes use of a tabu list within the simulated annealing process and uses a weighted objective function incorporating total time along with number of vehicles and travel cost. *Probably the main contribution here is the novel evaluation function and the additional evidence that minimal delay is a fundamental concept in minimizing the number routes.*

The second stage of our algorithm uses the LNS technique pioneered by [28]. In that paper, LNS was shown very effective on class 1 of the Solomon benchmarks. No results were given on class 2 because LNS could not reduce the number of routes satisfactorily [28] (page 426), since the class 2 benchmarks have a high number of customers per route. This fact was also confirmed by our own experimental results. Our implementation adds a restarting strategy, making our algorithm essentially similar to a variable neighborhood search [13]. It also adds a more precise lower bound based on minimal spanning k-trees. Both of these components were shown to have benefits experimentally, especially as far as robustness is concerned. But, of course, there is clearly much room left for improvements in implementations of LNS. *Probably the main contribution here is to show that LNS is particularly effective for minimizing travel cost across all Solomon benchmarks when given routing plans minimizing the number of routes.*

There are of course many other algorithms for vehicle routing. See, for instance, [11] for a good overview of techniques for solving vehicle routing problems using local search, [2] and [26] for tabu-search algorithms, [10] for an ant colony meta-Heuristic, [6] for guided local search on top of tabu Search, and [30] for the problem with soft time-windows.

8 Conclusion

This paper proposed a two-stage hybrid algorithm for multiple vehicle routing with capacity and time-window constraints. The algorithm first minimizes the number of vehicles using a simulated annealing algorithm. It then minimizes travel cost using a large neighborhood search which possibly relocates a large number of customers. Experimental results demonstrate the effectiveness of the algorithm which has improved 13 (23%) of the 58 best published solutions to the Solomon benchmarks, while matching or improving the best solutions in 47 benchmarks (84%). More important perhaps, the algorithm, with a fixed configuration of its parameters, is shown to be very robust, returning either the best published solutions (or improvements thereof) or solutions very close in quality on all Solomon benchmarks. Results on the extended Solomon benchmarks are also given. These results seem to indicate the benefits of using a two-stage approach, of using simulated annealing to minimize the number of routes, and of using LNS for minimizing travel costs.

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A Appendix

This appendix contains our improvements over the best published solutions at the time of writing (September 1st, 2001).

Data	Vehicle	Customers	Routes													Capacity	Distance
r108	1	12	28	12	80	76	3	79	78	34	29	24	68	77		169	106.0976
	2	11	31	88	10	62	11	64	63	90	32	30	70			154	118.5525
	3	13	6	96	59	93	99	5	84	17	45	83	60	18	89	165	84.9083
	4	10	52	7	48	82	8	46	47	36	49	19				155	119.9282
	5	11	2	57	15	43	42	87	97	95	94	13	58			160	84.6729
	6	10	50	33	81	51	9	35	71	65	66	20				153	121.7512
	7	12	92	98	91	44	14	38	86	16	61	85	100	37		200	106.0805
	8	11	73	72	75	56	23	67	39	55	25	54	26			186	112.2456
	9	10	27	69	1	53	40	21	4	74	22	41				116	106.6390
	9	100														1458	960.876

Data	Vehicle	Customers	Routes											Capacity	Distance
r110	1	11	92	98	44	16	86	38	14	37	100	91	93	168	112.0537
	2	10	21	72	75	56	23	67	39	25	55	4		172	107.7713
	3	11	28	76	12	29	81	79	3	50	77	68	80	188	106.9645
	4	9	88	62	19	47	36	49	64	32	70			144	127.5136
	5	10	2	41	22	74	73	40	53	26	54	24		108	117.8399
	6	9	52	7	82	18	8	46	48	60	89			106	103.7199
	7	10	83	45	17	84	5	6	94	96	97	13		138	88.8793
	8	11	27	69	30	51	9	71	35	34	78	33	1	130	106.919
	9	8	31	11	63	90	10	20	66	65				122	142.3861
	10	11	95	59	99	61	85	87	57	15	43	42	58	182	104.7907
	10	100												1458	1118.84

