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VEHICLE ROUTING WITH SOURCE SELECTION

INTEGRATING SOURCING IN FLEET DEPLOYMENT

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INTEGRATING SOURCING IN FLEET DEPLOYMENT

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ABSTRACT

Purpose

We analyse the benefits and limitations of the integration of sourcing decisions into the operational route compilation task of a road-haulage company. A trucking company has to supply several customer sides. The demanded quantities are given. The trucking company has to decide which truck serves which customer location(s) (routing decisions). In contrast to previously reported fleet deployment problems the trucking company can select from several loading positions for each individual transport request (sourcing decisions).

Design/methodology/approach

We propose a mathematical model for the integrated sourcing and vehicle routing decision problem. For this purpose, we merge a network flow model and a vehicle routing model. The first mentioned model represents the sourcing decision problem and the second model represents the fleet deployment (routing) decisions. We propose a matheuristic approach to solve the proposed integrated model. This matheuristic combines an algorithm for solving the network flow problem part and a metaheuristic that searches for least distance vehicle routes. Both algorithms interchange information through an adaptable distance matrix that is accessed by both algorithms. We use the proposed model-based approach to evaluate the benefits from integrating sourcing decisions in fleet deployment tasks and execute comprehensive computational experiments.

Findings

An analysis of the numerical results from the conducted computational experiments reveals a benefit for the trucking company if both the sourcing as well as the routing decisions are made in parallel compared to a consecutive decision making. Driven distances can be saved and, in some cases, the number of needed vehicles to serve all customers is reduced.

Research limitations/implications (if applicable)

Although we have observed benefits from integrating sourcing with routing decisions it is necessary to conduct additional experiments. Further research efforts should be spent to the interchange of information between the sourcing sub-problem and the routing sub-problem. In addition, constraints about delivery time restrictions as well as designated sources for different commodities must be included into the proposed model.

Practical implications (if applicable)

The here reported research enables a trucking company to extend their service portfolio. It therefore contributes to the preservation and extension of the economic success of a road-haulage company in a market with increasing competition.

Original/value

To the best of the author's knowledge the proposed model is the first model of an integrated sourcing and vehicle routing decision scenario in the context of road haulage. In addition, the proposed model solving approach is innovative since the interaction of a network flow algorithm with a routing model by means of an adaptable distance matrix has not reported before.

Keywords: fleet deployment, sourcing, decision support, mathematical programming, artificial intelligence, matheuristic.

1. INTRODUCTION

Due to increasing fuel-costs and congested road infrastructures the integration of transportation services with upstream as well as with downstream activities in the value chain becomes more and more attractive and necessary. One strategy to increase the efficiency of transportation processes comprises the transfer of decision competences related to upstream and/or downstream activities to the transportation service providers, e.g. to the freight carriers. Successful applications of integrated decision tasks especially comprise inventory routing concepts (Bertazzi and Grazia Speranza, 2012) in which delivery and storage re-filling times are commonly decided by the transportation service provider.

This contribution addresses the integration of sourcing decisions with transport process decisions as another approach to improve the coordination of transport services with associated value creating activities. In particular, we investigate the situation in which a freight carrier has to select from which depot a customer demand is fulfilled if more than one depot is able to provide the requested product quantities. The benefit from such an integrated routing and sourcing approach is obvious: freight carriers can increase the fill rate of their trucks so that the transportation costs per moved ton decreases.

Sourcing decisions in transportation are typically represented as network flow models while fleet deployment tasks fall into the category of vehicle routing problems. Hence, the simultaneous solving of sourcing and fleet deployment tasks requires the specification of an integrated network flow and vehicle routing decision model. Such a model is proposed and evaluated in this paper. Since both the vehicle routing problem as well as the network flow problem can be formulated in terms of (mixed) integer linear programs, we are going to develop a mixed-integer linear program for the integrated decision problem. For that, we introduce decision variables and constraints that couple the two separate decision models to one common integrated model.

Vehicle routing problems are known as quite complex decision tasks. In order to manage this complexity, heuristic solving approaches are usually used as core decision support method (Burke and Kendall, 2014). Metaheuristics, which mimic natural optimization strategies, have demonstrated their power and effectiveness for solving vehicle routing problems and are preferentially used to solve vehicle routing models. In contrast, network flow problems can be solved quite efficiently using mathematical programming approaches like the simplex algorithm or more specifically designed methods. Taking into account that the two subproblems require the incorporation of different solving techniques, we propose solving the integrated model using a hybrid model solving strategy consisting of a genetic algorithm for the vehicle routing subproblem and the simplex algorithm for the network flow determination subproblem. The combination of a heuristic and a mathematical programming method is called a model-based heuristic or a Matheuristic (Maniezzo et al., 2009).

The contribution of the here reported research can now be separated into two parts. First, we present an innovative solving method for the complex decision situation of integrated routing and sourcing situations in the road haulage business. Second, we quantify the possible cost benefits from considering sourcing and routing decisions simultaneously instead of consecutively.

We start with the statement of the investigated decision challenge in Section 2. Our proposed solving approach is presented in Section 3. The setup and the results of a computational evaluation of the proposed solving approach and the managerial impacts are reported in Section 4.

2. INTEGRATED ROUTING AND SOURCING IN ROAD HAULAGE

The simultaneous decision making on vehicle routes and sources of supply opens a new research direction with respect to realizing economies of scale in the freight forwarding business. We summarize previous contributions to this research area in Subsection 2.1. An informal description of the here investigated decision challenge is presented in Subsection 2.2. A mathematical optimization model for this challenge is proposed in Subsection 2.3. Subsection 2.4 introduces parameterizable test cases as the basis for a computational assessment of the integration of sourcing and routing decisions.

