AN ANT COLONY ALGORITHM FOR THE TIME-INDEPENDENT AND TIME-DEPENDENT VEHICLE ROUTING PROBLEM WITH TIME WINDOWS

by

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To my family

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Abstract

The Vehicle Routing Problem (VRP) determines a set of vehicle routes originating and terminating at a single depot such that all customers are visited exactly once and the total demand of the customers assigned to each route does not violate the capacity of the vehicle. The objective is to minimize the total distance traveled by all vehicles. An implicit primary objective is to use the least number of vehicles The Vehicle Routing Problem with Time Windows (VRPTW) is a variant of VRP in which lower and upper limits are imposed to the delivery time of each customer. The arrival at a customer outside the specified delivery times is either penalized (soft time windows) or strictly forbidden (hard time windows). In the time-dependent VRP, the travel times between the customers vary due to different traffic conditions in time intervals throughout the scheduling horizon beside different road types. In this thesis, both the time-independent and -dependent VRP with hard time windows are addressed. We tackle these problems using an Ant Colony Optimization approach. The performance of the proposed algorithm is tested on the well-known benchmark instances from the literature.

ZAMAN-BAĞIMSIZ VE ZAMAN-BAĞIMLI ZAMAN KISITLI ARAÇ ROTALAMA PROBLEMİNE BİR KARINCA KOLONİSİ YAKLAŞIMI

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Özet

Araç Rotalama Problemi (ARP), tüm müşteriler yalnızca bir kez ziyaret edilecek ve tek bir rotaya atanan müşterilerin toplam talepleri araç kapasitesini aşmayacak şekilde depodan başlayan ve depoda sonlanan rotaların belirlenmesi problemidir. Amaç, toplamda katedilen mesafenin enküçüklenmesidir. Bir diğer örtülü amaç ise en az sayıda aracın kullanılmasıdır. ARP'nin bir uzantısı olan Zaman Kısıtlı ARP (ZKARP), her bir müşteriye gidilebilecek zaman için en erken ve en geç sınırların tanıtıldığı problemdir. Bu sınırlar dışındaki varış zamanları ya cezalandırılmakta (gevşek zaman kısıtı) ya da tamamıyla yasaklanmaktadır (sıkı zaman kısıtı). Zaman-Bağımlı ARP'nde ise yolculuk zamanları, farklı yol tipleri yanında zaman aralıklarındaki farklı trafik koşullarına bağlı olarak değişkenlik göstermektedir. Bu tezde, hem zaman-bağımlı hem de zaman-bağımsız sıkı zaman kısıtlı ARP ele alınmaktadır. Çözüm yöntemi olarak karınca kolonisi algoritması kullanılmaktadır. Önerilen yaklaşımın performansı literatürdeki problemler üzerinde test edilmektedir.

Table of Contents

List of Figures

List of Tables

CHAPTER 1

INTRODUCTION

Optimizing a distribution network has been and remains an important topic both in the literature and real-life applications, and the routing of a fleet of vehicles is one of the most widely addressed problem in a distribution network. The Vehicle Routing Problem (VRP) firstly introduced by Dantzig and Ramser (1959) determines a set of vehicle routes originating and terminating at a single depot such that all customers are visited exactly once, and the total demand of the customers assigned to each route does not violate the capacity of the vehicle. The objective is to minimize the total distance traveled by all vehicles. An implicit primary objective is to use the least number of vehicles. The Vehicle Routing Problem with Time Windows (VRPTW) is a variant of VRP in which an earliest and a latest delivery time are imposed for each customer. The arrival at a customer outside the specified delivery times is either penalized (soft time windows) or strictly forbidden (hard time windows). While modeling VRP many assumptions are made to simplify the problem and to reduce the solution process since the VRP is an NP-hard problem. However, as the number of assumptions increases, the model becomes less successful to represent real-life conditions. The most widely made assumption is that the travel times are constant and insensitive to the changing traffic conditions during the scheduling horizon. In the Stochastic Vehicle Routing Problem, the customer demands and/or the travel times between the customers may vary. Although stochastic travel times and demand distributions have been frequently used in the literature, time-varying travel speeds and Time-dependent Vehicle Routing Problem with Time Windows (TDVRPTW) have seldom been addressed.

Many exact and heuristic solution approaches are used to solve VRP and its extensions. From both the computational time and solution quality point of view, metaheuristics have gained much importance (compared to the exact solution methods). Metaheuristics such as Tabu Search (TS), Genetic Algorithm (GA), Simulated Annealing (SA), Greedy Randomized Adaptive Search Procedure (GRASP) and the recently introduced Ant Colony Optimization (ACO) are solution methods capable of avoiding getting trapped in a local optimum while performing an extensive search in the solution space by utilizing the interaction between local search improvement procedures and higher level strategies (Glover and Kochenberger, 2003).

ACO is a population-based metaheuristic that can be used to find approximate solutions to difficult optimization problems (Dorigo, 2008). It is based on the observation of the behavior of real ant colonies searching for food sources. Real ants deposit an aromatic essence, called pheromone, on the path they walk. Other ants searching for food sense the pheromone and use this information in selecting their path. The quantity of pheromone deposited on a path is based on the length of the path and the quality of the food source. As more ants follow a path the level of pheromone on that path will increase, increasing its selection probability by other ants. In ACO, artificial ants are used for searching good solutions to an optimization problem by taking advantage of this cooperative learning process (Çatay, 2008).

The aim of this thesis is to develop an ACO approach to efficiently solve both the time-dependent and -independent VRP with hard time windows. The thesis is organized as follows. In Chapter 2, the mechanisms of the ACO metaheuristic are described and some of its variants proposed in the literature are summarized. Chapter 3 is devoted to the description of TDVRPTW and the overview of the approaches proposed for solving the problem. Chapter 4 introduces the proposed ACO approach and Chapter 5 presents the computational study to test its performance and the results achieved. Finally, concluding remarks and future research are given in the last chapter.

CHAPTER 2

ANT COLONY OPTIMIZATION

ACO, introduced by Dorigo (1992), is a metaheuristic approach, developed to attack hard combinatorial optimization problems. The approach is motivated from the common behaviors of the real ant colonies. A foraging member of a real ant colony communicates with the other members via stigmergy, an indirect form of communication based on the modification of the environment. The main component of stigmergy in a real ant colony is a chemical substance called *pheromone* which an ant deposits on the trail it walks while searching for food. As the number of ants that follow the path increases, the pheromone amount on the path and the selection probability of the path will increase. The other ants are likely to follow the path on which they sense pheromone instead of traveling at random. Pheromone on a trail is also subject to evaporation and even to exhaustion unless the path is traversed, which in turn will decrease the chance of other ants to follow the path. The amount of pheromone deposited and evaporated is correlated with the distance between the nest and the food source. The longer the path between the nest and the food source the more the pheromone evaporates. On the other hand, the shorter the path the more the pheromone is deposited. Thus, the pheromone levels remain higher on the shorter paths. Also, the quality of the food is another factor that affects the amount of pheromone deposited.

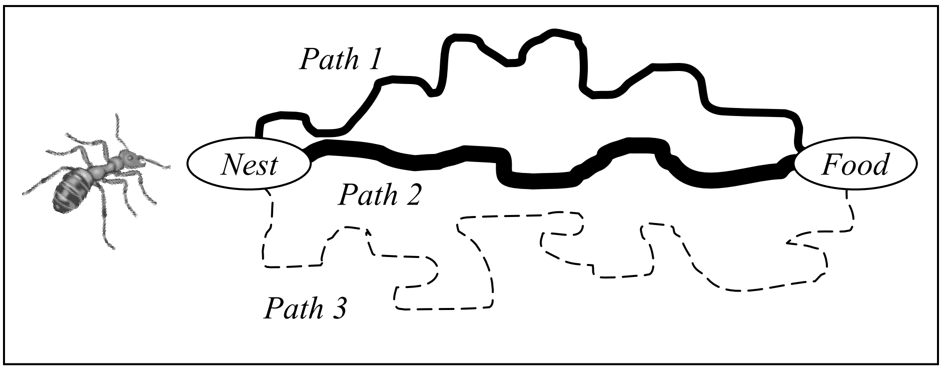

Figure 2.1. Illustration of pheromone deposit

Figure 2.1 illustrates an ant ready to depart from the nest for the food which can be reached via three paths. The pheromone levels on these three paths are determined by the path choice of the previous ants. The weights of the paths in Figure 2.1 are proportional to the amount of pheromone they are deposited. Pheromone on the longest path, path 3, has totally evaporated. The ant in the nest is most likely to choose path 2 having the largest amount of pheromone, thus reinforcing the path.

The behavior of real ants is simulated via artificial ants in ACO to solve combinatorial optimization problems. The artificial ants search the solution space for a good solution while the real ants search their environment for food of good quality. In order to implement ACO, a transformation of the optimization problem into the problem of finding the path that best serves the objective function on a weighted graph is performed. The artificial ants incrementally build solutions by moving on the graph using a stochastic construction process guided by artificial pheromone and a greedy heuristic known as visibility (Dorigo, 2008). As the solution quality increases, the amount of pheromone deposited increases accordingly.

The first ACO algorithm is the Ant System (AS) which was applied for solving the well-known Traveling Salesman Problem (Dorigo, 1992; Dorigo et al., 1996). In AS, each ant probabilistically chooses the next city to visit based on a heuristic combining the distance to that city and the amount of virtual pheromone deposited on the arc to that city. The ants explore, depositing pheromone on each arc that they cross, until they have all completed a tour. At this point the ant which has completed the shortest tour deposits virtual pheromone along its complete tour. The amount of pheromone deposited is inversely proportional to the tour length; the shorter the tour, the more it deposits.

Although AS provided competitive results its performance was still inferior in large instances compared to other algorithms specifically designed for the TSP. However, its successful application has led to many extensions for various combinatorial optimization problems utilizing the similar construction mechanism. Some early applications include the elitist strategy for Ant System (EAS) proposed by Dorigo (1992) and Dorigo et al. (1996), rank-based version of Ant System (AS_{rank}) by Bullnheimer et al. (1999), *MAX-MIN* Ant System (*MM*AS) by Stützle and Hoos (1997), and Ant Colony System (ACS) by Dorigo and Gambardella (1997).

In the next section, we explain the mechanisms of the AS approach and discuss its extensions applied to the TSP following the detailed description provided in Çatay (2008).

2.1. Ant System

In AS, K artificial ants probabilistically construct tours in parallel exploiting a given pheromone model. Initially, all ants are placed on randomly chosen cities. At each iteration, each ant moves from one city to another, keeping track of the partial solution it has constructed so far. The algorithm has two fundamental components:

- The amount of pheromone on arc (i, j), τ_{ij}
- Desirability of arc (i, j), η_{ij}

where arc (i, j) denotes the connection between city i and city j.

At the start of the algorithm an initial amount of pheromone τ_0 is deposited on each arc: $\tau_{ij} = \tau_0 = K/L_0$, where L_0 is the length of an initial feasible tour and K is the number of ants. In AS, the initial tour is constructed using the nearest-neighbor algorithm; however, another TSP heuristic may as well be utilized. The desirability value (also referred to as visibility or heuristic information) between a pair of cities is the inverse of their distance $\eta_{ij} = 1/d_{ij}$, where d_{ij} is the distance between cities i and j. So, if the distance on the arc (i, j) is long, visiting city j after city i (or vice-versa) will be less desirable.

Each ant constructs its own tour utilizing a transition probability: an ant k positioned at a city i selects the next city j to visit with a probability given by

$$p_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{l \in \mathcal{N}_i^k} \tau_{il}^{\alpha}\eta_{il}^{\beta}}, & \text{if } j \in \mathcal{N}_i^k \\ 0, & \text{otherwise} \end{cases} \tag{2.1}$$

Here, $\mathcal{N}_i^k$ denotes the set of not yet visited cities; α and β are positive parameters to control the relative weight of pheromone information τ_{ij} and heuristic information η_{ij}. Note that $\tau_{il}^{\alpha}\eta_{il}^{\beta}$ is also referred to as the attractiveness and is denoted as φ_{ij}.

After each ant has completed its tour, the pheromone levels are updated. The pheromone update consists of the pheromone evaporation and pheromone reinforcement. The pheromone evaporation refers to uniformly decreasing the pheromone values on all arcs. The aim is to prevent the rapid convergence of the algorithm to a local optimal solution by reducing the probability of repeatedly selecting certain cities. The pheromone reinforcement process, on the other hand, allows each ant to deposit a certain amount of pheromone on the arcs belonging to its tour. The aim is to increase the probability of selecting the arcs frequently used by the ants that construct short tours. The pheromone update rule is the following:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \sum_{k=1}^{K} \Delta\tau_{ij}^{k} \qquad \forall\, (i,j) \tag{2.2}$$

In this formulation, ρ $(0 < \rho \leq 1)$ is the pheromone evaporation parameter and $\Delta\tau_{ij}^{k}$ is the amount of pheromone deposited on arc (i, j) by ant k and is computed as follows:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{1}{L^k}, & \text{if ant k uses edge } (i,j) \text{ on its tour} \\ 0\,, & \text{otherwise} \end{cases} \tag{2.3}$$

where L^k is the length of tour constructed by ant k.

Note that prior to the pheromone update a local search procedure may be applied on the tours constructed by the ants to reduce the distance traversed. It has been observed that such a procedure enhances the performance of the AS algorithm (Çatay, 2008).

2.2. The Extensions of AS

In the EAS (Dorigo, 1992; Dorigo et al., 1996) an elitist strategy is implemented by further increasing the pheromone levels on the arcs belonging to the best tour achieved since the initiation of the algorithm. That best-so-far tour is referred to as the "global-best" tour. Then, the pheromone update rule performed as follows:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \sum_{k=1}^{K} \Delta\tau_{ij}^{k} + w\Delta\tau_{ij}^{gb} \qquad \forall\, (i,j) \tag{2.4}$$

Here, w denotes the weight associated with the global-best tour and $\Delta\tau_{ij}^{gb}$ is the amount of pheromone deposited on arc (i, j) by the global-best ant and calculated by the following formula:

$$\Delta\tau_{ij}^{gb} = \begin{cases} \frac{1}{L^{gb}}, & \text{if global best ant uses edge } (i,j) \text{ on its tour} \\ 0 \;, & \text{otherwise} \end{cases} \tag{2.5}$$

where L^{gb} is the length of global-best tour.

In the AS_{rank} (Bullnheimer et al., 1999) a rank-based elitist strategy is adopted in an attempt to prevent the algorithm from being trapped in a local minimum. In this strategy, w best-ranked ants are used to update the pheromone levels and the amount of pheromone deposited by each ant decreases with its rank. Furthermore, at each iteration, the global-best ant is allowed to deposit the largest amount of pheromone. The update rule is the following:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \sum_{r=1}^{w-1} (\mathrm{w}-\mathrm{r})\Delta\,\tau_{ij}^{r} + w\Delta\tau_{ij}^{gb} \qquad \forall\,(i,j) \tag{2.6}$$

The ACS presented by Dorigo and Gambardella (1997) attempts to improve AS by increasing the importance of exploitation versus exploration of the search space. This is achieved by adopting a strong elitist strategy to update pheromone levels and a pseudo-random proportional rule in selecting the next node to visit. The strong elitist strategy is applied by using the global-best ant only to increase the pheromone levels on the arcs that belong to the global-best tour:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \rho\Delta\tau_{ij}^{gb} \quad \forall\,(i,j) \text{ belonging to global best tour} \tag{2.7}$$

The mechanism of the pseudo-random proportional rule is as follows: an ant k located at customer i may either visit its most favorable customer or randomly select a customer. The selection rule is the following:

$$j^k = \begin{cases} \underset{j \in \mathcal{N}_i^k}{argmax}\, \tau_{ij}^{\alpha}\eta_{ij}^{\beta} \;, & \text{if } z \le z_0 \\ j^k \;, & \text{otherwise} \end{cases} \tag{2.8}$$

where z is a random variable drawn from a uniform distribution $U\,[0,1]$ and z_0 ($0 \le z_0 \le 1$) is a parameter to control exploitation versus exploration. J^k is selected according to the probability distribution (2.1). ACS also uses local pheromone updating while building solutions: as soon as an ant moves from city i to city j the pheromone level on arc (i, j) is reduced in an attempt to promote the exploration of other arcs by other ants. The local pheromone update is performed as follows:

$$\tau_{ij} \leftarrow (1 - \xi)\tau_{ij} + \xi\tau_0 \tag{2.9}$$

where ξ is a positive parameter less than 1.

Similar to ACS, $\mathcal{MM}$AS (Stützle and Hoos, 1997) uses either the global-best ant or the iteration-best ant alone to reinforce the pheromones. It has been observed that using iteration-best ant at the start of the algorithm and then gradually increasing the frequency of using the global-best ant for the pheromone update performs good. However, this strategy may cause a rapid convergence to a sub-optimal solution. Thus, maximum and minimum limits on the pheromone levels are imposed to avoid stagnation. The interval in which the pheromones may vary is set to $[\tau_{min}, \tau_{max}]$. The pheromone levels are initialized at τ_{max} to allow the exploration of the search space at the beginning. In addition, the pheromone levels are reinitialized whenever the system approaches stagnation or no improvement has been achieved after a number of consecutive iterations.

The interested reader is referred to Dorigo and Stützle (2004) for more details on ACO metaheuristic and its variants.

CHAPTER 3

VEHICLE ROUTING PROBLEM WITH TIME WINDOWS

VRP determines a set of vehicle routes originating and terminating at a single depot such that all customers are visited exactly once and the total demand of the customers assigned to each route does not violate the capacity of the vehicle. The objective is to minimize the total distance traveled by all vehicles. An implicit primary objective is to use the least number of vehicles. VRPTW is a variant of VRP in which an earliest and a latest delivery time are imposed for each customer. The arrival at a customer after the specified delivery time interval is either penalized (soft time windows) or strictly forbidden (hard time windows). An extension of the classical VRPTW is the time-dependent VRPTW (TDVRPTW) where the travel times vary due to different factors such as traffic and road conditions.

3.1. Description of the VRPTW

In VRPTW, N geographically dispersed customers are serviced by a homogenous fleet of K vehicles with capacity Q. All vehicle routes start and end at the depot, denoted with 0, visiting each customer i, $i \in \{1,..., N\}$, exactly once. Each customer has a demand q_i, service time s_i and time window $[e_i, l_i]$. The time window refers to the time interval in which the demand must be met and may prohibit the visit of certain customer pairs one after the other. The concept is illustrated in Figure 3.1. The service time shown by the shaded region is the loading or unloading service time at the customer i where the terms e_i and l_i denote the earliest and latest available service start time for customer i. As no arrival is allowed after l_i, this type of time window is referred to as a hard time window. In the soft time window, the

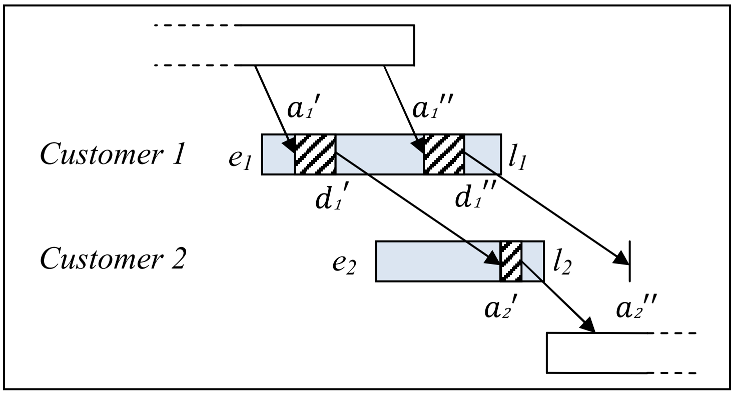

Figure 3.1. Illustration of time window concept

arrival out of the time window is allowed but penalized. If the vehicle arrives at customer i before e_i it must wait. In Figure 3.1, if the vehicle departs from customer 1 at d'_1 after a service time of d'_1-a'_1, it arrives at customer 2 at a'_2. However, if the vehicle departs from customer 1 at d''_1 after a service time of d''_1-a''_1, it arrives at customer 2 at a''_2, beyond the corresponding time window. Thus, the vehicle that is currently visiting customer 1 and will depart at time d''_1 cannot visit customer 2 on its route.

3.2. Description of the TDVRPTW

An extension of the classical VRPTW is the time-dependent VRPTW (TDVRPTW) where the travel time between any source and destination pair on the road network is not a function of the distance alone and is subject to variations due to accidents, weather conditions or other random events. Hourly, daily, weekly or seasonal cycles in the average traffic volumes also result in temporal variations in travel times (Malandraki and Daskin, 1992). Speed limitations imposed by the road type and the traffic density distribution of the road which is also affected by the time of the day are two main components that cause fluctuations in travel speeds. That is, the travel time between two customers is not constant during the entire scheduling horizon and changes with the changing sub-divisions of the horizon, called *time-periods.* This time dependency on both road type and time-period is embedded in the model where deterministic travel times are used by using a travel speed matrix.

Table 3.1. A travel speed matrix example

	Period 1	Period 2	Period 3
Road Type 1	0.6	0.9	0.7
Road Type 2	0.8	1.2	0.5

A sample discrete travel speed distribution is given in Table 3.1. The scheduling horizon is divided into three time periods and the road network composes two types of roads. A travel speed with value 1.0 corresponds to the time-independent VRP. The higher the travel speed, the lighter the traffic density. Road type 1 in Table 3.1 is mostly congested during the day. In period 2, traffic density is lighter and is modeled by a higher travel speed coefficient. Having lower travel speed coefficients, period 1 and period 3 are more congested during the day. The rush hours for road type 2 are in period 3. The travel time is found by multiplying the distance with the corresponding coefficient. Thus, in period 2 for road type 2, the travel time is less than the time-independent case as the travel speed coefficient is bigger than 1.

