

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/223369558>

The pickup and delivery problem with time windows

Article in *European Journal of Operational Research* · September 1991

DOI: 10.1016/0377-2217(91)90319-Q

CITATIONS

410

READS

486

3 authors, including:



Jacques Desrosiers

HEC Montréal - École des Hautes Études com...

127 PUBLICATIONS 8,734 CITATIONS

SEE PROFILE



François Soumis

Polytechnique Montréal

155 PUBLICATIONS 6,582 CITATIONS

SEE PROFILE

Some of the authors of this publication are also working on these related projects:



Optimization of aircraft trajectories [View project](#)



Treatment of Degeneracy in Optimization [View project](#)

A Grouping Genetic Algorithm
for the Pickup and Delivery Problem
with Time Windows

Giselher Pankratz

Diskussionsbeitrag Nr. 337
Mai 2003

Diskussionsbeiträge des Fachbereichs Wirtschaftswissenschaft
der FernUniversität in Hagen

Herausgegeben vom Dekan des Fachbereichs

A Grouping Genetic Algorithm for the Pickup and Delivery Problem with Time Windows

Giselher Pankratz

Abstract:

The Pickup and Delivery Problem with Time Windows (PDPTW) is a generalization of the well studied Vehicle Routing Problem with Time Windows (VRPTW). Since it models several typical planning situations in operational transportation logistics and public transit, the PDPTW has attracted growing interest in recent years. This paper proposes a Grouping Genetic Algorithm for solving the PDPTW which features a group-oriented genetic encoding in which each gene represents a group of requests instead of a single request. The GGA is subject to a comparative test on the basis of two publicly available benchmark problem sets that comprise 9 and 56 PDPTW instances, respectively. The results show that the GGA is able to consistently find high quality solutions.

Fachbereich Wirtschaftswissenschaft, FernUniversität in Hagen
Profilstr. 8, D-58084 Hagen, BRD

Tel.: 02331/987-4432

Fax: 02331/987-4447

E-Mail: giselher.pankratz@fernuni-hagen.de

A Grouping Genetic Algorithm for the Pickup and Delivery Problem with Time Windows

Giselher Pankratz

1 Introduction

The Pickup and Delivery Problem with Time Windows (PDPTW) can be described as follows (Savelsbergh and Sol, 1995): A set of transportation requests that is known in advance has to be satisfied by a given fleet of vehicles. Each request is characterized by its pickup location (origin), its delivery location (destination) and the size of the load that has to be transported from the origin to the destination. For each pickup and delivery location, a time window and loading and unloading times are specified. The load capacity, the maximum length of its operating interval, a start location and an end location are given for each vehicle. In order to fulfill the requests, a set of routes has to be planned such that each request is transported from its origin to its destination by exactly one vehicle. Basically, the PDPTW differs from the VRPTW by the additional precedence constraints, i.e. the restriction that the origin of each request has to be visited before the corresponding destination.

In accordance with definitions of the PDPTW usually found in the literature and in order to make the proposed approach comparable to other recently published approaches, it is assumed that the number of vehicles is unlimited and all vehicles have the same capacity and the same home location where all routes start and end. A reasonable objective function may use optimization criteria such as, number of vehicles employed, total distance traveled, total schedule duration or combinations of these.

Formulations of the PDPTW as an integer program have been presented by, e.g., Dumas et al. (1991) and Savelsbergh and Sol (1995). Because this contribution concentrates on solution approaches, a review of formal models for the PDPTW is omitted here. Since the PDPTW is a generalization of the Vehicle Routing Problem with Time Windows (VRPTW), it is at least as complex as the latter, which has been proven by Lenstra and Rinnoy Kan (1981) to be NP-hard.

The PDPTW models a variety of operational planning problems in transportation logistics. Applications range from local area courier services to less-than-truckload transportation and long-distance haulage. In addition, the PDPTW also matches typical situations in public transit. For example, the Dial-a-Ride Problem with Time Windows (DARPTW) is a PDPTW in which people instead of goods are to be transported. While in the past research mainly concentrated on the VRPTW, increasing interest in the PDPTW can be observed in recent years. Nevertheless there is still relatively little attention paid to the PDPTW in the literature.

The paper is organized as follows. Section 2 gives a review of previous work on the PDPTW and similar problems. In Section 3 the proposed solution approach, a Grouping Ge-

netic Algorithm (GGA), is described in detail. Section 4 reports computational results obtained by the GGA for two publicly available benchmark data sets. Finally, the main findings are summarized in section 5.

2 Literature Review

In this section, an overview of important previous approaches for solving the PDPTW is given. Compared to the comprehensive review of models and approaches of Savelsbergh and Sol (1995), a rather brief survey is presented here, taking into account some more recent developments. The methods can be divided into optimal approaches, problem specific heuristics and metaheuristics.

2.1 Optimal approaches

The first optimization algorithms for the PDPTW were restricted to the single vehicle case, which is considerably easier to solve than the regular PDPTW with multiple vehicles. Important approaches of this kind are the dynamic programming algorithms by Psaraftis (1980, 1983a) and Desrosiers et al. (1986). In the 1990s, the first exact approaches for the multi-vehicle PDPTW were published. Based on a formulation as a set partitioning problem, Dumas et al. (1991) proposed a branch-and-price algorithm for the multiple-vehicle PDPTW. Feasible routes are found by solving a constrained shortest path problem. As the authors point out, the algorithm is appropriate for instances in which each request occupies a relatively large percentage of vehicle capacity. By means of this algorithm, they were able to optimally solve two practical problems with 19 and 30 requests respectively, which at 40 per cent, represent full truck loads. Savelsbergh and Sol (1998) also developed a branch-and-price algorithm for the multiple-vehicle PDPTW. In this algorithm, several sophisticated techniques, such as embedded heuristics and a special column management scheme, are employed in order to speed up search. Optimal solutions to several test cases with 30 requests each are reported. Since Savelsbergh and Sol observe significant differences in solution times, even for instances in the same problem class, they classify their optimization algorithm as unsuitable for practical planning situations.

2.2 Problem specific approximation methods

Due to the complexity of the PDPTW, several heuristic algorithms for the PDPTW have been published. Some of them construct solutions following a “cluster first, route second” approach. For example, Bodin and Sexton (1986) propose an iterative procedure, which, in each iteration, first (re)assigns requests to vehicles and then solves a single-vehicle PDPTW for each vehicle. A more fine-grained approach is presented by Desrosiers et al. (1988) who introduce the notion

of a mini-cluster, i.e. a feasible route segment that serves one or more requests starting and ending with an empty vehicle. Each mini-cluster is treated as a single full truck load. After a large number of mini-clusters has been generated heuristically, a set partitioning problem is solved. Ioachim et al. (1995) pick up the idea of mini-clusters and present a method that employs an exact algorithm to produce an optimal set of mini-clusters.

Since insertion heuristics have proven successful for the VRPTW (Solomon, 1987), it appears reasonable to apply similar principles to the PDPTW as well. A frequently cited insertion procedure for the DARPTW, which can be easily adapted to the PDPTW, is presented by Jaw et al. (1986). Madsen et al. (1995) develop an insertion algorithm for the DARPTW which is a generalized and improved version of the heuristic of Jaw et al.