2.1. Survey on related work

The here investigated combined sourcing and fleet deployment problem initiates a new class of the well-known and well-studies (capacitated) vehicle routing problem (Golden et al., 2008). Simultaneously to the inventory routing problem category (Bertazzi and Grazia Speranza, 2012) it combines the complex routing task with another sophisticated decision problem, which here is the selection of the right loading place.

Since the combined routing and sourcing problem requires the consideration of individual loading sites for each customer request it falls into the category of pickup and delivery problems. This variant of the vehicle routing problem is surveyed by Parragh at al. (2008) as well as Berbeglia et al. (2010).

There are only few contributions dealing with the option to select an individual pickup or delivery location for each customer. Hennig et al. (2012) reports about a routing problem class in which available unloading time windows requires the selection of an appropriate unloading location. In Crevier et al. (2007) a variant of the VRP with multiple depots is investigated in which the routing includes the (indirect) assignment of a vehicle depot to a customer.

Selective vehicle routing problems investigated by Allahviranloo et al. (2014) represent another vehicle routing problem category. Here, the constraint to visit each customer request is relaxed but only an a priori unknown subset of customer location has to be selected for fulfilling the overall demand. Similarly, the prize-collecting vehicle routing problem (Stenger et al., 2013) as well as the team-orienteering problem (Dang et al., 2011) require the selection of locations to be served by the vehicle fleet.

The third category of routing problems related to the incorporating of sourcing decisions is formed by the split delivery vehicle routing problem (Archetti and Speranza, 2008). In such a problem setup, the fleet dispatcher is allowed to split the demand of a customer into several parts which are served from different sources. Typically, the split is made with respect to the capacity of the available vehicles in order to generate as much full truck loads as possible. Nowak et al. (2008) reports on a split load pickup and delivery problem. To the best of the author's knowledge, Gulczynski et al. (2011) are the only researchers that consider load splitting in cooperation with multi-depot vehicle routing problems.

There are several application areas in which a choice of source of a commodity can be made during the route compilation. Hennig et al. (2012) investigate a crude oil tanker routing problem. Ho and Liu (2006) discuss an application with automated guided vehicles. Schönberger et al. (2013) reports on a container hinterland drayage problem. Stenger et al. (2013) investigates an application is the small parcel logistics business. Perl and Daskin (1985) use request selection approaches in an investigation about a combined warehouse location and routing problem.

2.2. Informal problem statement

The general setup of the decision situation in the integrated routing and sourcing challenges in road haulage is as follows. There are three types of locations: demanding customer locations and supplying warehouse locations as well as a depot that serves as starting and terminating location for the vehicle operations to be determined. We collect all of these locations in the set N. Furthermore, we assume that each pair of locations $i,j \in N$ is connected by an arc $(i;j)$ that originates from i and that terminates in j. We collect all these arcs in the set A. For each arc $(i;j)$ we know the travel distance $d(i;j)$ for going directly without any intermediate stops from i to j. The weighted mathematical graph $G:=(N;A;d)$ serves as the base for the definition of a mathematical optimization model for the integrated sourcing and vehicle routing problem.

Only one product (commodity) is considered. Let R be the set of customers demanding some quantities of this commodity. The set of warehouses is named by W. Actually W is the subset of N comprising the nodes that represent the warehouse nodes. Customer $r \in R$ requests the quantity Q_r. This quantity can be delivered from one or several of the warehouses contained in W to the location of customer r. In the latter mentioned case, the demanded quantity Q_r is split into several smaller quantities which are provided by the different. The decision how to split Q_r is part of the integrated sourcing and vehicle routing decision task. In case that a split of Q_r is made then it becomes necessary to consider the induced transportation demand for the compilation of vehicle routes.

Each warehouse k provides the quantity P_k for distribution to the requesting customers. The available quantity P_k might be scarce so that a split of Q_r for one or several customer requests r might become necessary.

A fleet F of identical trucks is available for fulfilling the customer demand by picking up goods at the warehouses and delivering these quantities at the customer locations. The capacity of truck v is C_v. A customer demand can be fulfilled from one or more warehouses and a customer is allowed to be visited by several vehicles but each vehicle is allowed to visit each customer location at most once.

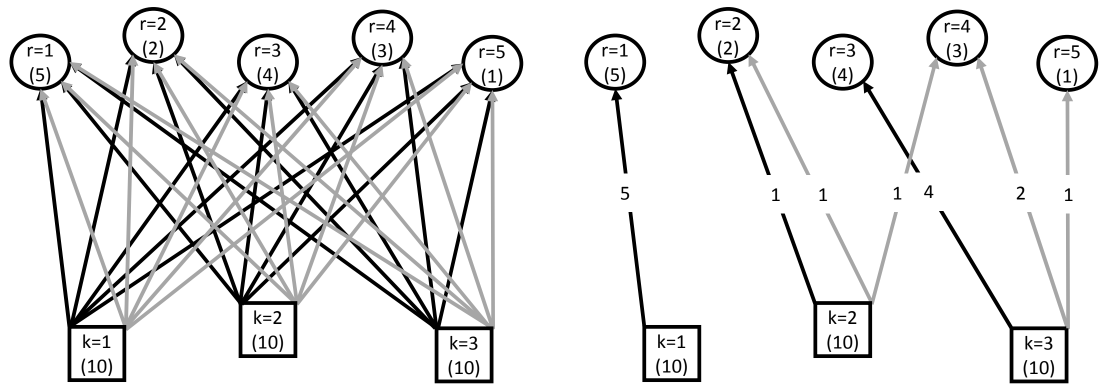


Figure 2.1: Complete OD-network before request completion (left) and after completion of the OD-requests (right).