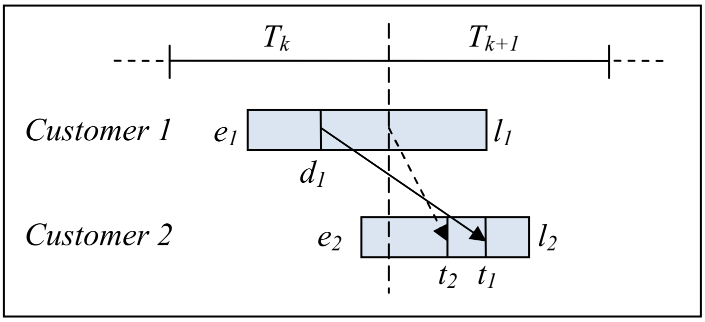

Figure 3.2. Illustration of unrealistic waiting time in constant travel speed case

Ignoring the time dependency of the travel times may result in sub-optimal solutions or solutions in which the time-windows constraints are violated. Besides, assuming a constant speed over the entire length of an arc may lead to waiting time at a customer until the end of the current time interval when it is more advantageous to wait than departing to the next customer immediately. This situation is exemplified in Figure 3.2. The vehicle at customer 1 with time window $[e_1, l_1]$ is ready for departure at time d_1. The travel speed is higher in time-period T_{k+1} compared to the time-period T_k in which the vehicle resides currently. Under the constant travel speed assumption, the vehicle is motivated to wait until the end of time-period T_k rather than departing immediately. When the vehicle departs immediately, it arrives at customer 2 at t_1 whereas it arrives at t_2 in the former case. That is, departing later results in an earlier arrival. In other words, the vehicle that departs later passes the vehicle which departs earlier.

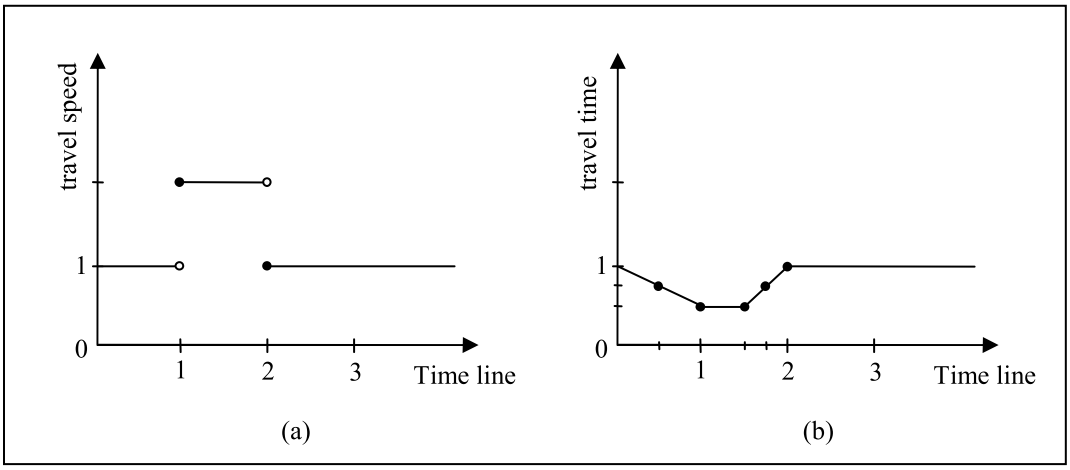

Figure 3.3. An example of travel speed and travel time functions (Ichoua et al., 2003)

To overcome this unrealistic effect of passing, Ahn and Shin (1991) considered the travel speed as a step function of the time of the day (Figure 3.3 (a)). This leads to a piecewise continuous travel time function and guarantees that a customer with an earlier departure time will always arrive earlier (Figure 3.3 (b)). This property is named as *non-passing property*.

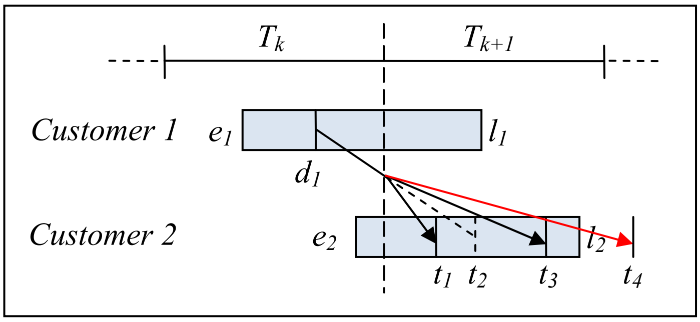

Figure 3.4. Changing arrival times in time-dependent case

In TDVRPTW, the feasible and unfeasible customer pairs are not necessarily same as in the time-independent case. A dynamic travel time calculation is required to check feasibility in the route construction phase. The arrival time to the next customer may be realized earlier or later compared to the time-independent case which are illustrated in Figure 3.4 as t_1 and t_3, respectively, where t_2 shows the arrival time in the time-independent case. Visiting customer 2 after customer 1 is infeasible when the arrival time at customer 2 is t_4 due to a slower travel speed. Similarly, an infeasible customer may become feasible due to the changing travel speeds as illustrated in Figure 3.5.

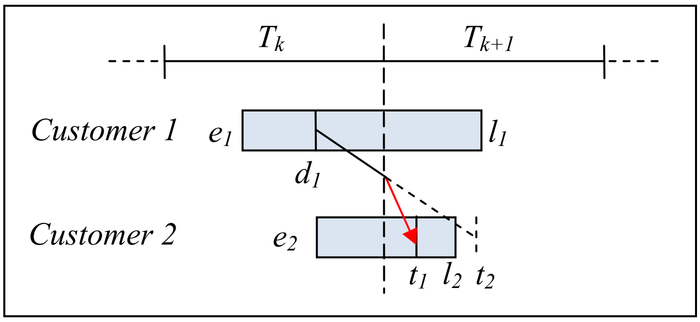

Figure 3.5. Illustration of an infeasible customer that becomes feasible

3.3. Literature Review

VRP has been extensively studied in the literature. However, research related to the time-dependent VRP with and without time windows is relatively scarce. In TDVRPTW, time-dependency is taken into consideration in two ways: stochastic travel times and deterministic travel times. Variable travel times which include real time information on traffic congestion and variable demands have also been studied in the literature. Since these cases are beyond the scope of this thesis we skip further discussion and refer the reader to Fleischmann et al. (2004), Taniguchi et al. (2004), Haghani et al. (2005), Kim et al. (2005) and Chen et al. (2006) (variable time) and Gendreau et al. (1996) (variable demand) for a more detailed description and discussion.

3.3.1. Stochastic travel times

Laporte et al. (1992) introduced the stochastic travel times in the vehicle routing problem where the fleet consists of uncapacitated vehicles. They presented three mathematical programming models and used a branch-and-cut approach to solve instances with 10 to 20 customers and 2 to 5 scenarios where target route completion times are incorporated. Kenyon and Morton (2003) examined the same problem by developing two models. The first model aimed at minimizing the expected completion time. The probability that the operation is completed without exceeding a preset target time is maximized by the second model. The actual travel times of the routes regarding the random travel times are computed after the route construction phase. Van Woensel et al. (2007) incorporated the traffic congestion into their model through a queuing approach by modeling the behavior of the traffic flows. They used the mean of the speed distributions as the expected total travel time. Potvin et al. (2006) described a dynamic version of the problem where the customer demands occur in real time and the travel times are subject to stochastic variations. The stochastic nature of the travel times arise from the short term bias factor that depended on a random variable distributed uniformly. Hsu et al. (2007) have extended the literature by considering TDVRPTW in perishable food delivery industry where the commodity is subject to quality changes due to the time-varying temperatures and time-dependent travel times. Besides the transportation costs, they try to minimize the inventory, energy and penalty costs related to late deliveries.

3.3.2. Deterministic travel times

In the deterministic case, the travel times are not subject to randomness and are known in advance. The most widely used approach is to divide the scheduling horizon into time intervals and use the travel times, which depend on the distance and the time of the day, accordingly. The first study in VRPTW where the time-varying congestion and time-dependent travel times are considered in a deterministic setting belongs to Ahn and Shin (1991). In this study, the important *non-passing* or *first-in-first-out* (*FIFO*) property was introduced. Using this property, they extended the basic routing heuristics efficiently. Malandraki and Daskin (1992) examined mixed integer linear programming formulations for the VRP as well as for the TSP. They presented several nearest neighbor heuristic based algorithms. Hill and Benton (1992) proposed a time-dependent travel speed based model for the VRP without time windows. However in Malandraki and Daskin (1992) and Hill and Benton (1992), the travel time is a step function disregarding the FIFO/non-passing property. Park and Song (2006) used a structure that utilizes different passing areas and discrete time intervals. They considered the travel time as a function of the travel speeds at the customers where the vehicle departs and arrives, the time of the day and the corresponding passing areas. The model of Hill and Benton (1992) is modified and savings, proximity priority searching and insertion techniques are applied in the solution phase. Park (2000) extended this research by proposing a heuristic named BC-saving algorithm to solve a model that minimizes the total operation time and total weighted tardiness.

The proposed solution methodology of Ichoua et al. (2003) for solving TDVRPTW satisfies the FIFO property. Taking the rush hours into account, they divide the scheduling horizon into three time intervals and consider three types of roads which also affect the travel time. As the customers have soft time windows, the infeasible solutions are avoided but the exceeded time windows are penalized. They implemented a parallel tabu search approach and tested its performance both in dynamic and static environments. Furthermore, Zheng and Liu (2006) addressed VRPTW where the travel time was regarded as a fuzzy variable. They employed a hybrid intelligent algorithm to minimize the total distance traveled. In a very recent study Donati et al. (2008) have utilized ant colony optimization in a multi-colony setting. The first colony aims to minimize total number of vehicles whereas the second colony aims to minimize the total travel time. A speed distribution related with the arc length accounts for the time dependency. Proven to be efficient on time-independent problems, the algorithm was tested on time-dependent version of the problems.

CHAPTER 4

AN ANT ALGORITHM FOR THE VRPTW

In this chapter, we propose an ant algorithm for solving the VRPTW with hard time windows and discuss its mechanisms such as the heuristic information, route construction phase, local search procedures and rules on pheromone trails. At the end of the chapter, the approach is extended to the time-dependent case. When no time dependency exists for the travel times, the objective function of the discussed problem is to minimize the total distance traveled. However, in the time-dependent case, the objective function becomes minimizing the total tour time, which is the sum of the total routing times of each vehicle. The flowchart of the proposed algorithm is also provided in Appendix A.

4.1. Heuristic Information

As the objective function of the problem is to minimize the total distance traveled, a distance based visibility function will best serve to this purpose. Two main distance-based heuristics are widely used in the literature. The first one (η_{ij}^{I}) uses the inverse of the distance between the customers and is as follows:

$$\eta_{ij}^{I} = 1/d_{ij} \tag{4.1}$$

where d_{ij} denotes the distance between customers i and j. The second visibility function (η_{ij}^{II}) is the well-known Clarke and Wright's (1964) savings function which is

$$\eta_{ij}^{II} = d_{i0} + d_{0j} - d_{ij} \tag{4.2}$$

where d_{i0} is the distance between customer i and depot and d_{0j} is the distance between depot and customer j.

The experimental results in the literature (as well as our own results) revealed that η_{ij}^{II} performs in general better than η_{ij}^{I}.

4.2. Route Construction

At the start of the route construction procedure, K ants are placed at the K nearest customers to the depot. These ants move in parallel, that is, the number of customers visited by all ants at each step is equal. After a vehicle has returned to the depot, it continues its tour from the customer with the largest attractiveness value.

To put a limit on the exploration and to speed up the algorithm, we use a candidate list which consists of the nearest CL (candidate list size) neighbors of customer. Neighbors that satisfy all of the following conditions are included in the candidate list:

- The vehicle departing from customer i arrives at the neighbor before its latest possible arrival time (also referred to as due date);
- The remaining capacity of the vehicle can accommodate the demand of the neighbor;
- After visiting the neighbor the vehicle can return to the depot before the depot's due date.

If the list is empty, then there exists no feasible customer to visit after customer i and the vehicle returns to the depot. If the candidate list includes only one customer, it is selected; otherwise, the next customer is selected using the probabilistic action choice rule given in equation (2.1).

4.3. Local Search

Dorigo and Stützle (2004) analyzed the efficiency of ACO with and without local search procedures and showed that ACO is more efficient when combined with a local search procedure. As the neighborhood structures of ACO and local search are different, there is a good chance that the quality of our solution constructed by ACO will improve by the local search.

In this thesis, two types of local search procedures, namely Move and Exchange, are utilized to further improve the routes constructed by the ants. These procedures are applied at the end of each iteration and pheromone trails are updated accordingly.

4.3.1. Move Procedure

Move procedure attempts to improve the solution by removing a customer and inserting it between two other customers, intra-route or inter-route. The procedure is illustrated in Figure 4.1 (intra-route) and Figure 4.2 (inter-route).

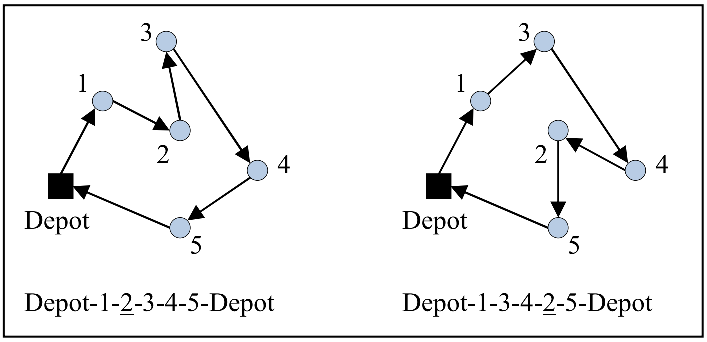

Figure 4.1. Intra-route move

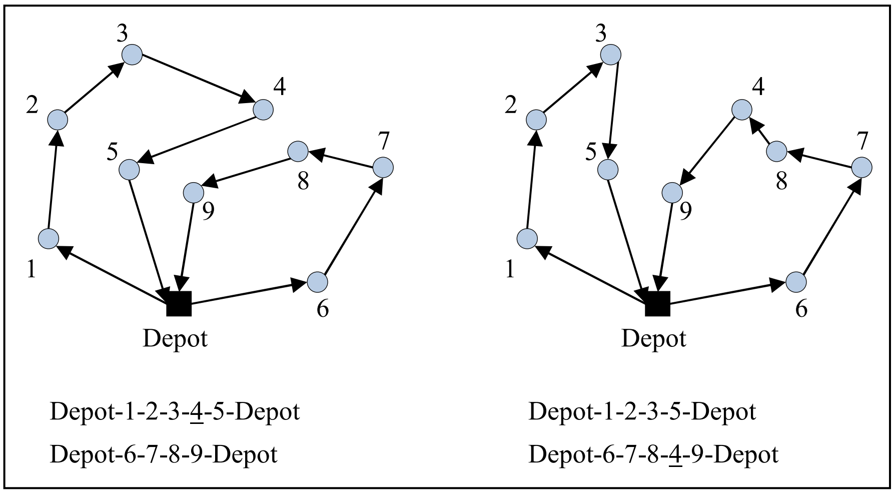

Figure 4.2. Inter-route move

The underlined customer in Figure 4.1 and Figure 4.2 is the customer that is being considered for "moving". Note that the inter-route move procedure may reduce the total number of vehicles by moving all the customers on one route to other routes.

4.3.2. Exchange Procedure

The "exchange" procedure was first proposed for TSP by Croes (1958). The simple idea behind this procedure is to exchange two customers in a single route (intra-route) or between routes (inter-route) until no further improvements are available. Intra-route "exchange" and inter route "exchange" procedures are illustrated in Figure 4.3 and Figure 4.4, respectively.

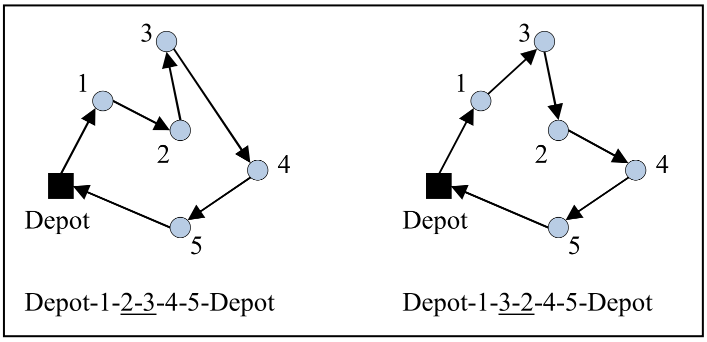

Figure 4.3. Intra-route exchange

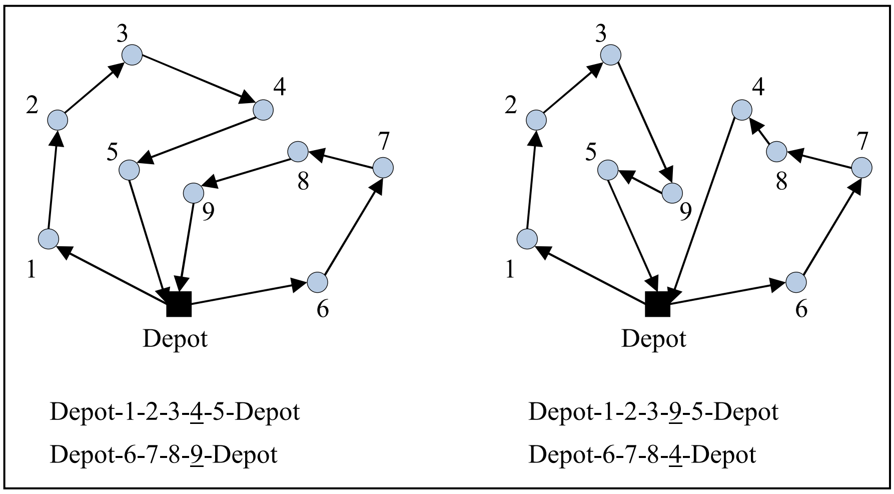

Figure 4.4. Inter-route exchange

The customers to be exchanged are underlined in Figure 4.3 and Figure 4.4. In a problem with N customers, there exist a maximum number of $N(N\text{-}1)/2$ possible customer exchanges. However, possible number of exchanges in our problem decreases significantly due to the feasibility rules.

4.3.3. Push Forward Approach

To speed up the local search, we utilize a structure called *push forward* (*PF*), which is similar to the structure introduced by Solomon (1985). In the route construction process, the maximum available *PF* value of each customer is calculated and stored. Then in the local search, the new *PF* values are compared with the stored values. If any of the new *PF* values exceeds the corresponding stored values, then the exchange/move under consideration is infeasible.

The calculation of the new values is as follows. First, the *PF* values at the customers that are to be exchanged (in "exchange") or to be moved (in "move") are calculated. The vehicle might be waiting at the next customer before the move or the exchange and *PF* is calculated accordingly (Figure 4.5).

```
if (waitingTime > 0)
   PF = MAX(newArrival-readyTime, 0)
else
   PF = MAX(newArrival, readyTime)-arrivalTime
end if
```

Figure 4.5. PF calculation for the exchanged/moved customers

Time spent at the next customer before the start of the service time is denoted as *waitingTime*. The arrival times at the next customer before and after the move or the exchange are denoted as *arrivalTime* and *newArrival* respectively where *readyTime* denotes the earliest possible arrival time. For the other customers, the change in travel time (referred to as *change*) due to the possible time interval changes is calculated. The *PF* is again calculated by taking the waiting times into consideration (Figure 4.6).

```
if (waitingTime > 0)
   if (PF + change > 0)
       PF = MAX(PF + change - waitingTime, 0)
   else
       PF = 0
   end if
else
   if (PF + change > 0)
       PF = PF + change
   else
       PF = MAX(readyTime – arrivalTime, PF + change)
   end if
end if
```

Figure 4.6. PF calculation for the remaining customers

This calculation continues for the remaining customers until an infeasible customer is found, all customers are evaluated or *PF* is zero. A *PF* value of zero means no change in the arrival and departure time of the customer.

Figure 4.7 illustrates the calculation of the *PF* values. The *PF* values of the customers in circles are calculated first and then the calculation is done for the customers in rectangles. The arrival and departure times of the other customers in the figure do not change.

Exchange – Intra-Route	Move – Intra-Route
0-53-**26**-52-77-**20**-58-96-0	0-53-**26**-52-77-20-58-96-0
↓	↓
0-53-**20**-52-77-**26**-58-96-0	0-53-52-77-20-58-**26**-96-0

Exchange – Inter-Route	Move – Inter-Route
0-53-**26**-52-77-20-0	0-53-**26**-52-77-20-0
0-50-5-32-6-**25**-3-2-0	0-50-5-32-6-25-3-2-0
↓	↓
0-53-**25**-52-77-20-0	0-53-52-77-20-0
0-50-5-32-6-**26**-3-2-0	0-50-5-32-6-25-**26**-3-2-0

Figure 4.7. Illustration of push forward calculations

4.4. Update of Pheromone Trails

There is a high correlation between the size of the search space and the amount of pheromone deposited and evaporated. In a setting where the evaporation is relatively high, a slower convergence is observed. Besides, the ratio of the initial pheromone to the amount of pheromone deposited at each iteration is also another factor on the convergence rate. The initial pheromone should be high enough to prevent a quick stagnation. In this study the nearest neighbor solution with distance L_0 is used for the initial pheromone setting. Pheromone amount on each arc is initialized as N/L_0.

