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Towards an IT-based Planning Process Alignment: Integrated Route and Location Planning for Small Package Shippers

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ABSTRACT

To increase the efficiency of delivery operations in small package shipping (SPS), numerous optimization models for route and location planning decisions have been proposed. This "operations research view" of defining independent problems has two major shortcomings: First, most models from literature neglect crucial real-world characteristics, thus making them useless for small package shippers. Second, business processes for strategic decision making are not well-structured in most SPS companies and significant cost savings could be generated by an IT-based support infrastructure integrating decision making and planning across the mutually dependent layers of strategic, tactical and operational planning. We present an integrated planning framework that combines an intelligent data analysis tool, which identifies delivery patterns and changes in customer demand, with location and route planning tools. Our planning approaches extend standard Location Routing and Vehicle Routing models by crucial, practically relevant characteristics like the existence of subcontractors on both decision levels and the implicit consideration of driver familiarity in route planning.

Keywords

Business process alignment, supply chain management, logistics planning, small package shipping

INTRODUCTION

Competition in the logistics sector significantly increases driven by high cost pressure and new legal regulations. In particular, the new rules for CO2 emissions increase the pressure on logistics companies to improve their network efficiency. On the strategic level, the network efficiency of small package shippers (SPS) mainly depends on the locations of hubs and depots. Since customer demand as well as customer locations vary within the planning horizon of a strategic decision, which is about 10-15 years, a reasonable approximation of those values and a powerful planning tool are required. Concerning these strategic decisions, a huge body of solution methods for Location Routing Problems (LRP) have been proposed in literature to determine the optimal number and location of depots while considering the underlying vehicle routing.

However, existing approaches neglect a very important trend in package delivery: SPS involve subcontractors in the delivery of packages in order to increase the cost efficiency. In detail, two types of subcontracting are common for SPS: a) long-term subcontraction of unprofitable delivery areas and b) subcontraction of single customers on a daily basis in order to tackle demand peaks and to avoid deliveries to unprofitable customers. Thus, on the strategic level, depots of subcontractors must be considered in the LRP such that the assignment of unprofitable delivery areas to a specific subcontractor is simultaneously decided with the planning of the self- owned depots since those decisions are clearly related.

On the operational level, an efficient allocation of customers to vehicles and the related delivery sequences have to be determined, considering practical aspects such as customer time windows. The routing operations of SPS have several additional characteristics that have to be considered in the planning process. On the one hand, subcontracting options should be included into the applied planning model, i.e., the model should allow to subcontract single customers if this leads to a cost reduction. On the other hand, the explicit exploitation of driver familiarity with routes and customers plays a prominent role in SPS routing operations. If customers or neighborhoods are visited repeatedly by the same driver, the driver becomes acquainted with the territory and the customer locations therein and thus both service quality and driver efficiency can be increased (Smilowitz et al., 2009). Moreover, service consistency creates a bond between customer and driver that not only enhances the customer's loyalty but may also improve the reputation of the package shipping company (Smilowitz et al., 2009; Christofides, 1971). Any solution method to achieve these benefits has to aim at repeatedly assigning each driver to the same customers and regions within the whole depot area, thus enabling the driver to gain enhanced experience in servicing its regular customers.

Furthermore, business processes for strategic decision making are not well-structured in most SPS companies and do not yet make use of the potential cost savings, which could be generated by an IT-based support infrastructure. Such an IT-platform integrates decision making and planning not only along the supply chain but also across the mutually dependent layers of strategic, tactical and operational planning. As strategic decisions set the constraints for short-term planning, a suitable IT platform supporting strategic business processes should anticipate their impact on a wide range of subsequent operational problems not by "guessing" this impact based on crude abstractions. Instead, simulations based on realistic assumptions and the constraints imposed should be performed. Whereas the pursuit of such an integration might have been too ambitious 10 years ago, the ongoing decline of the cost of computational resources on the one hand and the ongoing rise in cost of physical logistics on the other hand makes it obvious that an optimal alignment will require (and has to solve) models of increasing integration and complexity.