It is to decide for each customer r which warehouse k provides which quantity to fulfill the demanded quantity Q_r (sourcing decision). The determination of the source(s) for the demand of a customer r is equivalent to the determination of the origin of a flow of goods that terminates at the site of r. The set W of warehouses is linked with the set of customer locations R by several origin-to-destination arcs (OD-arcs) of which each originates from exactly one warehouse and terminates in one customer request site. Such an OD-arc is established for each vehicle. The left picture in Figure 2.1 shows the resulting OD-network for a situation with three warehouse (*k=1,2,3*) and five customers (*r=1,2,3,4,5*). The numbers in brackets represent the available supply quantities P_k (for the warehouses) and the demanded quantities Q_r (for the customers) respectively. Two trucks are available. The black arcs correspond to the first truck and the gray arcs belong to the second truck. The numbers appended to the arcs give the quantity that is assigned to the arc.

The quantity q_{rvk} assigned to each OD-arc *(k;r)* must not exceed the capacity C_v of the vehicle v that is selected to serve this connection. We call the triple $(k;r,q_{rvk})$ an OD-request assigned to vehicle v. The right part of Figure 2.1 shows a feasible set of generated OD-requests assigned to the two vehicles. Such an OD-request is prepared for truck v since it does not exceed its maximal payload.

In the example customer 2 is served by both trucks but these two trucks both load the quantities for customer 2 at warehouse 2. In addition, this warehouse also contributes to the fulfillment of the demand from customer 4. This customer is served by both trucks but from different origins.

After all sourcing decisions have been made a set of routes must be compiled so that each truck fulfills one (possible empty) feasible route. The sum of travelled distances must be minimized. Here a route is feasible if (a) the route starts unloaded at the initial position (the vehicle depot) (b) terminates empty at the depot (c) the pickup location of an OD-request is visited prior to the associated delivery location by the same vehicle (d) the capacity of the truck is not exceeded along the determined route and (e) no route duration exceeds a maximal duration T^{max}. The routing problem is similar to the pickup-and-delivery-problem (Parragh et al., 2008). We allow that the assignment of OD-requests to the vehicles is revised during the routing as long as the maximal vehicle payload is not exceeded.

2.3. Integrated Decision model

The here proposed mathematical optimization model consists of three parts. Each model part is built by a set of linear constraint families. The first part addresses the specification and completion of the OD-requests (Paragraph 2.3.1). The second part ensures the compilation of feasible vehicle routes (Paragraph 2.3.2). A set of constraint families that couples sourcing decisions with routing decisions forms the third part of the decision model (Paragraph 2.3.3).

2.3.1. Request completion

As proposed by Hennig et al. (2012) we use the family of continuous non-negative decision variables q_{rvk} to code the quantity that is picked up at warehouse k by vehicle v for contributing to the fulfillment of the demand associated with customer r.

$$\sum_{r\in R}\sum_{v\in F} q_{rvk} \le P_k \ \forall k \in W \tag{1}$$

$$\sum_{k\in W}\sum_{v\in F} q_{rvk} = Q_r \ \forall r \in R \tag{2}$$

$$0 \le q_{rvk} \le C_v \ \forall r \in R, v \in F, k \in W \tag{3}$$

The quantities associated with all OD-requests originating from warehouse k must not exceed the supply quantity stored at this warehouse (1). The sum of quantities associated with all OD-requests terminating in the location at customer r has to cover the requested quantity (2). The quantity associated with an OD-request must be non-negative but must not exceed the capacity of the vehicle which will serve this OD-request (3).

2.3.2. Vehicle routing model

We incorporate the commonly used mixed-integer linear program formulation for the routing part of the here presented model. It is based on the declaration of the family of binary decision variables x_{ijk} that code the decision whether vehicle k travel along arc $(i;j)$ or not. The proposed constraints ensure that the feasible route conditions (a)-(e) stated in 2.2 are respected by the generated set of routes. Since these constraints can be found in any vehicle routing programming model, we do not present these constraints here due to limited available space. We refer to Golden et al. (2008) for a detailed description.

2.3.3. Coupling vehicle routing and request completion decisions

$$M \cdot u_{rvk} \geq q_{rvk} \ \forall\, r \in R, v \in F, k \in W \tag{4}$$

$$u_{rvk} \leq \sum_{i \in N} x_{ikv} \ \ \forall k \in W, v \in F, r \in R \tag{5}$$

$$u_{rvk} \leq \sum_{i \in N} x_{irv} \ \ \forall k \in W, v \in F, r \in R \tag{6}$$

A second family of binary decision variables u_{rvk} is deployed in order to represent the information if vehicle v visits warehouse k as well as customer location r and k is visited earlier than r by v. If and only if vehicle v provides the aforementioned service ($u_{rvk}=1$) then warehouse k can contribute to the fulfilment of demand from customer r using vehicle v ($q_{rvk}>0$) (4). The parameter M is a sufficient large number. A service by vehicle v that contributes to the fulfilment of request r from warehouse k is only possible if vehicle v visits both warehouse k (5) as well as customer r (6).

2.3.4. Common objective function

$$Z^{dist} = \sum_{i \in N} \sum_{j \in N} \sum_{f \in F} d(i;j) \cdot x_{ijf} \rightarrow min. \tag{7}$$

Sourcing decisions related to the completion of OD-requests as well as truck routing decisions are coordinated so that the total sum of driven distances (7) is minimized.