In the latter iterations, first the pheromone trails are evaporated at the rate ρ and then k elitist ants are allowed to reinforce the trails. In our pheromone reinforcement strategy, we utilize k-1 best-ranked ants for the first P iterations (referred to as preliminary iterations) and in the remainder of iterations we allow *best-so-far* ant along with the k-1 best-ranked ants to deposit pheromone. Our aim in adopting this strategy is to avoid a quick stagnation.

A heuristic procedure called pheromone re-initialization is also implemented in order to assist the exploration of the search space. If the objective function value does not change for a certain amount of iterations, after a number of preliminary iterations, all of the pheromone deposited on each arc is evaporated and re-initialized using the *best-so-far* ant's total distance, $best^{\Psi}$.

```
procedure re-initializePheromone
  input currentIteration
  input index
  i ← currentIteration
  if (i > preliminaryIterations and bestΨ(i)=bestΨ(i-1)) then
     index ← index + 1
  else
     index ← 0
  end if

  if (index =nonImprovingIterations) then
     reset all pheromone trails
     initialize pheromone trails with bestΨ(i)
  end if
end procedure
```

Figure 4.8. Pseudo-code of the pheromone re-initialization

Figure 4.8 gives the implementation of the pheromone re-initialization procedure. The performance of re-initializing the pheromones is analyzed in Chapter 5 within the context of preliminary experiments.

4.5. Extensions to the Time-dependent VRPTW

In TDVRPTW, the objective function and travel speeds are adapted accordingly. In addition, the local search and pheromone update procedures are modified in line with the new objective function of minimizing the total travel time.

4.5.1. Time Dependency / Travel Speeds

In this study, deterministic time-dependent travel times are obtained by dividing the scheduling horizon into time intervals. In addition to the time interval of the day, the travel times depend on the road types. Each arc between customer pairs is assigned a road type randomly. Also, each road type has its own travel time distribution over the time intervals. During rush hours, the travel time increases and it may become infeasible to visit a customer after the current customer. Time-dependent travel speeds are embedded in the algorithm by utilizing a travel time matrix similar to Ichoua et al’s (2003) approach. Different from their approach, the scheduling horizon is also divided to time intervals of inequal length and the performances of the settings with equal and unequal time intervals are compared. The whole travel speed matrix used in this study is given in Chapter 5 (Experimental Study 3).

In the algorithm, the travel speeds are calculated via a procedure named *calculateTravelTime* by taking the travel times and the current time into consideration. The pseudo-code of the *calculateTravelTime* procedure is given in Figure 4.9.

```
procedure calculateTravelTime
   input t_0
   input d_ij
   input v_cT_k
   t ← currentTime
   d ← d_ij
   t′ ← t + (d_ij/v_cT_k)
   while (t′ > t̄_k ) do
        d ← d - v_cT_k(t̄_k-t)
        t ← t̄_k
        t′ ← t + (d/v_cT_k+1)
        k ← k + 1
   end while
   return (t′- t_0)
end procedure
```

Figure 4.9. Pseudo-code of the *calculateTravelTime* procedure

The start time of the travel is denoted by t_0 while $d_{ij}$and v_{cT_k}denote the distance between the customers i and j and the corresponding travel speed coefficient respectively. $\bar{t}_k$ denotes the start time of period k.

4.5.2. Local Search

As the objective function of the time-dependent problem discussed in this thesis is minimizing the total tour time, the local search procedures are modified accordingly.

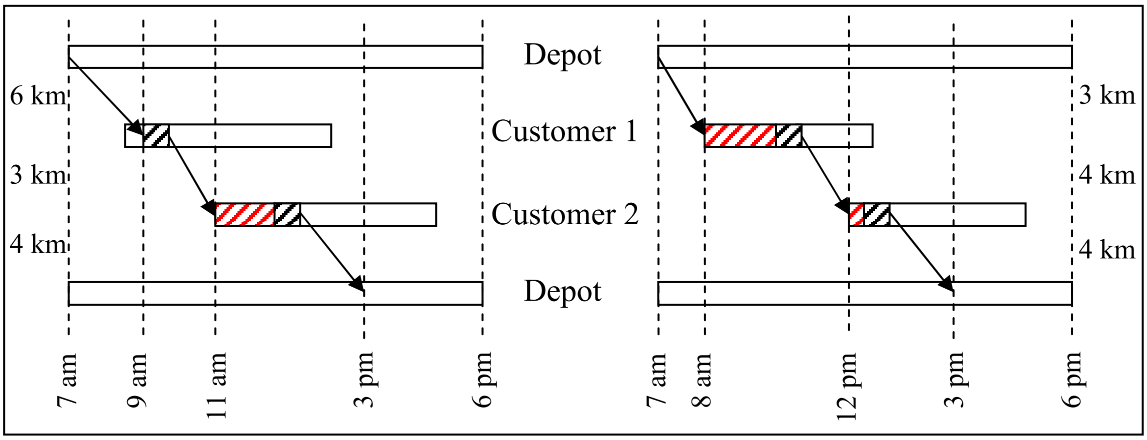

Figure 4.10. Illustration of an exchange where no gain in terms of tour time is obtained

Figure 4.10 illustrates an exchange resulting in a shorter tour distance but the same tour time. Local search procedure is applied on a route with 2 customers (depot - customer 1 - customer 2 - depot) and an anonymous route (not included in the figure). The waiting times resulting from arrivals earlier than the start of the time windows are shown in red shaded regions. The first customer with time windows [8.30 am-2.00 pm] is exchanged with a customer with time windows [8.00 am-1.00 pm]. However, both routes end at the depot at 4.00 pm. So, although this exchange decreases the total distance it does not improve the solution in the time-dependent case.

4.5.3. Pheromone Update

Since the objective is minimizing the total tour time, the initial pheromone level is set to N/L_0^T where L_0^T is the total tour time obtained using the nearest neighbor solution. The reinforcement of the pheromone trails is also performed based on the tour travel times. Since the scheduling horizon is divided into multiple time intervals, the pheromone network also comprises multiple dimensions. An ant in a time interval deposits pheromone on the corresponding dimension on the network.

CHAPTER 5

COMPUTATIONAL STUDY

This chapter is dedicated to the test of the performance of the proposed algorithm. The most widely used VRPTW benchmark instances in the literature were introduced by Solomon (1985). Though, there is not one common objective and data type that the literature agreed upon. The lack of agreement on the objective function can be observed in different studies which try to minimize the total distance traveled, the number of vehicles, total waiting time, total tour time and combinations of them. The disagreement on the data type arises from the usage of truncated and real arithmetic numbers. These differences lead to difficulties in comparing the results. However, the use of Solomon instances is still the best way to perform an evaluation on the performance of a new approach (Alvarenga et al., 2007). Thus, the proposed algorithm is tested on these problems using real numbers (float precision) only.

The benchmark problems of Solomon include six different problem types, namely C1, C2, R1, R2, RC1 and RC2. Each type of problem consists of 100 customers which reside in a 100x100 square area. In the C-type problems the customers are clustered whereas they are uniformly randomly distributed over the area in the R-type. The RC problem sets include a combination of clustered and randomly distributed customers. Problem sets of type 1 and type 2 differ not only by the length of the time windows but also by the vehicle capacity. In type 2 problem sets the customers have larger time windows and the vehicles have larger capacity. Thus, the number of routes is less compared to type 1 problems.

Due to the random assignment of road types to the arcs in the network, a direct comparison with the studies on the time-dependent version of the problem (which are scarce in the literature) is not possible. Therefore, the performance of the algorithm is tested on the time-independent benchmark problems. The algorithm is first shown to be efficient and then applied for the time-dependent version.

Three main experimental studies are executed. First, the effect of using a multi-dimensional pheromone network of time intervals is tested. After determining the best parameter set, the second experimental study is carried out on the time-independent case. In these experiments, some best-known solutions in the literature are outperformed. Finally the algorithm is tested on the time-dependent case utilizing the findings in the first two experimental studies.

A trade-off exists between the solution quality and computational time. Although narrowing the neighborhood in local search decreases computational time, the whole neighborhood is searched to increase the diversification. To reduce the computational effort, an elitist local search approach can also be applied in which only the solutions obtained by a subset of ants (selected with respect to the solution quality they have achieved) are subject to the local search. However, we do not adopt such an approach since we attach more importance to the solution quality.

The order of the local search procedures may also affect the solution quality. In addition to decreasing the total distance/total tour time, "move" procedure may decrease the total number of vehicles. Applying first the "exchange" procedure narrows down the search space of the "move" procedure, thus, resulting in more vehicles. As an implicit objective function is minimizing the total number of vehicles, "exchange" procedure is applied after the application of "move".

The algorithm is coded in C# and executed on a Pentium 2.40 GHz processor.

5.1. Preliminary experiments

The preliminary experiments are performed to gain some insights on the algorithm. These experiments include the stand-alone performance comparison of ACO and local search and the performance evaluation of the *re-initializing pheromone* procedure.

5.1.1. ACO and Local Search comparison

ACO without being supported by a local search procedure exhibits poor performance whereas the performance of a local search procedure increases with the increasing quality of the initial solution (Dorigo and Stützle, 2004). In this experimental study, the contribution of the ACO and the local search procedures to the solution quality are compared. This comparison is made on the first problems of each set of the instances of Solomon, namely C101, C201, R101, R201, RC101 and RC201.

ACO performs diversification in the initial iterations. The weight of the intensification increases with the increasing number of iterations thank to the evaporation of pheromone. Thus, the contributions at the 50th iteration over 5 runs are used for comparison.

Table 5.1. Stand-alone solutions of ACO and local search procedures

	ACO		After Move		After Exchange		Optimal	
Problem	TD	VN	TD	VN	TD	VN	TD	VN
C101	891.875	10.4	828.936	10	828.936	10	827.3	10
C201	714.674	4.8	633.161	4.2	632.651	4.2	589.1	3
R101	1749.108	20.8	1657.517	20.2	1655.633	20.2	1637.7	20
R201	1568.053	10.2	1247.214	9.4	1247.133	9.4	1143.2	8
RC101	1882.978	18.4	1687.613	17	1683.501	17	1619.8	15
RC201	1840.711	11.2	1424.418	10	1421.064	10	1261.8	9

Table 5.1 summarizes the average results. TD and VN denote the total distance traveled and the total number of vehicles used, respectively. In the second and the third columns, the total distance and the total number of vehicles found by ACO without utilizing any local search procedures are given. The fourth and the fifth columns give the results gained after the application of Move procedure whereas the two columns that follow give the results gained after the application of Exchange procedure. In C type problems the gap between the optimal solution and the ACO without local search procedures is small due to the clustered network structure. The gap increases in R and RC type problems. The average gap over all problem types is 22.1%. However, it reduces to 5.5% after the application of the local search procedures. The total distance decreases by 13.5% on the average after the application of “move”. In addition, the total number of vehicles, which is expected to decrease implicitly by the “move”, is 6.5% less than the ACO solutions. After the “exchange” procedure the total distance decreases by 0.13% on the average.

Although the local search procedures improve the solution quality considerably, they add up to the computational effort much more than the ACO. Figure 5.1 shows the average results of the runs made on the first problems of each problem set in order to compare the computational times of ACO and local search procedures.

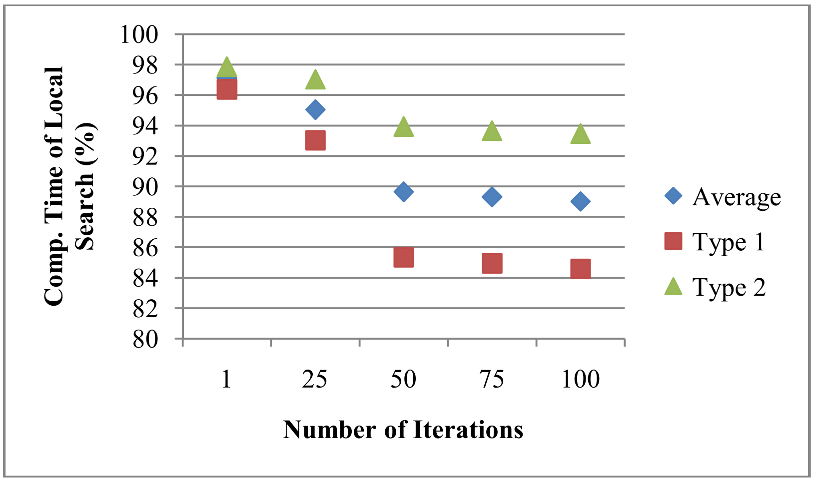

Figure 5.1. Computational Time of Local Search in iterations 1, 25, 50, 75 and 100

It can be observed from the Figure 5.1 that nearly 92.02% of the computational time is consumed by the local search procedures. For the type 1 problems with tight constraints, this percentage decreases to 88.86% whereas it is 95.18% for the type 2 problems.

The contributions of ACO and the local search procedures to the overall solution quality inquire the role of ACO. One may think that the local search, given any initial solution, may bring the objective function to a good value. However, this is not the case. The performance of the local search procedures without interacting with ACO is also tested using the nearest neighbor solution as the initial solution. The test is again carried on a sample including only the first problem of each problem set.

Table 5.2. The performance of the local search procedures on the nearest neighbor solution

Problem	Nearest Neighbor TD	Nearest Neighbor VN	After Local Search TD	After Local Search VN	Optimal TD	Optimal VN
C101	1779.251	21	857.825	11	827.3	10
C201	1982.492	15	900.865	8	589.1	3
R101	2623.245	37	1845.213	25	1637.7	20
R201	2011.562	15	1342.217	13	1143.2	8
RC101	2780.442	27	1832.121	18	1619.8	15
RC201	2487.719	14	1677.929	11	1261.8	9

The results are given in Table 5.2. The average gap with the optimal solutions is 19.4%. There is also a tremendous gap of 32.3% on the number of vehicles. This gap was 8.9% in the previous experiment.

The experiments presented above show that the local search procedures contribute a lot to the solution quality of ACO. However, the local search mechanism is efficient if it is fed by a good initial solution, such as the solution obtained through ACO.

5.1.2. Re-initialization of Pheromones

The re-initialization of the pheromones would allow diversification when stagnation is observed in the algorithm. In a run with 150 iterations, this approach is applied when no improvements in the objective function is observed for 25 consecutive iterations. The first 25 iterations are set for diversification and are not accounted for. The effect of re-initializing the pheromones is tested on a sample comprising the first problem of each set.

Table 5.3. Effects of pheromone re-initialization procedure

Problem	TDB	TDA	Improvement (%)
C101	828.936	828.936	0.00
C201	591.556	591.556	0.00
R101	1647.428	1644.937	0.15
R201	1171.934	1165.981	0.51
RC101	1660.904	1659.346	0.09
RC201	1297.818	1295.556	0.17
Average	1199.763	1197.719	0.15

The results are given in Table 5.3 with TDB and TDA indicating the total distance before and after re-initializing pheromones, respectively. After re-initialization, the objective function improves 0.15% on the average with the best improvement being 0.51%. As the gain of this procedure is very small considering the additional computational effort it creates for searching the solution space from the beginning, it is not utilized in the rest of the experiments.

A snapshot of a sample run in which the pheromones are re-initialized is given in Appendix E.

5.2. Experimental Study 1 – One-dimensional network – multi-dimensional network comparison

In this experimental study, a multi-dimensional pheromone network is compared with the one-dimensional pheromone network. To our knowledge, there is no previous study on ACO that utilizes multi-dimensional pheromone network for time-independent VRP. In our experimental setting, the multi-dimensional pheromone network consists of three dimensions, each representing a time interval. All ants deposit pheromone on the same single pheromone network in one-dimensional case. However, an ant in time interval *t* deposits pheromone on the corresponding dimension in multi-dimensional case as illustrated in Figure 5.2.

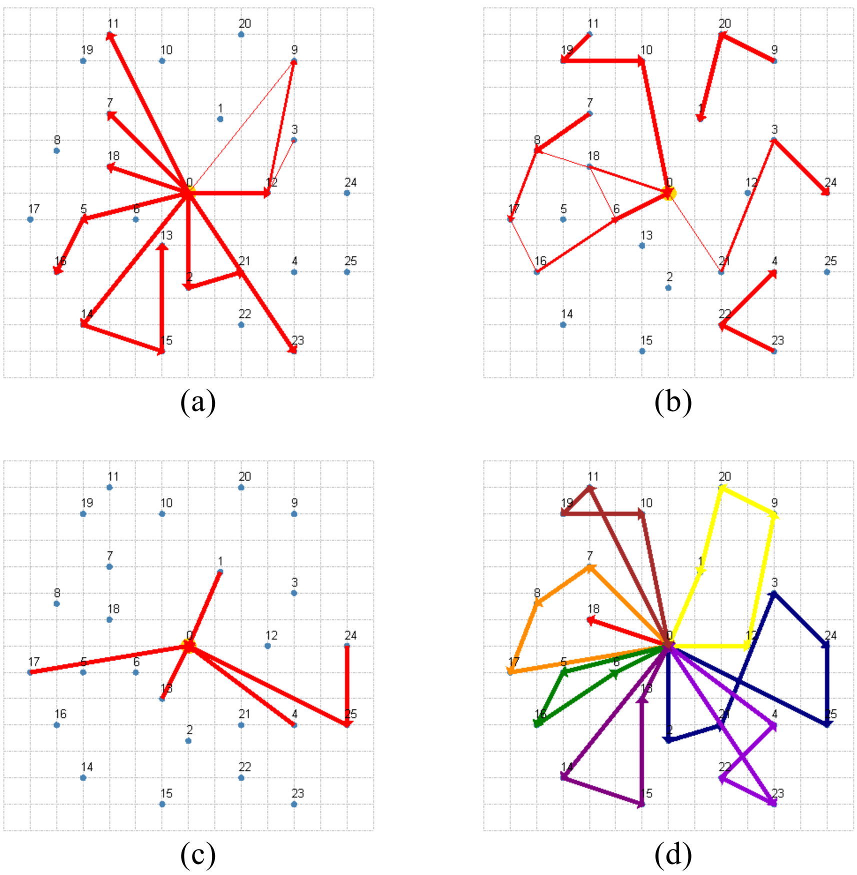

Figure 5.2. Pheromone levels on a three-dimensional network for a 25-customer problem: (a) Pheromones in the first time interval, (b) Pheromones in the second time interval, (c) Pheromones in the last time interval, (d) Route assignments.

This figure shows the pheromone levels on each network in a sample solution of the problem R101 with 25 customers found by using a three-dimensional network. The length of each interval is found by dividing the due date of the depot by the number of intervals and the first (second, third) network is used to keep track of the pheromone levels in the first (second, third) time interval. It can be observed that on the first network, the arcs directed from the depot to the customers have high pheromone levels whereas on the third network the pheromone levels on the arcs directed from the customers to the depot are higher. In the second network, pheromone is accumulated only on the arcs which are traversed in the second time interval. Multi-dimensional network structure implicitly indicates the most suitable time interval for the travel between each customer pair. The pheromone trails and the final routes overlap strictly.

For each problem, 10 runs are made with the following parameter settings that are found to perform well in the preliminary experiments; $\alpha = 1$, $\beta = 0$, $\rho = 0.15$, number of iterations = 100, number of preliminary iterations = 25, number of ants = 100, elitist ants = 6, $CL = 50$.

Table 5.4. The summary of the results of experimental study 1

Problem	1 Network		3 Networks		Best Known	
Set	TD	NV	TD	NV	TD	NV
C1	828.380	10.00	828.380	10.00	828.380	10.00
R1	1186.501	13.58	1187.282	13.58	1181.453	13.08
RC1	1352.620	13.13	1357.403	13.25	1339.235	12.75
C2	589.859	3.00	589.859	3.00	589.859	3.00
R2	908.767	5.82	901.507	5.55	898.067	5.55
RC2	1033.056	6.38	1027.401	6.50	1015.738	6.38

The average results of the experiment 1 are given in Table 5.4. ‘1 Network’ and ‘3 Networks’ columns show the results for the one-dimensional and multi-dimensional pheromone network settings respectively. For C problem sets, both one-dimensional and multi-dimensional pheromone networks find the best-known distances as a result of the clustered network structure which narrows the feasible solution space. For R and RC problem sets there is no global best pheromone network policy. One-dimensional pheromone network outperforms the multi-dimensional pheromone network in type 1 problems where time windows are narrower and vehicle capacities are smaller compared to the type 2 problems. However, a multi-dimensional policy is more suitable for type 2 problems. When the overall performances are analyzed, the multi-dimensional network with the average gap of 0.67% slightly outperforms the one-dimensional network with the average gap of 0.79%. This improved solution quality comes at the cost of an increased computational effort. The usage of a multi-dimensional network increases the average computational time by 22.2%.