In order to improve the quality of solutions obtained by a construction heuristic, Van der Bruggen et al. (1993) propose a local improvement procedure for the single-vehicle PDPTW based on arc exchanges following the variable-depth search procedure of Lin and Kernighan (1973) for the Traveling Salesman Problem (TSP). Similar arc exchange operators for routing problems with precedence constraints are described by Psaraftis (1983b). In contrast to these arc-centered approaches, Toth and Vigo (1996) choose a request-oriented improvement method. They distinguish between intra-route movements that only affect the relative order of the locations in a route and inter-route movements that shift requests between routes.

2.3 Metaheuristics

Problem specific heuristics hold the danger of the search being trapped in a local optimum. Metaheuristics have become widely accepted as an appropriate means of avoiding this undesirable behavior. Compared to the VRPTW for which a considerably large number of metaheuristic approaches is reported in the literature, until now only a few metaheuristics have been reported for the PDPTW. Most of them are adaptations of the tabu search algorithm.

In the tabu search heuristic of Gendreau et al. (1998) the neighborhood definition is based on the concept of ejection chains. In an ejection chain, a request is eliminated from one route and inserted into another route, which in turn causes a request from that route to be shifted to a third route, and so on. As a diversification strategy, the authors make use of a so-called adaptive memory, which contains a number of the best solutions found thus far. After the search has terminated, a new solution is constructed from the routes in the memory, serving as a new starting solution.

Based on the definition of three distinct moves, Nanry and Barnes (2000) propose a reactive tabu search for the PDPTW in which the search progress is continuously analyzed and search parameters such as the length of the tabu list are adjusted accordingly during search. Additionally, a special procedure is employed in order to detect and escape from chaotic attractor basins in the search space. In order to evaluate their approach, the authors use problem instances that were derived from Solomon test cases for the VRPTW (Solomon, 1987) for which

optimal solutions are known. During problem transformation, for each PDPTW instance, the feasibility of its corresponding optimal VRPTW solution was maintained. Thus, the results can be directly compared to the optimal VRPTW solutions. It should be noted that Nanry and Barnes were the first to make their PDPTW benchmark problems publicly available.

Yet another tabu search is presented by Lau and Liang (2001). A special construction algorithm, called a “partitioned insertion heuristic”, is used in order to build starting solutions. The neighborhood definitions in this approach are adapted from Nanry and Barnes (2000). Instead of moving or exchanging single requests, they allow the exchange of so-called clusters, which are very similar to the notion of mini-clusters introduced by Desrosiers et al. (1988). The approach is tested on the nine 100-node instances provided by Nanry and Barnes (2000). Furthermore, the authors give a detailed description of a transformation scheme by which they generate additional PDPTW instances based on a selection of another 27 Solomon VRPTW instances. The results for these instances are compared to the best, near-optimal VRPTW solutions that have been published.

Li and Lim (2001) developed a hybrid metaheuristic called tabu-embedded simulated annealing. Three different request swapping moves are used to define local search neighborhood structures. Basically, a simulated annealing procedure is performed, and is restarted from the current best solution every time a given number of iterations without improvement has been observed. In addition, a tabu list keeps track of the recently visited solutions in order to avoid cycling. The approach is evaluated using the nine 100-node test cases of Nanry and Barnes. Additionally, Li and Lim report results on 56 own problem instances generated on the basis of the full set of all 56 Solomon VRPTW instances with 100 customers and the respective best solutions from the literature.

Despite the success of Genetic Algorithms for the VRPTW (see e.g. Blanton and Wainwright, 1993; Thangiah, 1995; Potvin and Bengio, 1996; Berger et al., 1998), until now only few applications of Genetic Algorithms have been reported for varieties of the PDPTW.

A Genetic Algorithm for the Dial-a-ride Problem (DARP) is presented by Potter and Bosmaier (1995). Since the DARP does not comprise time windows, it is a simplified special case of the PDPTW. In this approach, the grouping and the routing part of the problem are solved separately: On the upper level, a Genetic Algorithm is responsible for assigning transportation requests to vehicles, whereas on the lower level a second Genetic Algorithm for each vehicle determines a route covering the requests assigned to this vehicle.

Jih and Hsu (1999) have developed a hybrid Genetic Algorithm for solving the single-vehicle PDPTW. The initial population contains a set of routes generated by a dynamic programming algorithm which is aborted prior to completion.

Schönberger et al. (2003) propose a Genetic Algorithm for solving the so-called Pickup and Delivery Selection Problem which extends the PDPTW by the decision of acceptance or rejection of transportation requests. The goal is to maximize overall profit. To this end, a reve-

nue value is assigned to each request, so this problem significantly differs from the PDPTW considered in this contribution.

To our knowledge, up to now only Jung and Haghani (2000) have reported a Genetic Algorithm for solving the multi-vehicle PDPTW. In contrast to the PDPTW treated by this paper, the authors consider so-called soft time windows, i.e. the violation of time window constraints leads to penalty cost but does not compromise feasibility of a solution.

3 A Grouping Genetic Algorithm for solving the PDPTW

As shown by the literature review, only a few approaches exist which apply Genetic Algorithms to variants of the PDPTW, most of them treating simplified special cases of the PDPTW. Probably the major reason why Genetic Algorithms for solving the PDPTW are rare is the fact that it is very difficult to find an appropriate genetic representation for this complex problem.

Thus, it is an interesting task to verify the appropriateness of Genetic Algorithms for this problem class. In particular, Genetic Algorithms appear attractive because of their population-based approach, which allows the parallel exploration of different paths through the solution space of a problem. In addition, Genetic Algorithms are considered to be robust and easy to implement (Rayward-Smith, 1994).

In this section, a Genetic Algorithm for solving the PDPTW is proposed. Because it employs an adaptation of the group-oriented genetic encoding introduced by Falkenauer (1998), it is denoted as a Grouping Genetic Algorithm (GGA). This section gives a top-down description of the proposed GGA: First, the basic search scheme of the GGA is outlined. Second, the group-oriented genetic encoding for PDPTW solutions is explained. Third, the genetic operators are described in detail. Finally, a rough characterization of the embedded insertion algorithm that is used at several stages of the search is given.

3.1 Genetic search scheme

The concept of Genetic Algorithms was first introduced by Holland (1975). Systematic treatments of Genetic Algorithms as a class of optimization algorithms can be found in Goldberg (1989) and Davis (1991). Figure 1 describes the general search scheme of the proposed GGA.


```

initialize population  $P$  and evaluate all individuals in  $P$ ;
while not (termination criterion is met)
    select a pair of individuals  $x, y$  from  $P$  as parents;
    generate two children  $x', y'$  applying the crossover operator to  $x$  and  $y$  with
    probability  $p^{cross}$ ;
    generate two modified children  $x'', y''$  applying the mutation operator to  $x'$  and  $y'$ ,
    respectively, with probability  $p^{mut}$ ;
    evaluate  $x''$  and  $y''$ , insert them into  $P$  and in turn remove the two worst individuals
    from  $P$ ;
return best individual from  $P$  as solution.

```

Figure 1: General search scheme of the proposed GGA.

