# Analyzing combined vehicle routing and break scheduling from a distributed decision making perspective

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**Abstract**

We analyze the problem of combined vehicle routing and break scheduling from a distributed decision making perspective. The problem of combined vehicle routing and break scheduling can be defined as the problem of finding vehicle routes to serve a set of customers such that a cost criterion is minimized and legal rules on driving and working hours are observed. In the literature, this problem is always analyzed from a central planning perspective. In practice, however, this problem is solved interactively between planners and drivers. In many practical scenarios, the planner first clusters the customer requests and instructs the drivers which customers they have to visit. Subsequently, the drivers decide upon the routes to be taken and their break schedules. We apply a framework for distributed decision making to model this planning scenario and propose various ways for planners to anticipate the drivers' planning behavior. Especially in the case of antagonistic objectives, which are often encountered in practice, a distributed decision making perspective is necessary to analyze

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this planning process. Computational experiments demonstrate that a high degree of anticipation by the planner has a strong positive impact on the overall planning quality, especially in the case of conflicting planner's and drivers' objectives.

*keywords:* Vehicle routing; Break scheduling; Distributed decision making

# 1 Introduction

In order to increase safety on the European road network, the European Union entered Regulation (EC) No 561/2006 on drivers' driving hours into force in April 2007. This regulation poses restrictions to the amount of driving time until breaks and rest periods have to be scheduled, such that driver fatigue, which is an important cause for road accidents, is prevented. Moreover, Directive 2002/15/EC gives restrictions on drivers' working hours. Together, these legal acts are referred to as EC social legislation. Since violations of the EC social legislation can be severely fined, drivers should respect these regulations. Due to the fact that drivers have to schedule breaks and rest periods, planners at companies such as logistics service providers and distribution firms should account for them in their planning. Therefore, such companies have to deal with combined vehicle routing and break scheduling problems.

Despite the vast literature on vehicle routing problems (VRPs), combined vehicle routing and break scheduling has drawn only minor attention. Recently, there has been some more attention due to the introduction of Regulation (EC) No 561/2006 (Goel, 2009; Kok et al., 2009). These papers focus on a central planning perspective, implying that the planner is responsible for the complete combined vehicle routing and break scheduling problem. Meyer et al. (2009) propose a problem description from a hierarchical planning perspective.

The problem of combined vehicle routing and break scheduling basically comprises three subproblems: clustering the customer requests, routing, and break scheduling. In practice, these subproblems are distributed over different decision makers: the planner and the drivers. Semi-structured interviews with 5 medium-sized logistics service providers in Germany pointed out (Onken, 2009) that in practice planners are responsible for the clustering of the customer requests, while the drivers schedule their breaks. Whether the routing is done by the planner or the driver depends on the application at hand.

In the literature, different strategies have been proposed to deal with the problem of break scheduling within vehicle routing. Some propose explicit break scheduling, in which the rules of Regulation (EC) No 561/2006 are explicitly considered in the VRP (Goel, 2009; Kok et al., 2009; Zäpfel and Bögl, 2008). Others propose implicit break scheduling, in which slack travel time is created by using a lower average speed (e.g., Bartodziej et al., 2009). This latter approach for accounting for breaks can often be encountered in practice (Onken, 2009). Explicit break scheduling is more complex, but allows for finding better results and guarantees feasible break schedules for the resulting vehicle routes. This trade-off between complexity and solution quality has, to the best of our knowledge, never been analyzed and quantified so far.

To account for the different decision makers involved, we analyze the problem of combined vehicle routing and break scheduling from a distributed decision making (DDM) perspective. For this purpose, we apply the framework for DDM proposed by Schneeweiss (2003). We consider two different decision makers: the planner and the driver. The planner's main task is to determine the customer clusters. His decision results in an instruction to each driver (visit a certain customer set), implying a hierarchical planning situation. In order to ensure that the drivers can find feasible routes and break schedules, we propose various anticipation functions for the drivers' behavior. As we shall argue in Section 3.1, we consider all relevant degrees of anticipation for the problem of combined vehicle routing and break scheduling. The planner's final decision is based on the clustering problem and his anticipation of the drivers' behavior. The primary objective of the planner is to minimize the number of clusters. His secondary objective is to minimize the total travel distance.

For the drivers' behavior, we consider two different cases. The first one is that the drivers' objective meets the company's primary objective, e.g. minimizing the total travel distance. The second case, which better represents practice in many cases, is when the drivers apply their own objective, e.g. minimizing the return time. This objective may conflict with the company's objective to minimize travel distance. The practical problem of conflicting objectives is another strong motivation to study the problem of combined vehicle routing and break scheduling from a distributed decision making perspective.

By proposing different anticipation functions of the drivers' behavior, we can compare different strategies for break scheduling, e.g., implicit and explicit break scheduling. We perform computational experiments to quantify the quality of these different strategies. Clearly, some of the strategies are more complex (explicit break scheduling) than others (implicit break scheduling). By quantifying the quality of these different strategies, the trade-off between complexity and solution quality is demonstrated.