Table 5.5. New best values found in experimental study 1

Problem	TD	NV	Number of Networks	Best Known TD	NV	Ref.
R110	1079.097	12	1	1080.360	11	RT[1]
R202	1048.510	7	3	1049.730	7	A[2]
R203	884.752	6	3	900.080	5	A
R204	756.185	5	3	772.330	4	A
R211	782.815	4	1	787.511	5	A
RC203	942.059	5	3	945.960	5	A

The proposed algorithm (ACO-TI) finds the same best-known results reported in the literature in 23 instances and gives better results for 6 instances out of 56 instances. The new best distances are given in Table 5.5. Two of the new best distances are of type 1 problems and found by utilizing a one-dimensional pheromone network. The rest are found by using a three-dimensional pheromone network. Detailed results of the experimental study 1 can be found in Appendix B.

5.3. Experimental Study 2 – Extension of Experimental Study 1 with parameter analysis

Experimental study 2 aims at analyzing the role of the heuristic information on the solution quality. We first perform a preliminary experimental study to determine the best parameter setting. The following parameters are taken into consideration: $\alpha = 1$, $\beta = 0, 1, 2, 3$, $\rho = 0.05, 0.10, 0.15$, number of iterations = 100, number of preliminary iterations = 25, number of ants = 100, elitist ants = 6, 12, 18, CL = 25, 50, 100. A total number of 108 parameter sets are tested on a sample set that consists of the first problems of each set again.

[1] Rochat, Y. And Taillard, E.D. (1995)
[2] Alvarenga, G.B. et al. (2007)

Table 5.6. Results of the parametric analysis

Parameter Set	ρ	*CL*	Elitist Ants	β	Average TD	Average VN	Gap
1	0.15	25	6	1	1441.245	13.75	-
2	0.15	25	6	2	1441.566	13.70	0.02%
3	0.15	50	6	1	1441.887	13.90	0.04%
4	0.10	25	6	1	1442.411	13.70	0.08%
5	0.15	100	12	1	1443.554	13.55	0.16%

The results of the parametric analysis are shown in Table 5.6. The 5 best parameter sets and the gaps between the first and the other parameter sets are reported. The results show that the difference between the best performing parameter setting and the fifth is minor. We have conducted our experiments on the best parameter with the values $\alpha = 1$, $\beta = 1$, $\rho = 0.15$, number of iterations = 100, number of preliminary iterations = 25, number of ants = 100, elitist ants = 6 and $CL = 25$.

Table 5.7. The summary of the results of experimental study 2

Problem	1 Network		3 Networks		Best Known	
Set	TD	NV	TD	NV	TD	NV
C1	828.380	10.00	828.380	10.00	828.380	10.00
R1	1187.465	13.58	1183.613	13.50	1181.453	13.08
RC1	1362.345	13.63	1352.636	13.13	1339.235	12.75
C2	589.930	3.00	589.859	3.00	589.859	3.00
R2	920.780	6.20	900.940	5.73	898.067	5.55
RC2	1035.055	6.38	1029.411	6.50	1015.738	6.38

The average results of the experiment 2 are given in Table 5.7. For C problem sets of type 1, both one-dimensional and multi-dimensional pheromone networks find the best known distances. In C problem sets of type 2, multi dimensional pheromone network finds the best results and the one-dimensional network exhibits the same performance except the instance C204. For both R and RC problem sets, the best pheromone network policy is to use the multi-dimensional version. The average gap of the multi-dimensional network with the optimal is 0.44% whereas it is 0.92% for the one-dimensional network. The gap between one-dimensional and multi-dimensional network settings is only a 0.66%.

Table 5.8. New best values found in experimental study 2

Problem	TD	NV	Number of Networks	Best Known TD	NV	Ref.
R104	977.547	11	3	982.010	10	RT[3]
R108	946.422	10	3	948.573	10	A[4]
R110	1075.911	12	3	1080.360	11	RT
R202	1046.281	7	3	1049.730	7	A
R203	883.025	6	3	900.080	5	A
R204	759.775	5	3	772.330	4	A
R205	964.870	6	1	970.880	6	A
R211	785.813	4	3	787.511	5	A
RC202	1111.796	8	3	1113.520	8	A

Table 5.8 gives the new best values found in this experimental study. The new best value of the instance R205 is found using one-dimensional network whereas all other 8 problems are found by using a multi-dimensional setting. The proposed algorithm (ACO-TI) also finds the same results in the literature in 21 instances. Detailed results of the experimental study 2 can be found in Appendix C.

5.4. Experimental Study 3 – Time-dependent Vehicle Routing Problem

In this experimental study, the performance of the algorithm (ACO-TD) is tested on TDVRPTW using an objective function that minimizes the total tour time in a multi dimensional setting. Ichoua et al. (2003) set the number of dimensions to three besides introducing three types of roads. The first and the third dimensions stand for the morning and evening rush hours. The second dimension represents the middle of the day. Their approach and travel speed matrix given in Table 5.9 is used in this thesis.

Table 5.9. The travel speed matrix

	Period 1	Period 2	Period 3
Road type 1	0.54	0.81	0.54
Road type 2	0.81	1.22	0.81
Road type 3	1.22	1.82	1.22

The travel speed coefficients are given in such a way that the average of the coefficients is approximately 1 to keep the difficulty of the problems same as

[3] Rochat, Y. And Taillard, E.D. (1995)
[4] Alvarenga, G.B. et al. (2007)

Solomon's original problems (Ichoua et al., 2003). The assignment of road types to arcs is done randomly. However, these assignments are same for all instances, as reported in Appendix G. Thus, they can be utilized in any future research as a benchmark data.

Three settings are used for dividing the scheduling horizon into three time-periods. In the first setting, the length of each period is equal to each other which are the mostly used method in the literature. Alternatively, the second and the third settings assume the rush hours to be more close to the beginning and the end of the horizon by increasing the length of the second time-period.

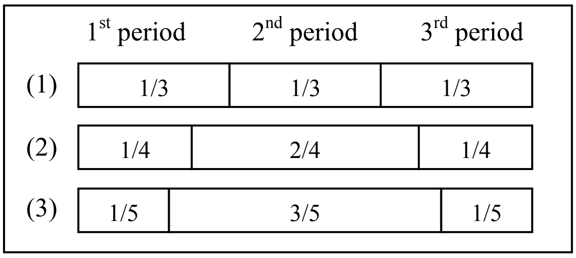

Figure 5.3. The first (1), the second (2) and the third (3) time-period settings

Experimental study 3 includes three main experiments, namely 3.1, 3.2 and 3.3, each corresponding to a time-period setting described in Figure 5.3. In each experiment, the following parameters are used: $\alpha = 1$, $\beta = 0$, $\rho = 0.15$, number of iterations = 100, number of preliminary iterations = 25, number of ants = 100, elitist ants = 6, $CL = 50$.

Table 5.10. Summary of the results of experimental study 3

	Experiment 3.1			Experiment 3.2			Experiment 3.3		
	TD	NV	TT	TD	NV	TT	TD	NV	TT
C1	1093.140	10.47	9946.00	1021.797	10.42	9898.02	1026.571	10.41	9875.36
C2	941.016	4.16	9854.87	952.494	4.06	9841.83	967.617	4.00	9829.22
R1	1499.805	12.72	2298.31	1495.079	12.42	2215.54	1516.487	12.44	2193.30
R2	1627.551	3.69	2352.81	1648.421	3.55	2283.58	1667.776	3.52	2252.03
RC1	1645.410	12.64	2405.31	1639.316	12.21	2301.62	1653.922	12.06	2270.71
RC2	1988.114	4.25	2672.62	2034.117	4.01	2589.75	2035.624	4.04	2550.01

Table 5.10 gives the average results of the time-dependent problem using three mentioned settings. As the problem gets closer to the time-independent version of the

problem, the total tour time is decreased regardless of the problem type. The average tour time of experiment 3.2 is 1.35% less compared to the experiment 3.1. Besides, the average tour time of experiment 3.3 is also 0.54% less compared to the experiment 3.2. When the average number of vehicles is analyzed it is observed that as the rush hours gets more close to the beginning and the end of the scheduling horizon, less vehicles are used.

The detailed results of experiment 3.1, experiment 3.2 and experiment 3.3 are given in Appendix D.

5.5. Summary of Results

The main difference between experimental study 1 and experimental study 2 is the usage/utilization of the visibility function in the second study. However, there is only a slight difference when the average total distances are compared. Unless the parameters are changed dramatically, the algorithm exhibits the same performance due to the robustness of the local search procedures.

Table 5.11. Comparison of experimental studies 1 and 2

3 Networks	Equal	21
	Exp. Study 1 is better	13
	Exp. Study 2 is better	22
	Exp. Study 1 Average Gap	0.556%
	Exp. Study 2 Average Gap	0.461%
	New best known values in Exp. Study 1	4
	New best known values in Exp. Study 2	8
1 Network	Equal	19
	Exp. Study 1 is better	17
	Exp. Study 2 is better	20
	Exp. Study 1 Average Gap	0.723%
	Exp. Study 2 Average Gap	0.925%
	New best known values in Exp. Study 1	3
	New best known values in Exp. Study 2	3

A comparison of the experimental studies 1 and 2 is summarized in Table 5.11. For a multi-dimensional network setting, the results of the experimental study 2 which uses a visibility function are more satisfactory. Although the average gap is smaller for the experimental study 1 using a one-dimensional network, the number of instances that the experimental study 2 finds better is higher. The solutions found in experimental study 1 and experimental study 2 overcome 10 of the recently known best known solutions.

From the type of problem point of view, it is observed that a centralized pheromone deposit policy is more successful in problems where a small feasible solution space exists. As the problem become less constrained, it is more advantageous to use a distributed pheromone structure.

The distances of experiment 3 are longer on the average compared to the time-independent case. This is an expected result since two problems have different objective functions. On the other hand, the average number of vehicles is smaller in time-dependent case. It is also observed that type 2 problems are more sensitive to the time-dependent travel times. The distances for type 2 problems increase dramatically due to the existence of tighter constraints.

Table 5.12. Standard deviations of Experimental Study 3

Problem Set	Setting 1	Setting 2	Setting 3
C1	0.58%	0.33%	0.31%
C2	0.66%	0.47%	0.57%
R1	0.97%	1.01%	0.99%
R2	1.58%	1.49%	1.59%
RC1	1.19%	1.03%	1.10%
RC2	1.97%	1.73%	1.89%

As there exists no base for comparison for time-dependent problems, the efficiency of the algorithm is shown via standard deviations given in Table 5.12. The algorithm is shown to be robust over the average standard deviations.

CHAPTER 6

CONCLUSION AND FUTURE RESEARCH

In this thesis, we propose an ACO algorithm for solving the VRPTW and TDVRPTW. Our experimental results show that the proposed algorithm provides good quality results; however, the computation times are rather long. We have observed that the local search procedure enhances the solution quality of ACO significantly. On the other hand, a large portion of the computational time is consumed by the local search procedure.

Further research may focus on a selective local search policy to reduce the computational effort. To improve the performance of the algorithm, a visibility function using the time window information can be implemented and a more detailed analysis on the trade-off between the solution quality and computational effort may be conducted.

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Appendix A

Flow chart of the algorithm

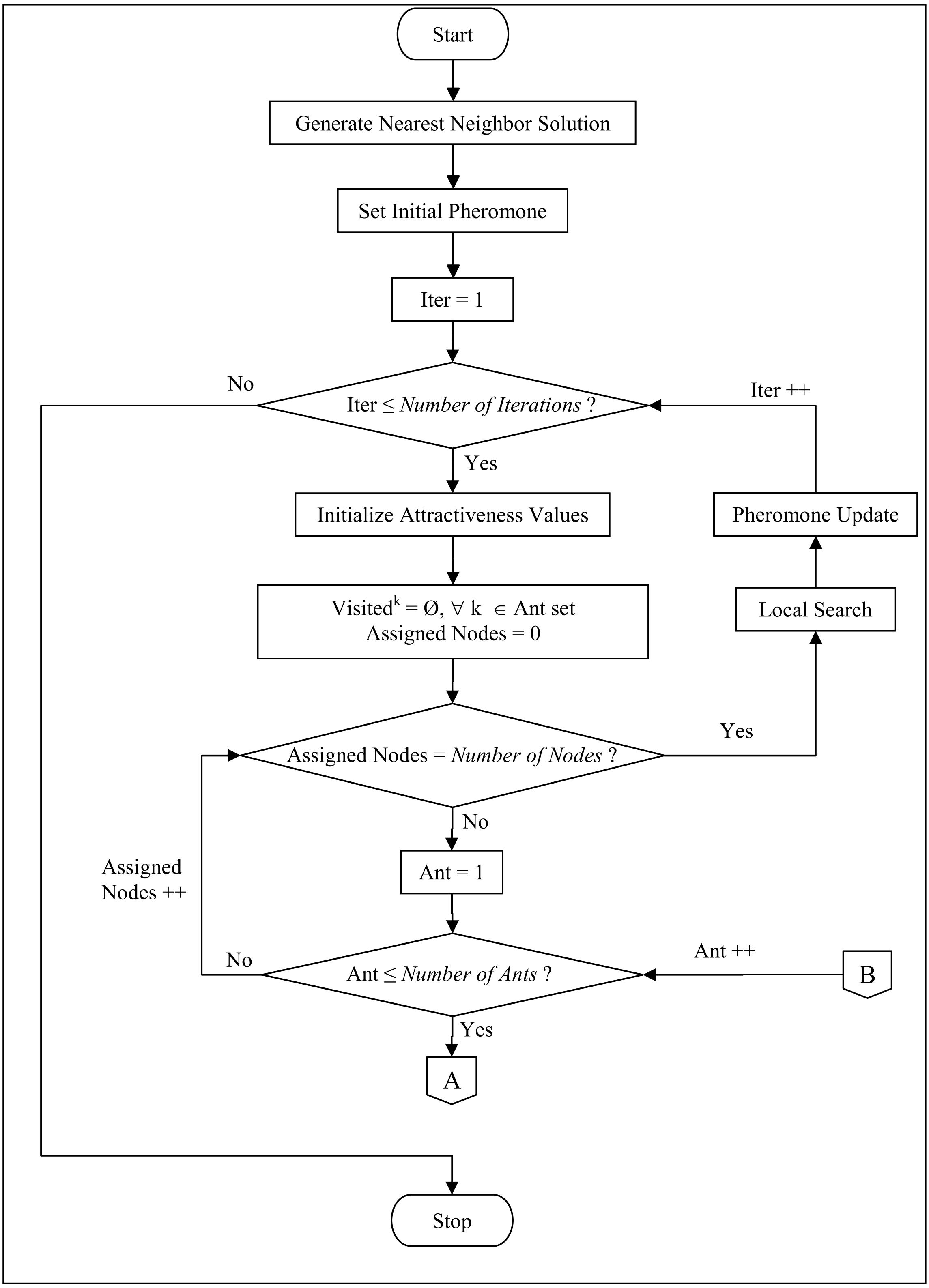

Figure A.1.1. Flow chart of the algorithm

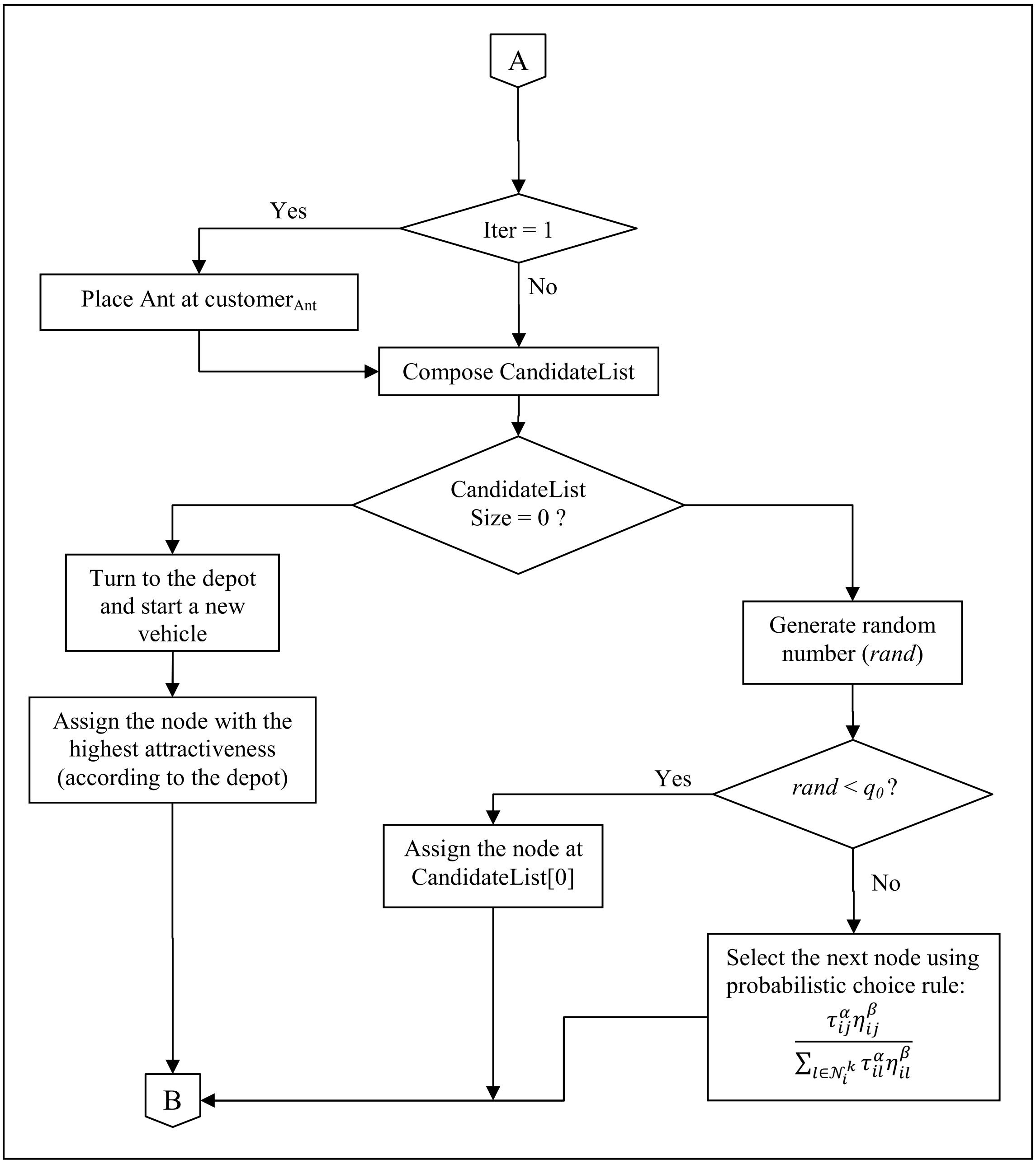

Figure A.1.2. Flow chart of the algorithm

Appendix B

Detailed results of the experimental study 1

A : Alvarenga, G.B. et al. (2007),
C : Cordeau, J-F. et al. (2000),
M : Mester, D. (2002),
RT : Rochat, y. and Taillard, E.D. (1995),
S : Shaw, P. (1998)

Table B.1 The average results of experimental study 1 for type 1 problems with 1 network and 3 networks

	ACO-TI 1 Network			ACO-TI 3 Networks		
Problem	NV	TD	Comp. Time (min)	NV	TD	Comp. Time (min)
C101	10.00	828.936	4.76	10.00	828.936	6.01
C102	10.00	828.936	9.00	10.00	828.936	10.79
C103	10.00	828.064	14.25	10.00	828.065	16.32
C104	10.00	824.776	23.50	10.00	824.812	26.52
C105	10.00	828.936	5.47	10.00	828.936	6.89
C106	10.00	828.936	6.15	10.00	828.936	7.71
C107	10.00	828.936	6.57	10.00	828.936	8.50
C108	10.00	828.936	8.22	10.00	828.936	10.52
C109	10.00	828.936	13.32	10.00	828.936	16.46
R101	20.50	1652.607	3.75	20.00	1644.863	4.31
R102	18.30	1477.616	6.56	18.00	1475.424	7.16
R103	15.00	1225.745	9.34	14.60	1219.238	10.32
R104	11.40	995.296	13.19	11.80	1003.092	15.61
R105	16.00	1375.951	4.78	16.00	1373.015	5.67
R106	14.00	1254.128	7.76	13.90	1256.158	8.79
R107	12.00	1088.860	11.13	12.00	1093.655	12.13
R108	10.50	956.968	14.95	10.60	957.833	16.92
R109	12.80	1153.232	7.87	12.90	1156.430	8.81
R110	12.00	1085.842	10.33	12.00	1086.740	10.96
R111	12.00	1057.948	10.70	12.00	1057.781	11.91
R112	10.90	972.314	15.42	11.00	972.953	16.37
RC101	16.90	1667.407	4.30	16.70	1655.778	4.92
RC102	15.00	1495.219	6.10	15.00	1486.899	7.01
RC103	12.00	1281.044	8.38	12.00	1286.142	9.65
RC104	10.60	1157.701	13.38	10.90	1162.586	14.29
RC105	15.80	1544.204	5.85	16.10	1547.280	6.42
RC106	13.90	1402.267	6.62	14.00	1402.879	7.48

Table B.2 The average results of experimental study 1 for type 2 problems with 1 network and 3 networks.