An initial population is generated using the embedded insertion heuristic described below. The population size, n^{pop} , is a parameter of the GGA. Unlike the classical GA, which employs generational replacement, the population management is done following the steady-state approach without duplicates (Syswerda, 1989; Whitley, 1989). According to this approach, each newly generated pair of offspring is inserted immediately into the current population where it replaces the two worst individuals. This incremental approach ensures the survival of the best solution over the whole search and prevents the occurrence of duplicate individuals. Thus, it often reveals higher performance than generational replacement (Davis, 1991). In order to detect duplicates, a simple comparison of objective values proved satisfactory for the proposed GGA, so it was preferred over any other time consuming procedure seeking genotypical or phenotypical differences between individuals. Note that crossover and mutation are employed in a sequential fashion. The crossover operator is applied to each selected pair of parent chromosomes with probability p^{cross} , whereas the mutation operator is applied to each offspring with probability p^{mut} . Both p^{cross} and p^{mut} are parameters of the GGA. If the crossover operator is not applied according to its execution probability p^{cross} , the children are simply clones of their parents. Similarly, if the mutation operator is not applied, the offspring leave the mutation operator unchanged. The search terminates after a given total number, \tilde{n}^{max} , of individuals has been generated without improvement but no later than after a given maximum number, n^{max} , of generated individuals has been reached.

The adaptation of the described genetic search scheme to the problem at hand involves the following components of the algorithm:

- The genetic encoding, i.e. the way solutions to the PDPTW are represented by chromosomes (strings);
- the genetic operators, i.e. selection, crossover and mutation;

- the embedded heuristic, i.e. the subordinate heuristic procedure that is employed by the GGA in order to generate an initial population and to produce feasible offspring.

The design decisions concerning these components are dealt with in the following sections.

3.2 Group-oriented genetic encoding for the PDPTW

The way in which solutions to the problem at hand are encoded is crucial for the success of any Genetic Algorithm. One difficulty of finding a good genetic encoding for solutions to the PDPTW is the fact that the PDPTW – like the VRPTW – is a combination of two interdependent subproblems: On the one hand, the subproblem of clustering requests and assigning them to a vehicle has to be solved (clustering or grouping problem). On the other hand, for each cluster of requests, a feasible route has to be specified in which the corresponding pickup and delivery nodes are visited (ordering or routing problem). It is not obvious how these two aspects of a solution can be represented simultaneously by a homogeneous encoding such as the standard binary representation of the classic Genetic Algorithm.

For pure routing problems like the TSP sometimes a representation is chosen which encodes the sequence in which the nodes are visited as a permutation of all locations. A number of specialized crossover operators that preserve the permutation property of the offspring have been developed. However, such an encoding brings about some troubles when being applied to highly constrained multi-vehicle routing problems like the PDPTW:

- Because only the routing part of the PDPTW can be represented by such an encoding, the grouping part must be covered otherwise, e.g. by external heuristics.
- Due to capacity, precedence and time window constraints a large portion of all possible permutations will turn out to be infeasible solutions. Thus, special mechanisms have to be implemented in order to maintain feasibility of the generated solutions.

Among the Genetic Algorithms mentioned in the literature review, Potter and Bossomaier (1995), Jih and Hsu (1999) as well as Schönberger et al. (2003) use such a permutation-based encoding.

Jung and Haghani (2000) used a so-called random key representation in order to simultaneously encode both the routing and the grouping part of the PDPTW. Under this encoding, a random four-digit key number is assigned to each location. The first digit denotes the index of the vehicle visiting that location whereas the last three digits represent a sort key to determine the position of that location within the route. A solution is decoded by sorting all locations in ascending order of their key numbers. When generating the chromosome, it is assured that the value of the pickup location is always less than the value of the corresponding delivery location. In addition, the pickup and delivery nodes for the same request always have the same

number in the first digit. Though, many of the individuals generated are infeasible with regard to capacity and time restrictions and therefore have to be discarded.

Alternatively, a representation could be chosen which encodes a solution as a permutation of all requests. At the phenotype level, a chromosome of this kind can be decoded by a heuristic which constructs a solution considering the requests in the order given by the permutation. In the GA literature this rather indirect encoding is quite popular. Applications to the VRP and the VRPTW are reported for example by Kopfer et al. (1994) and Blanton and Wainwright (1993), respectively. To our knowledge, this order-based representation has not yet been applied to the PDPTW.

Nevertheless, the order-based representation with a heuristic decoder has some important drawbacks, especially for problems with a strong grouping component (see Falkenauer, 1998):

- Identical solutions are often represented by a large number of different permutations. This redundancy obviously weakens the efficiency of the genetic search.
- The phenotypical meaning of a gene strongly depends on its genotypical context, e.g. the genes that precede it in the permutation. Most order-based crossover operators are context-insensitive and do not take into account such contextual information during recombination. Thus, in many cases, even small modifications in a chromosome, e.g. by a crossover operator, will cause the offspring to have almost no phenotypical similarities to its parents. As a consequence, it is hard for the GA to sample meaningful building blocks.
- Due to the strong context-dependency of the genes, good schemata are long, which in turn increases the probability of them being destroyed by a syntactic crossover operator. This severely obstructs the search progress of the GA.

There is evidence that the disadvantages of an order-based encoding mentioned above will also apply to the PDPTW. Furthermore, the grouping part of the PDPTW obviously is of great importance for the overall quality of a solution to the PDPTW (Savelsbergh and Sol, 1998). In particular, because both the time windows and the precedence constraints considerably restrict the number of routing alternatives for a given allocation of requests, the grouping aspect turns out to be dominant over the routing aspect in many cases.

Because of this dominance of the grouping part of the PDPTW, and in order to avoid the drawbacks of an order-based encoding, a representation of solutions to the PDPTW is proposed which refers to the encoding principles of the so-called Grouping Genetic Algorithm (GGA) introduced by Falkenauer (1998). In this representation, each gene represents a group of objects instead of a single object. Thus, the groups are the building blocks that are sampled and recombined by the genetic operators to produce solutions of potentially higher quality. Falkenauer originally developed his GGA for pure grouping problems such as the Bin Packing Problem (BPP). The following describes how the original encoding was adapted to the PDPTW.

Each gene in a chromosome represents a cluster of all requests that are assigned to a single vehicle. The length of a chromosome, i.e. the number of genes is variable and depends on the number of vehicles required by a given solution. Figure 2 illustrates the encoding of a solution by means of a simple example with seven requests that are carried out by three vehicles.

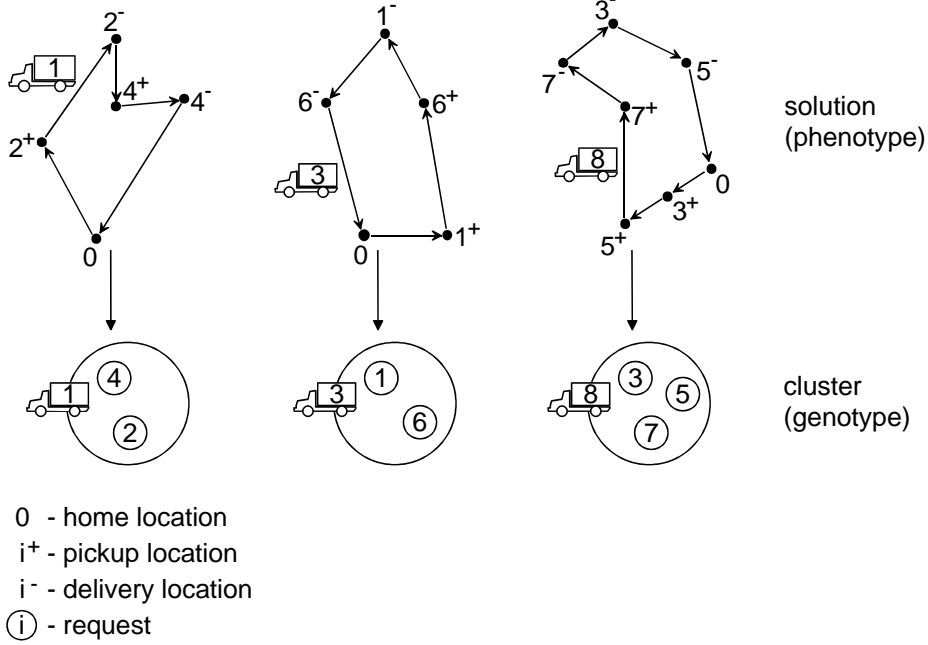


Figure 2: Group-oriented encoding (example).