The contributions of this paper are the following. First, to the best of our knowledge, this is the first paper that quantitatively analyzes the problem of combined vehicle routing and break scheduling from a distributed decision making perspective including all relevant degrees of anticipation. This perspective fits in practice, as opposed to a central planning perspective. Second, we consider both the case of complementary planner's and drivers' objectives, as well as the case of conflicting planner's and drivers' objectives. Third, we propose various anticipation functions for the combined vehicle routing and break scheduling problem within a framework for DDM. Fourth, we quantify the quality of these anticipation functions, allowing for a comparison of different strategies for considering break scheduling within vehicle routing. Fifth, we apply the framework for DDM by Schneeweiss (2003) to a new application. Therefore, this paper contributes both to the VRP-literature and the DDM-literature.

This paper is organized as follows. In Section 2, we introduce the problem of combined vehicle routing and break scheduling and discuss the distribution of tasks between planners and drivers. In Section 3, we show how the problem can be embedded into a framework for DDM. We will consider two different settings. In the first case, the drivers act in a way that fits within the planner's objective while in the second case, the drivers deviate from the planner's objective, following their own criterion. In Section 4, we analyze the impacts of various anticipation functions of the drivers' behavior using computational experiments. Both, the case in which drivers' and planner's objectives coincide, and the case in which these objectives conflict are considered. Finally, in Section 5, we give a summary of our main findings and draw some conclusions.

## 2 Problem description

The problem of combined vehicle routing and break scheduling can be defined as the problem of finding routes to serve a set of customers such that a cost criterion is minimized and legal rules on driving and working hours are observed. As in traditional VRPs, we assume that there is a fleet of homogeneous vehicles starting from a central depot and delivering goods to a set of customers. Each vehicle makes at most one route and the total customer demand along each route does not exceed the capacity of one vehicle. Each customer may only be visited once and its service must start within a given time window. If a vehicle arrives early at a customer, it has to wait until the opening of the time window. After finishing their route, the vehicles return to the depot. All travel times and all customer requests are known in advance. So far, these restrictions are similar to those for the well-known vehicle routing problem with time windows (VRPTW).

Moreover, on their routes drivers have to take breaks and rest periods according to the EC social legislation. We assume that each vehicle is manned by one driver who stays with it for the whole planning period. Therefore, the driving times of the vehicle equal those of its driver. A planning period of one week is considered and we assume that all drivers have just had a weekly rest period. Breaks and rest periods have to be included into the vehicle routes such that the legislation is satisfied and the time windows are met. We call this partial planning task 'break scheduling'.

Regulation (EC) No 561/2006 concerns three different time horizons: single driving periods, daily driving times, and weekly driving times. For these time horizons, a complex set of restrictions consisting of basic and optional rules is imposed on the drivers' schedules. The optional rules are relaxations of the basic rules: they allow the drivers additional possibilities for scheduling breaks and rest periods. For example, the regulation restricts the driving time in each single driving period to a maximum of 4.5 hours. The basic rule states that drivers are obliged to take a break of at least 45 minutes after each driving period. However, there is the option to divide this break into two parts of at least 15 minutes and 30 minutes, respectively.

As driving times are considered as working times, they are also affected by Directive 2002/15/EC, which contains restrictions on working times and breaks. For example, the directive postulates that after a working time of no more than 6 hours workers have to take a break of at least 30 minutes. If the daily working time exceeds 9 hours the total break time has to amount to at least 45 minutes. These break times can be divided into parts of at least 15 minutes each. Consequently, a break that meets the requirements of EC Regulation No 561/2006 also satisfies Directive 2002/15/EC. For a comprehensive description of the legal rules of the EC social legislation, we refer to Kok et al. (2009).

The problem of combined vehicle routing and break scheduling comprises three interconnected partial planning problems: the clustering of customer requests, the routing of vehicles, and the planning of breaks and rest periods. These problems can be solved either simultaneously or in sequence. Since in our scenario the tasks are divided among different decision makers, we consider the case that these problems are addressed sequentially by planners and drivers. First, the planner carries out the clustering of customer requests. When performing his planning task, the planner tries to minimize the number of vehicles used to serve the customers in order to save costs for the company. His second objective is to minimize the total travel distance to serve all customers. The customer clusters are then passed on to the drivers. Within their assigned set of customers, each driver carries out the routing and break scheduling such that the EC social legislation is satisfied on his route. The drivers may follow different objectives when performing their planning tasks. If they act according to the company's objectives, they may try to minimize the travel distance in order to save costs. In the following, we will refer to this situation as the team situation between planner and drivers. However, since the drivers can freely decide on their route, they might also follow their own objectives, even if they are not in line with the company's objectives. For example, instead of minimizing the travel distance, each driver can try to minimize his return time to the depot in order to maximize his leisure. This hidden action cannot be observed by the planner. We refer to this antagonistic setting as the non-team situation.

To avoid infeasibilities in the drivers' subsequent planning, the planner might take into account the drivers' planning process when generating customer clusters. This means that when performing their planning task, planners anticipate the routing and break scheduling that will be performed subsequently. However, since the legislation on driving and working hours is very complex, planners might not anticipate the exact planning process but rather use some simplified approach to anticipate the drivers' planning model. We will propose different degrees of anticipation and analyze their impact on the resulting vehicle schedules.