2.4. Test case definition

We construct test cases for the computational evaluation of the proposed decision model. The common setup of all instances is as follows. A fleet of 10 identical vehicles is available and each deployed vehicle travels at constant speed of one distance units per time unit. All vehicles start their operations (if deployed) from the central depot at position (0;0) and terminate their trip there. Three warehouses and $N^{REQ}:=|R|=50$ customer locations are randomly positioned around the depot in the area $[-250;250]\times[-250;250]$. We generate five different sets of locations $\alpha \in \{0;1;2;3;4\}$. We define a maximal route duration T^{max} for each of the generated location sets. The values for T^{max} (expressed in time units) are taken from the set $\{1000;2000;15000\}$, whereas the largest T^{max} value represents the situation without any effective route duration limitation.

In order to evaluate the capabilities to compile least distance routes while the completion of OD-requests is considered, we refrain from postulating capacity scarceness. Therefore, neither the available capacity of the trucks nor the stored quantities in the warehouses lead to active capacity limitation constraints. Each customer requests 1 capacity unit.

Overall, we have $|\{0;1;2;3;4\}|\cdot|\{1000;2000;15000\}|=5\cdot 3=15$ test cases available. An individual test case is described by the pair $(\alpha; T^{max})$.

3. A MATHEURISTIC MODEL SOLVING APPROACH

This section addresses the setup of the solving approach for the outlined integrated sourcing and vehicle routing problem. In Subsection 3.1, the framework of the proposed heuristic is motivated and described. In Subsection 3.2, we introduce several configuration options for the matheuristic. In Subsection 3.3, the metaheuristic used to solve the vehicle routing part of the integrated model is outlined.

3.1. The matheuristic framework

For solving instances of the integrated sourcing and routing problem, we propose the usage of a heuristic approach based on a genetic algorithm (GA) metaheuristic. We use the GA to determine adequate x_{ijk}-values.

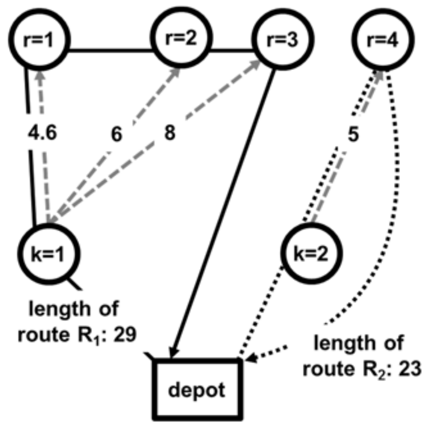
$$Z^{OD} = \sum_{k\in W}\sum_{r\in R}\sum_{v\in F} c^*_{rvk} \cdot q_{rvk} \tag{8}$$

We have seen that the set of constraints (*1*)-(*3*) of the sourcing sub-model is equal to the constraint set of the well-known Hitchcock Distribution Problem (HDP, “transportation problem”) (Hitchcock, 1941) if we use the objective function (8) with the OD-arc-cost coefficients c^*_{rvk} Since a least cost solution of the transportation problem can be found very efficiently (e.g. by linear programming or specialized algorithms like the MODI-method), we incorporate CPLEX as linear program solver for the determination of the OD-request quantities q_{rvk}. The consistency of the q_{rvk}-values determined by CPLEX with the x_{ijk}-values determined by the GA is ensured by the consideration of the u_{rvk}-values in the coupling constraints (4)-(6). In the following, we describe how we can ensure that the coupling constraints (4)-(6) can be fulfilled if the GA takes care about the vehicle route generation and if CPLEX determines the OD-requests.

In order to ensure the consistency between the proposed x_{ijk}-values and the proposed q_{vrk}-values with respect to the feasibility of the integrated model, it is necessary to establish a bidirectional communication link between the two model solving algorithms, i.e. between the GA and CPLEX. The information exchanged via this link ensure that it is possible to find feasible u_{rvk}-values that couple the x_{ijk}-values with the q_{rvk}-values. As soon as CPLEX has instantiated the q_{rvk}-values it submits the proposed values to the GA. In a preprocessing step, the GA uses the q_{rvk}-values for the determination of the OD-requests to be covered by the vehicle routes. Then, the GA starts determining feasible vehicle routes. Since the maximal vehicle capacity is considered while CPLEX determines the q_{rvk}-values (3), it is always possible to fulfill the generated OD-requests. The GA tries to minimize the necessary travel distances.

This hybrid algorithm combines a heuristic decision making algorithm, the GA, with an exact mathematical programming approach (linear programming). Both algorithms commonly solves the model of the combined sourcing and routing model. ,

