Distributed Decision Making in Combined Vehicle Routing and Break Scheduling

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Abstract: The problem of combined vehicle routing and break scheduling comprises three subproblems: clustering of customer requests, routing of vehicles, and break scheduling. In practice, these subproblems are usually solved in the interaction between planners and drivers. We consider the case that the planner performs the clustering and the drivers perform the routing and break scheduling. To analyze this problem, we embed it into the framework of distributed decision making proposed by Schneeweiss (2003). We investigate two different degrees of anticipation of the drivers' planning behaviour using computational experiments. The results indicate that in this application a more precise anticipation function results in better objective values for both the planner and the drivers.

1 Introduction

In practice, apart from the task of vehicle routing and scheduling, also the problem of scheduling breaks and rest periods has to be addressed by planners when creating vehicle schedules. According to the European legislation, when creating vehicle schedules planners have to make sure that drivers can adhere to the legislation on driving and working hours as laid down in Regulation (EC) No 561/2006 and in Directive 2002/15/EC. We call the arising planning problem the problem of combined vehicle routing and break scheduling. It comprises three subproblems, namely the clustering of customer requests, the routing of the vehicles, and the scheduling of breaks and rest periods (Meyer and Kopfer, 2008). A main characteristic of the problem of combined vehicle routing and break scheduling is that these planning tasks are usually divided over several decision making units (DMUs), namely planners and drivers. Therefore, the problem is characterized by hierarchies in distributed decision making. To analyze this problem, we apply the framework for distributed decision making as presented by Schneeweiss (2003). The objective of this paper is to investigate the effects of different degrees of anticipation of the drivers' planning behaviour both on the planner's and on the drivers' objectives.

The paper is structured as follows. Section 2 presents the European legislation on driving and working hours in road transportation. Section 3 embeds the problem of combined vehicle routing and break scheduling into the framework for distributed decision making. In Section 4, computational experiments illustrate the effects of different planning approaches by the planner. Section 5 summarizes the main findings and gives some conclusions.

2 EC Legislation on Driving and Working Hours

The European social legislation for drivers in road transportation mainly comprises two legal acts. Regulation (EC) No 561/2006 lays down rules on drivers' driving hours and Directive 2002/15/EC restricts working hours of persons engaged in road transportation.

EC Regulation No 561/2006 concerns three different time horizons: single driving periods and daily and weekly driving times. Figure 1 depicts the relationship between these different time horizons.

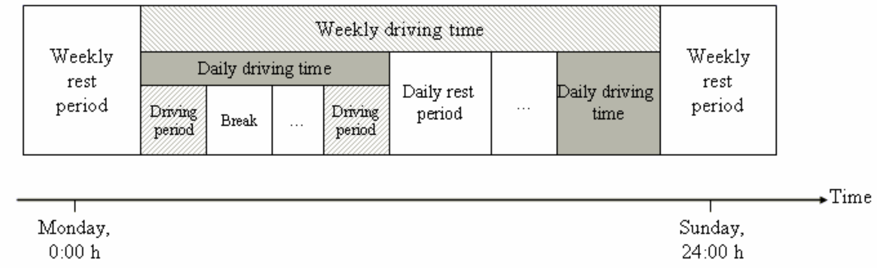

Figure 1: Relation of the different time horizons (Kopfer et al. (2007))

The regulation restricts the driving time in each single driving period to 4.5 hours. Drivers are obliged to take a break of at least 45 minutes after each driving period. Optionally, this break can be divided into two parts of at least 15 minutes and 30 minutes, respectively. A driving period ends, when a break of sufficient length has been taken.

The daily driving time is restricted to 9 hours. However, there is the optional rule that twice a week, i.e. twice between Monday 0:00 am and Sunday 12:00 pm, the daily driving time may be extended to 10 hours. Daily driving times are defined as the accumulated driving time between two daily or between a daily and a weekly rest period respectively. A daily driving time ends when a daily rest period is taken or a weekly rest period starts. Within 24 hours after the end of a daily or weekly rest period the next daily rest period must have been taken. A regular daily rest period is defined as a period of at least 11 hours in which a driver may freely dispose of his time. A reduced daily rest period is a rest period of at least 9 hours.

The regulation provides the option to take up to three reduced daily rest periods between two weekly rest periods. Moreover, it allows splitting a regular daily rest period into two parts of at least 3 hours and 9 hours, respectively.