# 3 Embedding the Problem into the Framework for DDM

The framework for DDM presented by Schneeweiss (2003) was first introduced as a framework for hierarchical planning by Schneeweiss (1995). Since then it has been applied successfully to investigate problems in diverse areas, such as production planning (Gfrerer and Zäpfel, 1995), resource planning (Pesenti, 1995), supply chain management (Schneeweiss and Zimmer, 2004), managerial accounting (Eichin and Schneeweiss, 2001), financial planning (Goedhart and Spronk, 1995), and contract design (Schenk-Mathes, 1995).

In the framework for DDM presented by Schneeweiss (2003), two decision making units (DMUs) are considered. In the case of hierarchies in distributed decision making, these DMUs are situated on different levels. The top-level uses a planning model $M^T(C^T, A^T)$ and takes its decision in such a way that it optimizes its criterion $C^T$ over all possible actions $a^T \in A^T$ within its decision field $A^T$. The top-level's criterion consists of a private criterion $C^{TT}$ and a top-down criterion $C^{TB}$ (which depends on the base-level's behavior), i.e. $C^T = \left\{C^{TT}, C^{TB}\right\}$. The top-level derives an optimal instruction $IN^* = IN(a^{T*})$ and communicates it to the base-level. Subsequently, the base-level takes its decision based on the top-level's instruction using its planning model $M^B(C^B, A^B)$ such that its criterion $C^B$ is optimized.

To improve its planning results, the top-level can try to anticipate the base-level's subsequent planning in order to avoid giving an infeasible instruction or to account for the base-level's influence on the top-down criterion. Therefore, the top-level can apply an anticipation function $AF(IN)$, which is a function of the top-level's instruction and gives possible reactions of the expected base-level's behavior. The anticipation function does not need to be a precise representation of the base-level's reaction but can also be an approximation of the expected base-level's planning model $Exp(M^B(C^B, A^B))$. Figure 1 depicts this hierarchical coordination structure.

Schneeweiss (2003) distinguishes between four different degrees of anticipation: perfect reactive anticipation, approximately perfect reactive anticipation, implicit reactive anticipation, and non-reactive anticipation. Perfect reactive anticipation means that the base-level's planning model is exactly known and it is anticipated by the top-level without any approximations. In the case of approximately perfect reactive anticipation the base-level's planning model is taken into account only approximately, e.g. by making sim-

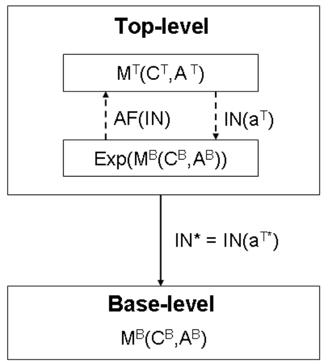


**Figure 1: Coordination in Hierarchical Systems (Schneeweiss, 2003)**

plifying assumptions. Implicit reactive anticipation means that only some features of the base model are considered and the anticipation function does no longer explicitly describe the base-level's decision model. These three degrees of anticipation incorporate the base-level's planning behavior as a reaction to the top-level's instruction. In the case of non-reactive anticipation, such an anticipation function does not exist, but only some general features of the base-level may be included in the top-level's criterion.

## 3.1 Planner's and Drivers' Models

In the problem of combined vehicle routing and break scheduling, the planner constitutes the top-level and the drivers constitute the base-level. In the pure top-down hierarchy where the planner does not account for the drivers' planning, the planner's criterion $C^T$ is to minimize the number of vehicles required to serve all customer requests. This criterion is independent of the drivers' behavior and therefore the planner's criterion only comprises his private criterion, i.e. $C^T = C^{TT}$. The planner's decision field $A^T$ comprises all possible customer clusters satisfying the capacity restrictions of the vehicles. In the case that the planner does not anticipate the drivers' planning model, the planner's decision problem results in solving the following assignment problem with capacity restrictions:

$$C^T : Minimize \sum_{k \in K} z_k \tag{1}$$

$$A^T : \sum_{k \in K} x_{ik} = 1, \qquad \forall i \in P \tag{2}$$

$$Qz_k \geq \sum_{i \in P} l_i x_{ik}, \qquad \forall k \in K \tag{3}$$

Where

$P = \{1, ..., n\}$ : set of customers
$K = \{1, ..., m\}$ : set of vehicles
$x_{ik} \in \{0, 1\}$ : takes value 1 iff customer $i$ is served by vehicle $k$
$z_k \in \{0, 1\}$ : takes value 1 iff vehicle $k$ is used
$Q$ : capacity of one vehicle
$l_i$ : demand of customer $i$

After deriving the customer clusters $CL_k \subseteq \{1, ..., n\}$ for each vehicle $k$, the planner passes them on to the corresponding drivers who constitute the base-level. Therefore, the instruction equals the customer clusters, i.e. $IN^* = \{CL_k^* | k \in K\}$, with $CL_k^* = \{i \in P | x_{ik}^* = 1\}$ and $x_{ik}^*$ the optimal assignments in (1) - (3).

The drivers have to perform the routing and break scheduling within their customer clusters. Therefore, each driver $k'$ has to solve a traveling salesman problem with time windows and EC social legislation (TSPTW-EU) for his customer cluster $CL_{k'}^*$. A mathematical description of this problem can be found in Kopfer and Meyer (2009) who propose a position based ILP-formulation for the TSPTW-EU.