The generated OD-requests influence the travel distance of the vehicle fleet. It is necessary to select appropriate OD-requests by selecting appropriate q_{rvk}-values in order to contribute to the minimization of the sum of travelled distances. The HDP does not know the vehicle routes and, therefore, it does not have information about the impacts of q_{rvk}-values to the Z^{dist}-value. Therefore, it is necessary to adjust die coefficients c^*_{rvk} so that the OD-requests that can be served with low costs are selected preferentially. The following c^*_{rvk}-value adjustment strategy is incorporated. We establish a feedback link from the GA to CPLEX to enable the adjustment of the c^*-values. Along this feedback link, we send two types of information. First, we submit for each vehicle v the travel length $L(v)$ of the determined route. Second, we calculate the sum $S(v)$ of the distances $d(k;r)$ of the OD-requests assigned to vehicle v for all vehicles v and submit this information to CPLEX. Before CPLEX is used to update the q_{rvk}-values, a preprocessing calculation is invoked. Here, the OD-distance-values c^*_{rvk} are updated by setting $c^*_{rvk} := {}^{L(v)}\!/_{S(v)} \cdot c^*_{rvk}$. The fractional value represents the number of distance units to be driven by vehicle v in order to bridge one distance unit between warehouse k and customer location r. Hence, it distorts the Euclidean distance between k and w using information from executable and feasible vehicle routes. In case that the fractional value is larger than 1 then the decision to serve r from k using vehicle v becomes less beneficial, since detours are expected. In case that the fractional value is less than 1 then several OD-request quantities can be consolidated and the (partial) fulfillment of r from k using vehicle v becomes more promising. The update of the c^*_{rvk}-values can be interpreted as "learning of the best OD-requests with respect to the minimization of the total sum of travel distances".



i-th distance matric

	r=1	r=2	r=3	r=4
k=1	**4,5**	**6**	**8**	11
k=2	10	5	4	5

i+1-th distance matric

	r=1	r=2	r=3	r=4
k=1	**7,02**	**9,36**	**12,48**	11
k=2	10	5	4	23

Figure 3.1: Example for the route-based update of the c^*_{rvk}-values

An example for the update of the c^*_{rvk}-values based on routes is presented in Figure 3.1. Two vehicles are incorporated in order to serve four customers from two warehouses. For vehicle 1 route R_1 is proposed (continuous black lines) and vehicle 2 should execute route R_2 (dotted black lines). The three customers served by vehicle 1 are served from warehouse $k=1$ so that it is $S(1):=4.6+6+8=18.6$. Similarly, it is $S(2):=5$. We assume that the length of route R_1 is $L(1):=29$ and the length of route R_2 is $L(2):=23$. We get the correction factors $L(1)/S(1):= 29/18.6\approx1.56$ as well as $L(2)/S(2):=23/5\approx4.6$. The distances between warehouse 1 and the customers 1, 2 and 3 are multiplied with 1.56 (black-shaded entries in the matrices in the right part of Figure 3.1) and the distance between warehouse 2 and customer 4 is multiplied with 4.6 (gray-shaded entry). After the update of the i-th distance matric we get the $i+1$-th distance matric and in the updated matric the ranking of assignments with respect to the fulfillment costs c^*_{rvk} are different compared to the i-th matric. For example, the distance from warehouse 1 to customer 4 was the most expensive distance in the *i*-th matric but in the *i+1*-th matric it is the relation between warehouse 2 and customer 4 that comes with the largest costs.

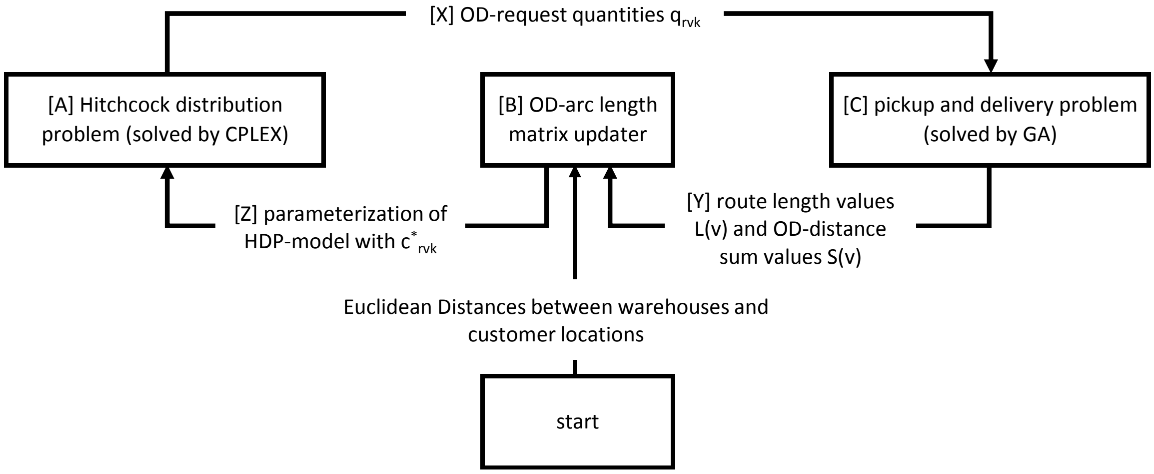


Figure 3.2: Learning matheuristic

The algorithmic framework of this learning matheuristic is shown in Figure 3.2. The main objects of the algorithm are the HDP-part [A], the PDP-component [C] and the updater of the distance matric [B] linking the warehouses with the customer requests as explained in Subsection 2.2. These components are connected by the information channels [X]-[Z]. The matheuristic starts with the submission of the Euclidean distances between each pair consisting of a warehouse as well as a customer location to the distance matric updater [B]. This updater initializes the c^*_{rvk}-values by the Euclidean distance *d(k;r)*. These values are forwarded along link [Z] for the setup of the recent HDP-instance [A]. After CPLEX has solved this HDP-instance it submits the determined q_{rvk}-values along link [X] to the PDP-component [C]. Here, the OD-requests are setup (or updated) and the recent PDP-instance is processes by the GA. After the GA has terminated it forwards the route length values as well as the sum of length of OD-arcs served by a vehicle to the distance matric updater [B] along link [Y]. Herewith, an algorithm cycle is completed. The mutual exchange of information between the HDP-part as well as the PDP-part enables the matheuristic to combine different OD-request sets with different route sets.