In this paper, we present a framework for an integrated logistics planning tool. Its main focus lies on the tools that allow to determine optimal numbers and locations of depots while paying attention to the currently established network structure, as well as daily delivery tours. The underlying optimization models are tailored to consider all of the practically relevant aspects described above, such as the existence of subcontractors and the exploitation of driver knowledge. To this end, the framework makes use of the logistics information system used by carriers to collect data of daily deliveries. Appropriate tools are designed to analyze collected data including customer demand, customer locations, flow within the network etc. in order to approximate the future development in the delivery areas. Furthermore, results of the data analysis support the SPS by identifying general problems in the delivery organization, such as unused depot capacity or unbalanced routes. To the best of our knowledge, we are the first designing such a framework including various location and route planning tools based on recently developed, state-of-the-art heuristic solution methods.

The remainder of the paper is structured as follows: First, we provide a brief overview of literature related to route and location planning of SPS. Subsequent, we describe the general design of our framework and detail the characteristics and functionality of the associated tools with special emphasis on the location and route planning tools. Finally, we give a short conclusion.

PRELIMINARIES AND LITERATURE

In this section, we give a brief overview of the relevant location planning literature, give a short introduction to route planning models and provide a review of the literature addressing the industry considerations that are central to this work: driver learning aspects and subcontracting options.

Location Planning

Of the vast body of literature on LRP, the following works are of relevance to our paper because they present the currently best-performing methods for solving basic LRPs, which form the core of our problem at hand. We refer the reader to Min et al. (1998) and Nagy and Salhi (2007) for an extensive literature review.

Prins et al. (2007) present a cooperative metaheuristic based on lagrangian relaxation and granular tabu search (TS). In the location phase, they solve a Facility Location Problem to form supercustomers out of each route. Subsequently, the vehicle routes are optimized by means of the granular TS heuristic. The algorithm alternates between the two phases, which collect information about the most promising edges in order to use them in the next iterations. The heuristic proposed by Duhamel et al. (2010) adapts an evolutionary local search (ELS) to optimize the initial solution found by a multi-start GRASP approach, based on an extended Clarke and Wright algorithm. ELS starts with building giant traveling salesman tours which are split into LRP solutions and are then further improved.

Route Planning

The VRP is one of the oldest and most discussed optimization problems in the Operations Research literature. The goal of the VRP is to find a set of minimum-cost vehicle routes that cover a set of nodes (customers) so that each route starts and ends at a central depot and each customer is serviced. Among the numerous variants of VRP that have evolved over the years, the

VRP with time windows (VRPTW) is probably the most important and most studied. It requires that each customer is serviced within an individual time window and it can be used to model many real-world distribution management problems, like e.g., parcel deliveries in various industries or solid waste collection. Due to its computational complexity, VRPTW can only be solved by exact methods for moderate-sized instances, a fact that has given rise to a large number of successful (meta-)heuristic solution methods that are able to produce high-quality solutions for instances of reasonable size in limited time (Bräysy and Gendreau, 2005a;b; Gendreau et al., 2008).

Routing with Driver Learning Aspects

As described in the first section, routing in SPS companies pays attention to the available drivers' local knowledge. The following works addressing this aspect are mostly based on fixed or partially fixed service territories. Such a preassignment of drivers to service territories not only yields driver familiarity benefits in a straightforward manner but also simplifies the daily vehicle routing operations to a great extent.

Wong and Beasley (1984) divide the complete depot area into a number of fixed delivery areas based on historical demand data, each of which is visited by a single driver. Due to this preassignment of the drivers to territory, the VRP to solve becomes a traveling salesman problem, which greatly simplifies the operational planning. The disadvantage of such an approach is the flexibility forfeited by having fixed driver assignments, which makes it difficult to absorb daily workload fluctuations and thus yields route configurations that are suboptimal concerning the total traveled distance.

This tradeoff between driver familiarity benefits and routing flexibility is investigated in comprehensive simulation studies by Haughton (2008). He studies the effect of exclusive territory assignment on route design efficiencies as compared to non-exclusive assignment, where drivers are assigned flexibly based on the day-to-day demand situation.

Zhong et al. (2007) pool customers into "cells" and, based on historical demand data, assign only a given proportion of all cells to fixed "core areas", which are always visited by the same driver. Customers located in the "flex zone" around the depot are not assigned to core areas but assigned flexibly to different drivers depending on their workload because they can be reached by practically every route without making long detours. The remaining customers, which are located in the space between the core areas are also assigned on a daily basis.

Haugland et al. (2007) present a two-stage approach to the districting problem for the VRP. In the first stage, a number of service territories, called "districts", are designed. In the second stage, the order of delivery of the customers within each district is optimized for each day of delivery by means of a local search heuristic which basically moves border customers from one district to another until the objective function cannot be improved any further.