When performing the routing and break scheduling, we assume that drivers try to exploit the optional rules of the EC social legislation in order to better fulfill their objectives. This results in the decision field $A^B$ which comprises the set of all possible routes for the customer clusters $CL_k$ such that the customer time windows are met and the legislation is fulfilled, including all optional legal rules. Clearly, for a given set of customers derived by the planner, $A^B$ could be empty (e.g., in (1) - (3) the time windows are

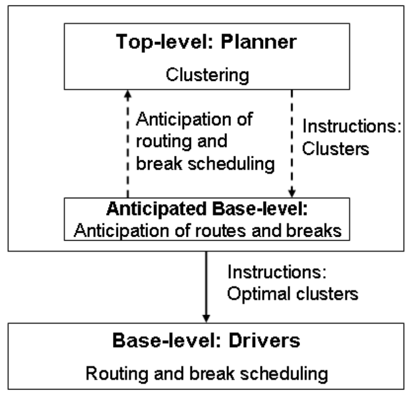


**Figure 2: Decision structure of the DDM problem**

not considered).

In order to avoid infeasible customer clusters, the planner must anticipate the drivers' planning behavior via the anticipation function $AF(IN)$. We propose three of such anticipation functions in the following. We only consider reactive anticipation, since non-reactive anticipation does not make sense in this case (in case of non-reactive anticipation, the time windows and the EC social legislation are not considered, such that $A^B$ is very likely to be empty). Figure 2 depicts the entire planning situation arising in combined vehicle routing and break scheduling.

## 3.2 Team Situation

If we assume a team situation between planner and drivers, the planner correctly expects each driver $k'$ to use the criterion of minimizing the total travel distance within their customer cluster ($i = 0$ and $i = n + 1$ represent the depot; $d_{ij}$ is the travel distance from customer $i$ to customer $j$):

$$Exp(C^B) = Min \sum_{i \in CL_k \cup \{0\}} \sum_{j \in CL_k \cup \{n+1\}} d_{ij} x_{ij}^{k'}$$

Now, the planner is able to account for the drivers' criterion. The planner's private criterion $C^{TT}$ is to minimize the number of vehicles. If there are different customer clusters resulting in the minimum number of vehicles, he will use his top-down criterion $C^{TB}$, which is to minimize the expected total travel distance. However, to estimate the total travel distance, he needs to anticipate the routing that is performed by the drivers. We propose the following anticipation functions for all relevant degrees of anticipation.

Perfect reactive anticipation means that the planner considers the full planning model used by the drivers. In this case, the planner expects each driver to solve a full TSPTW-EU, i.e., $Exp(M^B) = M^B$. By anticipating this driver model, the planner is able to instruct customer clusters that allow feasible routes and break schedules for the drivers.

In case of approximately perfect reactive anticipation, the planner simplifies the drivers' planning model. We propose to do this by leaving out the optional rules of the legislation. This means that the planner's anticipated base model is reduced to a TSPTW-EU without the optional rules. By including only the basic rules of the legislation, the planner can still guarantee that the clusters he instructs to the drivers allow for feasible routes and break schedules.

Implicit anticipation means that the planner does only consider some features of the base model. Therefore, we model this planning approach by assuming that the planner does not explicitly consider the task of break scheduling. However, since the planner knows that the drivers require breaks and rest periods, he considers a lower travel speed than the average travel speed in order to create slack travel time which can be used to schedule breaks and rest periods. Consequently, the anticipated base model is a basic TSPTW.

## 3.3 Non-Team Situation

In practice, the drivers' objective might deviate from the company's objective, which results in a principal-agent setting. In this case the drivers follow their own objective $C'^{B}$, instead of following the company's objective, represented by $C^{TB}$. To model this case, we assume that instead of minimizing the travel distance, the drivers try to minimize their return time in order to finish their duty as early as possible:

$$C'^{B} = Min\, t^{k'}_{return},$$

where $t^{k'}_{return}$ is the return time to the depot of driver $k'$. In this case we assume that the drivers' planning behavior is not correctly observable by the planner. The drivers' objective differs from the planner's anticipated base criterion, implying $Exp(C^B) \neq C'^B$. However, since this is a situation in which the drivers have some hidden action, the planner cannot account for the drivers' behavior correctly and will still use the minimization of the travel distance as the anticipated base criterion. Therefore, in this situation the planner's model $M^T$ and also his anticipation functions $AF(IN)$ are maintained. Moreover, the drivers' decision space $A^B$ still comprises all vehicle routes within their assigned customer clusters such that the EC social legislation is fulfilled. Applying the new base criterion, the base model $M^B$ changes to $M'^B = (C'^B, A^B)$.

# 4 Computational Experiments

We conduct various computational experiments to quantify the impacts of the different anticipation functions. This quantification also allows us to compare different strategies to schedule breaks and rest periods within vehicle routing. We both test the team- and the non-team situation. To solve the planner's and drivers' problems, we use the following approach.

In all scenarios, each driver has to solve a TSPTW-EU. Only the objective is depending on the team character of the situation considered. The planner's problem is a clustering problem, in which the decision space $A^T$ is restricted by the anticipation function of the drivers' behavior; also the top-down criterion $C^{TB}$ is estimated through the anticipation function. For each degree of anticipation, we describe the resulting problem to solve. After describing the different problems, we describe the solution algorithm.