A pseudo-code representation of the matheuristic procedure is given in Figure 3.3. First the OD-distances are initialized and set to the Euclidean distances between source location and target location (a). Next, the resulting initial HDP-model is solved (b) and the first OD-request set is instantiated (c). The initial population of (infeasible) solutions of the integrated model is generated (d). During the evolution of this population ((e)-(m)), infeasibilities are eliminated and the objective function value is successively reduced. At the beginning of an iteration it is checked whether the termination criterion is fulfilled (e). If this is not true then, it is checked if the OD-requests used in the subsequently generated solution proposals require an update (f). In this case, new OD-requests are generated. For this purpose, the c^*_{rvk}-values are updated by determining the *L(v)*-values as well as the *S(v)*-values for the best solution found so far (g). The updated c^*_{rvk}-values are used to re-parameterize a next HDP-model which is solved afterwards (h). The updated q_{rvk}-values are used to update the set of OD-requests (i). From now on, all subsequently generated solution proposals use the new OD-requests (k) but previously generated solution proposals use the old OD-requests. The procedure jumps back to the beginning of the iteration loop (l) but it returns the best solution found as soon as the termination criterion is fulfilled (m).

Procedure matheuristic()

(a) set (c^*_{rvk}) to Euclidean distance between warehouse k and request location r for all vehicles v;

(b) (q_{rvk}):=solve_HDP(c^*_{rvk});

(c) ODREQ:=complete_OD_requests((q_{rvk}));

(d) create initial_GA_population(ODREQ);

(e) **while** not (termination_criterion_fulfilled)

(f) **if**(ODREQ_update_necesessary) **then**

(g) (c^*_{rvk}) = update_from_best_solution_identified();

(h) (q_{rvk}):=solve_HDP(c^*_{rvk});

(i) ODREQ:=complete_OD_requests(q_{rvk});

(j) **end** if;

(k) generate_new_population_using_genetic_operators(ODREQ);

(l) **end** while;

(m) **return(**best solution found**)**

Figure 3.3: Pseudo-code of the matheuristic

3.2. Configuration of the matheuristic procedure

Request Completion Control (RCC). The function *complete_OD_requests((q_{rvk}))* implements the completion of the OD-requests. We consider two realizations RRC (random request completion) as well as ARC (adaptive request completion). In the first mentioned configuration, a warehouse is selected at random for each request. We use this configuration as referential configuration in order to demonstrate the existence of a positive impact of the more elaborated ARC-strategy. Here, the q_{rvk}-values determine the sources to be selected for each customer. The function *complete_OD_requests()* determines how the matric update component [B] process the received information.

Request Update Control (RUC). In order to control the update of the OD-requests it is necessary to evaluate the criterion **ODREQ_update_necesessary** within each iteration of the GA. Several updating rules are compared. For reference purposes, we test the strategy NU (NO UPDATE), in which no update is applied after the source locations have been fixed in step (c). The NU-strategy represents the situation with consecutive sourcing and routing decisions (no integration of sourcing and routing decisions). First, a source is selected for each OD-request. Second, vehicle routes are constructed in order to fulfill the OD-requests but the request portfolio remains unchanged. In contrast, the following two strategies represent integrated strategies, in which sourcing and routing decisions are mixed. If we follow the strategy DU-*y* (DYNAMIC UPDATE *y*) then we invoke an update of the OD-requests every *y* iterations. Finally, the strategy AU-*z* (ADAPTIVE UPDATE *z*) invokes the OD-request update only, if there have been no improvement of the average objective function value among the population by the GA for *z* iterations. NU, DU-*y* as well as AU-*z* determine when the HDP-component [C] receives new information along link [Y] from the GA.

Only offspring solution proposals generated after the update of the warehouse selection use the new warehouses. Solutions that have been created with the old warehouse-to-customer assignments remain unchanged. Due to this setting it is possible to maintain solution proposals with different warehouse-to-customer assignments into the population so that a more diversified sampling of the search space is enabled.

3.3. Genetic algorithm route generator

While instances of the HDP-model can be solved by well-known solver software, it is necessary to develop a problem-specific (meta-)heuristic to solve instances of the PDP-model. We have decided to configure a metaheuristic algorithm based on the idea of a GA since we are not aware of appropriate neighborhoods that are a prerequisite for using neighborhood-based search algorithms. The GA develops several parallel trajectories throughout the search space determined by the integrated decision model. Along each trajectory, a sequence of solutions of the proposed model is generated with the intention to improve the objective function value whenever a new solution is generated. Information are regularly exchanged between these trajectories by crossover-operators with the goal to explore the overall search space (identification of promising areas of the search space). Arbitrary variations of the search trajectories are implemented by mutation operators in order to avoid premature convergence of search trajectories in local optima. Locally acting hill climbing procedures are used to exploit the vicinity of a generated solution in the search space and to repair infeasibilities.

Our GA maintains a population of solution proposals (individuals). In each iteration (e)-(m) of the procedure shown in Figure 3.3 this population is evolved. New solution proposals (offspring) are generated and replace some (or all) of the already generated solution proposals. We use a $\mu+\lambda$-population model. Here, μ offspring are merged with the existing λ solutions in an intermediate solution pool. All individuals in the intermediate population are evaluated, infeasibilities (w.r.t. capacities and makespan) are quantified and the objective function value is determined. The evaluated individuals are ranked, so that a feasible solution proposal precedes each infeasible proposal. The feasible proposals are sorted by increasing objective function values. The infeasible solutions are sorted by increasing infeasibilities. Only the first λ solutions according to this ranking are kept and form the next population.