Routing with Subcontracting Options

Besides fixed subcontracted delivery areas, SPS additionally assign customers to subcontractors in a flexible manner if the available vehicle capacity is not sufficient. The VRP with private fleet and common carriers (VRPPC) represents this practical problem. In a VRPPC, deliveries to customers can either be performed by a vehicle of the private fleet located at the depot, or be assigned to a subcontractor. In general, a fixed price for subcontracting a customer is assumed which depends on the demand (Bolduc et al., 2008).

Available heuristics to solve the VRPPC are quite scarce. Bolduc et al. (2008) propose a perturbation metaheuristic and present a large set of benchmark instances with up to 483 customers on which the solution method is tested. Côté and Potvin (2009) use an adapted TS heuristic, originally proposed by Cordeau et al. (1997), to solve the VRPPC which outperforms the approach of Bolduc et al. (2008) on benchmark instances in terms of solution quality. However, similar to the currently best-performing heuristic, a TS with ejection chains (Potvin and Naud, 2010), total computation times are quite high.

ROUTING AND LOCATION PLANNING FRAMEWORK

In practice, big SPS companies require a sizeable IT infrastructure to manage business from administrative processes to the tracking and tracing of packages. Every day millions of incoming packages, each assigned to a specific customer, are scanned and delivered. From these processes, SPS companies retrieve and collect all data relevant for the strategic and operational decisions. The data collection is performed continuously and information about customers served, such as address, package volume, delivery date and time, number of delivery attempts, etc. are stored.

On the strategic level, data collected over several years builds the basis for location decisions. Here, sophisticated data analysis methods are applied to, e.g., forecast the distribution of customers within the areas of interest and the future customer demand. Subsequent, location problems specifically tailored to the practical problem at hand are solved with the approximated values. On the operational level, data collected about the routes performed in the past are, e.g., used to estimate a driver's familiarity with customers. This information is considered when constructing delivery regions as well as in the daily routing.

Our Route and Location Planning (RLP) framework and the associated modules are illustrated in Figure 1. The RLP-Server is directly connected to the SPS Daily Operations Server (DOS) of the SPS as well as to the SPS Data Warehouse (DW). The DOS transfers the daily delivery routes to the handhelds of the drivers in the morning, and collects all delivery information such as customer signatures, failed deliveries, performed routes etc. in the evening. This information is stored on the DW. From there, the RLP-Server retrieves the data and a Data Analysis module preprocesses and stores the relevant information. Furthermore, the module performs a number of simple tests and analyses to enrich the data, which serves as input to the Route Planning and the Data Forecast module.