In the case of perfect anticipation, while minimizing the number of customer clusters, the planner expects each driver to solve a TSPTW-EU with the objective of minimizing the travel distance. The planner's problem can be addressed by solving a VRPTW-EU, with minimizing the number of vehicles as the primary objective. All rules of the EC social legislation are considered. The planner's secondary objective is to minimize the total travel distance.

In the case of approximately perfect reactive anticipation, the planner also considers a TSPTW-EU for each driver. However, he ignores the optional rules. Therefore, the planner's problem is a VRPTW-EU, without considering the optional rules of the EC social legislation.

With implicit anticipation, the planner considers a TSPTW for each driver, but with driving time estimations based on a lower travel speed than the average travel speed. Therefore, in this case the planner's problem can be solved by solving a VRPTW with minimizing the number of vehicles as the primary objective and minimizing the travel distance as the secondary objective.

We solve all problems (VRPTW-EU, VRPTW-EU without optional rules, VRPTW, TSPTW-EU) with the restricted dynamic programming (DP) algorithm proposed by Kok et al. (2009). We use this approach, since the DP algorithm can solve all problem types and is currently the only algorithm that can solve the VRPTW-EU with the full EC social legislation. The algorithm is designed for the VRPTW-EU. Kok et al. (2009) also describe how to use the DP algorithm to solve the VRPTW-EU restricted to the basic rules. Furthermore, to solve a VRPTW we can simply relax all break scheduling constraints by setting the allowed accumulated driving and working times very high (e.g., to the time horizon of the problem instance). Finally, since the VRPTW-EU is a generalization of the TSPTW-EU, the DP algorithm can also solve the TSPTW-EU.

The DP algorithm is based on the dynamic programming algorithm for the TSP proposed by Held and Karp (1962) and Bellmann (1962). The DP algorithm is applied to the VRP through the giant-tour representation (GTR, Funke et al., 2005) of vehicle routing solutions. To apply this GTR, an ordering of the vehicles is required and the start- and end-node of succeeding vehicles are connected. We consider a homogeneous vehicle fleet, so without loss of generality we can order the vehicles arbitrarily.

In order to obtain practical computation times, the state space of the DP algorithm is restricted. In each stage, only the $H$ states with smallest costs are maintained and expanded to generate states for the next stage. As a result, the total number of states that will be calculated is limited by a polynomial in the number of customers and $H$. This results in a trade-off between solution quality and computation time, which is controlled by the value of $H$.

We test the different anticipation functions on the benchmark instances proposed by Goel (2009), who adjusted the well-known Solomon benchmark instances (Solomon, 1987) for the VRPTW to the VRPTW-EU. For each problem instance and anticipation function, we first solve the planner's problem as described above and then the resulting drivers' problem for each driver. We implemented the DP algorithm in Delphi 7 on a Pentium 4, 3.40GHz CPU and 1.00 GB of RAM and use $H = 10.000$ for all experiments.

## 4.1 Team Situation

We first describe the results of the team situation, in which the drivers' objective is to minimize his travel distance. For perfect and approximately perfect anticipation, the planner's solution results in feasible vehicle routes for the drivers. We assume that a driver only changes the route and break schedule found by the planner, if this driver finds a better route and break schedule in terms of his objective.

Table 1 presents the results on perfect and approximately perfect anticipation. The first column indicates the different problem sets and, between brackets, the number of problem instances: in the C-instances, customer locations are clustered, in the R-instances they are random, and in the RC-instances they are semi-clustered; the 2-instances have a relatively longer time horizon and larger vehicle capacities than the 1-instances, allowing for longer vehicle routes (in terms of number of customers). Next, the results on the situation with perfect anticipation and the situation with approximately perfect anticipation contain three columns each: the average (over all problem instances in each problem set) number of clusters found by the planner, the average travel distance if the routes found by the planner are followed, and the average distance of the final routes found by the drivers. Note that, even in case of perfect anticipation, the drivers may find better routes than the planner, since the state space of each driver's problem is smaller than the state space of the planner's problem, while the state space restrictions for both problems are the same ($H = 10.000$).

| Problem | Perfect Ant. | | | Approx. Perfect Ant. | | |
|---|---|---|---|---|---|---|
| Set | # clusters | Pl. Dist. | Dr. Dist. | # clusters | Pl. Dist. | Dr. Dist. |
| C1 (9) | 10.00 | 947.39 | 946.38 | 10.33 | 951.84 | 949.50 |
| C2 (8) | 5.50 | 787.00 | 785.17 | 5.63 | 817.24 | 811.39 |
| R1 (12) | 9.42 | 1157.75 | 1154.37 | 9.75 | 1158.67 | 1152.60 |
| R2 (11) | 7.27 | 1092.68 | 1091.36 | 7.73 | 1106.28 | 1102.40 |
| RC1 (8) | 10.25 | 1333.28 | 1331.68 | 10.13 | 1297.58 | 1290.00 |
| RC2 (8) | 7.88 | 1219.54 | 1218.99 | 8.50 | 1269.66 | 1261.23 |

**Table 1: Results for team situation: perfect and approximately perfect anticipation**

The results demonstrate that perfect anticipation clearly outperforms approximately perfect anticipation. For all but one problem set, the average number of clusters is smaller in case of perfect anticipation. On average over all problem instances, perfect anticipation results in 3.5% less clusters than approximately perfect anticipation. Also the travel distances are smaller in case of perfect anticipation than in case of approximately perfect anticipation. On average, the difference is 0.90% for the routes found by the planner, and 0.56% for the final routes found by the drivers.