Data	Vehicle	Customers	Routes										Capacity	Distance
rc105	1	4	90	53	66	56							46	73.4507
	2	7	63	62	67	84	51	85	91				70	129.2931
	3	8	72	71	81	41	54	96	94	93			120	127.5447
	4	9	65	82	12	11	87	59	97	75	58		188	142.5070
	5	7	33	76	89	48	21	25	24				116	167.0530
	6	9	98	14	47	15	16	9	10	13	17		149	121.0211
	7	9	42	61	8	6	46	4	3	1	100		132	144.5349
	8	9	39	36	44	38	40	37	35	43	70		193	132.9280
	9	8	83	19	23	18	22	49	20	77			171	143.0536
	10	10	31	29	27	30	28	26	32	34	50	80	183	134.6232
	11	8	92	95	64	99	52	86	57	74			114	122.7596
	12	5	69	88	78	73	60						95	81.7005
	13	7	2	45	5	7	79	55	68				147	108.9662
	13	100											1724	1629.44

Data	Vehicle	Customers	Routes											Capacity	Distance
rc106	1	9	95	62	63	85	76	51	84	56	66			120	109.9733
	2	9	72	71	67	30	32	34	50	93	80			127	139.6437
	3	11	2	45	5	8	7	6	46	4	3	1	100	193	109.7512
	4	8	92	61	81	90	94	96	54	68				125	119.8648
	5	8	14	11	87	59	75	97	58	74				161	151.8380
	6	9	69	98	88	53	12	10	9	13	17			160	109.3652
	7	10	42	44	39	40	36	38	41	43	37	35		200	131.8505
	8	9	15	16	47	78	73	79	60	55	70			168	132.3484
	9	7	33	31	29	27	28	26	89					125	167.7646
	10	10	82	52	99	86	57	22	49	20	24	91		161	120.0993
	11	10	65	83	64	19	23	21	18	48	25	77		184	132.2345
	11	100												1724	1424.73

Data	Vehicle	Customers	Routes													Capacity	Distance
r203	1	31	27	94	92	42	57	15	43	14	44	38	86	16	85	484	275.2821
			99	96	6	84	8	82	48	47	49	19	63	90	32		
			10	70	31	7	52										
	2	40	89	18	60	83	45	46	36	64	11	62	69	88	30	556	368.2665
			1	76	3	79	78	9	51	20	66	71	35	68	12		
			26	13	95	59	93	5	17	61	91	100	98	37	97		
			58														
	3	29	50	33	81	65	34	29	24	39	67	23	72	73	21	418	297.8592
			40	53	87	2	41	22	75	56	74	4	55	25	54		
			80	77	28												
	3	100														1458	941.408

Data	Vehicle	Customers	Routes													Capacity	Distance
r204	1	48	6	94	96	92	97	42	43	15	57	41	22	75	56	712	348.8720
			23	67	39	12	76	79	9	51	50	28	53	26	54		
			55	4	72	74	73	2	13	95	59	93	85	98	37		
			100	91	16	61	5	60	83	18	89						
	2	52	27	52	7	88	31	10	30	70	1	69	62	11	19	746	476.6472
			46	45	17	86	44	38	14	99	87	84	8	82	48		
			47	36	49	64	63	90	32	20	66	65	71	35	34		
			78	81	33	3	77	68	80	29	24	25	21	40	58		
	2	100														1458	825.519

Data	Vehicle	Customers	Routes													Capacity	Distance
r207	1	55	95	92	42	91	61	45	46	36	64	11	62	7	88	724	418.6453
			69	1	30	51	9	78	79	3	76	28	53	40	2		
			87	57	41	22	73	21	72	74	75	56	4	25	55		
			54	80	68	77	12	26	58	13	97	37	100	98	93		
			59	96	94												
	2	45	27	50	33	81	65	34	29	24	39	67	23	15	43	734	474.6823
			14	44	38	86	16	85	99	6	5	84	8	82	48		
			47	49	19	10	63	90	32	66	71	35	20	70	31		
			52	18	83	17	60	89									
	2	100														1458	893.328