The weekly driving time is limited to a maximum of 56 hours. Additionally, the maximum driving time of any two consecutive weeks must not exceed 90 hours. The weekly driving time is defined as the accumulated driving time during a week, i.e. between Monday, 0:00 am and Sunday, 12:00 pm. A weekly rest period is a recreation period in which a driver may freely decide how to spend his time. The regular length of a weekly rest period is at least 45 hours; the reduced duration is at least 24 hours. A driver is allowed to use this optional reduction once in any two consecutive weeks. Reductions have to be compensated by equal extensions of other rest periods of at least 9 hours before the end of the third week following the week considered. A weekly rest period has to be started within 144 hours after the end of the previous weekly rest period.

EC Regulation No 561/2006 only comprises restrictions on driving times. As driving times are considered as working times, they are also affected by Directive 2002/15/EC, which contains restrictions on weekly working times and breaks. In the directive the working time is defined as the time devoted to all road transport activities, i.e. driving time, time for loading and unloading, for assisting passengers while boarding and disembarking from the vehicle, time spent for cleaning and technical maintenance, and the time a driver has to wait at the workstation when the end of the waiting time is not foreseeable. The directive postulates that after a working time of no more than 6 hours workers have to take a break. The total duration of breaks during working periods of 6 to 9 hours must equal 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. Consequently, a break which meets the requirements of EC Regulation No 561/2006 also satisfies Directive 2002/15/EC.

Furthermore, the directive restricts the weekly working time to a maximum of 60 hours. Moreover, an average working time of 48 hours per week over a period of 4 months must not be exceeded. When creating vehicle routes, planners have to make sure that both driving time restrictions and working time restrictions for drivers are satisfied.

3 Combined Vehicle Routing and Break Scheduling as a Problem of Distributed Decision Making

As mentioned before, in combined vehicle routing and break scheduling three interconnected planning problems have to be solved: the clustering of customer requests, the routing of vehicles, and the planning of breaks and rest periods for the drivers. These problems can be solved either simultaneously or in sequence. In the case of sequential planning, the possibility of solving two of the three planning problems simultaneously remains. However, not all sequences are reasonable in practice since the requirements for breaks and rest periods arise from the duration of the routes for the drivers. Therefore, the break scheduling should be performed last.

Apart from the three interconnected planning problems, there is another factor that adds to the complexity of combined vehicle routing and break scheduling: usually the planning process is divided over two DMUs, namely the planner and the driver. Therefore, the overall problem is characterized by hierarchical structures in distributed decision making. These hierarchies can be found both in the relationship between schedulers and drivers and in the structure of the planning problems to be solved. In the following the framework of Schneeweiss (2003) is used to analyze the decision problem.

In this framework for distributed decision making, two DMUs are considered. In the case of hierarchies in distributed decision making, these DMUs are situated on different levels. The top-level takes its decision first and instructs the base-level with the resulting plans. Subsequently, the base-level takes its decision based on the frame set by the top-level’s decisions. However, when performing its planning, the top-level can try to anticipate the subsequent planning of the base-level in order to avoid infeasibilities on the base-level or if the base-level’s decisions also influence the top-level’s objectives. To consider the base-level’s planning, the top-level can apply some sort of anticipation function. This anticipation function needs not be a precise representation of the base-level’s planning model but can also be an approximation. In the following two different degrees of anticipation will be suggested for the problem of combined vehicle routing and break scheduling.

According to the classification in Schneeweiss (2003), the planning situation between planners and drivers can be described as a situation with several DMUs, in which a conflict-free team situation can be assumed. This results in a situation of organizational hierarchies in distributed decision making. The encountered information asymmetry mainly results from the fact that when taking their decisions, drivers have more accurate information about when it is possible to schedule breaks than the planner has.

In practice usually two different divisions of the subproblems over planners and drivers are encountered. The clustering of customer requests is typically performed by the planners. Moreover, the break scheduling is always carried out by the drivers for two reasons. First, drivers know best when they require a break or rest period. Therefore, leaving this autonomy to the driver seems reasonable. Second, a planner does not know exactly when it is possible for drivers to take a break. Drivers cannot stop their vehicles directly on the highway but require a service area. Consequently, in practice this task cannot be performed by the planners. The only task that can possibly be carried out by both DMUs is the routing. A rough conceptualization by whom the routing is performed for vehicle routing problems (including a central depot) can be made according to the characteristics of the transports. In the case of full truckload transports, only one possible route exists for each vehicle. Therefore, this task needs not be considered in the total planning process of the planner. In less than truckload transports, the routing is mainly carried out by the planners. In parcel services and other services operating in a restricted area, the routing is mainly carried out by the driver, especially if the locations of the customers are very close to each other and if the set of customers is not the same from day to day. For the remainder of this paper we concentrate on this last situation. Figure 2 depicts this division of the tasks between the DMUs using the framework of distributed decision making by Schneeweiss (2003).