The improvements found by the drivers with respect to the routes found by the planner in terms of reduced travel distance are not too big. However, for a significant number of customer clusters, the drivers find better routes than the planner: 7.7% in case of perfect anticipation and 19% in case of approximately perfect anticipation. The larger portion in case of approximately perfect anticipation is due to the larger solution space that the drivers consider by including the optional rules, which are ignored by the planner in this case. The average reductions of the travel distances for these customer clusters are 1.4% and 2.4% in case of perfect and approximately perfect anticipation, respectively.

Table 2 presents the results for implicit anticipation. We tested different speed reductions applied by the planner to incorporate breaks that the drivers have to schedule. We conducted experiments for the speeds of 2, 3, 4, and 5 distance units per hour, where 5 is the reference speed in each problem instance. The case in which the speed is set to the reference speed is the extreme situation in which the planner neglects all breaks and rest periods that the drivers have to schedule. However, since the planner still does account for the routing including time windows, this is also a case of implicit anticipation.

Since with implicit anticipation certain customer clusters may not allow for feasible routes and break schedules, we have to consider such infeasibilities. Therefore, we report for each problem set the average number of clusters found by the planner (column 3), the average number of routes found by the planner that allow feasible break schedules (column 4), and the average number of clusters for which the drivers can find feasible routes and break schedules (column 6). Next, to make a fair comparison between the travel distances found by the planner and by the drivers, we present for each problem set the average total travel distance per problem instance of those customer clusters, for which the routes found by the planner allow feasible break schedules. We present these travel distances both for the routes found by the planner (column 5), and for the routes found by the drivers (column 7). We do not include the travel distances of the routes found by the planner and the drivers for those customer clusters for which the routes found by the planner do not allow feasible break schedules, because it does not make sense to compare travel distances of infeasible vehicle routes with other (in)feasible vehicle routes.

The results indicate that the smaller the speed reduction, the smaller the number of clusters, but also the larger the number of infeasible clusters. The smallest and largest speeds do not seem to be suitable, since a speed of 2 results in many clusters (on average 80% more than with perfect reactive anticipation), while a speed of 5 results in many infeasible clusters (for 30% of the customer clusters the drivers could not find a feasible route and break schedule). However, the speeds of 3 and 4 show an interesting trade-off between solution quality (12% less clusters with speed 4 than with speed 3) against feasibility (13% infeasible clusters with speed 4 against 4% with speed 3).

For all speeds, there are customer clusters for which the routes found by the planner do not allow feasible break schedules, while the drivers do find feasible routes and break schedules. On average, the drivers' routing results in 2.4%, 15%, 37%, and 43% more feasible vehicle routes than the routes found by the planner with speeds 2, 3, 4, and 5, respectively. The reductions in travel distances are similar to the case with perfect anticipation.

## 4.2 Non-Team Situation

We now consider the non-team situation in which the drivers' (hidden) objective is to optimize their return time. This case can be easily implemented within the DP algorithm, since we only need to adjust the objective function for the TSPTW-EU. This objective can be set by changing the cost of each state from the total distance traveled to the completion time of the last visited customer.

Table 3 presents the results for the non-team situation with perfect and approximately perfect anticipation. The number of clusters is the same as in the team situation, since the planner's problem does not change, and each customer cluster allows for a feasible route and break schedule. Table 3 presents the average total travel distance and the average return time for the routes found by the planner, and for the routes found by the drivers.

The results indicate that drivers can improve the routes found by the planner with respect to the drivers' (hidden) objective. The average return time reductions over all problem instances are 1.9% and 3.9% in case of

| Speed | Problem Set | # clusters | Planner Feas. [a] | Planner Dist. [b] | Drivers Feas. [c] | Drivers Dist. [d] |
|---|---|---|---|---|---|---|
| 2 | C1 | 13.89 | 13.89 | 1219.67 | 13.89 | 1219.67 |
| | C2 | 14.38 | 13.00 | 1285.17 | 13.50 | 1284.76 |
| | R1 | 14.25 | 13.50 | 1229.34 | 14.00 | 1228.93 |
| | R2 | 13.82 | 13.18 | 1212.38 | 13.82 | 1209.57 |
| | RC1 | 18.75 | 18.63 | 1840.88 | 18.75 | 1839.77 |
| | RC2 | 19.38 | 19.13 | 1894.00 | 19.38 | 1889.82 |
| 3 | C1 | 10.00 | 9.89 | 891.23 | 10.00 | 891.05 |
| | C2 | 8.00 | 6.88 | 764.10 | 7.25 | 764.10 |
| | R1 | 10.08 | 7.92 | 897.43 | 9.42 | 895.66 |
| | R2 | 9.00 | 6.64 | 805.11 | 8.91 | 803.54 |
| | RC1 | 11.00 | 9.13 | 1074.80 | 10.75 | 1073.47 |
| | RC2 | 10.50 | 8.63 | 1030.28 | 9.88 | 1027.50 |
| 4 | C1 | 10.00 | 9.22 | 875.84 | 9.78 | 875.24 |
| | C2 | 6.00 | 4.25 | 575.20 | 5.00 | 574.72 |
| | R1 | 9.08 | 5.25 | 621.87 | 7.58 | 621.00 |
| | R2 | 7.64 | 3.64 | 492.16 | 6.09 | 490.63 |
| | RC1 | 10.13 | 6.75 | 844.85 | 9.63 | 843.14 |
| | RC2 | 8.38 | 3.50 | 438.56 | 6.50 | 437.20 |
| 5 | C1 | 10.00 | 8.22 | 801.89 | 9.22 | 799.46 |
| | C2 | 5.25 | 3.75 | 510.07 | 4.13 | 510.04 |
| | R1 | 8.58 | 3.67 | 453.58 | 5.92 | 452.32 |
| | R2 | 6.55 | 1.82 | 270.02 | 3.18 | 269.58 |
| | RC1 | 9.50 | 4.63 | 629.32 | 7.88 | 629.14 |
| | RC2 | 7.63 | 2.25 | 272.97 | 4.13 | 272.62 |