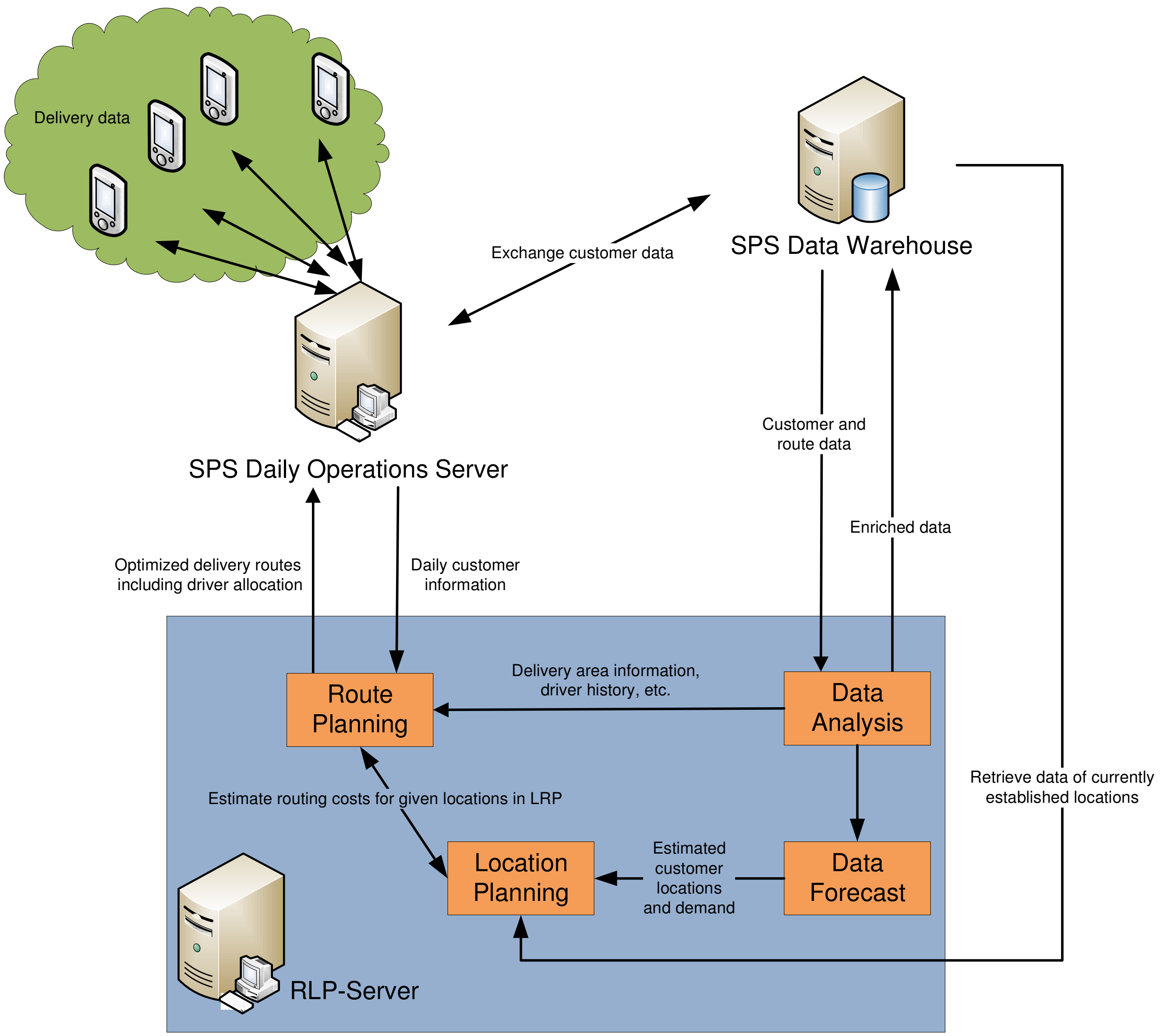

Figure 1. The RLP-Framework

Route Planning considers the current day's customer set and package volumes as well as information gathered from Data Analysis, such as delivery histories of drivers and possibly established delivery areas. The determined delivery routes and the drivers' allocation to the routes are transmitted to the DOS in order to feed the drivers' handhelds.

The Location Planning module works on approximated customer data provided by the Data Forecast. Additional information about currently established locations is retrieved from the DW. For estimating the routing costs resulting from a given network structure, Location Planning cooperates with the Route Planning module.

Data Analysis

The Data Analysis module processes all information about customers served, such as address, package volume, delivery date and time, number of delivery attempts, routes on which deliveries are performed, the associated driver and vehicle used. Based on this data, Data Analysis performs preliminary tests to detect fundamental problems with the network organization and delivery operations as the following examples show:

- When comparing the average total package volume of a route and the capacity of the vehicle used, a high amount of unused capacity signals that reassigning vehicles to routes might be beneficial. Results might also show that some routes exceed the maximum allowed travel time while other drivers return to the depot one or two hours before finishing time.
- Unprofitable depot locations are indicated by the following two measures. First, the degree of capacity utilization is determined by comparing average daily package volume to the maximum number of packages that can be handled in the depot. Second, the average distance of the depot to all customers can be used as a simple measure to indicate the quality of the chosen location within a delivery area. If the average distance is clearly higher than the average over all depots, a relocation might be reasonable.

Moreover, Data Analysis enriches stored data, e.g. by analyzing delivery patterns of customers. For example, if delivery to a regular customer is only successful in the evening, the customer is assigned a time window. Thus, the information is integrated in the future tour planning in order to reduce the number of delivery attempts.

Another important task of Data Analysis is the examination of performed vehicle routes in order to record for each driver the set of visited customers as well as for each of these customers the visiting frequency and the days of the visits. Together with an estimation of daily demand for each customer, this information is vital for the Route Planning module to be able to consider driver knowledge in the generation of service territories and daily routes.

Data Forecast

A reliable forecast is of great importance to strategic decisions like location planning that involve high investments. Due to the large amount of collected data and the high number of analyses performed by the Data Analysis module, the information basis for forecasting future customer demand values and the customers' geographic distribution is sufficiently large. In addition to the data collected by Data Analysis, the Data Forecast module incorporates demographic information published by the government, such as official figures about, e.g., the growth of population in the concerned regions. In order to reduce the complexity, Data Forecast aggregates customer into clusters, and determines forecast values for the average number of stops as well as the average package volume per day in those areas.