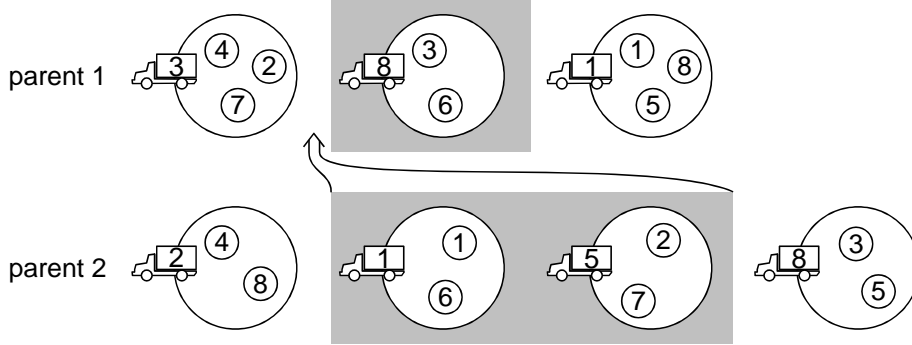
By representing a partitioning of all transportation requests, a chromosome under this encoding only covers the grouping aspect of a PDPTW solution. As a consequence, the remaining routing aspect of a solution has to be added while decoding the chromosome. This is done by associating each chromosome with separate data structures containing the routing information for each gene. Since this information is hidden from the GGA, it cannot be manipulated directly by the genetic operators. Instead, the routes are constructed and maintained using a separate heuristic according to the grouping information encoded in the chromosome.

3.3 Genetic operators

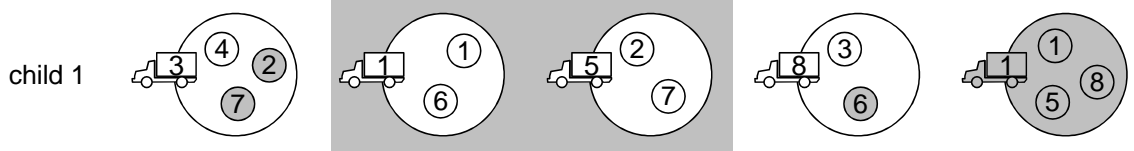
In the proposed GGA, the binary tournament selection mechanism (see e.g. Goldberg et al., 1990) is applied as the selection operator. In this scheme, two individuals are chosen randomly and the one which represents the better solution is selected as the first parent. To obtain the second parent, the procedure is repeated. An important advantage of tournament selection is its low time complexity compared to the classical “roulette wheel” selection scheme. Furthermore, because a simple comparison of the objective values is sufficient, tournament selection does not require the calculation of special fitness values.

The crossover operator for the proposed GGA is an adaptation of the general group-oriented crossover scheme presented in Falkenauer (1998) and proceeds in five steps, as illustrated in Figure 3.

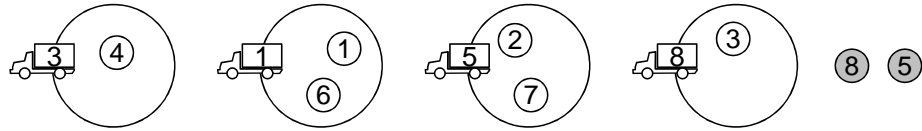
1. Specify crossing sections



2. Insert groups



3. Clean up chromosome



4. Re-insert unassigned requests

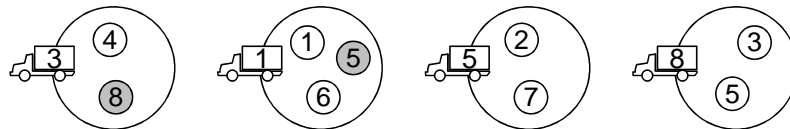


Figure 3: The group-oriented crossover operator.

1. Specify a crossing section, i.e. a coherent segment of clusters, by randomly selecting two crossing points in each of the two parent chromosomes.
2. Insert the clusters in the crossing section of the second parent at the first crossing point in the chromosome of the first parent. The respective routes are directly adopted from the second parent without reconstruction. As a result of this operation a number of requests may occur twice (requests 1, 2, 6 and 7 in Figure 3). Moreover, two clusters may be assigned to the same vehicle (vehicle 1 in Figure 3).

3. To resolve the conflicts mentioned above, remove all clusters originally belonging to the first parent if they refer to a vehicle that is already allocated by any of the newly inserted clusters. If afterwards some requests still occur twice, eliminate them from those clusters that originally belong to the first parent. At the phenotype level, all eliminations are reproduced immediately in the routes appendant to the changed clusters. Note that the clusters and the respective routes imported from the second parent are left unchanged. After this step, some requests may remain unassigned (requests 5 and 8 in Figure 3).
4. Reinsert the unassigned requests in random order into the individual applying the insertion heuristic. This may require the allocation of an additional vehicle in order to assure feasibility. As a result of this step, a complete offspring is obtained.
5. Generate the second offspring by repeating steps 2 through 4 with reversed roles of the parents.

The group-oriented mutation operator for the PDPTW works as follows:

1. Select a cluster at random in the individual.
2. Eliminate this cluster from the chromosome and remove the associated route from the phenotype.
3. Re-insert all removed requests into the individual by means of the insertion heuristic, allocating a new vehicle if necessary to maintain feasibility.

3.4 Embedded insertion heuristic

At several stages during search, the GGA employs a subordinate insertion heuristic while constructing and modifying solutions. The general procedure of this heuristic can be described as follows: For each request to be inserted, all feasible insertions in all existing routes of the current (partial) solution are examined. To this end, all possible insertion positions for the pickup and the delivery node in a route are tested taking into consideration precedence, capacity and time constraints. Additionally, a new vehicle is allocated and a new route for this vehicle is tentatively initialized with the current request. Among all feasible insertions, the one that causes minimal additional cost is selected and implemented.

In order to generate an initial solution by means of this procedure, all transportation requests are considered in random order, starting with a single, empty vehicle. After all transportation requests have been inserted, a feasible initial solution is available. The procedure is repeated until an initial population of the desired size is obtained.

In order to re-adjust the routing part of a solution due to grouping modifications caused by the genetic operators, the insertion procedure is also used. Instead of constructing a new solution from scratch every time the grouping is modified by crossover or mutation, each request that is subject to regrouping is deleted from its original route and reinserted without dis-

turbing the relative order in which the remaining nodes are visited. Thus, the original routing decisions in the unchanged parts of a solution are preserved.