Data	Vehicle	Customers	Routes													Capacity	Distance
r209	1	31	28	76	12	29	39	67	23	75	72	73	21	40	53	433	304.1939
			18	7	62	64	49	36	46	8	45	17	84	96	37		
			100	91	97	13	58										
	2	38	52	83	5	59	98	92	95	2	42	14	44	38	86	557	316.3450
			16	61	85	93	99	6	94	87	57	15	43	41	22		
			74	56	4	26	54	55	25	24	80	68	77	1			
	3	31	27	69	31	88	82	47	19	11	63	90	70	30	71	468	288.6244
			9	51	81	33	50	3	79	78	34	35	65	66	20		
			32	10	48	60	89										
	3	100														1458	909.163

Data	Vehicle	Customers	Routes													Capacity	Distance
r211	1	48	28	27	52	69	31	30	63	64	11	19	62	88	7	709	433.4937
			82	18	83	84	5	99	85	61	16	44	14	38	86		
			17	45	8	46	48	47	36	49	90	32	10	70	1		
			50	77	68	24	55	25	4	56	74						
	2	52	95	59	92	98	42	15	2	21	73	72	39	67	23	749	459.2191
			75	22	41	57	87	94	6	53	40	12	76	29	79		
			33	81	9	71	65	66	20	51	35	34	78	3	80		
			54	26	58	13	97	96	37	43	100	91	93	60	89		
	2	100														1458	892.713

Data	Vehicle	Customers	Routes													Capacity	Distance
rc205	1	29	2	45	5	42	39	36	72	71	62	94	61	44	40	455	400.1436
			38	41	81	90	53	98	55	68	43	35	37	54	96		
			93	91	80												
	2	22	92	95	33	28	27	29	31	30	63	76	85	67	84	310	292.3013
			51	49	22	20	24	74	13	17	60						
	3	28	65	83	64	19	23	21	18	57	86	52	99	9	87	566	418.4251
			59	75	97	10	66	56	50	34	32	26	89	48	25		
			77	58													
	4	21	69	82	11	15	16	47	14	12	88	78	73	79	7	393	186.7777
			6	8	46	4	3	1	70	100							
	4	100														1724	1297.65

Data	Vehicle	Customers	Routes													Capacity	Distance
rc206	1	32	65	83	52	82	12	14	47	16	15	11	59	75	23	621	335.3131
			21	18	19	49	22	57	99	86	87	97	9	10	13		
			17	60	55	100	70	68									
	2	35	72	92	95	62	31	29	27	28	30	33	63	85	76	511	476.6132
			51	64	84	67	71	94	81	90	66	56	50	34	32		
			26	89	20	24	48	25	77	58	74						
	3	33	69	98	2	45	5	44	42	39	38	36	40	41	61	592	334.3909
			88	53	78	73	79	7	6	8	46	4	3	1	43		
			35	37	54	96	93	91	80								
	3	100														1724	1146.32

Data	Vehicle	Customers	Routes													Capacity	Distance
rc207	1	38	65	83	64	95	67	31	29	28	30	33	63	76	51	667	408.5984
			19	21	18	23	75	59	87	74	86	57	22	20	49		
			25	77	58	97	13	10	17	60	55	100	70	68			
	2	27	82	99	52	9	11	15	16	47	14	12	53	78	73	480	232.7173
			79	7	6	8	46	4	45	3	1	43	36	35	37		
			54														
	3	35	69	98	88	2	5	42	44	40	38	39	41	72	71	577	419.8289
			93	81	61	90	56	84	85	94	96	92	62	50	34		
			27	26	32	89	48	24	66	91	80						
	3	100														1724	1061.14

Data	Vehicle	Customers	Routes													Capacity	Distance
rc208	1	34	65	83	64	95	92	71	72	38	39	44	42	61	81	519	309.4247
			94	67	62	50	34	31	29	27	26	28	30	32	33		
			76	89	63	85	51	84	56	66							
	2	33	69	98	88	53	12	11	15	16	47	78	73	79	7	633	243.3111
			6	2	8	46	4	45	5	3	1	43	40	36	35		
			37	41	54	96	93	91	80								
	3	33	90	82	99	52	57	23	21	18	19	49	22	24	20	572	275.4057
			48	25	77	58	75	97	59	87	74	86	9	13	10		
			14	17	60	55	100	70	68								
	3	100														1724	828.141