Location Planning

Depot location decisions are of high strategical importance since they strongly influence the efficiency of daily route operations as well as the total network and thus the company's profitability. Based on a good approximation of the changes in customer locations and package volume, we use an LRP to determine optimal number and locations of depots of an SPS. Our Location Planning module bases on a model extending the classical LRP. Since the currently established network exists, we consider relocation aspects within the optimization process (Stenger et al., 2010a). In detail, we use the current network as initial solution and consider fixed costs of establishing and closing depot locations during the optimization process. Furthermore, we also include subcontracted depots in the LRP which helps to decide with which subcontractor a delivery contract should be closed (Stenger et al. 2010c). By doing so, delivery areas are fixedly assigned to a subcontractor in the long term. The simultaneous consideration of all these aspects in combination with reasonable forecast values ensures that resulting depot locations are close to the optimum for real-world applications.

The solution method proposed for the LRP with subcontracting options (LRPSO) iterates between a location and a routing phase. In the location phase, a simulated annealing heuristic, combined with a tabu list (TL) to avoid cycling, determines which depots to open, close or swap as well as which depots to switch from self-operation to subcontracting and vice versa. The influence of all moves on the routing costs is quickly evaluated by means of the savings algorithm. In order to reduce the complexity, we introduce the Adjustable Area of Influence (AAOI) concept which restricts the recalculation of routing costs on a small area around the depot modification. In the subsequent routing phase, given a fixed depot location setting, a

Variable Neighborhood Search (VNS) algorithm based on CROSS-exchange neighborhoods is used to solve the underlying Multi-Depot VRP (MDVRP). An overview of the algorithm is depicted in Figure 2. The solution method proved its competitiveness against state-of-the art methods on benchmark sets available for the standard LRP.