4 Computational Study

This section reports the results of the proposed GGA for a number of benchmark problems when compared to previous metaheuristics for the PDPTW. First, the benchmark data sets are described, then the numerical results are discussed.

4.1 Benchmark Data Sets

It seems that up to now only two benchmark data sets for the PDPTW for which results have been published in the literature are publicly available:

1. The nine 100-node-instances provided by Nanry and Barnes (2000), in the remainder referred to as problem set 1. These instances are available via ftp from www.me.utexas.edu/pub/barnes. Results for these instances are also reported by Li and Lim (2001) and Lau and Liang (2001).
2. The 56 100-node-instances provided by Li and Lim (2001), in the remainder referred to as problem set 2. Problem set 2 can be downloaded from www.comp.nus.edu.sg/~lihb/Pdptw.html.

In these problem sets, each PDPTW instance was derived from a certain instance out of Solomon's 100-customer VRPTW problems by pairing up customers within the routes of a given reference solution. Supplementary dummy nodes were introduced for coupling purposes if an odd number of customers is present in a route of the original solution. So each instance has at least 100 nodes, which is equivalent to at least 50 requests. As Li and Lim (2001), as well as Lau and Liang (2001) point out, it seems that Nanry and Barnes paired customers directly adjacent to each other in the reference solution while generating most of their problem instances. In contrast to this, Li and Lim used a random approach.

Nanry and Barnes restricted themselves to Solomon instances for which optimal solutions are known. They only generated instances from Solomon's C1 class. In all problems of this class, the customers are spatially clustered and the problems have a short scheduling horizon. For example, the instance denoted as nc101 is derived from Solomon's VRPTW instance c101. For consistency reasons, minor adjustments were necessary to some of the instances of Nanry and Barnes (2001) because, for some requests, the pickup and delivery quantities were not equal.

In order to generate PDPTW test problems from all Solomon instances, Li and Lim refer to near-optimal solutions in cases where the optimal solution is unknown. Following the classification of Solomon, they organized their instances into six classes, denoted as LC1, LC2, LR1,

LR2 LRC1 and LRC2, indicating the respective spatial distribution of the nodes and the length of the scheduling horizon. In LC1 and LC2 problems, nodes are clustered, whereas in LR1 and LR2 problems, they are randomly distributed. The nodes in LRC1 and LRC2 instances are partially clustered and partially randomly distributed. While the instances in LC1, LR1 and LRC1 have a short scheduling horizon, the horizon is longer in instances of classes LC2, LR2 and LRC2.

4.2 Numerical Results

The GGA was implemented in JAVA and evaluated using problem set 1 and problem set 2. All tests were carried out on a PC (Pentium 4 processor, 2 GHz). The GGA was run 30 times on each instance under the objective of minimizing total travel distance. Euclidean distances and travel times were calculated to two decimal places as is standard practice in the recent VRPTW literature. The parameter settings for the GGA, which were determined in a small number of preliminary experiments, are shown in table 1. The values were chosen mainly with the idea of performing a thorough search but also to keep computation times reasonable.

Table 1: GGA parameter values

Parameter	value	description
n^{pop}	200	population size
p^{cross}	1.0	crossover probability
p^{mut}	0.5	mutation probability
n^{max}	15,000	max. number of individuals
\tilde{n}^{max}	3,000	max. number of individuals without improvement

In the remainder, the results obtained by the GGA on problem set 1 will be compared to the results reported by Nanry and Barnes (2000), Li and Lim (2001) and Lau and Liang (2001). Since no other results are published for problem set 2, the GGA results for these instances are compared to the results of Li and Lim (2001) only. However, it is difficult to directly compare the results of the different approaches.

One important problem is that the approaches apply slightly different objective criteria. Nanry and Barnes (2000) conducted their experiments under the objective of minimizing the sum of total travel time and total service time. Since vehicle speed is set to 1 and total service time is a constant if all nodes are visited, this objective is basically equivalent to minimizing total travel distance, which was chosen as the objective for the GGA. In contrast, Li and Lim (2001) used a weighted sum of the number of vehicles, total travel distance, schedule duration and total waiting time as the objective function. Similarly, the objective function considered by

Lau and Liang (2001) is a weighted sum of the number of vehicles and total travel distance. Furthermore, the approaches differ in the way euclidean distances are calculated. Even though it is not explicitly stated in the paper, the objective values of the optimal VRPTW solutions used as a benchmark reveal that in Nanry and Barnes (2000), distance is rounded or truncated to one decimal position. In contrast, it seems that Lim and Li (2001) as well as Lau and Liang (2001) calculate distance to at least two decimal points. Therefore, even identical solutions may lead to significantly different objective values. Moreover, only best results are reported in the relevant literature, even if the proposed methods have stochastic components, as in the approaches of Li and Lim (2001) and Lau and Liang (2001). The overall number of independent runs per instance and average solution quality, which are important pieces of information when judging a stochastic method, are not disclosed. Finally, due to different computer platforms, a comparison of computing times is difficult.

The results obtained by the GGA for problem set 1 and problem set 2 are listed in table 2 and table 3, respectively. In these tables, td denotes total travel distance, nv the number of vehicles, and ct the computing time in seconds. Since Lau and Liang (2000) did not report a solution to nc102 nor any computing times, the respective cells in table 2 are empty. For the GGA, aside from the values of the respective best solution (td^{best} and nv^{best}), average solution quality and average computing time is reported for each instance (td^{avg} , nv^{avg} , and ct^{avg}). Under the assumption that the optimal VRPTW solutions remain very good, if not optimal solutions to the derived PDPTW instances, each of them provides a high quality upper bound for the total travel distance of the corresponding PDPTW instance. For this reason, table 2 also shows the optimal values for the corresponding VRPTW instances of problem set 1 (columns two and five). In order to allow a careful comparison of the approaches despite different distance calculations, the results of Nanry and Barnes are compared to the optimal VRPTW solutions of Desrochers et al. (1992) and Kohl and Madsen (1997), which were calculated using distance truncation after one decimal place (Opt A). When calculated to two decimal places, the objective values of the optimal VRPTW solutions are slightly different (Opt B, taken from Homberger, 2000). These values should be taken into account when comparing the results of the rest of the approaches, including the GGA.

The results presented in table 2 can be summarized as follows:

- For problem nc103, the GGA, like the competing methods, fails to find a solution of the same quality as the corresponding optimal VRPTW solution (Opt B). The relative error is 0.5 percent. Only the solution reported by Nanry and Barnes for this instance has a lower relative error (0.4 percent).
- For all other problems, the GGA finds solutions of identical or better quality in terms of total travel distance when compared to the corresponding optimal VRPTW solutions. Since the average computing times are less than 2.5 minutes even in the worst case, this solution quality is achieved at reasonable computational cost.