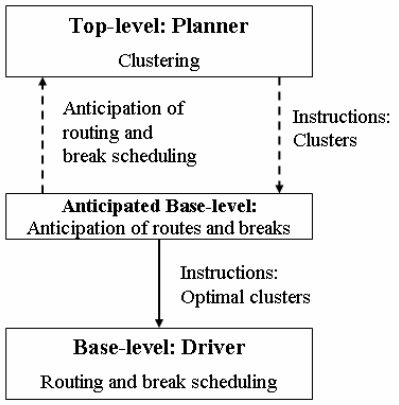

Figure 2: Hierarchical planning situation

In distributed decision making, different decision levels are considered. In our case the planner constitutes the top-level. His objective is to create vehicle schedules using as few vehicles as possible. The planner carries out the clustering of the customer requests. He derives his optimal instructions and advises the drivers which customers they have to service. When creating the customer clusters, he has to make sure that the drivers can service all customer requests within their delivery time windows and can also adhere to the European social legislation. Therefore, the planner has to anticipate the planning behavior of the drivers, who constitute the base-level. To accomplish this task, he uses an anticipation function to take into account the routing and break scheduling that will be performed by the drivers subsequently. He does this to avoid creating infeasible plans with respect to the base-level's behaviour. The base-level receives the top-level's instructions and carries out the routing and break scheduling within the clusters it is assigned using some sort of planning model. We assume that each driver's objective is to minimize the travel distance.

The planner considers the base-level's planning model using anticipation functions. These anticipation functions are approximations of the expected base-level's planning model and need not be precise representations. Schneeweiss (2003) distinguishes between four different degrees of anticipation: perfect reactive anticipation, approximately perfect reactive anticipation, implicit reactive anticipation, and non-reactive anticipation. The first three take into account the base-level's behaviour via some sort of anticipation function. Non-reactive anticipation means that no anticipation function exists but that some general features of the base-level may be taken into account in the top-level's objective function.

For further analysis we consider only two different degrees of anticipation. First, in perfect reactive anticipation the mathematical structure of the base-level's planning model is completely considered (Schneeweiss (2003)). In combined vehicle routing and break scheduling we model this situation such that the planner minimizes the number of vehicles used. Thereby, for each vehicle, he takes into account the drivers' task of finding a shortest route exploiting all optional rules of the legislation on driving and working hours as described in Section 2. So when creating the clusters the planner uses the drivers' planning model that tries to find the minimum travel distance under consideration of the EC social legislation including all optional rules. The drivers may still improve on these routes and break schedules, since they only focus on their specific route and break schedule, while the planner has to distribute his computational power over the clustering problem and several different routing and break scheduling problems.

Second, in the case of approximately perfect reactive anticipation the anticipation function uses some approximate solution procedure of the base-level's planning model (Schneeweiss (2003)). In our case the driver's planning tasks of routing and break scheduling are approximated by the planner. Therefore, as an approximation of the driver's planning model we use a model that finds the shortest travel distance including only the basic rules of the EC social legislation. Omitting the complex set of optional rules simplifies the planner's task. However, when carrying out the routing and break scheduling, the drivers do use the full planning model including all optional rules. By anticipating the drivers' planning model including only the basic rules of the social legislation the planner makes sure that a feasible solution for the whole planning problem can be found by the drivers since the application of the optional rules by the drivers will cause an enlargement of the solution space compared to the solution space considered by the planner. We assume that the planner also communicates his routes and break schedules to the drivers, but the drivers do not have to follow these routes and break schedules, trying to reoptimize the routes according to their objectives. In a dynamic planning scenario the driver will also try to adapt the schedules to actual situations.

In Section 4, we analyze the described scenarios with some computational experiments. Our approach to addressing the planner's problem is to solve a vehicle routing problem with time windows (VRPTW) and EC social legislation. Both anticipation functions allow drivers to find feasible vehicle routes and break schedules. However, the effects of the different degrees of anticipation on the objective functions are investigated at both levels: at the top-level, i.e., the number of vehicles used, and at the base-level, i.e., the total travel distances.

4 Computational Experiments

To solve the customer clustering problem, we apply the dynamic programming algorithm presented by Kok et al. (2009). This algorithm is based on the restricted dynamic programming framework proposed by Gromicho et al. (2008) in which the idea of dynamic programming for the travelling salesman problem is applied and the number of states to be expanded in each stage is restricted. To use the dynamic programming approach to solve vehicle routing problems, the giant-tour representation of vehicle routing solutions proposed by Funke et al. (2005) is used. The algorithm includes the EC legislation on drivers' driving and working hours as described in Section 2. It applies a local perspective when scheduling breaks and rest periods which fits well into the concept of dynamic programming. The algorithmic parameters are set such that it first minimizes the number of vehicles used and second the total distance travelled.