[a] Average number of routes found by the planner that allow feasible break schedules

[b] Average total travel distance per problem instance for the feasible routes found by the planner

[c] Average number of customer clusters for which the drivers could find feasible routes and break schedules

[d] Average total distance per problem instance for the routes found by the drivers for those customer clusters for which the routes found by the planner allow feasible break schedules

**Table 2: Results for team situation: implicit anticipation**

| Anticipation Function | Problem Set | Planner | | Drivers | |
|---|---|---|---|---|---|
| | | Dist. | Ret. | Dist. | Ret. |
| Perfect | C1 | 947.39 | 979.08 | 1045.13 | 956.58 |
| | C2 | 787.00 | 684.13 | 791.67 | 681.16 |
| | R1 | 1157.75 | 959.97 | 1256.69 | 938.34 |
| | R2 | 1092.68 | 821.21 | 1151.91 | 805.82 |
| | RC1 | 1333.28 | 1041.40 | 1473.23 | 1012.01 |
| | RC2 | 1219.54 | 921.74 | 1279.46 | 914.37 |
| Approximately Perfect | C1 | 951.84 | 1008.52 | 1055.97 | 965.57 |
| | C2 | 817.24 | 702.24 | 850.74 | 689.08 |
| | R1 | 1158.67 | 1014.32 | 1350.24 | 960.17 |
| | R2 | 1106.28 | 878.76 | 1200.71 | 847.73 |
| | RC1 | 1297.58 | 1064.81 | 1472.51 | 1021.15 |
| | RC2 | 1269.66 | 1015.06 | 1389.64 | 985.26 |

**Table 3: Results for non-team situation: perfect and approximately perfect anticipation**

perfect and approximately perfect anticipation, respectively. However, by improving the routes according to their private criterion, the drivers deteriorate the planner's secondary objective, the total travel distance, by 7.1% and 11%, respectively. The percentage of routes that could be improved by the drivers in terms of their objective is 30% in case of perfect anticipation and 57% in case of approximately perfect reactive anticipation. Since the planner's top-down criterion (minimizing travel distance) conflicts with the base level's criterion (minimizing return time), there is much more room for improvement by the drivers than in the team situation, in which these criteria are in line (both minimizing travel distance).

Another interesting observation for the non-team situation is that the difference between perfect and approximately perfect anticipation is bigger with respect to the secondary objective than in the team situation. The difference between perfect and approximately perfect anticipation in terms of travel distance for the routes found by the drivers is 4.71%. This is much larger than the 0.56% in case of the team situation. This difference is due to the fact that perfect anticipation results in tighter routes found by the planner than approximately perfect anticipation. Therefore, if drivers find other routes, better with respect to their objective, it is unlikely that the total travel distance is much bigger. However, in case of less tight routes with approximately perfect anticipation there may be larger increases in the travel distance. The difference in return time between perfect and approximately perfect anticipation is also significant: 5.2% for the routes found by the planner and 3.0% for the routes found by the drivers. These results indicate that a more precise representation of the base level's model within a non-team situation has a positive impact on the quality of the planning, both in terms of top-down criterion and in terms of the base-level's criterion. Within a non-team situation, this impact is even larger than within a team situation.

Table 4 presents the results for implicit anticipation for the non-team situation. The results on the number of feasible clusters are similar as in the team situation, however, there are some small differences for the number of feasible routes found by the drivers, due to the different objective function (this is caused by the fact that all problems are solved using a heuristic and not an exact approach). The reductions in return time found by the drivers with respect to the feasible vehicle routes found by the planner are 1.7%, 1.8%, 1.2%, and 2.0% for speeds 2, 3, 4, and 5, respectively. These improvements of the drivers' criterion result in a deterioration of the planner's top-down criterion, the total travel distance, of 7.7%, 8.9%, 6.4%, and 6.5%, respectively. Therefore, they are similar to the case with perfect anticipation. The percentage of routes that could be improved by the drivers are 29%, 25%, 13%, and 13%, respectively. The fact that larger speeds allow for less improvements by the drivers is probably due to tighter routes with respect to the time windows for these higher speeds. Apparently, introducing less slack travel time not only reduces the number of routes found by the planner for which a feasible break schedule exists, but also allows less improvement possibilities for the drivers for such routes.