Table 2: Results for problem set 1

Inst.	Opt. A	Nanry/Barnes (2000)		Opt. B	Li/Lim (2001)		Lau/Liang (2001)		GGA		
	td nv	td nv	ct	td nv	td nv	ct	td nv	ct	td ^{best} nv ^{best}	td ^{avg} nv ^{avg}	ct ^{avg}
nc101	827.3 10	827.3 10	0.25	828.94 10	828.9 10	35	828.9 10	–	828.94 10	828.94 10	64.93
nc102	827.3 10	827.3 10	1.91	828.94 10	828.9 10	130	–	–	828.94 10	828.94 10	83.1
nc103	826.3 10	829.9 10	16.50	828.06 10	831.9 10	156	837.7 10	–	831.87 10	831.87 10	117.13
nc104	822.9 10	834.7 10	328.87	824.78 10	869.5 9	1539	989.7 9	–	816.74 10	816.74 10	143.67
nc105	827.3 10	827.3 10	0.51	828.94 10	828.9 10	25	829.8 10	–	828.94 10	828.94 10	69.83
nc106	827.3 10	827.3 10	0.54	828.94 10	828.9 10	31	828.9 10	–	828.94 10	828.94 10	74.73
nc107	827.3 10	826.1 10	9.36	828.94 10	827.8 10	22	828.9 10	–	827.82 10	827.82 10	74.10
nc108	827.3 10	826.1 10	31.49	828.94 10	827.8 10	39	826.1 10	–	827.82 10	829.11 10	84.9
nc109	827.3 10	827.3 10	184.76	828.94 10	827.8 10	85	828.9 10	–	827.82 10	827.82 10	116.87

- For problem nc104, the GGA has found a new best solution with regard to total travel distance. Interestingly, total travel distance in this case is significantly less compared to the corresponding optimal VRPTW solution. This also holds for three further instances (nc107, nc108 and nc109). Due to load modifications at the customer nodes during transformation into PDPTW instances, the capacity constraint obviously has lost its original tightness. Thus, the optimal solutions for the corresponding VRPTW are no longer optimal for the generated PDPTW instances. Note that for problem nc104, Li and Lim as well as Lau and Liang report solutions with greater travel distance but one vehicle saved.
- An interesting observation is the robustness of the proposed GGA with regard to problem set 1, since except for instance nc108, the GGA finds its best solution to each problem consistently in all 30 runs.

In order to facilitate comparison, in table 3, the respective best values with regard to travel distance and number of vehicles for each instance are highlighted as bold figures. From table 3 the following conclusions can be drawn:

- In comparison to the method of Li and Lim (2001), the best results of the GGA are better with respect to total travel distance in 15 cases. On the other hand, in 9 cases the method of Li and Lim yields solutions with less travel distance than the GGA.

Table 3: Results for problem set 2

Inst.	Li and Lim (2001)			GGA				
	td	nv	ct	td ^{best}	nv ^{best}	td ^{avg}	nv ^{avg}	ct ^{avg}
lc101	828.94	10	33	828.94	10	828.94	10.00	55.03
lc102	828.94	10	71	828.94	10	828.94	10.00	68.67
lc103	827.86	10	191	827.86	10	827.86	10.00	85.33
lc104	861.95	9	1254	818.60	10	818.67	10.00	139.90
lc105	828.94	10	47	828.94	10	828.94	10.00	58.33
lc106	828.94	10	43	828.94	10	828.94	10.00	63.60
lc107	828.94	10	54	828.94	10	828.94	10.00	65.97
lc108	826.44	10	82	826.44	10	826.44	10.00	81.00
lc109	827.82	10	255	827.82	10	827.82	10.00	118.10
lc201	591.56	3	27	591.56	3	591.56	3.00	59.27
lc202	591.56	3	94	591.56	3	591.56	3.00	115.50
lc203	585.56	3	145	591.17	3	591.17	3.00	191.67
lc204	591.17	3	746	590.60	3	620.38	3.00	346.13
lc205	588.88	3	190	588.88	3	588.88	3.00	94.07
lc206	588.49	3	88	588.49	3	588.49	3.00	124.20
lc207	588.29	3	102	588.29	3	588.35	3.00	137.03
lc208	588.32	3	178	588.32	3	588.75	3.00	141.93
lr101	1650.78	19	87	1650.80	19	1650.80	19.00	67.00
lr102	1487.57	17	1168	1487.57	17	1488.74	17.00	89.53
lr103	1292.68	13	169	1292.68	13	1292.67	13.00	82.87
lr104	1013.39	9	459	1013.99	9	1037.16	9.43	136.83
lr105	1377.11	14	69	1377.11	14	1377.11	14.00	70.97
lr106	1252.62	12	87	1252.62	12	1252.63	12.00	81.33
lr107	1111.31	10	287	1111.31	10	1112.26	10.03	95.67
lr108	968.97	9	415	968.97	9	969.02	9.00	102.50
lr109	1239.96	11	348	1208.96	11	1233.99	12.00	103.80
lr110	1159.35	10	547	1165.83	11	1176.20	11.13	142.13
lr111	1108.90	10	179	1108.90	10	1113.60	10.20	105.53
lr112	1003.77	9	638	1003.77	9	1040.34	10.27	168.70
lr201	1263.84	4	193	1253.23	4	1260.41	4.20	103.43
lr202	1197.67	3	885	1197.67	3	1255.78	4.03	234.50
lr203	949.40	3	1950	952.29	3	962.82	3.00	381.50
lr204	849.05	2	2655	849.05	2	879.01	2.27	486.50
lr205	1054.02	3	585	1054.02	3	1078.84	3.03	166.37
lr206	931.63	3	747	931.63	3	941.67	3.00	259.03
lr207	903.056	2	1594	903.60	2	927.58	2.43	418.77
lr208	734.85	2	3572	736.00	2	760.95	2.03	531.07
lr209	937.05	3	2773	932.43	3	955.96	3.07	236.90
lr210	964.22	3	1482	964.22	3	972.34	3.00	286.13
lr211	927.80	2	4204	888.15	3	897.03	3.07	478.53
lrc101	1708.80	14	119	1703.21	15	1704.05	15.00	76.07
lrc102	1563.55	13	152	1558.07	12	1559.65	12.17	95.53
lrc103	1258.74	11	175	1258.74	11	1260.45	11.00	92.80
lrc104	1128.40	10	202	1128.40	10	1129.32	10.00	108.23
lrc105	1637.62	13	179	1637.62	13	1639.87	13.10	88.17
lrc106	1425.53	11	459	1424.73	11	1441.82	11.77	95.63
lrc107	1230.15	11	154	1230.14	11	1237.91	11.07	97.73
lrc108	1147.97	10	650	1147.43	10	1159.82	10.40	111.67
lrc201	1468.96	4	266	1407.21	4	1438.12	4.77	101.47
lrc202	1374.27	3	987	1385.25	4	1400.11	3.97	161.70
lrc203	1089.07	3	1605	1093.89	4	1114.40	4.00	268.17
lrc204	827.78	3	3634	818.66	3	838.55	3.00	457.30
lrc205	1302.20	4	639	1302.20	4	1305.37	4.00	147.20
lrc206	1162.91	3	445	1159.03	3	1176.90	3.63	139.57
lrc207	1424.60	3	607	1062.05	3	1070.56	3.03	218.97
lrc208	852.76	3	4106	852.76	3	882.78	3.20	322.13

- In 11 cases the GGA finds solutions with less travel distance without an increase in the number of vehicles reported by Li and Lim. These new best results are printed in bold italics in table 3. For problem lrc102, the GGA finds solutions that have less total travel distance and a smaller number of vehicles than the best solutions of Li and Lim. In 6 cases, Li and Lim report solutions with a smaller number of vehicles than the GGA.
- Even though the GGA fails to find its best solution for each instance of problem set 2 throughout all runs, the GGA turns out to be reasonably robust: for almost 90 percent of all instances, a standard deviation of total travel distance of less than 2 percent was observed.
- In order to solve the instances of problem set 2, the GGA requires moderate average computational times that range from less than one minute to less than nine minutes.

