1 Introduction

Scheduling the routes of trucks to pick-up and deliver containers is a complex problem. In general such Vehicle Routing Problems (VRPs) are known to be NP-complete, and therefore inherently hard and time consuming to solve to optimality. Fortunately, these problems have a structure that can facilitate efficient derivation of feasible (if not optimal) solutions. Specifically, the routes of different trucks are more or less independent. Such “locality” in a problem is a first sign that an agent-based approach may be viable. We think it is safe to assume, based on its long history, that current global-optimization practice in operations research (OR) outperforms local agent-based approaches in settings where all information is known in advance (static settings). However, in situations with high uncertainty, agent-based approaches are expected to outperform these traditional methods [3].

In this paper we investigate whether a distributed agent-based planning approach indeed suffers less from job arrival uncertainty than a centralized optimization-based approach. In order to compare the two different approaches, we use the best available algorithms for both sides.

2 Agent-based Approach

Since we are primarily interested in distributed agent models, we use an uncompromisingly flat architecture: no agents can concentrate information from a multitude of other agents. Our agents use a combination of existing techniques to compute the solution. The basic model is similar to that of Fischer et al. [1]. Order agents hold auctions in order of their arrival, and truck agents bid in these auctions. Every truck agent submits a bid that reflects its cost associated with transporting the given order. This cost is a quantity in the time domain. To calculate it, a truck considers inserting the new order into its plan, or alternatively substituting one of the already contracted orders by the new one. Substitution draws motivation from leveled commitment contracts as described by Sandholm and Lesser [5], and applied by ’t Hoen and La Poutré in a transportation problem [2]. To clear an auction, order agents choose the best bid as winner, and respond positively to the winner and negatively to the others. For this we chose a one-shot auction (and more specifically, a Vickrey auction) for its computational efficiency.

In addition to bidding on auctions for new orders, truck agents have another way to enhance the overall solution. At random time intervals, every truck randomly selects an order in its plan and releases it. An order that is released (just as those order agents that are substituted) initiates a new auction to find another place. In most cases, these auctions result in the very same allocation as before the release. Nevertheless, sometimes they do manage to find a better place and make a contract with another truck. This implements a distributed improvement technique, similarly to Kohout and Erol, who implemented a distributed order-swapping protocol in their logistical multi-agent system [4].
3 On-line Optimization Approach

To estimate the value of the agent-based solution approach, we study it in comparison to two optimization based solution approaches: (i) a mixed-integer program for solving the static *a priori* case in order to provide a baseline benchmark, and (ii) an on-line optimization approach, which can solve the same dynamic problem instances are the agent approach, and designed to represent current vehicle routing decision support systems.

At the core of both the static *a priori* solution and the on-line optimization is a mixed integer program (MIP) for a truck-load vehicle routing problem with time windows [6], which is given to CPLEX. In the static *a priori* approach, we solve the MIP using all available information, including the dynamic order releases. This is similar to computing at the end of the day what would have been the best to do. In our on-line approach, the MIP is invoked periodically at fixed intervals. At each interval, the full and current state of the world is encoded in the MIP, and solved via a call to CPLEX. The solution given by CPLEX is parsed and any jobs that are within two intervals of being late are permanently assigned. Any jobs that were designated for rejection in the solution are rejected only if they are within two intervals of violating a time window; otherwise they are considered available for scheduling in a subsequent interval. The procedure continues in this fashion until the end of the working day at which point all jobs have been served or rejected.

4 Results

The instances we used for the comparison was based on data provided to us by a Dutch logistics service provider. We rendered their data into 26 days with four separate scenarios of varying levels of order arrival uncertainty. In every scenario, different amount of orders were released during the day, while the rest at the beginning of the day. In one of the extreme scenarios every order was released at the beginning of the day, and in the other extreme scenario, all orders were released during the day.

Running the *a priori*, the on-line optimization, and the agent-based methods on the four instances and averaging over 26 days revealed that the on-line optimization method outperforms the agent-based method when all orders were known at the beginning of the day. Contrarily, when fifty percent or more of the orders were dynamic (released during the day), agent-based methods performed competitively.

This comparison study of agent-based and centralized vehicle routing approaches featured dynamic order releases, and a uniform distribution of time windows. It is left for future work to compare the methods on time-window distributions with bursts, and alternatively use other sources of uncertainty, such as travel-time or loading/unloading-time uncertainty.

References