After the customer clusters are generated using the above algorithm, they are given to the drivers and in these clusters the drivers carry out the routing and break scheduling also using the algorithm by Kok et al. (2009) where only one vehicle is allowed. Moreover, we assume that the planner communicates the routes and break schedules he establishes to the drivers. If a driver cannot improve upon the routes suggested to him in terms of his objective function, i.e. if a driver cannot reduce his travel distance, he follows the planner's advice. To test the scenarios, the Solomon (1987) test problems for the VRPTW are used in the adjusted form proposed by Goel (2009).

Table 1 presents the average numbers of vehicles used for the different problem types for the two anticipation functions. The Solomon instances consist of 6 problem types in which the C-instances have clustered customer nodes, the R-instances have randomly located customer nodes, and in the RC-instances the customer nodes are semi-clustered. The difference between the 1- and 2-instances is that the demands and distances in the 2-instances are, on average, smaller than in the 1-instances, allowing for longer (and, as a consequence, fewer) vehicle routes. The results indicate the change in the planner's objective, i.e., the number of vehicles used, by using the two different anticipation functions.

The results show a strong reduction in the number of vehicle routes (5% on average) if the perfect anticipation function is used by the planner. Therefore, this case is superior to the case of approximately perfect anticipation in terms of the planners' objective value.

Table 2 presents the resulting average total travel distances for the vehicle routes found by the drivers. Again, the perfect anticipation function results in the best vehicle routes, also in terms of the drivers' objective. The average total travel distance over all problem instances is reduced by 1.4%.

Table 1: Planner's objective

Problem sets (# of instances)	Average # of vehicles: perfect reactive anticipation	Average # of vehicles: approximately perfect reactive anticipation
C1 (9)	10.00	10.22
C2 (8)	5.25	6.00
R1 (12)	9.25	9.83
R2 (11)	7.27	7.82
RC1 (8)	9.88	10.25
RC2 (8)	8.25	8.38
All (56)	8.36	8.80

Table 2: Drivers' objective

Problem sets (# of instances)	Average travel distance: Perfect reactive anticipation	Average travel distance: Approximately perfect reactive anticipation
C1 (9)	927.23	948.56
C2 (8)	780.59	836.32
R1 (12)	1130.52	1152.03
R2 (11)	1084.17	1091.19
RC1 (8)	1323.96	1291.30
RC2 (8)	1238.99	1257.80
All (56)	1081.89	1097.28

To analyze the impact of the rerouting performed by the drivers, we determine the percentage of vehicle routes for which drivers' found better vehicle routes in terms of travel distances by rerouting. We also determine the average improvement in travel distance for these routes. Table 3 presents these results.

Table 3: Improvements found by the drivers (rerouting)

Problem sets (# of instances)	Perfect reactive anticipation		Approximately perfect reactive anticipation	
	% routes improved	Average improvement	% routes improved	Average improvement
C1 (9)	4.44%	0.73%	8.79%	1.14%
C2 (8)	5.00%	0.60%	3.33%	4.93%
R1 (12)	13.20%	2.14%	13.40%	2.08%
R2 (11)	18.26%	0.66%	17.79%	1.78%
RC1 (8)	10.58%	2.79%	16.21%	2.28%
RC2 (8)	5.12%	2.02%	27.27%	1.68%
All (56)	9.94%	1.62%	14.86%	1.89%

The results show that the improvements found by the drivers are significant. In case of perfect reactive anticipation 9.94% of the routes are improved and the average improvement of these routes is 1.62%. The improvements are even larger in case of approximately perfect reactive anticipation. This is due to the fact that the planner does not exploit the optional rules of the EC social legislation in this case. Therefore, using also the optional rules of the social legislation, the drivers can improve the routes even further.

5 Conclusions

We analyzed the problem of combined vehicle routing and break scheduling from a distributed decision making perspective. The problem was embedded into the framework for distributed decision making proposed by Schneeweiss (2003). This framework is very suitable for the analysis of this problem from a practical point of view. We incorporated different degrees of anticipation of the drivers' planning model into the scheduler's planning procedure. Our computational experiments showed that a more accurate anticipation function results in better vehicle routes and break schedules. This holds both for the planner's and the drivers' objectives: the perfect reactive anticipation function clearly dominates the approximately perfect anticipation function.

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