The initial population is formed by solution proposals generated by a construction procedure (d). This procedure distributes the customer locations randomly among the vehicles and inserts the determined warehouses at an arbitrary route position prior to the customer visit. In case that the generated route duration exceeds T^{max}, randomly selected requests contained in this route are shifted to another route until the route duration becomes less than T^{max} or if no other vehicle is able to serve an additional request without exceeding the maximal allowed route duration.

Each offspring solution is generated from two parental solutions by a precedence preserving crossover-operator that merges the routes of a vehicle from two donating solutions (the parents). Again, T_{max}-exceeding are tried to be resolved by the aforementioned shifting of requests towards other vehicles if possible. Each generated offspring solution proposal is slightly and randomly varied by one of several mutation operators.

The population evolution process is stopped as soon as the average objective function value of the population members have not been improved for 20 iterations.

4. COMPUTATIONAL EXPERIMENTS

4.1. Experimental setup

Within preliminary experiments, we have identified the best suitable parameters for the update rules DU-y and AU-z. We set $y=100$, so that the OD-requests are updated every 100 iterations as long as DU-y is used. For AU-z, we set $z=10$, so that the OD-requests are updated as soon as the average objective function value of the population has not been improved for 5 iterations.

We apply the six different matheuristic configurations introduced in Subsection 3.2 to each of the 15 test cases whose construction is outlined in Subsection 2.4. One experimental run is defined as the 5-tuple $(\alpha;T^{max};RCC;RUC;\Omega)$ where $\alpha\in\{0;1;2;3;4\}$, $T^{max}\in\{1000;2000;15000\}$, $RCC\in\{RRC;ARC\}$, $RUC\in\{NU, DU\text{-}100, AU\text{-}10\}$. Since the GA is a randomized search procedure, we repeat each matheuristic run 5 times using the seeding $\Omega\in\{0;1;2;3;4\}$. In total, $5\cdot3\cdot2\cdot3\cdot5=450$ individual computational experimental runs are executed.

We observe three performance indicators. Each is averaged over all seeding α and Ω. The average sum of exceedings of T^{max} (measured in time units) over all vehicles is recorded and saved in $M(T^{max};RUC;RCC)$. Second, we store the best found value of the objective function (7) in $Z(T^{max};RUC;RCC)$. Finally, we save the number of deployed vehicles in $V(T^{max};RUC;RCC)$.

4.2. Presentation and Discussion of Results

Table 4.1: Average results from the different experimental runs with different matheuristic configurations.

T^{max}	RUC	RCC	$M(T^{max};RUC;RCC)$	$Z(T^{max};RUC;RCC)$	$V(T^{max};RUC;RCC)$
15000	NU	RRC	0	4545	1
	NU	ARC	0	4156	1
	DU-100	RRC	0	7613	1,13
	DU-100	ARC	0	4379	1
	AU-10	RRC	0	4854	1
	AU-10	ARC	0	4188	1,07
2000	NU	RRC	0	8692	5,53
	NU	ARC	0	5162	3,73
	DU-100	RRC	0	10201	7,73
	DU-100	ARC	0	8194	6,06
	AU-10	RRC	0	5479	3,93
	AU-10	ARC	0	5046	3,733
1000	NU	RRC	280	10590	9,6
	NU	ARC	0	5676	7,4
	DU-100	RRC	664	12769	9,47
	DU-100	ARC	75	7770	9,07
	AU-10	RRC	280	10590	9,6
	AU-10	ARC	0	5480	6,93

Table 4.1 contains the calculated average performance indicator values. These values enable us to derive first conclusions about the appropriateness of the proposed approach. Furthermore, we can quantify the expected monetary benefit from integrating sourcing and routing decisions. Independently from the allowed route duration T^{max}, we observe that the DU-strategy leads to the worst results. Compared to the NU- as well as the AU-approach, the total travel distance sum associated with the NU-generated approach is significantly worse than the travel distances associated with the solution proposals generated by the two other approaches.

Independently from the applied request update control strategy and from the T^{max}-values, we observe that the adaptive request completion strategy (ARC) leads to improved travel distances compared the random request update strategy (RRC). In most of the cases, the number of vehicles incorporated by the ARC-based approaches is reduced compared to the number of vehicles incorporated by the RRC-based approaches.