5 Conclusions

In this paper, a Grouping Genetic Algorithm (GGA) for the Pickup and Delivery Problem with Time Windows (PDPTW) has been presented. To our knowledge this is the first time a Genetic Algorithm has been applied to the multi-vehicle PDPTW with hard time window constraints. Furthermore, it appears to be the first published application of the group-oriented genetic encoding of Falkenauer (1998) to a generalization of the Vehicle Routing Problem. The GGA was tested using two publicly available sets of benchmark problems for the PDPTW. The experimental results have demonstrated that the GGA is able to find high quality solutions when compared to previous metaheuristic methods for solving the PDPTW. The overall findings seem to justify the employment of Genetic Algorithms in general, as well as the group-oriented encoding in particular, as suitable techniques for solving the PDPTW.

References

- BERGER, J.; SALOIS, M.; BEGIN, R. (1998): A Hybrid Genetic Algorithm for the Vehicle Routing Problem with Time Windows. In: Mercer, R.E.; Neufeld, E. (eds.), *Advances in Artificial Intelligence – Proceedings of the 12th Biennial Conference of the Canadian Society for Computational Studies of Intelligence*, Springer, Berlin, pp. 114–127.
- BLANTON, J.L.; WAINWRIGHT, R.L. (1993): Multiple Vehicle Routing with Time und Capacity Constraints using Genetic Algorithms. In: Forrest, S. (ed.), *Proceedings of the Fifth International Conference on Genetic Algorithms*, Morgan Kaufmann, San Mateo/California, 452–459.
- BODIN, L.; SEXTON, T. (1986): The Multi-Vehicle Subscriber Dial-a-Ride Problem. *TIMS Studies in the Management Sciences* 26, pp. 73–86.
- DAVIS, L. (ed.) (1991): *Handbook of Genetic Algorithms*. Van Nostrand Reinhold, New York.
- DESROCHERS, M.; DESROSIERS, J.; SOLOMON, M.M. (1992): A New Optimization Algorithm for the Vehicle Routing Problem with Time Windows. *Operations Research* 40, pp. 342–354.
- DESROSIERS, J.; DUMAS Y.; SOUMIS, F. (1986): A Dynamic Programming Solution of the Large-Scale Single-Vehicle Dial-a-Ride Problem with Time Windows. *The American Journal of Mathematical und Management Sciences* 6, pp. 301–325.
- DESROSIERS, J.; DUMAS, Y.; SOUMIS, F. (1988): The Multiple Vehicle Dial-a-Ride Problem. In: Daduna, J.R.; Wren, A. (eds.), *Computer-Aided Transit Scheduling: Proceedings of the Fourth International Workshop on Computer-Aided Scheduling of Public Transport*, Springer, Berlin, pp. 15–27.
- DUMAS, Y.; DESROSIERS, J.; SOUMIS F. (1991): The Pickup und Delivery Problem with Time Windows. *European Journal of Operational Research* 54, pp. 7–22.
- FALKENAUER, E. (1998): *Genetic Algorithms und Grouping Problems*, Wiley, Chichester.
- GENDREAU, M.; GUERTIN, F.; POTVIN, J.-Y.; SÉGUIN, R. (1998): Neighborhood Search Heuristics for a Dynamic Vehicle Dispatching Problem with Pick-ups und Deliveries. Technical Report CRT-98-10, Centre de recherche sur les transports, Université de Montréal, Montréal.
- GOLDBERG, D.E. (1989): *Genetic Algorithms in Search, Optimization, und Machine Learning*. Addison-Wesley, Reading, Massachusetts.
- GOLDBERG, D.E.; KORB, B.; DEB, K. (1990): Messy Genetic Algorithms: Motivation, Analysis, und First Results. *Complex Systems* 3, pp. 493–530.
- HOLLAND, J.H. (1975): *Adaptation in Natural und Artificial Systems – An Introductory Analysis with Applications to Biology, Control, und Artificial Intelligence*. The University of Michigan Press, Ann Arbor.

- HOMBERGER, J. (2000): Verteilt-parallele Metaheuristiken zur Tourenplanung – Lösungsverfahren für das Standardproblem mit Zeitfensterrestriktionen, Deutscher Universitäts-Verlag, Wiesbaden.
- IOACHIM, I.; DESROSIERS, J.; DUMAS, Y.; SOLOMON M.M.; VILLENEUVE D. (1995): A Request Clustering Algorithm for Door-to-Door Handicapped Transportation. *Transportation Science* 29, pp. 63–78.
- JAW, J.-J.; ODONI, A.R.; PSARAFTIS, H.N.; WILSON, N.H.M. (1986): A Heuristic Algorithm for the Multi-Vehicle Advance Request Dial-A-Ride Problem with Time Windows. *Transportation Research Part B* 20, pp. 243–257.
- JIH, W.-R.; HSU, Y.-J. (1999): Dynamic Vehicle Routing Using Hybrid Genetic Algorithms. In: IEEE Computer Society (ed.), *Proceedings of the 1999 IEEE International Conference on Robotics & Automation*, IEEE Computer Society, Los Alamitos, California, pp. 453–458.
- JUNG, S.; HAGHANI, A. (2000): A Genetic Algorithm for Pick-up and Delivery Problem with Time Windows. In: *Transportation Research Record* 1733, Transportation Research Board, pp. 1–7.
- KOHL, N.; MADSEN, O.B.G (1997): An Optimization Algorithm for the Vehicle Routing Problem with Time Windows Based on Lagrangian Relaxation. *Operations Research* 45, pp. 395–406.
- KOPFER, H.; PANKRATZ, G.; ERKENS, E. (1994): Die Entwicklung eines hybriden Genetischen Algorithmus für das Tourenplanungsproblem. *OR Spektrum* 16, pp. 21–32.
- LAU, H.C.; LIANG, Z. (2001): Pickup und Delivery with Time Windows, Algorithms und Test Case Generation. In: IEEE Computer Society (ed.), *Proceedings of the 13th IEEE International Conference on Tools with Artificial Intelligence (ICTAI)*, IEEE Computer Society, Los Alamitos, California, pp. 333–340.
- LENSTRA, J.K.; RINNOY KAN, A.H.G. (1981): Complexity of Vehicle Routing und Scheduling Problems. *Networks* 11, pp. 221–227.
- LI, H.; LIM, A. (2001): A Metaheuristic for Solving the Pickup und Delivery Problem with Time Windows. In: IEEE Computer Society (ed.), *Proceedings of the 13th IEEE International Conference on Tools with Artificial Intelligence (ICTAI)*, IEEE Computer Society, Los Alamitos, California, pp. 160–167.
- LIN, S.; KERNIGHAN, B. (1973): An Effective Heuristic Algorithm for the Traveling Salesman Problem. *Operations Research* 21, pp. 498–516.
- MADSEN, O.B.G.; RAVN, H.F.; RYGAARD, J.M. (1995): A Heuristic Algorithm for a Dial-a-Ride Problem with Time Windows. Multiple Capacities and Multiple Objectives. *Annals of Operations Research* 60, pp. 193–208.
- NANRY, W.P.; BARNES, J.W. (2000): Solving the Pickup und Delivery Problem with Time Windows using Reactive Tabu Search. *Transportation Research Part B* 34, pp. 107–121.