	ACO-TI 1 Network			ACO-TI 3 Networks		
Problem	NV	TD	Comp. Time (min)	NV	TD	Comp. Time (min)
C201	3.00	591.556	8.69	3.00	591.556	10.59
C202	3.00	591.556	20.95	3.00	591.556	24.47
C203	3.00	591.908	33.76	3.00	591.173	39.86
C204	3.00	591.643	65.83	3.00	593.789	71.77
C205	3.00	588.876	12.94	3.00	588.876	15.99
C206	3.00	588.493	17.96	3.00	588.493	20.93
C207	3.00	588.286	19.49	3.00	588.286	23.78
C208	3.00	588.374	24.28	3.00	588.341	28.76
R201	9.40	1177.562	12.97	8.80	1175.163	14.06
R202	8.00	1074.425	26.74	7.80	1056.298	28.30
R203	7.20	913.204	48.60	6.20	897.163	52.47
R204	4.80	771.894	89.33	4.70	768.836	98.10
R205	5.90	1000.514	26.27	5.70	994.279	29.26
R206	6.00	936.137	43.18	5.90	925.800	47.07
R207	5.50	859.701	66.36	5.40	850.008	74.04
R208	4.10	750.516	128.87	3.50	739.571	129.35
R209	6.10	896.446	36.28	5.40	899.955	41.23
R210	6.40	948.861	40.36	6.00	942.684	43.03
R211	4.20	796.871	71.62	4.20	802.108	80.52
RC201	9.60	1298.338	12.69	8.60	1295.461	13.38
RC202	8.60	1146.624	23.51	8.20	1132.250	25.27
RC203	6.30	982.383	40.22	5.60	960.726	42.65
RC204	4.60	829.874	84.48	4.20	823.992	88.80
RC205	7.30	1178.932	18.91	7.90	1183.235	20.55
RC206	6.40	1111.072	26.56	6.20	1113.660	28.43
RC207	6.60	1023.812	38.26	6.60	1013.357	41.44
RC208	5.10	825.959	73.46	5.10	836.571	78.89

Table B.3 Best total distance (TD) published heuristic results and ACO-TI results for type 1 problems. The results are emphasized in bold when ACO-TI overcomes the previous best solutions

	Previous best TD solution			**ACO-TI**				
Problem	**Ref.**	**NV**	**TD**	**NV**	**TD**	**Gap**	**Number of Networks ***	**Comp. Time (min) ****
C101	RT	10	828.940	**10**	**828.940**	0.000%	1 – 3	4.81
C102	RT	10	828.940	**10**	**828.940**	0.000%	1 – 3	8.75
C103	RT	10	828.060	**10**	**828.060**	0.000%	1 – 3	14.36
C104	RT	10	824.780	**10**	**824.780**	0.000%	1 – 3	23.61
C105	RT	10	828.940	**10**	**828.940**	0.000%	1 – 3	5.40
C106	RT	10	828.940	**10**	**828.940**	0.000%	1 – 3	6.37
C107	RT	10	828.940	**10**	**828.940**	0.000%	1 – 3	6.65
C108	RT	10	828.940	**10**	**828.940**	0.000%	1 – 3	8.28
C109	RT	10	828.940	**10**	**828.940**	0.000%	1 – 3	13.34
R101	A	20	1642.870	**20**	**1642.876**	0.000%	3	3.91
R102	A	18	1472.620	18	1472.815	0.013%	1 – 3	6.60
R103	RT	14	1213.620	**14**	**1213.624**	0.000%	3	10.01
R104	RT	10	982.010	11	984.204	0.223%	1	13.51
R105	A	15	1360.780	16	1369.080	0.610%	3	5.76
R106	A	13	1241.518	14	1250.756	0.744%	1	7.69
R107	A	11	1076.125	12	1087.041	1.014%	1	11.10
R108	A	10	948.573	**10**	**948.573**	0.000%	1	15.48
R109	A	13	1151.839	**13**	**1151.838**	0.000%	1	8.07
R110	RT	11	1080.360	**12**	**1079.097**	-0.117%	1	10.01
R111	A	12	1053.496	**12**	**1053.496**	0.000%	1 – 3	10.16
R112	RT	10	953.630	10	968.621	1.572%	1	15.58
RC101	RT	15	1623.580	16	1646.532	1.414%	3	4.95
RC102	A	14	1466.840	15	1480.458	0.928%	3	7.01
RC103	S	11	1261.670	11	1276.059	1.140%	3	9.83
RC104	C	10	1135.480	10	1147.546	1.063%	1	12.61
RC105	A	16	1518.600	**16**	**1518.599**	0.000%	3	6.26
RC106	A	13	1377.352	13	1389.098	0.853%	1	7.54
RC107	A	12	1212.830	12	1224.244	0.941%	1	8.81
RC108	A	11	1117.526	11	1119.830	0.206%	1	11.19

* Multiple numbers indicate that each of the algorithms with the corresponding number of networks has found the same best solution
** Computational time is taken as the average of the algorithms with the corresponding number of networks

Table B.4 Best total distance (TD) published heuristic results and ACO-TI results for type 2 problems. The results are emphasized in bold when ACO-TI overcomes the previous best solutions.

	Previous best TD solution			ACO-TI				
Problem	**Ref.**	**NV**	**TD**	**NV**	**TD**	**Gap**	**Number of Networks ***	**Comp. Time (min) ****
C201	RT	3	591.560	**3**	**591.560**	0.000%	1 – 3	8.87
C202	RT	3	591.560	**3**	**591.560**	0.000%	1 – 3	20.58
C203	RT	3	591.170	**3**	**591.170**	0.000%	1 – 3	32.53
C204	RT	3	590.600	**3**	**590.600**	0.000%	1 – 3	66.20
C205	RT	3	588.880	**3**	**588.880**	0.000%	1 – 3	12.53
C206	RT	3	588.490	**3**	**588.490**	0.000%	1 – 3	17.65
C207	RT	3	588.290	**3**	**588.290**	0.000%	1 – 3	18.96
C208	RT	3	588.320	**3**	**588.320**	0.000%	1 – 3	24.40
R201	A	9	1148.480	9	1157.269	0.765%	1	12.85
R202	A	7	1049.730	**7**	**1048.510**	-0.116%	3	27.92
R203	A	5	900.080	**6**	**884.752**	-1.703%	3	48.97
R204	A	4	772.330	**5**	**756.185**	-2.090%	3	99.43
R205	A	6	970.880	5	978.551	0.790%	3	28.94
R206	A	5	898.914	5	919.315	2.269%	3	47.18
R207	RT	4	814.780	5	827.821	1.601%	3	73.51
R208	A	3	723.610	3	724.228	0.085%	3	128.53
R209	A	6	879.531	6	886.648	0.809%	1	40.24
R210	A	7	932.887	6	933.597	0.076%	3	42.10
R211	A	5	787.511	**4**	**782.815**	-0.596%	1	71.64
RC201	A	9	1274.530	10	1282.432	0.620%	3	12.94
RC202	A	8	1113.520	8	1118.766	0.471%	3	25.34
RC203	A	5	945.960	**5**	**942.059**	-0.412%	3	41.99
RC204	M	3	798.410	4	801.938	0.442%	3	87.40
RC205	A	7	1161.810	7	1168.217	0.551%	3	20.98
RC206	A	7	1059.886	6	1089.589	2.802%	3	28.17
RC207	A	7	976.400	7	1001.923	2.614%	3	40.49
RC208	A	5	795.390	5	811.898	2.076%	1	72.40

* Multiple numbers indicate that each of the algorithms with the corresponding number of networks has found the same best solution
** Computational time is taken as the average of the algorithms with the corresponding number of networks

Appendix C

Detailed results of the experimental study 2

Table C.1 The average results of experimental study 2 for type 1 problems with 1 network and 3 networks

	ACO-TI 1 Network			ACO-TI 3 Networks			
Problem	NV	TD	Comp. Time (min)	NV	TD	Comp. Time (min)	
C101	10.00	828.936	5.77	10.00	828.936	4.61	10.00
C102	10.00	828.937	9.04	10.00	828.936	8.91	10.00
C103	10.00	828.065	15.05	10.00	828.065	12.64	10.00
C104	10.00	828.305	24.66	10.00	825.322	20.53	10.00
C105	10.00	828.936	5.67	10.00	828.936	5.35	10.00
C106	10.00	828.936	5.94	10.00	828.936	6.21	10.00
C107	10.00	828.936	6.44	10.00	828.936	6.96	10.00
C108	10.00	828.936	8.35	10.00	828.936	8.57	10.00
C109	10.00	828.936	13.09	10.00	828.936	13.47	10.00
R101	20.00	1644.500	3.34	20.00	1643.502	3.39	20.00
R102	18.00	1473.129	6.02	18.00	1473.840	5.86	18.00
R103	15.00	1224.608	8.31	15.00	1224.332	8.13	15.00
R104	11.80	1004.532	14.01	11.60	999.277	13.15	11.80
R105	16.00	1373.692	4.61	16.00	1373.043	4.55	16.00
R106	13.60	1253.720	7.34	13.80	1255.105	7.21	13.60
R107	11.80	1088.170	10.33	11.90	1091.095	10.19	11.80
R108	10.70	959.761	14.42	10.60	956.589	13.82	10.70
R109	12.70	1155.462	7.42	13.00	1156.569	7.60	12.70
R110	12.00	1091.197	9.54	12.00	1084.813	9.15	12.00
R111	12.00	1054.402	10.10	12.00	1055.652	9.95	12.00
R112	11.00	973.624	14.29	10.80	970.898	14.05	11.00
RC101	16.70	1657.636	4.17	16.80	1654.072	4.22	16.70
RC102	15.00	1486.150	6.01	14.90	1485.018	6.12	15.00
RC103	12.30	1305.846	8.30	12.20	1304.595	8.13	12.30
RC104	11.00	1167.720	12.51	10.90	1164.156	12.18	11.00
RC105	16.00	1555.107	6.60	16.00	1547.663	6.14	16.00
RC106	14.00	1403.100	6.16	13.90	1399.774	5.82	14.00

Table C.2 The average results of experimental study 2 for type 2 problems with 1 network and 3 networks.

	ACO-TI 1 Network			ACO-TI 3 Networks		
Problem	NV	TD	Comp. Time (min)	NV	TD	Comp. Time (min)
C201	3.00	591.557	8.84	3.00	591.556	9.17
C202	3.00	591.556	20.55	3.00	591.556	21.43
C203	3.00	591.989	32.33	3.00	591.173	33.82
C204	3.00	596.534	69.74	3.00	593.426	58.45
C205	3.00	588.876	13.02	3.00	588.876	13.70
C206	3.00	588.493	17.23	3.00	588.493	18.40
C207	3.00	588.286	19.24	3.00	588.286	20.40
C208	3.00	588.374	23.66	3.00	588.341	24.96
R201	9.30	1179.243	12.33	9.40	1182.010	11.89
R202	8.20	1075.924	26.04	7.50	1066.827	26.53
R203	7.10	915.365	45.06	6.10	890.658	45.57
R204	5.00	778.274	90.51	4.90	769.571	87.76
R205	5.60	994.617	25.91	5.70	986.679	24.76
R206	5.80	935.904	42.50	5.80	925.597	43.17
R207	5.70	855.183	65.41	5.30	846.408	66.98
R208	3.90	750.499	115.32	3.40	736.690	117.94
R209	6.00	904.026	35.76	5.90	897.921	36.05
R210	6.70	954.080	39.49	6.50	943.136	38.65
R211	4.20	801.418	68.14	4.30	797.018	69.04
RC201	9.60	1289.744	11.52	9.30	1298.449	11.86
RC202	8.30	1144.355	22.67	8.10	1138.043	22.50
RC203	6.20	984.588	40.37	5.70	967.793	38.35
RC204	4.70	832.575	84.76	4.10	821.297	77.58
RC205	7.80	1186.877	20.79	8.00	1190.386	16.88
RC206	6.20	1100.560	24.27	6.20	1101.030	23.47
RC207	6.50	1024.169	36.61	6.60	1016.741	35.52
RC208	5.00	842.794	74.87	5.00	833.717	66.96

Table C.3 Best total distance (TD) published heuristic results and ACO-TI results for type 1 problems. The results are emphasized in bold when ACO-TI overcomes the previous best solutions

	Previous best TD solution			ACO-TI				
Problem	**Ref.**	**NV**	**TD**	**NV**	**TD**	**Gap**	**Number of Networks ***	**Comp. Time (min) ****
C101	RT	10	828.940	**10**	**828.940**	0.000%	1 - 3	5.23
C102	RT	10	828.940	**10**	**828.940**	0.000%	1 - 3	9.43
C103	RT	10	828.060	**10**	**828.060**	0.000%	1 - 3	14.12
C104	RT	10	824.780	**10**	**824.780**	0.000%	1 - 3	22.01
C105	RT	10	828.940	**10**	**828.940**	0.000%	1 - 3	5.73
C106	RT	10	828.940	**10**	**828.940**	0.000%	1 - 3	6.08
C107	RT	10	828.940	**10**	**828.940**	0.000%	1 - 3	6.65
C108	RT	10	828.940	**10**	**828.940**	0.000%	1 - 3	8.47
C109	RT	10	828.940	**10**	**828.940**	0.000%	1 - 3	13.26
R101	A	20	1642.870	20	1642.876	0.000%	1 - 3	3.42
R102	A	18	1472.620	18	1472.814	0.013%	1 - 3	5.75
R103	RT	14	1213.620	15	1222.050	0.695%	3	8.18
R104	RT	10	982.010	**11**	**977.547**	-0.454%	3	12.86
R105	A	15	1360.780	16	1371.423	0.782%	1 - 3	4.41
R106	A	13	1241.518	13	1247.875	0.512%	1	7.10
R107	A	11	1076.125	11	1076.567	0.041%	3	9.72
R108	A	10	948.573	**10**	**946.422**	-0.227%	3	12.99
R109	A	13	1151.839	**13**	**1151.838**	0.000%	1	7.41
R110	RT	11	1080.360	**12**	**1075.911**	-0.412%	3	9.23
R111	A	12	1053.496	**12**	**1053.496**	0.000%	1 - 3	9.86
R112	RT	10	953.630	10	961.287	0.803%	3	13.99
RC101	RT	15	1623.580	16	1637.999	0.888%	3	4.15
RC102	A	14	1466.840	14	1473.801	0.475%	3	6.03
RC103	S	11	1261.670	12	1277.433	1.249%	1 - 3	8.02
RC104	C	10	1135.480	10	1149.961	1.275%	3	12.17
RC105	A	16	1518.600	**16**	**1518.576**	-0.002%	3	5.94
RC106	A	13	1377.352	13	1382.944	0.406%	3	5.95
RC107	A	12	1212.830	13	1245.530	2.696%	3	8.61
RC108	A	11	1117.526	11	1134.846	1.550%	3	10.29

* Multiple numbers indicate that each of the algorithms with the corresponding number of networks has found the same best solution
** Computational time is taken as the average of the algorithms with the corresponding number of networks

Table C.4 Best total distance (TD) published heuristic results and ACO-TI results for type 2 problems. The results are emphasized in bold when ACO-TI overcomes the previous best solutions.

	Previous best TD solution			ACO-TI				
Problem	**Ref.**	**NV**	**TD**	**NV**	**TD**	**Gap**	**Number of Networks ***	**Comp. Time (min) ****
C201	RT	3	591.560	**3**	**591.560**	0.000%	1 - 3	8.87
C202	RT	3	591.560	**3**	**591.560**	0.000%	1 - 3	20.87
C203	RT	3	591.170	**3**	**591.170**	0.000%	1 - 3	33.12
C204	RT	3	590.600	**3**	**590.600**	0.000%	3	57.06
C205	RT	3	588.880	**3**	**588.880**	0.000%	1 - 3	12.85
C206	RT	3	588.490	**3**	**588.490**	0.000%	1 - 3	17.80
C207	RT	3	588.290	**3**	**588.290**	0.000%	1 - 3	20.08
C208	RT	3	588.320	**3**	**588.320**	0.000%	1 - 3	24.57
R201	A	9	1148.480	9	1165.922	1.519%	1	11.95
R202	A	7	1049.730	**7**	**1046.281**	-0.329%	3	26.20
R203	A	5	900.080	**6**	**883.025**	-1.895%	3	45.63
R204	A	4	772.330	**5**	**759.775**	-1.626%	3	87.06
R205	A	6	970.880	**6**	**964.870**	-0.619%	1	25.85
R206	A	5	898.914	6	914.477	1.731%	3	44.03
R207	RT	4	814.780	5	825.735	1.345%	3	66.24
R208	A	3	723.610	3	725.236	0.225%	3	118.17
R209	A	6	879.531	6	890.346	1.230%	3	35.21
R210	A	7	932.887	6	934.971	0.223%	3	39.49
R211	A	5	787.511	**4**	**785.813**	-0.216%	3	68.92
RC201	A	9	1274.530	9	1281.144	0.519%	1	11.51
RC202	A	8	1113.520	**8**	**1111.796**	-0.155%	3	22.25
RC203	A	5	945.960	5	947.068	0.117%	3	37.40
RC204	M	3	798.410	4	804.391	0.749%	3	75.06
RC205	A	7	1161.810	7	1164.085	0.196%	1	19.96
RC206	A	7	1059.886	6	1082.938	2.175%	1	23.80
RC207	A	7	976.400	6	1001.396	2.560%	3	34.56
RC208	A	5	795.390	5	822.992	3.470%	3	66.30

* Multiple numbers indicate that each of the algorithms with the corresponding number of networks has found the same best solution

** Computational time is taken as the average of the algorithms with the corresponding number of networks

Appendix D

Detailed results of the experimental study 3

Table D.1. Average results of experimental study 3 for setting 1

Problem	NV	TD	TT	Comp. Time (min)	Problem	NV	TD	TT	Comp. Time (min)
C101	10.10	902.87	9906.83	4.74	C201	3.00	590.66	9585.51	8.58
C102	10.10	1112.89	10017.36	10.29	C202	4.70	1016.16	10054.86	23.34
C103	10.80	1337.64	10119.23	20.85	C203	4.80	1562.93	10402.45	51.84
C104	10.30	1269.33	9981.59	47.16	C204	4.60	1318.27	10098.72	157.07
C105	10.10	927.79	9860.73	6.55	C205	4.00	678.84	9622.23	14.92
C106	10.50	1028.03	9938.79	7.92	C206	3.90	766.57	9658.75	22.34
C107	10.50	1007.53	9875.35	9.94	C207	4.20	784.30	9689.82	30.09
C108	10.80	1096.65	9906.17	14.58	C208	4.10	810.39	9726.64	34.64
C109	11.00	1155.53	9907.94	24.96	R201	4.20	2234.84	3077.85	12.95
R101	18.20	2015.73	3158.74	3.43	R202	4.30	2141.71	2903.67	29.69
R102	16.00	1922.04	2815.23	6.73	R203	4.00	1737.31	2419.06	62.01
R103	13.10	1642.10	2379.19	11.23	R204	3.40	1311.47	2030.86	173.75
R104	10.60	1265.50	2022.35	21.76	R205	4.20	1771.26	2462.77	37.15
R105	14.30	1676.78	2529.02	5.66	R206	3.90	1593.71	2281.10	64.85
R106	12.80	1568.63	2269.08	9.84	R207	3.40	1412.95	2112.79	117.42
R107	11.40	1395.35	2101.75	15.40	R208	3.00	1082.71	1859.22	291.81
R108	10.40	1192.59	1923.06	26.45	R209	3.30	1594.18	2279.22	62.86
R109	12.20	1468.52	2227.41	10.00	R210	3.90	1734.94	2455.90	53.86
R110	11.70	1352.23	2122.04	16.04	R211	3.00	1287.98	1998.45	215.95
R111	11.10	1311.29	2083.14	16.03	RC201	5.20	2412.80	3230.02	12.57
R112	10.80	1186.89	1948.70	31.41	RC202	4.70	2400.04	3027.71	25.04
RC101	14.70	1917.46	2792.24	4.69	RC203	4.20	1880.62	2535.23	55.18
RC102	13.30	1819.64	2539.36	7.67	RC204	3.50	1487.22	2171.92	151.51
RC103	12.00	1597.50	2283.71	15.57	RC205	5.00	2469.78	3131.98	19.58
RC104	11.20	1443.67	2132.13	20.99	RC206	4.30	2070.31	2709.94	33.47
RC105	13.60	1880.36	2650.75	6.70	RC207	4.10	1856.34	2530.22	54.93
RC106	13.00	1638.76	2438.62	8.14	RC208	3.00	1327.80	2043.92	198.22
RC107	12.00	1494.42	2258.71	13.26					
RC108	11.30	1371.47	2146.96	20.37					