# 5 Conclusions

We analyzed the problem of combined vehicle routing and break scheduling from a distributed decision making perspective. The impact of both a team and a non-team situation between planners and drivers on the resulting vehicle schedules was investigated. For both cases we proposed different degrees of anticipation for the drivers' planning behavior. In both situations it turns out that the explicit anticipation functions are superior to implicit anticipation functions both in terms of the planner's and the drivers' objectives. Even when only a small speed reduction is applied (speed 4, for which the

| Speed | Problem Set | # clusters | Planner Feas. | Planner Dist. | Planner Ret. | Drivers Feas. | Drivers Dist. | Drivers Ret. |
|---|---|---|---|---|---|---|---|---|
| 2 | C1 | 13.89 | 13.89 | 1219.67 | 1188.06 | 13.89 | 1268.54 | 1171.79 |
| | C2 | 14.38 | 13.00 | 1285.17 | 1333.05 | 13.63 | 1336.36 | 1320.98 |
| | R1 | 14.25 | 13.50 | 1229.34 | 1230.14 | 13.58 | 1343.04 | 1201.93 |
| | R2 | 13.82 | 13.18 | 1212.38 | 1242.96 | 13.82 | 1377.49 | 1216.44 |
| | RC1 | 18.75 | 18.63 | 1840.88 | 1588.59 | 18.50 | 1965.17 | 1555.87 |
| | RC2 | 19.38 | 19.13 | 1894.00 | 1784.48 | 18.88 | 2026.05 | 1758.44 |
| 3 | C1 | 10.00 | 9.89 | 891.23 | 954.75 | 10.00 | 968.36 | 935.59 |
| | C2 | 8.00 | 6.88 | 764.10 | 778.55 | 7.25 | 774.90 | 775.11 |
| | R1 | 10.08 | 7.92 | 897.43 | 791.89 | 9.42 | 1012.43 | 773.58 |
| | R2 | 9.00 | 6.64 | 805.11 | 685.09 | 9.00 | 869.38 | 671.63 |
| | RC1 | 11.00 | 9.13 | 1074.80 | 899.56 | 10.75 | 1165.78 | 878.53 |
| | RC2 | 10.50 | 8.63 | 1030.28 | 899.53 | 10.00 | 1145.04 | 885.49 |
| 4 | C1 | 10.00 | 9.22 | 875.84 | 866.41 | 9.78 | 929.03 | 850.78 |
| | C2 | 6.00 | 4.25 | 575.20 | 494.01 | 4.50 | 580.71 | 493.61 |
| | R1 | 9.08 | 5.25 | 621.87 | 527.80 | 7.58 | 672.39 | 523.75 |
| | R2 | 7.64 | 3.64 | 492.16 | 378.42 | 5.82 | 506.27 | 375.64 |
| | RC1 | 10.13 | 6.75 | 844.85 | 686.45 | 9.50 | 944.07 | 670.53 |
| | RC2 | 8.38 | 3.50 | 438.56 | 369.49 | 5.88 | 464.81 | 366.82 |
| 5 | C1 | 10.00 | 8.22 | 801.89 | 765.99 | 9.22 | 852.89 | 747.99 |
| | C2 | 5.25 | 3.75 | 510.07 | 455.07 | 2.88 | 518.24 | 454.26 |
| | R1 | 8.58 | 3.67 | 453.58 | 357.64 | 6.17 | 483.27 | 349.53 |
| | R2 | 6.55 | 1.82 | 270.02 | 198.71 | 2.82 | 284.53 | 194.92 |
| | RC1 | 9.50 | 4.63 | 629.32 | 477.33 | 7.75 | 711.27 | 461.92 |
| | RC2 | 7.63 | 2.25 | 272.97 | 196.32 | 3.75 | 279.27 | 192.98 |

**Table 4: Results for non-team situation: implicit anticipation**

percentage of infeasible clusters is still rather large: 12%), the average number of customer clusters is still larger than in case of perfect anticipation. However, there is a clear trade-off between the solution quality and the complexity of the planner's task. Furthermore, if planners resort to anticipating the drivers' planning behavior implicitly by applying speed reductions, they face a trade-off between solution quality in terms of the number of vehicles used and the feasibility of the tours.

In the case that the drivers do not follow the company's objectives, but instead optimize their own hidden criterion, the planner's main objective - the number of vehicles used - is not affected. However, the planner's secondary objective - the total travel distance - is deteriorated significantly by the drivers' hidden actions. Here it turns out that a more precise anticipation of the drivers' planning model results in a less severe deterioration of the planner's top-down criterion. This is due to the fact that drivers do not have so many possibilities for deviating from the routes found by the planner.

Our results suggest that in practice instead of solely creating time buffers to schedule breaks and rest periods, planners should try to use a more precise representation of the drivers' planning model. A more precise anticipation will help to better fulfill the planner's objectives, both in case of a team and in case of a non-team situation. Since the planner cannot observe the team character of his planning situation, this is a valuable guideline for him.

# Acknowledgment

This work was financially supported by Stichting Transumo through the project ketensynchronisatie and by the German Research Foundation (DFG) as part of the Collaborative Research Centre 637 "Autonomous Cooperating Logistics Processes - A Paradigm Shift and its Limitations"(subproject B9).

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