- POTTER, T.; BOSSOMAIER, T. (1995): Solving Vehicle Routing Problems with Genetic Algorithms. In: IEEE Computer Society (ed.), Proceedings of the 1995 IEEE International Conference on Evolutionary Computing, IEEE Computer Society, Los Alamitos, California, pp. 788–793.
- POTVIN, J.-Y.; BENGIO, S. (1996): The Vehicle Routing Problem with Time Windows – Part II: Genetic Search. *INFORMS Journal on Computing* 8, pp. 165–172.
- PSARAFTIS, H.N. (1980): A Dynamic Programming Solution to the Single Vehicle Many-to-Many Immediate Request Dial-a-Ride Problem. *Transportation Science* 14, pp. 130–154.
- PSARAFTIS, H.N. (1983a): An Exact Algorithm for the Single Vehicle Many-to-Many Dial-A-Ride Problem with Time Windows. *Transportation Science* 17, pp. 351–357.
- PSARAFTIS, H.N. (1983b): k-Interchange Procedures for Local Search in a Precedence-Constrained Routing Problem. *European Journal of Operational Research* 13, pp. 391–402.
- RAYWARD-SMITH, V.J. (1994): A Unified Approach to Tabu Search, Simulated Annealing and Genetic Algorithms. In: Unicom Seminars Ltd. (ed.), Adaptive Computing and Information Processing, Unicom Seminars Ltd., London, Vol. I, pp. 55–78.
- REGO, C.; ROUCAIROL, C. (1996): A Parallel Tabu Search Algorithm Using Ejection Chains for the Vehicle Routing Problem. In: Osman, I.H.; Kelly, J.P. (eds.), Meta-Heuristics: Theory and Applications, Kluwer, Norwell et al., pp. 661–675.
- SAVELSBERGH, M.W.P.; SOL, M. (1995): The General Pickup und Delivery Problem. *Transportation Science* 29, pp. 17–29.
- SAVELSBERGH, M.W.P.; SOL, M. (1998): DRIVE: Dynamic Routing of Independent Vehicles. *Operations Research* 46, pp. 474–490.
- SCHÖNBERGER, J.; KOPFER, H.; MATTFELD, D.C. (2003): A Combined Approach to Solve the Pickup und Delivery Selection Problem. In: Leopold-Wildburger, U.; Rendl, F.; Wäscher, G. (eds.), Operations Research Proceedings 2002, Springer, Heidelberg et al., pp. 150–155.
- SOLOMON, M. (1987): Algorithms for the Vehicle Routing und Scheduling Problem with Time Window Constraints. *Operations Research* 35 (2), pp. 254–265.
- SYSWERDA, G. (1989): Uniform Crossover in Genetic Algorithms. In: Shaffer, J.D. (ed.), Proceedings of the Third International Conference on Genetic Algorithms, Morgan Kaufmann, San Mateo/California, pp. 2–9.
- THANGIAH, S.R. (1995): Vehicle Routing with Time Windows using Genetic Algorithms. In: Chambers, L. (ed.), Practical Handbook of Genetic Algorithms 2 – New Frontiers. CRC Press, Boca Raton, pp. 253–277.
- TOTH, P.; VIGO, D. (1996): Fast Local Search Algorithms for the Handicapped Persons Transportation Problem. In: Osman, I.H.; Kelly, J.P. (eds.), Meta-Heuristics: Theory und applications, Kluwer, Norwell, pp. 677–690.

- VAN DER BRUGGEN, L.J.J.; LENSTRA, J.K.; SCHUUR, P.C. (1993): Variable Depth Search for the Single-Vehicle Pickup und Delivery Problem with Time Windows. *Transportation Science* 27, pp. 298–311.
- WHITLEY, L.D. (1989): The GENITOR Algorithm und Selection Pressure: Why Rank-Based Allocation of Reproductive Trials is Best. In: Shaffer, J.D. (ed.), *Proceedings of the Third International Conference on Genetic Algorithms*, Morgan Kaufmann, San Mateo/California, pp. 116–121.

Die Diskussionspapiere ab Nr. 183 (1992) bis heute, können Sie im Internet unter <http://www.fernuni-hagen.de/FBWIIW/> einsehen und zum Teil downloaden.
Die **Titel** der Diskussionspapiere von Nr. 1 (1975) bis 182 (1991) können bei Bedarf im Fachbereich Wirtschaftswissenschaft angefordert werden:

FernUniversität
z.Hd. Frau Huber oder Frau Mette,
Postfach 940
58084 Hagen

Die Diskussionspapiere selber erhalten Sie nur in den Bibliotheken.

Nr.	Jahr	Titel	Autor/en
322	2001	Spreading Currency Crises: The Role of Economic Interdependence	Berger, Wolfram Wagner, Helmut
323	2002	Planung des Fahrzeugumschlags in einem Seehafen-Automobilterminal mittels eines Multi-Agenten-Systems	Fischer, Torsten Gehring, Hermann
324	2002	A parallel tabu search algorithm for solving the container loading problem	Bortfeldt, Andreas Gehring, Hermann Mack, Daniel
325	2002	Die Wahrheit entscheidungstheoretischer Maximen zur Lösung von Individualkonflikten – Unsicherheitssituationen	Mus, Gerold
326	2002	Zur Abbildungsgenauigkeit des Gini-Koeffizienten bei relativer wirtschaftlicher Konzentration	Steinrücke, Martin
327	2002	Entscheidungsunterstützung bilateraler Verhandlungen über Auftragsproduktionen – eine Analyse aus Anbietersicht	Steinrücke, Martin
328	2002	Die Relevanz von Marktzinssätzen für die Investitionsbeurteilung – zugleich eine Einordnung der Diskussion um die Marktzinsmethode	Terstege, Udo
329	2002	Evaluating representatives, parliament-like, and cabinet-like representative bodies with application to German parliament elections 2002	Tangian, Andranik S.
330	2002	Konzernabschluss und Ausschüttungsregelung im Konzern. Ein Beitrag zur Frage der Eignung des Konzernabschlusses als Ausschüttungsbemessungsinstrument	Hinz, Michael
331	2002	Theoretische Grundlagen der Gründungsfinanzierung	Bitz, Michael
332	2003	Historical background of the mathematical theory of democracy	Tangian, Andranik S.
333	2003	MCDM-applications of the mathematical theory of democracy: choosing travel destinations, preventing traffic jams, and predicting stock exchange trends	Tangian, Andranik S.
334	2003	Sprachregelungen für Kundenkontaktmitarbeiter – Möglichkeiten und Grenzen	Fließ, Sabine Möller, Sabine Momma, Sabine B.
335	2003	A Non-cooperative Foundation of Core-Stability in Positive Externality NTU-Coalition Games	Finus, Michael Rundshagen, Bianca
336	2003	Combinatorial and Probabilistic Investigation of Arrow's paradox	Tangian, Andranik
337	2003	A Grouping Genetic Algorithm for the Pickup and Delivery Problem with Time Windows	Pankratz, Giseler
338	2003	Planen, Lernen, Optimieren: Beiträge zu Logistik und E-Learning. Festschrift zum 60. Geburtstag von Hermann Gehring	Bortfeldt, Andreas Fischer, Torsten Homberger, Jörg Pankratz, Giseler Strangmeier, Reinhard