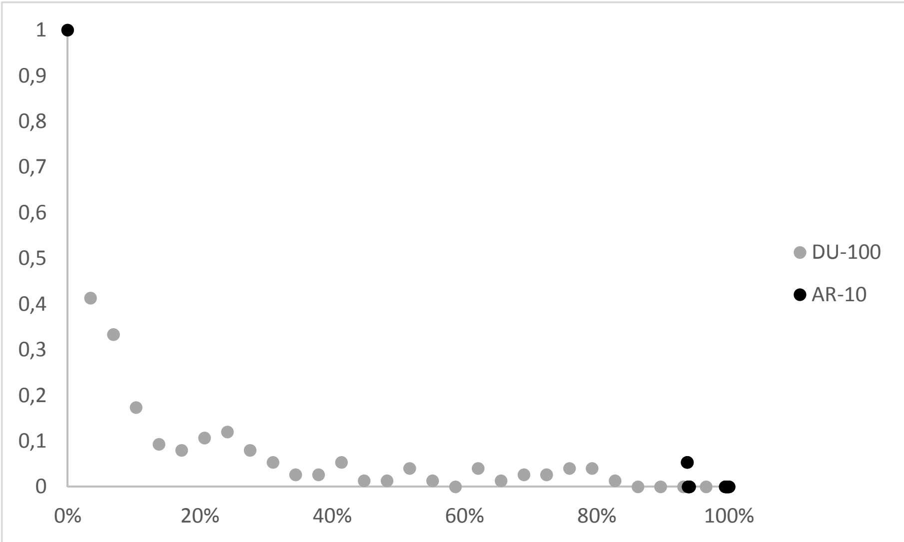


Figure 4.1: Variations of the assignment from warehouses to requests

In order to find out the reasons for the quite different behavior of DU-100 as well as AR-10, we observe the update activity during the progress of the matheuristic. Figure 4.1 shows the frequency and intensity (number of varied warehouse-to-customer assignments) in the problem instance *(4;2000)* in the application of the matheuristic with seeding $\Omega=1$. The objective function values of the best feasible solution identified were 4532.30 (AR-10) and 6560.93 (DU-100). First, AR-10 applies significantly less update calls than DU-100 and the AR-10 updates occur very late during the procedure execution. Second, during the quite seldom updates, only few modifications of the warehouse-to-customer assignments are carried out. It seems that AR-10 applies updates more carefully. However, these updates seem to be more effective than the frequently performed updated and re-assignments of warehouses to customers established by DU-100.

If the available route duration is rather short ($T^{max} \in \{1000;2000\}$), i.e. if the vehicle route length is short, then the integration of sourcing and routing decisions is promising. For T^{max}=2000 time units, we can save (5162-5046)/5162≈2.2% of travel costs and for T^{max}=1000 time units, the saving is (5676-5480)/5676≈3.5%.

We have learned that the DU-strategy fails here. The high frequency of the variation of the OD-requests seems to compromise the route compilation.

We have observed the development of individual c^*_{rvk}-values during the procedure is executed in order to check if and to understand how detour-information are acquired during the matheuristic processing. Figure 4.2 shows the development of the HDP-distance between warehouse 2 and customer location 4 in the problem instance *(4;2000)* if the matheuristic with seeding Ω=1 is applied. The continuous lines represent the corresponding c^*-value as used in the HDP for determining the pickup location associated with request 4. All values are scaled into the interval from 0 to 1 in order make the values comparable. The dots printed on the header line indicate when an update is invoked. DU-*100* and AR-*10* exhibit a quite different learning curve. While DU-*100* shows a quite rapid learning during the first 10% of the experiment AR-*10* makes less progress here. However, between 10% and 30% AR-*10* reduces the c^*_{rvk}-values more significantly. From approx. 32% AR-*10* maintains a larger c^*_{rvk}-value but at the end, both strategies DU-*100* as well as AR-*10* lead to the same final c^*_{rvk}-value.

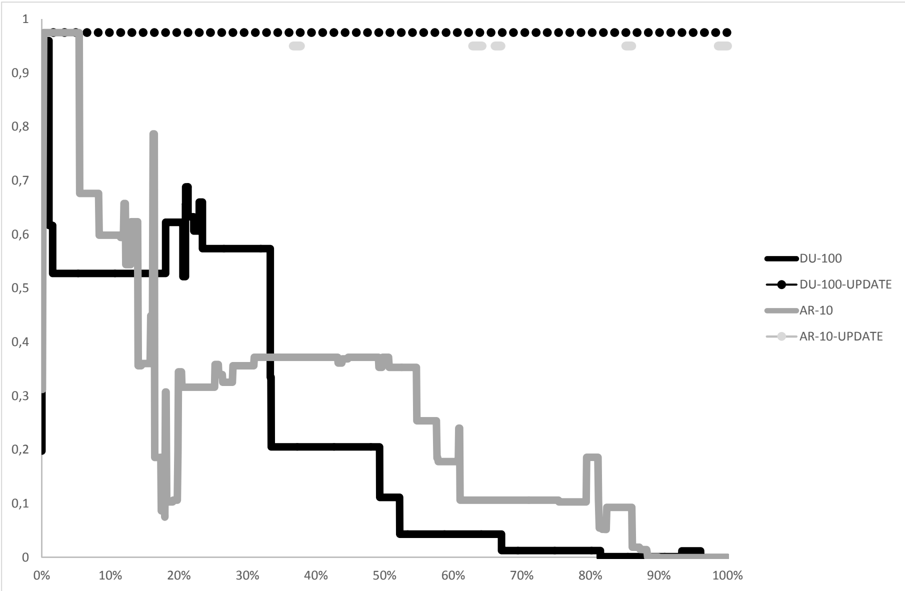


Figure 4.2: Learning of c^*_{rvk}-values during the algorithm running time (0%=start until 100%=end)

5. CONCLUSIONS

We have analysed a new class of vehicle routing problems in which sourcing decisions are made simultaneous with the vehicle routing decisions. A mathematical optimization model has been configured for this complex decision task. Here, this model integrates the well-known Hitchcock Distribution Problem model ("transportation model") with the pickup and delivery problem model. A matheuristic approach has been proposed for identifying high quality solutions of the integrated model. This approach combines a linear programing approach to the Hitchcock Distribution Problem sub-model and a genetic algorithm for the vehicle routing sub-model. Computational experiments have been executed. The here reported new algorithmic approach seems to be promising. However, additional analysis and experiments are needed in order to increase the algorithm performance but the reported experimental results are promising.

From the reported experimental results we learn that significant reductions of the total travel distances between 2.2% and 3.5% are possible. Furthermore, the number of required vehicles can be reduced by around 6% in case that sourcing as well as routing decisions are made simultaneously. Here, future investigations have to go into further details in order to find those setups with the highest cost saving potentials.

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