Table D.2. Best results of experimental study 3 for setting 1

Problem	NV	TD	TT	Comp. Time (min)	Problem	NV	TD	TT	Comp. Time (min)
C101	10.00	863.95	9851.08	4.76	C201	3.00	591.55	9576.35	8.51
C102	10.00	988.67	9904.66	9.98	C202	5.00	822.08	9935.95	23.31
C103	10.00	1254.40	10025.82	20.97	C203	5.00	1363.69	10261.57	51.64
C104	11.00	1184.44	9899.42	46.90	C204	4.00	1128.58	9913.54	156.75
C105	10.00	854.77	9816.66	6.48	C205	4.00	614.04	9562.56	14.82
C106	10.00	951.92	9839.86	7.78	C206	4.00	670.55	9548.86	23.11
C107	10.00	871.51	9795.89	9.98	C207	4.00	677.85	9579.18	31.35
C108	10.00	966.48	9822.43	14.60	C208	4.00	711.54	9661.52	34.39
C109	11.00	1056.79	9820.19	24.94	R201	4.00	2040.98	3034.64	13.15
R101	18.00	1941.23	3094.54	3.41	R202	4.00	2088.65	2838.19	29.28
R102	16.00	1925.17	2786.56	6.74	R203	4.00	1728.75	2370.29	61.95
R103	13.00	1584.00	2361.97	11.16	R204	3.00	1263.18	1995.52	173.54
R104	10.00	1170.88	1981.74	21.49	R205	4.00	1677.75	2399.73	36.69
R105	14.00	1606.65	2446.19	5.56	R206	3.00	1467.54	2167.96	65.71
R106	12.00	1507.79	2224.36	9.80	R207	3.00	1336.99	2061.17	119.92
R107	11.00	1325.76	2046.26	15.28	R208	3.00	1015.34	1817.93	289.42
R108	11.00	1148.16	1902.97	26.60	R209	4.00	1530.89	2220.23	62.35
R109	12.00	1418.11	2197.06	9.93	R210	4.00	1556.85	2321.06	53.86
R110	11.00	1350.43	2101.73	16.25	R211	3.00	1313.44	1985.90	217.02
R111	11.00	1283.76	2064.55	15.63	RC201	5.00	2344.24	3106.05	12.61
R112	11.00	1159.84	1936.80	31.10	RC202	5.00	2273.20	2950.51	24.94
RC101	14.00	1883.96	2720.96	4.71	RC203	5.00	1742.81	2446.02	58.20
RC102	13.00	1754.76	2484.83	7.60	RC204	4.00	1424.13	2122.75	167.82
RC103	11.00	1572.02	2215.22	15.29	RC205	5.00	2267.42	2981.71	19.62
RC104	11.00	1434.94	2108.85	20.77	RC206	4.00	2130.40	2655.50	33.19
RC105	13.00	1798.18	2584.76	6.55	RC207	4.00	1815.61	2429.87	54.91
RC106	13.00	1557.97	2421.90	8.32	RC208	3.00	1344.58	2013.95	199.71
RC107	12.00	1430.19	2210.52	12.95					
RC108	11.00	1310.27	2093.07	20.03					

Table D.3. Average results of experimental study 3 for setting 2

Problem	NV	TD	TT	Comp. Time (min)	Problem	NV	TD	TT	Comp. Time (min)
C101	11.00	1009.54	10032.95	4.94	C201	3.70	612.87	9652.78	9.32
C102	10.10	1018.01	9918.11	11.03	C202	4.10	1229.77	10123.65	25.52
C103	10.50	1255.57	10027.93	22.54	C203	4.90	1590.81	10332.17	57.16
C104	10.60	1156.91	9907.68	50.35	C204	4.40	1324.97	10038.40	172.42
C105	10.00	895.57	9852.66	6.71	C205	3.40	654.47	9614.93	15.41
C106	10.00	897.13	9820.24	8.07	C206	4.20	732.77	9659.13	22.70
C107	10.30	918.49	9837.93	10.14	C207	4.00	740.39	9665.69	31.31
C108	10.40	961.99	9815.40	14.90	C208	3.80	733.90	9647.87	35.77
C109	10.90	1082.96	9869.30	25.66	R201	4.00	2292.95	2973.24	14.03
R101	18.00	2056.02	3082.87	3.61	R202	4.30	2160.16	2809.11	32.12
R102	17.00	2025.54	2802.17	7.18	R203	3.80	1771.37	2344.64	67.58
R103	13.00	1610.46	2283.00	12.18	R204	3.50	1340.42	1998.17	191.56
R104	10.30	1260.29	1944.20	24.00	R205	3.60	1750.53	2347.82	40.83
R105	13.30	1617.97	2387.81	5.87	R206	3.60	1594.27	2199.32	69.87
R106	12.10	1513.24	2168.38	10.43	R207	3.40	1454.42	2067.00	126.72
R107	10.70	1348.08	2001.90	16.85	R208	2.90	1092.94	1808.43	323.54
R108	10.00	1207.51	1866.20	29.26	R209	3.20	1639.59	2231.45	68.15
R109	11.90	1457.14	2137.05	10.75	R210	3.70	1776.96	2402.43	56.90
R110	11.60	1364.29	2049.36	17.83	R211	3.00	1259.03	1937.78	236.14
R111	10.90	1315.80	2000.64	17.36	RC201	4.40	2452.96	3054.83	13.85
R112	10.20	1164.62	1862.94	33.59	RC202	4.70	2456.64	2961.43	28.36
RC101	13.70	1842.48	2591.52	5.00	RC203	4.30	1966.75	2490.87	61.67
RC102	12.90	1834.07	2442.30	8.75	RC204	3.30	1512.69	2110.28	163.50
RC103	11.70	1592.76	2208.60	13.82	RC205	4.20	2526.19	3096.84	20.80
RC104	10.80	1458.16	2047.30	23.37	RC206	4.10	2049.21	2567.64	37.51
RC105	13.10	1865.75	2542.06	7.29	RC207	4.10	1942.14	2445.84	60.47
RC106	12.30	1635.86	2322.96	9.06	RC208	3.00	1366.36	1990.26	217.70
RC107	12.00	1492.12	2182.92	15.12					
RC108	11.20	1393.34	2075.31	23.13					

Table D.4. Best results of experimental study 3 for setting 2

Problem	NV	TD	TT	Comp. Time (min)	Problem	NV	TD	TT	Comp. Time (min)
C101	11.00	969.30	9984.49	4.86	C201	4.00	607.94	9650.60	9.10
C102	10.00	937.55	9842.49	11.00	C202	4.00	893.58	9889.14	25.08
C103	10.00	1226.08	9960.42	21.93	C203	5.00	1492.50	10264.79	56.60
C104	11.00	1032.94	9835.28	50.84	C204	4.00	1192.75	9979.05	171.55
C105	10.00	879.69	9839.16	6.70	C205	3.00	660.30	9604.12	15.59
C106	10.00	893.49	9804.56	8.28	C206	4.00	662.23	9607.27	22.47
C107	10.00	859.31	9806.11	10.24	C207	3.00	660.56	9622.08	31.80
C108	10.00	878.09	9770.90	14.69	C208	3.00	666.30	9593.74	36.98
C109	10.00	978.52	9811.68	25.09	R201	4.00	2238.97	2927.79	14.18
R101	18.00	1990.56	3042.50	3.59	R202	4.00	1930.43	2747.34	31.76
R102	17.00	2049.31	2783.51	7.13	R203	3.00	1681.19	2281.52	67.33
R103	13.00	1594.65	2243.88	12.14	R204	3.00	1303.89	1942.93	188.68
R104	10.00	1229.17	1913.56	23.74	R205	4.00	1720.70	2309.52	40.43
R105	13.00	1577.03	2339.60	5.74	R206	4.00	1519.67	2130.07	69.34
R106	12.00	1515.77	2127.21	10.33	R207	3.00	1341.99	2024.03	124.42
R107	10.00	1305.37	1965.82	16.52	R208	3.00	1017.83	1780.26	319.10
R108	10.00	1158.81	1845.03	29.41	R209	3.00	1590.68	2178.45	67.40
R109	11.00	1360.85	2081.00	10.52	R210	3.00	1777.65	2364.38	56.79
R110	11.00	1361.66	2009.03	17.76	R211	3.00	1214.97	1910.64	232.68
R111	10.00	1246.98	1957.64	17.32	RC201	5.00	2437.26	2947.12	13.90
R112	10.00	1134.55	1827.04	32.91	RC202	5.00	2268.97	2812.06	28.65
RC101	13.00	1785.58	2524.76	4.94	RC203	4.00	1866.92	2405.15	61.58
RC102	12.00	1781.16	2404.62	8.51	RC204	3.00	1465.62	2065.42	166.52
RC103	11.00	1501.95	2155.57	13.56	RC205	4.00	2283.40	3027.85	20.94
RC104	11.00	1420.93	2021.43	23.28	RC206	4.00	1947.86	2465.96	38.09
RC105	13.00	1837.14	2521.03	7.28	RC207	4.00	1899.03	2392.23	60.86
RC106	12.00	1575.16	2268.39	8.96	RC208	3.00	1264.23	1966.05	215.51
RC107	12.00	1438.71	2157.73	14.64					
RC108	11.00	1408.51	2059.26	22.96					

Table D.5. Average results of experimental study 3 for setting 3

Problem	NV	TD	TT	Comp. Time (min)	Problem	NV	TD	TT	Comp. Time (min)
C101	11.00	1019.59	9987.98	4.91	C201	3.00	624.39	9629.35	9.94
C102	10.20	1052.37	9908.84	11.18	C202	4.60	1265.35	10155.34	26.26
C103	10.40	1227.17	9991.06	23.40	C203	5.10	1664.38	10357.89	61.56
C104	10.50	1176.29	9890.33	52.55	C204	4.60	1327.82	10023.94	175.72
C105	10.00	920.20	9839.18	6.77	C205	3.20	656.15	9588.98	15.63
C106	10.00	887.68	9794.75	8.04	C206	3.50	684.11	9592.49	23.43
C107	10.40	925.23	9821.81	10.19	C207	3.90	767.54	9657.92	32.20
C108	10.60	1014.88	9831.56	15.63	C208	4.10	751.17	9627.82	37.26
C109	10.60	1015.73	9812.76	25.96	R201	4.10	2246.08	2959.68	13.81
R101	18.00	2094.91	3059.83	3.46	R202	4.00	2206.86	2736.92	32.32
R102	17.00	2032.34	2799.06	7.02	R203	4.00	1859.31	2364.90	70.43
R103	13.00	1670.10	2289.40	13.28	R204	3.60	1340.71	1967.27	200.54
R104	10.50	1316.24	1952.45	25.28	R205	3.60	1756.02	2309.22	42.23
R105	13.40	1649.52	2364.60	6.01	R206	3.30	1639.64	2180.74	71.97
R106	12.00	1519.32	2129.78	10.73	R207	3.20	1473.58	2030.28	129.33
R107	11.00	1385.07	1985.35	17.70	R208	3.00	1115.19	1782.96	338.88
R108	10.40	1208.95	1840.55	31.24	R209	3.20	1648.31	2191.85	69.53
R109	11.90	1452.59	2100.07	11.23	R210	3.70	1811.36	2363.42	57.21
R110	11.40	1386.99	2003.59	18.66	R211	3.00	1248.48	1885.03	238.82
R111	10.70	1315.19	1970.27	18.24	RC201	4.70	2487.59	3078.38	13.76
R112	10.00	1166.62	1824.71	33.87	RC202	4.40	2484.23	2887.88	28.40
RC101	13.80	1857.99	2565.61	4.81	RC203	4.30	2052.87	2477.41	62.60
RC102	13.00	1832.52	2415.80	8.58	RC204	3.40	1515.57	2057.16	181.64
RC103	11.40	1615.34	2169.83	14.24	RC205	4.20	2386.66	3015.79	20.67
RC104	10.50	1457.38	2017.03	24.14	RC206	4.10	2060.74	2533.70	37.88
RC105	13.20	1919.42	2546.19	7.13	RC207	4.20	1898.30	2376.45	59.98
RC106	12.00	1637.96	2278.98	8.82	RC208	3.00	1399.02	1973.35	223.49
RC107	11.80	1540.16	2152.22	15.28					
RC108	10.80	1370.61	2019.98	23.46					

Table D.6. Best results of experimental study 3 for setting 3

Problem	NV	TD	TT	Comp. Time (min)	Problem	NV	TD	TT	Comp. Time (min)
C101	11.00	978.75	9945.98	4.96	C201	3.00	624.39	9629.35	9.82
C102	10.00	952.35	9818.89	10.91	C202	4.00	857.28	9787.07	26.68
C103	10.00	1104.43	9900.80	22.91	C203	5.00	1597.40	10286.84	61.12
C104	10.00	1151.68	9835.66	52.48	C204	5.00	1140.89	9867.49	177.80
C105	10.00	883.64	9823.73	6.87	C205	3.00	631.82	9569.05	15.71
C106	10.00	867.81	9780.38	8.04	C206	3.00	655.45	9560.62	23.62
C107	10.00	925.48	9810.74	10.21	C207	3.00	667.97	9591.49	32.81
C108	10.00	930.00	9772.20	15.61	C208	4.00	710.26	9575.48	37.30
C109	10.00	970.26	9780.26	26.19	R201	4.00	2150.06	2914.54	13.87
R101	18.00	2087.61	3025.75	3.47	R202	4.00	2160.29	2621.35	32.49
R102	17.00	1972.22	2774.60	6.96	R203	4.00	1737.35	2271.94	69.98
R103	13.00	1610.01	2244.79	12.42	R204	4.00	1291.80	1949.35	195.95
R104	10.00	1222.17	1910.62	25.00	R205	3.00	1745.25	2265.04	42.08
R105	13.00	1558.24	2307.95	5.87	R206	3.00	1592.12	2093.08	72.45
R106	11.00	1475.34	2078.31	10.58	R207	4.00	1411.36	1990.15	129.21
R107	11.00	1286.89	1952.55	17.53	R208	2.00	1043.58	1760.04	333.71
R108	10.00	1208.00	1810.95	31.03	R209	3.00	1575.59	2154.23	69.46
R109	12.00	1408.79	2077.64	11.02	R210	3.00	1687.86	2257.99	56.74
R110	11.00	1374.20	1982.58	18.33	R211	3.00	1205.98	1849.20	233.98
R111	10.00	1244.49	1940.88	17.83	RC201	4.00	2304.06	2953.21	13.71
R112	10.00	1143.69	1806.37	33.34	RC202	4.00	2352.83	2832.59	28.64
RC101	13.00	1820.05	2474.12	4.64	RC203	4.00	1847.65	2342.86	62.13
RC102	12.00	1757.89	2359.48	8.53	RC204	3.00	1482.43	2023.34	181.25
RC103	11.00	1605.22	2139.64	14.09	RC205	4.00	2385.13	2917.04	20.80
RC104	10.00	1432.40	1992.48	23.79	RC206	5.00	1829.91	2468.05	37.46
RC105	13.00	1908.21	2487.35	6.85	RC207	4.00	1650.16	2229.52	59.64
RC106	12.00	1596.21	2241.90	8.63	RC208	3.00	1332.30	1947.49	222.06
RC107	11.00	1466.13	2112.26	15.30					
RC108	10.00	1326.33	1999.06	23.48					

Appendix E

Pheromone Re-Initialization Illustration

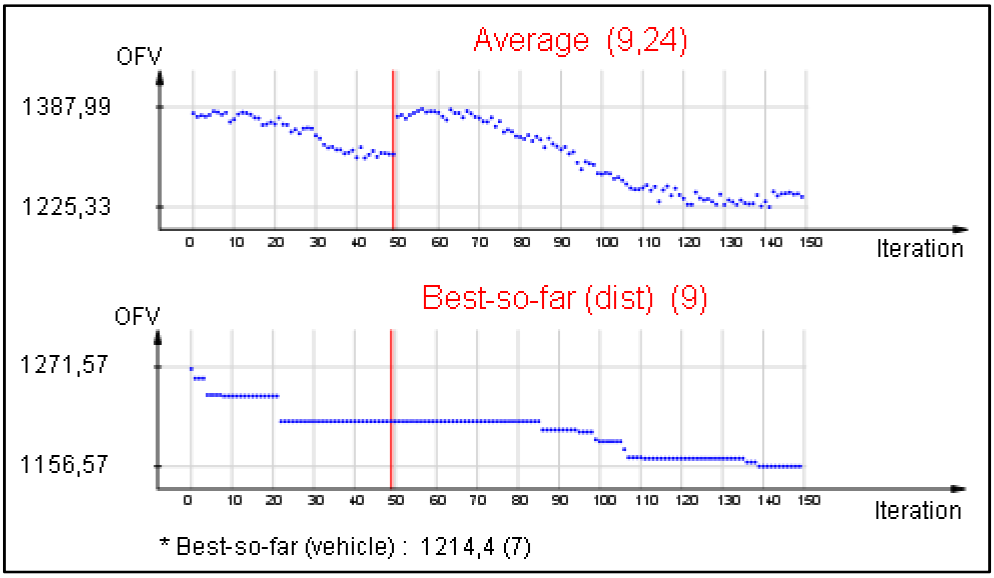

Figure E.1. Illustration of *pheromone re-initialization* procedure on instance R201. The red line indicates the iteration the procedure is applied.

Appendix F

The general interface of the software used

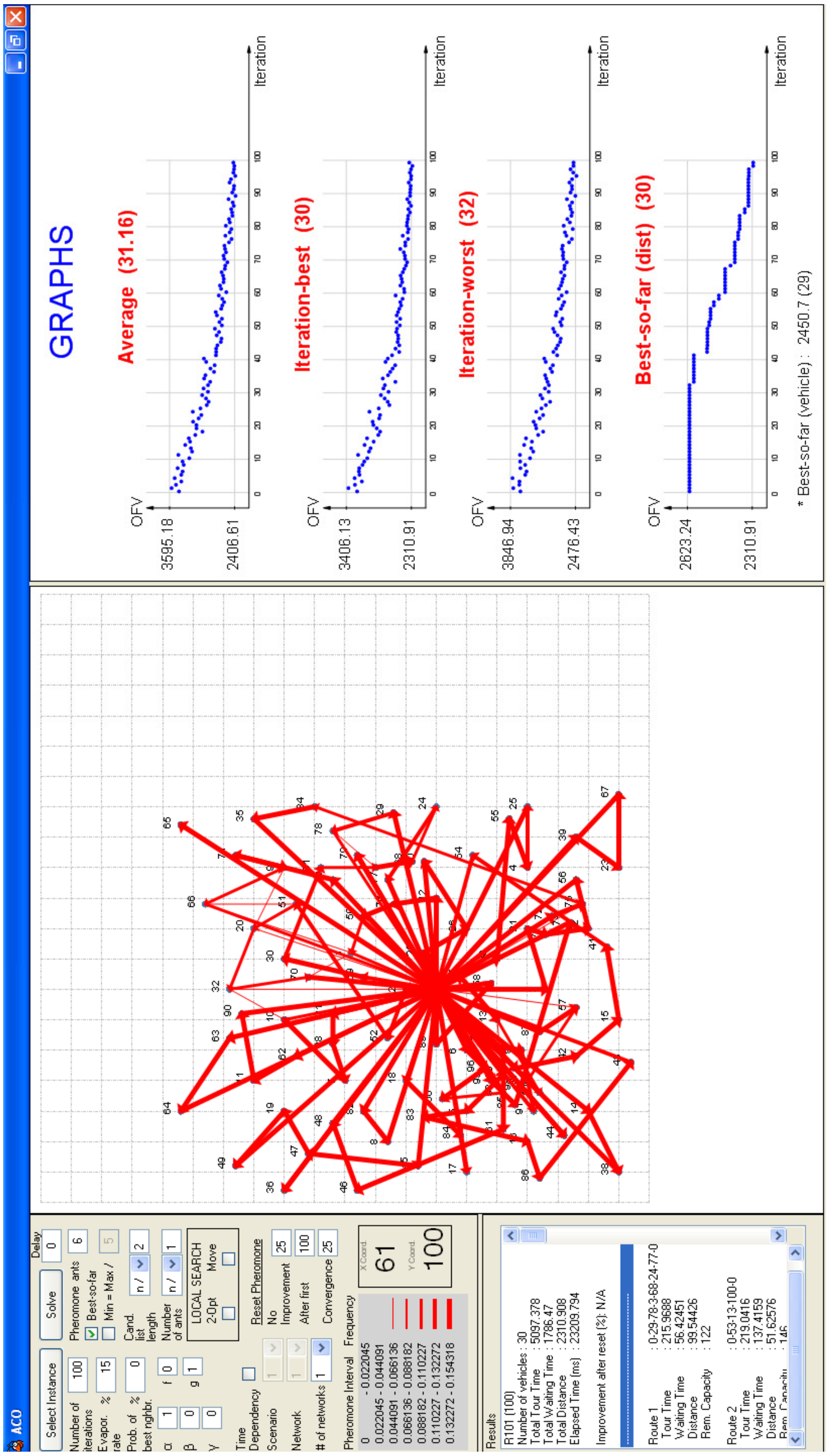

Figure F.1. The general interface of the generated software

Appendix G

Road Types Used in Experimental Study 3

Table G.1. One-way road types for traveling from the customers 0-50 to the customers 0-50. The matrix should be read over rows.

→	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
0	-	2	2	3	2	3	2	1	2	2	1	2	1	3	2	2	2	2	3	1	3	3	1	2	2	2	3	3	2	2	3	3	2	3	3	1	3	2	1	3	2	3	2	1	3	2	2	2	2	1	3
1	3	-	3	3	2	3	1	1	3	3	2	3	2	3	2	2	3	1	1	3	2	3	3	3	1	1	3	2	1	2	3	2	1	1	1	3	3	1	1	2	3	3	1	3	1	1	3	2	1	1	3
2	3	2	-	3	2	1	2	2	2	1	1	1	1	2	1	3	2	1	3	2	1	3	1	2	2	3	1	2	3	3	3	3	3	3	1	3	3	2	1	1	3	1	2	3	1	3	3	1	2	1	2
3	3	3	1	-	1	1	2	2	3	3	3	1	2	2	1	1	3	2	3	2	3	3	3	1	1	1	3	1	2	3	2	3	3	2	3	3	2	3	1	1	3	1	2	2	1	1	1	3	3	1	3
4	3	1	2	1	-	3	2	3	1	3	3	2	2	1	3	1	2	2	3	1	1	2	3	3	2	3	3	1	3	2	2	1	3	3	2	3	3	2	1	2	1	3	3	2	3	1	2	1	1	2	3
5	3	2	1	1	3	-	3	2	1	2	3	2	2	1	1	2	2	3	1	2	2	1	3	3	1	3	3	3	1	1	2	1	2	3	2	2	1	2	3	2	3	3	2	1	1	1	1	3	3	3	2
6	3	1	1	1	2	1	-	3	1	1	2	2	3	3	3	3	1	2	2	3	3	2	2	2	3	1	1	1	3	2	2	1	2	1	1	1	1	3	3	1	1	1	2	1	2	1	2	3	3	3	3
7	3	1	2	3	2	1	3	-	3	1	2	2	2	2	2	3	2	3	2	2	3	3	1	3	2	1	3	3	1	3	1	1	3	2	3	1	1	1	1	2	3	2	1	2	2	2	1	3	1	1	1
8	3	1	3	2	3	1	1	1	-	3	2	2	1	1	2	2	2	2	1	3	3	2	2	3	2	1	1	1	1	1	3	2	2	1	3	1	3	3	3	3	1	1	3	2	2	1	2	3	3	2	1
9	2	1	3	3	2	2	3	1	3	-	2	1	3	1	3	1	3	3	1	3	3	2	3	1	2	2	1	2	3	1	2	1	3	1	2	3	2	2	3	2	3	1	2	1	3	2	2	1	2	2	2
10	3	2	3	3	1	2	1	3	1	2	-	1	1	1	3	1	1	3	3	1	1	3	2	3	2	1	1	1	2	3	2	3	1	2	3	2	2	3	2	1	3	1	2	1	2	1	1	3	3	3	3
11	2	2	1	2	3	3	1	3	3	1	3	-	2	3	2	3	2	3	1	3	2	1	2	1	1	2	2	1	1	3	2	2	1	2	1	2	3	1	1	3	2	3	3	2	1	2	2	3	2	1	1
12	3	1	2	1	3	1	1	1	2	2	3	1	-	2	3	2	1	1	1	2	2	1	2	1	2	2	1	1	3	3	3	2	2	1	1	1	3	1	3	1	2	1	2	3	3	3	2	2	2	1	2
13	3	3	3	2	2	3	3	2	1	3	3	2	2	-	1	3	2	2	3	3	1	3	3	3	2	3	3	1	2	1	2	1	1	1	2	2	3	2	1	3	2	2	1	3	1	1	1	3	1	3	1
14	3	3	2	3	1	3	2	1	1	2	2	2	3	1	-	1	1	3	1	1	1	1	1	3	1	2	3	3	2	3	2	1	1	1	3	3	3	2	1	1	2	1	2	1	2	1	3	1	3	3	2
15	2	1	2	2	3	1	2	2	1	3	2	2	2	2	3	-	1	1	2	2	3	1	2	2	3	1	2	1	2	3	3	2	3	1	3	1	1	2	1	1	1	3	3	2	2	3	2	2	1	3	2
16	3	2	3	2	1	1	2	2	3	1	1	3	1	2	1	2	-	3	3	3	2	3	1	3	2	1	2	1	2	2	1	1	3	2	1	3	2	1	1	2	2	1	1	3	1	3	2	3	1	2	1
17	3	2	2	3	1	3	3	1	2	2	1	2	2	1	1	1	3	-	3	3	2	2	1	1	2	2	3	2	2	1	3	2	2	1	2	3	2	1	2	2	3	3	2	2	1	1	2	1	3	2	3
18	3	1	3	2	3	1	1	2	1	1	3	2	1	2	3	2	1	2	-	1	3	3	2	2	3	3	3	2	3	1	2	1	3	2	2	1	2	1	3	2	2	1	3	1	2	2	2	3	1	2	1
19	3	2	2	2	2	1	3	1	2	3	2	1	3	2	1	1	3	3	3	-	3	3	3	2	3	3	2	2	2	3	2	1	3	3	2	3	2	3	1	3	3	1	1	2	1	1	3	1	2	2	3
20	3	1	1	3	2	2	3	2	3	2	1	1	3	1	3	3	2	1	2	1	-	2	1	2	3	3	2	1	1	1	3	1	2	3	1	2	1	3	1	3	3	2	2	1	1	1	2	1	2	1	1
21	3	1	2	2	1	1	1	1	1	1	2	2	2	3	2	3	3	2	2	1	1	-	1	3	3	1	2	1	2	2	2	3	3	2	1	2	1	1	2	3	2	1	1	1	2	1	3	1	2	1	2
22	3	3	1	2	3	2	3	2	2	1	3	3	3	1	3	3	1	2	3	2	3	1	-	3	2	3	1	2	2	2	2	1	1	2	1	1	3	3	1	2	1	2	3	1	3	3	3	3	2	2	3
23	2	3	2	2	3	1	2	3	3	2	2	3	3	3	2	3	2	1	3	2	1	2	1	-	1	1	3	3	1	2	2	1	1	2	2	1	2	2	2	3	1	1	2	1	1	2	1	1	1	2	1
24	3	3	2	2	3	1	2	3	1	3	1	1	3	3	1	3	3	3	3	3	3	2	3	1	-	3	2	3	1	3	2	1	3	3	2	2	2	3	1	2	2	1	2	3	3	1	1	1	1	3	3
25	3	1	3	2	3	1	3	3	2	1	3	3	1	1	1	2	1	3	3	2	3	3	3	1	3	-	2	3	2	3	1	2	1	1	1	3	1	3	3	1	2	1	3	1	1	2	3	2	2	3	3
26	3	2	1	3	3	3	1	3	1	1	1	2	3	1	2	3	3	3	3	3	2	1	2	2	2	2	-	1	3	1	3	1	2	1	2	1	2	2	3	1	3	2	1	2	1	3	1	2	1	2	2
27	3	3	3	2	1	2	2	2	1	2	1	2	1	2	2	2	1	3	1	1	3	3	1	1	1	2	2	-	3	1	1	1	2	1	1	3	1	1	3	2	2	2	1	2	2	3	2	3	1	1	2
28	3	3	2	3	1	2	3	1	3	2	1	3	3	1	1	3	3	1	2	3	2	3	3	2	3	3	3	2	-	2	2	2	3	1	1	2	2	1	1	1	3	1	1	2	2	3	2	2	1	1	2
29	3	1	2	2	1	2	2	2	3	1	3	1	2	1	3	2	3	1	1	1	3	3	3	2	1	2	2	1	2	-	2	3	1	2	1	3	1	3	3	3	2	2	3	3	1	1	2	2	1	3	2
30	3	1	3	1	3	1	3	2	3	2	2	2	3	2	3	3	1	3	1	3	2	2	3	1	2	3	3	2	1	2	-	1	3	3	3	1	2	2	3	2	2	3	2	1	1	2	2	1	1	1	2
31	3	1	3	3	1	3	3	2	1	3	1	3	3	2	3	2	2	3	2	1	3	1	2	2	1	1	3	3	2	3	3	-	3	2	2	2	2	1	2	2	3	1	1	1	2	3	2	1	3	2	2
32	3	1	2	1	3	1	3	2	2	2	2	2	2	3	1	1	1	3	3	1	3	2	2	1	2	3	3	3	2	1	2	2	-	2	1	3	3	2	3	1	3	2	3	2	1	2	2	2	1	1	3
33	3	1	1	1	1	3	1	3	1	2	2	3	3	3	3	1	2	3	1	2	2	3	3	3	3	2	1	2	2	3	1	1	2	-	3	1	2	3	2	2	2	2	3	3	3	3	2	1	3	1	2
34	3	1	1	3	3	1	3	2	3	1	1	1	1	1	2	1	2	1	2	2	2	2	1	3	1	1	3	2	2	1	2	1	2	3	-	1	1	1	1	1	2	1	2	3	2	3	3	1	1	2	2
35	3	1	1	2	3	3	3	3	3	3	2	3	2	2	3	3	1	2	2	2	2	2	1	2	3	3	3	1	3	3	1	3	1	1	2	-	2	1	1	1	2	2	2	1	3	1	1	1	3	1	1
36	3	3	1	1	2	2	1	3	2	1	3	3	1	1	2	1	3	1	3	3	3	3	2	2	3	2	1	1	3	3	3	1	2	3	3	2	-	3	3	1	3	1	3	1	2	3	2	1	2	2	1
37	3	1	1	2	2	2	1	2	1	1	2	2	1	3	3	3	1	1	2	2	3	1	2	1	3	2	2	3	3	1	1	1	2	2	1	1	1	-	1	1	3	2	1	3	2	2	2	1	2	1	1
38	2	2	3	2	2	1	2	3	2	2	2	1	1	3	3	3	3	3	3	2	2	2	3	1	1	1	1	1	1	1	1	2	1	2	1	3	1	3	-	1	1	1	3	1	1	1	2	1	3	1	3
39	3	2	1	3	3	1	2	3	1	2	2	3	2	2	1	2	2	1	3	1	3	3	2	1	1	1	1	2	1	3	2	2	1	3	2	2	3	1	2	-	2	3	1	1	1	1	1	1	1	3	3
40	3	2	2	1	1	1	3	2	1	3	2	3	1	1	3	1	1	2	3	2	1	1	1	3	1	3	3	2	3	2	3	1	2	2	1	2	2	3	1	2	-	2	1	2	2	2	3	2	1	2	1
41	3	3	2	1	2	2	2	3	1	2	2	3	2	2	1	1	3	3	2	1	1	1	2	3	2	3	2	3	2	1	1	3	1	1	3	2	1	3	2	2	1	-	2	3	3	1	3	2	2	2	1
42	3	2	1	1	1	1	3	2	2	1	3	3	3	1	2	1	3	2	3	1	2	1	3	3	1	1	3	2	3	2	1	2	1	1	2	2	2	3	1	1	2	3	-	1	2	3	1	3	1	1	1
43	3	3	2	1	2	3	2	2	2	1	3	1	2	1	1	1	2	3	1	2	1	1	2	3	1	2	3	1	3	3	2	3	3	1	2	2	1	3	2	1	3	3	1	-	1	3	2	3	3	3	2
44	1	2	2	1	2	1	1	2	1	2	2	3	3	3	2	3	1	1	2	3	1	2	2	2	2	2	1	1	2	2	3	1	1	3	1	3	2	3	2	1	3	2	3	2	-	3	2	3	2	3	2
45	3	3	3	1	2	2	2	3	3	1	1	1	1	3	2	2	3	1	1	2	3	2	3	2	3	2	2	1	1	3	2	1	1	1	2	3	3	3	1	3	2	2	2	1	1	-	3	2	1	3	3
46	3	2	3	1	3	2	1	3	1	1	1	3	3	3	3	2	3	2	2	1	3	2	2	3	1	2	2	3	2	3	1	1	3	2	3	2	3	1	2	3	1	2	1	2	1	3	-	2	2	2	2
47	3	3	2	3	1	3	1	2	1	1	3	1	2	3	2	1	3	2	2	1	3	3	2	3	3	3	1	3	3	1	1	2	2	1	3	3	1	2	3	2	3	2	2	3	2	2	1	-	2	2	2
48	3	2	1	2	2	3	1	1	1	3	3	2	1	3	1	3	3	3	3	3	2	3	2	3	2	1	1	2	3	2	3	1	1	1	2	1	1	3	3	3	1	3	2	2	3	3	1	3	-	2	3
49	3	2	3	2	1	3	3	3	2	2	3	1	1	1	1	3	1	1	3	2	1	3	1	2	3	2	2	1	3	3	1	3	3	3	1	3	3	1	1	3	1	3	2	1	2	1	3	2	2	-	1
50	3	2	1	1	1	1	2	3	2	3	2	2	2	1	1	2	3	2	1	3	1	2	3	3	1	3	2	2	2	3	3	3	1	2	3	3	3	2	2	2	1	1	2	3	3	3	1	1	2	1	-

Table G.2. One-way road types for traveling from the customers 51-100 to the customers 0-50. The matrix should be read over rows.

→	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
51	3	1	3	2	1	2	2	3	2	2	2	1	3	3	2	3	3	3	2	3	2	1	1	1	1	2	3	3	2	1	2	1	3	3	3	3	1	3	1	2	3	2	3	1	2	1	2	2	3	2	2
52	3	2	2	1	3	2	1	3	1	1	2	1	1	1	3	3	3	2	1	3	3	1	3	1	2	1	2	3	3	3	1	3	2	2	1	2	2	2	3	2	1	3	2	3	1	3	2	1	3	1	1
53	1	1	3	3	1	3	3	2	3	3	3	3	1	3	1	1	1	1	3	1	3	2	1	3	2	3	2	2	1	3	2	2	3	1	2	2	2	1	3	3	3	1	1	2	2	3	1	3	1	2	2
54	3	2	2	2	3	2	1	2	2	1	1	1	1	3	3	3	1	3	1	3	1	2	2	2	3	1	1	1	2	3	3	3	2	2	1	1	1	3	3	2	2	2	3	1	3	1	1	1	3	2	1
55	3	2	2	1	3	2	1	1	1	2	1	2	1	3	1	1	3	3	2	1	2	1	1	3	2	3	2	3	2	3	3	3	2	3	1	3	2	1	1	1	3	3	2	3	2	2	1	1	3	1	2
56	3	3	2	2	2	3	2	2	1	1	2	1	2	3	2	1	2	1	1	1	1	2	2	3	1	2	1	2	1	3	1	2	1	1	2	3	2	2	3	1	2	1	2	2	1	1	2	2	2	1	1
57	3	1	1	1	2	1	3	1	2	3	1	2	3	1	3	1	1	1	3	1	1	1	2	3	3	3	3	1	2	1	1	2	1	2	1	1	2	3	3	2	2	2	2	1	2	1	1	1	2	1	1
58	3	1	3	3	3	3	2	3	1	3	2	3	3	1	1	2	1	2	3	1	2	3	2	2	2	3	1	1	2	2	2	1	3	2	3	3	1	2	3	2	3	3	2	2	3	1	2	3	1	2	1
59	3	2	2	3	1	2	2	3	1	2	3	2	3	1	3	2	1	1	1	2	3	1	2	3	3	3	2	2	2	1	2	2	3	2	1	3	2	2	1	3	1	3	1	2	3	3	3	3	1	2	1
60	3	2	2	2	2	2	2	1	1	2	1	3	1	2	2	2	3	2	1	3	1	3	1	1	2	2	3	1	2	3	3	3	2	1	2	1	1	2	2	1	2	3	3	2	3	2	2	1	2	2	2
61	3	2	1	1	1	2	3	3	3	1	1	3	3	2	1	3	1	1	3	1	1	2	1	2	2	2	2	2	2	2	3	3	2	2	3	2	2	3	1	1	1	2	2	2	1	1	3	1	1	3	1
62	3	2	2	2	2	3	3	2	1	3	2	1	1	1	1	2	3	1	1	3	2	3	2	1	1	1	1	3	2	3	2	3	3	3	3	1	1	3	2	2	3	2	2	1	3	1	3	1	2	3	1
63	3	3	2	2	1	3	3	2	2	1	1	3	2	3	1	2	3	1	1	2	1	3	3	2	3	2	1	3	3	1	2	1	1	2	3	2	2	3	2	1	3	1	1	1	3	2	2	1	1	1	2
64	3	1	1	2	1	2	2	1	1	3	3	1	3	1	2	2	3	3	2	3	1	1	3	3	3	3	2	3	2	1	2	1	2	3	2	3	3	3	3	1	2	3	1	2	1	2	2	1	1	3	3
65	3	3	2	2	1	3	1	1	3	2	2	1	1	2	1	2	1	1	3	1	1	2	3	3	1	3	2	3	2	3	1	1	1	3	2	2	3	3	2	2	3	2	1	2	2	2	1	3	2	2	2
66	3	3	3	3	3	2	3	1	2	1	1	2	2	3	3	2	1	2	1	3	3	2	3	1	3	3	3	3	1	1	2	2	3	1	1	3	3	2	2	3	2	2	3	1	3	1	2	3	1	2	1
67	2	3	1	2	3	2	1	2	1	1	1	2	1	1	2	3	2	2	1	3	1	1	1	1	1	2	3	3	1	1	2	2	3	2	1	2	2	1	2	2	2	1	1	1	2	1	3	1	3	2	2
68	3	3	1	2	1	1	3	2	3	3	2	2	3	3	3	1	2	2	3	2	2	3	1	2	2	3	2	1	3	3	1	2	2	3	3	2	2	2	2	1	3	2	3	3	3	1	2	1	1	2	2
69	3	3	1	3	3	2	2	1	2	1	2	1	3	2	1	2	3	2	2	3	3	2	1	2	2	3	2	3	3	1	1	1	2	2	1	2	3	1	2	3	2	1	3	3	1	3	1	3	3	1	2
70	3	2	3	2	1	2	2	3	2	1	2	1	2	2	2	2	2	2	1	2	1	3	3	1	1	1	3	1	3	3	3	1	2	2	3	1	1	1	2	1	1	2	3	2	1	3	3	2	1	1	2
71	3	2	3	1	2	1	3	1	3	2	1	3	2	1	2	3	1	1	1	1	3	1	2	1	2	1	2	3	2	1	3	2	1	3	3	3	1	3	3	1	3	1	2	1	2	3	3	2	3	2	3
72	3	1	2	1	3	2	1	3	3	3	2	2	1	3	1	3	1	2	2	3	1	3	1	2	3	3	1	3	3	3	1	3	3	3	3	1	2	3	1	3	2	3	1	3	1	1	2	2	1	2	2
73	3	1	1	1	3	3	2	3	2	2	3	3	2	1	2	3	3	2	2	2	2	3	2	2	3	3	2	1	2	1	1	1	3	1	1	1	1	2	2	3	2	2	2	1	1	2	3	1	3	1	2
74	3	3	1	2	2	1	3	1	3	2	3	2	2	3	1	3	1	3	1	3	2	2	2	1	3	1	1	2	2	3	3	1	2	3	3	1	1	3	3	2	3	1	1	2	3	3	3	1	2	2	3
75	3	2	1	2	3	2	3	1	1	3	3	3	1	3	1	2	1	3	1	1	2	3	2	2	3	2	2	1	2	1	3	1	2	2	1	3	2	2	1	2	2	1	1	1	3	1	1	1	2	3	2
76	2	1	2	1	1	3	3	1	2	2	1	1	1	1	1	3	3	2	3	1	2	3	1	2	1	3	1	1	2	1	1	1	3	2	1	1	3	2	1	2	1	3	1	1	3	2	3	1	2	2	1
77	3	1	2	3	3	2	2	3	3	1	1	1	1	1	3	1	3	3	2	3	3	3	3	3	3	3	1	2	1	2	3	2	3	2	3	3	3	1	1	2	3	3	3	1	3	3	1	3	3	2	1
78	3	2	2	3	1	2	2	3	3	2	2	3	2	3	1	1	1	2	1	3	3	3	2	1	2	1	2	1	3	1	2	2	1	1	1	1	2	3	3	3	1	3	3	3	2	2	3	1	3	1	3
79	3	2	2	3	2	2	1	2	2	1	1	2	2	1	3	2	3	1	3	2	1	2	2	3	1	1	3	3	3	1	1	2	3	1	1	3	3	2	2	1	2	1	3	3	2	2	3	1	1	2	2
80	3	2	1	1	3	1	1	1	3	1	2	1	1	1	2	2	2	2	1	3	3	3	2	3	1	2	1	1	3	3	2	3	1	2	2	1	2	2	2	2	3	3	3	2	2	2	3	3	3	1	2
81	3	1	1	2	1	2	2	3	1	3	1	2	2	1	3	3	2	3	3	3	2	3	1	1	1	2	2	3	2	3	3	1	1	1	1	1	1	3	1	3	3	2	2	3	1	3	3	3	1	2	2
82	3	1	3	2	3	3	3	1	3	1	2	2	1	2	3	2	1	2	3	2	1	1	2	1	2	3	3	3	3	3	3	1	2	1	1	2	3	1	1	2	2	2	2	3	1	2	3	1	3	2	1
83	3	3	3	2	3	1	3	1	1	3	1	3	3	2	2	2	3	3	1	2	1	2	1	3	2	3	2	1	3	1	2	2	1	3	2	1	2	1	3	3	2	3	1	3	1	3	1	3	3	1	1
84	3	1	3	2	2	2	1	1	1	2	2	1	1	1	3	3	2	3	1	2	1	3	3	1	3	1	1	3	1	1	3	2	1	3	3	3	3	3	1	2	3	3	3	2	1	2	2	3	1	2	2
85	3	2	3	3	2	1	1	1	1	3	1	3	2	2	3	3	2	1	2	3	2	2	2	1	2	2	2	1	1	1	2	3	3	1	2	1	2	3	2	2	3	2	2	3	3	3	3	2	2	2	3
86	3	2	2	3	1	2	3	1	3	1	1	1	1	2	3	3	2	3	2	2	3	1	1	3	3	1	3	1	2	3	3	2	1	3	1	1	1	3	3	3	1	1	3	3	3	1	1	1	2	2	3
87	3	3	3	3	3	1	2	2	3	2	2	3	3	2	2	1	1	2	1	1	2	2	2	1	3	1	3	3	2	1	2	1	1	2	3	2	3	2	1	1	3	3	2	2	3	1	3	1	2	1	1
88	3	2	2	2	3	2	3	3	3	1	3	1	2	3	2	2	2	3	3	1	3	2	2	2	3	1	2	2	3	2	3	1	1	3	2	3	1	3	2	2	3	2	1	2	1	3	2	2	2	2	2
89	3	3	1	3	2	3	3	2	3	2	3	3	3	2	1	1	1	2	1	1	1	1	3	3	3	1	2	1	1	1	1	1	3	2	1	2	3	1	3	2	1	3	3	1	2	1	1	3	3	1	1
90	3	1	2	2	1	1	3	2	3	1	2	2	2	2	2	3	2	3	1	1	1	3	1	3	3	1	1	3	2	2	1	1	2	2	1	2	3	2	2	2	1	3	2	3	1	1	1	2	1	1	1
91	3	1	1	1	1	3	3	2	2	1	1	2	2	1	3	2	1	2	1	3	1	3	1	2	1	1	1	2	1	3	2	2	2	2	3	3	2	2	1	2	1	2	2	3	2	2	2	2	3	3	3
92	2	3	1	3	2	1	3	1	1	3	2	1	2	2	2	3	2	3	3	1	3	2	3	1	3	1	2	1	3	1	2	3	2	1	1	3	2	3	3	2	2	2	1	3	3	1	2	3	3	3	3
93	3	1	3	1	2	2	1	2	3	3	2	2	3	1	3	1	3	1	2	3	1	3	2	2	1	2	2	3	1	3	2	2	1	2	2	1	2	1	3	2	2	2	1	1	3	1	2	2	3	1	2
94	3	1	3	1	2	1	2	2	2	1	2	2	1	2	1	3	3	3	3	2	1	1	3	2	1	2	2	3	1	1	3	2	3	3	1	2	1	2	2	1	2	2	3	2	3	1	1	2	3	3	2
95	3	2	2	1	3	1	3	3	3	1	1	3	3	3	2	2	3	2	1	2	1	2	1	2	1	3	3	3	3	1	3	2	2	3	2	3	2	3	2	3	3	1	1	3	2	2	3	2	3	2	1
96	3	3	3	1	2	1	1	1	3	3	3	3	2	2	1	2	1	2	2	1	1	2	3	1	1	1	3	1	3	1	2	1	2	2	2	1	2	3	3	3	3	2	3	2	2	3	1	2	2	1	2
97	3	1	2	3	1	3	2	3	2	3	3	3	1	3	3	3	1	3	3	3	1	2	1	1	3	1	3	1	1	1	2	2	3	3	1	2	3	3	3	3	1	2	2	3	3	1	3	3	2	2	3
98	3	3	1	2	2	3	1	3	2	1	3	1	3	1	3	3	2	3	1	3	3	2	1	2	3	1	1	1	1	3	2	3	2	1	1	2	1	1	1	1	2	2	3	3	2	1	3	3	1	1	1
99	2	1	3	2	2	2	1	3	2	3	2	1	1	1	1	1	3	3	3	1	1	3	1	2	2	1	1	2	1	3	3	2	1	3	3	1	1	2	2	1	2	3	1	3	3	2	2	2	2	2	3
100	3	3	1	1	1	3	3	2	3	3	3	3	3	1	1	3	2	2	3	3	1	2	3	1	3	3	3	2	3	2	2	2	2	2	2	1	1	2	2	1	2	2	2	2	2	1	1	2	3	1	1

Table G.3. One-way road types for traveling from the customers 0-50 to the customers 51-100. The matrix should be read over rows.

→	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100
0	2	3	1	2	3	1	3	1	3	1	3	2	3	2	3	2	1	2	2	2	2	1	1	3	2	1	1	2	3	3	3	3	1	3	2	1	3	1	2	2	1	2	3	3	3	1	3	1	2	3
1	3	2	2	3	3	1	3	2	2	1	3	1	2	3	1	2	1	3	2	3	3	1	3	3	2	2	3	3	3	2	1	1	3	2	1	3	3	1	2	3	1	2	3	1	1	3	3	1	3	3
2	2	1	2	2	1	2	3	1	3	1	3	3	2	2	2	1	1	2	1	1	1	1	2	3	3	1	1	1	3	3	1	3	2	2	1	3	2	1	1	1	3	1	1	1	3	2	1	1	3	3
3	3	1	3	1	1	3	2	1	3	2	2	1	3	1	3	2	1	2	1	3	1	2	2	3	2	1	1	1	1	3	1	1	2	1	3	3	1	1	3	3	3	2	1	3	1	1	3	2	1	2
4	2	1	1	3	1	1	2	1	2	3	2	1	2	2	3	3	2	3	1	2	3	2	2	1	2	2	2	3	1	2	2	3	1	2	3	1	2	3	1	3	2	1	3	2	3	3	1	1	1	2
5	1	1	3	3	1	1	2	3	2	3	1	2	1	1	3	1	2	3	2	2	3	3	2	2	3	3	2	2	1	3	1	1	1	3	2	3	3	1	1	2	2	3	2	2	3	1	2	1	2	3
6	3	1	2	2	2	1	2	2	1	1	3	3	2	2	1	1	3	2	2	3	1	2	1	2	2	1	2	3	3	3	2	2	1	3	3	1	1	2	3	1	2	2	2	3	2	2	3	2	1	1
7	3	2	3	2	1	2	2	1	3	2	1	2	3	1	2	2	3	2	1	3	1	2	1	3	2	3	3	2	3	1	3	3	1	3	2	2	3	1	3	3	2	1	2	1	2	3	1	2	1	1
8	1	1	3	1	2	2	2	2	1	2	3	1	3	1	3	1	3	2	1	3	2	3	1	2	2	3	1	2	2	2	2	1	2	3	2	1	3	3	1	3	1	1	2	2	2	1	3	1	2	3
9	1	3	2	3	2	3	3	1	1	1	3	1	1	2	2	1	3	3	3	3	2	3	3	3	2	1	3	2	3	1	1	3	2	2	1	1	2	2	3	1	2	1	3	1	1	1	1	3	1	1
10	1	2	2	3	2	1	3	1	2	1	1	2	3	3	3	3	3	2	2	2	1	1	2	2	1	1	1	1	2	3	1	2	3	3	1	1	3	2	1	2	3	2	1	1	2	2	3	1	3	1
11	3	2	2	1	3	3	1	1	3	1	3	1	3	1	2	3	3	2	1	1	1	2	2	2	3	2	3	1	2	3	3	2	3	3	3	1	3	2	2	3	2	1	2	2	2	3	3	2	3	2
12	2	3	1	2	1	1	3	1	2	2	1	1	1	2	3	2	3	2	2	3	3	2	3	3	1	2	2	1	3	1	3	2	2	1	2	2	2	3	3	3	3	1	2	2	2	3	2	2	1	1
13	1	2	2	3	2	3	1	2	2	3	3	2	1	2	2	3	2	3	3	1	3	2	1	2	2	3	1	2	2	2	3	3	3	1	2	2	2	1	1	3	2	1	3	3	3	1	3	1	2	2
14	1	2	3	1	2	2	3	2	1	1	1	3	2	3	1	2	2	3	1	1	2	3	1	2	3	2	1	2	3	2	2	1	3	1	2	2	1	3	2	1	1	1	3	3	2	1	1	2	2	3
15	1	3	1	2	2	1	3	2	1	2	1	1	2	2	2	3	2	3	2	2	2	3	1	2	3	2	3	3	1	3	1	3	2	2	3	3	3	2	1	1	2	1	3	3	3	3	1	1	1	1
16	1	2	1	3	1	3	3	1	1	2	1	1	1	3	3	2	1	1	3	3	1	3	2	1	2	3	2	2	2	2	2	3	3	2	3	3	3	3	3	3	2	3	3	3	2	1	1	3	1	2
17	2	1	1	3	3	2	2	1	2	2	2	1	1	2	1	3	2	1	1	3	3	1	1	3	3	3	3	3	1	3	2	3	1	2	2	1	1	1	2	2	1	1	3	1	2	2	2	3	1	2
18	2	3	3	1	3	2	2	3	3	1	2	1	1	3	3	1	1	2	2	1	2	2	1	3	3	3	1	1	1	2	3	2	2	1	3	1	1	1	3	2	1	1	3	2	3	1	2	2	2	2
19	1	3	2	2	2	2	3	3	2	3	3	2	1	3	2	2	2	1	2	2	2	3	3	1	2	3	1	2	3	1	1	3	1	1	2	2	1	1	3	2	3	1	3	3	1	3	3	2	2	2
20	2	3	1	2	1	2	3	1	1	3	2	3	2	1	2	3	2	3	3	2	1	1	2	3	2	3	3	1	3	2	1	3	3	3	2	2	2	1	3	3	2	2	1	3	1	3	1	1	3	2
21	3	2	2	2	1	3	1	2	2	2	3	3	2	2	2	3	1	1	1	2	2	2	3	1	1	3	3	2	2	1	2	3	2	1	2	1	1	3	1	2	3	2	3	2	3	2	3	2	3	2
22	1	2	3	2	2	2	3	2	3	3	3	1	3	1	1	2	2	3	3	1	1	1	3	3	3	1	1	1	3	3	1	1	3	3	1	3	2	3	3	3	3	1	1	3	1	1	3	1	3	1
23	3	3	2	2	1	3	3	2	1	3	2	2	1	1	1	2	2	1	3	1	2	3	1	2	1	2	2	3	3	1	2	2	2	2	2	2	2	1	2	2	2	1	1	1	3	3	1	3	3	1
24	3	1	1	1	1	1	1	1	3	2	1	2	3	2	2	2	2	1	2	2	3	2	2	1	3	1	2	1	1	2	1	2	1	1	3	3	3	2	1	1	2	2	2	1	1	2	2	1	1	3
25	2	3	1	2	1	3	1	2	2	2	1	2	3	2	2	2	3	3	2	1	3	2	2	2	2	3	3	3	2	1	3	2	2	1	2	3	1	2	1	3	3	1	1	3	1	3	3	2	2	1
26	3	1	3	2	2	3	3	2	1	2	2	2	2	1	1	2	2	2	1	3	1	1	2	1	2	1	3	2	2	2	1	1	1	3	1	1	3	2	1	1	3	3	2	2	1	1	3	1	1	1
27	3	1	1	1	1	3	3	3	1	3	1	2	2	3	1	3	1	3	3	2	1	1	1	3	2	3	2	3	1	3	2	2	3	2	2	1	2	1	1	1	2	1	2	2	1	1	2	2	2	3
28	1	2	1	2	2	2	1	3	3	1	3	1	3	1	1	2	3	2	3	3	2	3	3	2	2	1	2	1	2	2	2	2	2	3	1	3	2	3	2	1	2	1	1	3	3	1	1	1	2	2
29	1	1	1	2	2	3	1	1	2	3	1	2	3	2	2	3	2	2	2	3	3	1	2	2	3	1	1	2	2	3	3	1	1	1	2	3	1	1	2	1	1	3	2	1	2	1	3	1	3	2
30	3	1	1	1	3	1	2	2	2	3	1	2	2	1	1	2	3	3	1	2	1	1	2	3	3	1	1	2	2	1	3	3	1	2	3	3	3	2	1	3	1	1	2	2	1	1	1	1	1	1
31	3	2	3	3	1	2	2	1	2	1	1	1	3	2	3	1	1	1	1	2	2	3	2	2	1	3	1	1	3	3	3	1	1	1	3	2	1	3	2	1	3	3	3	2	3	3	2	3	3	2
32	3	2	3	2	2	2	2	2	3	1	1	1	3	1	1	1	3	1	3	1	2	1	2	1	2	1	1	2	2	3	2	3	2	3	1	3	2	1	2	1	2	1	3	1	3	2	1	1	1	2
33	1	1	1	3	1	1	1	2	2	3	2	3	1	1	2	2	2	3	3	2	2	3	2	2	3	3	3	3	1	1	1	1	1	3	2	3	3	3	3	3	1	1	1	3	3	3	2	2	2	1
34	1	1	3	1	3	2	1	1	3	2	2	1	3	3	3	3	3	2	3	2	1	1	1	1	1	1	2	2	1	1	1	3	1	3	1	1	2	1	3	3	3	1	2	2	1	1	2	1	3	3
35	2	3	1	2	2	1	1	2	3	1	1	2	3	1	2	3	2	1	3	1	3	3	2	1	3	1	1	1	2	2	2	3	3	3	2	2	3	3	3	2	2	2	2	1	1	1	2	1	2	2
36	2	1	2	2	2	3	2	3	1	1	2	1	1	3	1	2	1	1	1	1	2	3	1	1	2	1	2	3	2	2	1	2	3	3	1	2	3	1	2	3	1	1	2	1	1	1	3	1	2	1
37	3	2	2	3	1	3	2	3	2	1	1	2	2	3	1	1	1	2	3	3	2	3	1	3	1	3	2	1	3	2	1	1	2	3	1	2	2	3	2	2	2	2	3	3	3	1	3	3	1	2
38	1	3	1	3	3	3	2	2	1	1	3	2	2	2	1	3	1	3	2	1	3	3	2	2	2	2	1	3	1	3	3	1	1	2	3	1	1	1	2	2	1	2	3	3	2	2	1	2	3	1
39	1	3	3	2	2	2	1	1	3	3	1	3	3	2	1	3	3	2	3	3	2	1	3	1	2	2	3	2	3	3	3	3	3	1	2	2	3	2	2	1	2	3	1	2	1	3	2	3	3	1
40	3	1	3	2	1	2	2	2	3	2	1	2	2	2	1	2	1	3	3	2	3	1	2	1	1	3	3	2	1	2	2	3	3	3	3	3	1	1	2	3	3	3	3	2	2	3	2	1	2	1
41	1	3	2	2	3	1	2	2	2	3	1	3	1	3	2	3	3	1	2	2	1	1	1	1	3	3	2	2	2	2	1	3	1	2	1	1	1	2	2	3	1	3	1	3	1	2	2	3	2	2
42	2	3	1	1	3	3	3	2	3	3	1	2	2	3	3	1	3	3	2	3	2	3	2	3	3	3	1	2	3	3	2	3	1	3	3	1	1	3	1	2	3	1	3	1	3	3	1	1	2	2
43	2	2	1	3	2	2	2	3	1	1	3	2	2	3	3	3	2	1	2	3	3	2	2	3	3	1	3	2	3	2	2	3	1	1	1	3	3	3	3	1	1	2	2	1	2	2	1	2	2	3
44	1	1	1	2	3	3	1	3	3	1	3	3	1	2	2	1	3	3	3	2	1	2	2	1	3	3	2	1	3	1	3	2	1	3	2	3	1	2	1	1	3	3	3	2	1	3	2	1	3	2
45	1	1	1	1	2	1	1	1	2	3	3	1	3	1	2	3	3	1	1	3	3	3	1	1	1	2	3	2	2	3	1	2	2	2	2	1	1	1	2	2	2	2	1	1	3	1	2	2	2	1
46	2	1	1	1	2	2	3	1	3	2	1	2	2	1	3	3	3	2	1	2	2	2	3	2	1	1	2	3	2	1	3	3	2	3	2	3	1	3	3	1	2	3	2	1	3	3	1	3	2	1
47	3	2	2	2	2	2	2	3	1	1	3	1	3	3	1	1	2	2	1	2	1	2	3	1	2	1	2	3	1	1	2	2	2	1	1	2	1	3	2	2	2	2	1	2	3	2	2	2	2	1
48	3	3	3	1	2	1	3	1	3	1	2	3	1	3	1	2	2	3	1	3	2	1	3	1	3	3	2	3	1	2	1	2	3	1	3	3	2	3	3	2	1	1	3	2	1	1	2	2	1	1
49	1	2	3	3	1	3	2	1	3	2	2	2	3	3	2	1	1	2	1	2	1	3	1	1	2	2	1	3	3	2	2	3	3	2	2	2	1	3	2	2	2	2	2	2	2	2	3	2	3	2
50	3	2	2	3	2	2	3	2	1	1	3	3	1	2	1	3	2	1	2	1	3	1	3	3	2	3	3	3	3	1	3	1	1	2	1	1	1	1	3	1	1	1	2	1	2	1	1	3	3	1

Table G.4. One-way road types for traveling from the customers 51-100 to the customers 51-100. The matrix should be read over rows.

→	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100
51	-	2	2	1	2	1	3	2	1	3	3	3	2	1	3	2	1	1	1	2	3	1	2	3	3	1	2	3	2	1	1	1	3	3	3	1	2	3	1	3	3	2	2	2	3	1	1	2	1	1
52	2	-	2	2	1	2	3	1	3	3	3	1	3	2	1	2	2	2	1	1	1	2	2	3	2	1	3	3	1	3	2	2	3	3	2	3	2	3	2	2	3	2	3	1	3	3	3	1	3	3
53	2	2	-	2	3	3	3	1	1	1	2	2	2	1	2	1	3	3	2	2	2	1	2	3	1	3	2	2	1	2	2	2	1	2	1	3	1	2	2	3	2	1	3	2	2	2	3	3	3	2
54	3	3	1	-	1	2	3	3	2	2	1	1	3	2	1	2	3	2	2	2	3	2	3	2	1	2	2	1	3	3	1	1	1	1	3	3	1	2	2	3	1	1	1	1	1	2	3	2	3	1
55	3	3	2	3	-	2	2	3	3	1	1	1	2	1	3	1	1	2	3	2	2	2	2	2	2	2	3	1	1	3	2	1	3	2	1	3	3	3	3	3	2	3	2	1	1	3	1	1	1	1
56	1	1	1	3	3	-	1	2	1	3	3	3	2	2	1	3	1	2	2	2	2	1	2	1	2	1	3	3	3	1	1	3	3	1	2	1	2	3	1	2	3	3	1	1	2	2	3	1	2	1
57	3	1	2	3	3	3	-	2	1	3	1	2	2	1	3	2	1	1	3	2	2	2	1	2	2	3	3	1	2	2	2	3	3	1	3	1	2	3	2	2	1	1	2	1	1	1	1	1	1	3
58	3	2	2	3	1	2	2	-	2	3	2	2	1	2	2	2	1	1	2	1	2	2	2	2	2	2	1	3	3	1	1	1	1	1	2	3	3	1	3	3	2	3	1	3	3	2	3	3	1	1
59	2	2	2	2	1	3	3	3	-	1	1	3	2	1	3	1	3	1	1	3	3	3	1	2	2	1	3	1	3	1	3	3	1	1	3	1	1	1	3	1	1	2	3	3	3	2	1	1	2	2
60	3	3	3	2	1	2	1	3	1	-	2	1	2	1	2	1	1	3	1	1	1	1	3	1	1	1	3	2	1	1	3	3	3	1	2	1	1	2	3	2	3	3	3	2	2	2	2	3	1	3
61	1	1	3	2	2	1	2	2	2	3	-	1	1	2	2	2	2	2	3	2	1	2	1	2	3	3	1	3	2	2	2	2	2	3	1	3	3	2	3	2	2	1	1	2	1	1	1	1	1	3
62	3	1	2	1	3	3	1	2	1	3	1	-	3	1	1	3	2	1	2	3	2	1	3	2	3	3	2	1	2	3	1	1	1	3	3	3	2	2	2	1	1	3	1	1	3	2	2	2	1	1
63	1	1	3	3	3	3	1	2	3	2	1	2	-	1	3	1	2	1	3	2	1	3	3	1	2	1	3	3	2	2	1	3	2	3	3	1	3	2	2	1	3	1	2	3	2	2	2	3	1	3
64	2	2	2	3	2	2	2	3	1	1	3	3	1	-	1	3	2	3	2	2	3	3	1	2	2	1	1	1	2	1	1	2	2	2	2	1	2	1	1	3	2	1	1	2	3	3	1	1	1	2
65	3	1	3	2	2	3	3	2	2	1	2	2	1	1	-	2	3	1	1	2	3	1	3	1	2	2	1	1	1	3	2	3	2	1	1	2	3	1	2	3	3	3	2	1	1	1	1	3	2	3
66	2	3	2	1	3	1	3	3	3	3	1	1	1	2	3	-	2	2	2	3	2	2	1	1	2	1	3	2	2	2	2	3	2	2	1	3	2	2	1	2	3	1	2	2	1	1	2	2	3	3
67	3	1	3	3	2	3	1	1	2	3	2	1	1	2	3	3	-	3	1	1	1	2	1	3	1	1	3	1	2	1	2	2	1	3	2	3	1	3	2	2	3	1	1	1	3	1	3	1	3	3
68	2	2	1	1	2	2	2	3	2	3	3	2	3	3	3	3	3	-	3	2	3	1	3	2	2	1	1	2	2	2	1	1	1	1	1	3	1	2	3	2	3	3	2	1	2	1	3	3	1	1
69	2	2	1	1	3	3	3	1	1	1	2	1	1	3	1	2	1	2	-	3	2	2	3	3	2	3	2	1	2	3	2	2	1	3	3	3	3	1	2	2	2	1	1	1	2	3	3	3	1	3
70	1	3	1	3	1	2	2	2	1	3	1	3	2	1	1	2	1	3	1	-	2	1	1	3	1	2	3	2	1	1	2	1	3	2	1	3	1	2	2	3	3	2	3	2	1	1	3	1	2	1
71	2	3	1	2	1	1	2	2	2	3	1	2	3	2	2	3	3	1	2	2	-	1	1	1	2	2	2	2	2	3	1	3	3	1	1	2	2	1	2	3	3	2	1	2	2	2	2	3	3	3
72	3	2	3	3	1	3	3	2	3	2	1	3	3	2	3	3	1	1	1	2	2	-	2	3	2	1	2	1	2	2	2	2	2	2	2	1	1	3	3	3	1	2	1	1	1	1	3	2	1	1
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