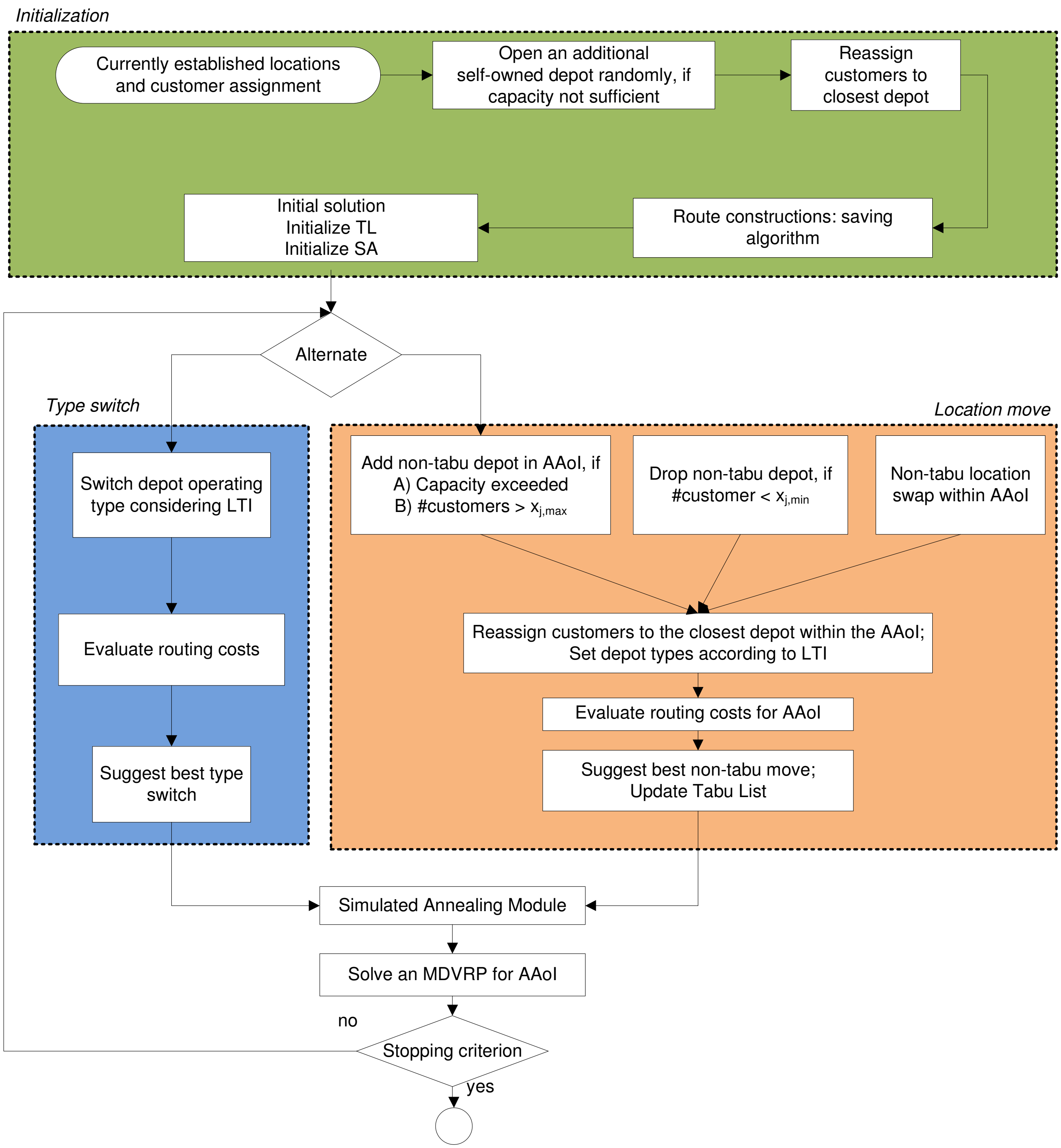

Figure 2. Overview of the combined SA and VNS solution method for the LRPSO

Route Planning

On the operational level, delivery tours from given depots to the daily set of customers have to be determined. For this task, the Route Planning module incorporates algorithms for several VRPs that differ in the characteristics of the planning problem. For optimizing the delivery routes of one single depot and a given set of vehicles, we use an Ant Colony Optimization (ACO) algorithm which proves able to find high-quality solutions to VRPTW in reasonable time (Schneider et al., 2010b). Due to the large size of real-world problem instances, we make use of graph sparsification methods in order to reduce the complexity and to achieve short computation times (Doppstadt et al., 2011). To incorporate relevant practical considerations, Route Planning offers two methods addressing driver familiarity aspects and one method studying subcontracting options. These are detailed in the following sections.

Driver Learning

All of the above described works considering driver learning aspects neglect the existence of time windows. However, up to 60% of the orders of our industry partner are time-definite, which is also consistent with the industry statistics given in Campbell and Thomas (2009). If time windows are considered, routing flexibility is not only needed to achieve distance-efficient route configurations but also to fulfill customer delivery time requirements. Thus, the value of routing flexibility increases, which is likely to have significant negative effect on the solution quality of any approach based on fixed delivery areas.

Therefore, Route Planning incorporates an approach that forgoes any fixing of delivery areas. Instead, it accounts for delivery consistency by using driver specific travel and service times and thus explicitly considering driver knowledge. In this way, drivers have an incentive to stay in familiar areas due to shorter driving and service times while still maintaining their flexibility (Schneider et al., 2010a). Route Planning uses an ACO algorithm as solution method: Each ant represents a single driver and creates a route dependent on driver-specific heuristic information and pheromone values that are traded off against each other. The ACO procedure, the complementary local search method and all parameter settings are described in Schneider et al. (2010b).

To address the common fixed area approach of SPS, Route Planning also offers an intelligent method for generating partially fixed service territories (and performing the resulting daily routing). As described above, this procedure is relevant because 1) strong driver familiarity benefits can be achieved by this straightforward method, 2) it is implemented in one form or the other in most SPS companies, and 3) the simplification of daily routing operations achieved by a preassignment of drivers to service territories, i.e., route optimization based on fixed areas is much easier since a TSP has to be solved instead of a VRP. This makes it possible to concentrate on other relevant real-world constraints and characteristics, such as lunch breaks for drivers, route duration issues, etc. within the routing problem.

Route Planning's method for routing with "fixed" areas bases on the work of Wong and Beasley (1984). Instead of completely fixing the delivery areas, which results in significant problems if demand varies strongly or if time windows are to be considered, we design fixed service territories which only include a predefined proportion of customers (cf. Zhong et al., 2007). In order to balance the tradeoff between familiarity effects and routing flexibility, the remaining flexible customers are integrated into the routes that serve the fixed service territories based on the actual workload on each particular day.

The solution approach can be divided into three basic phases, which are illustrated in Figure 3 (cf. Schneider et al., 2010c).

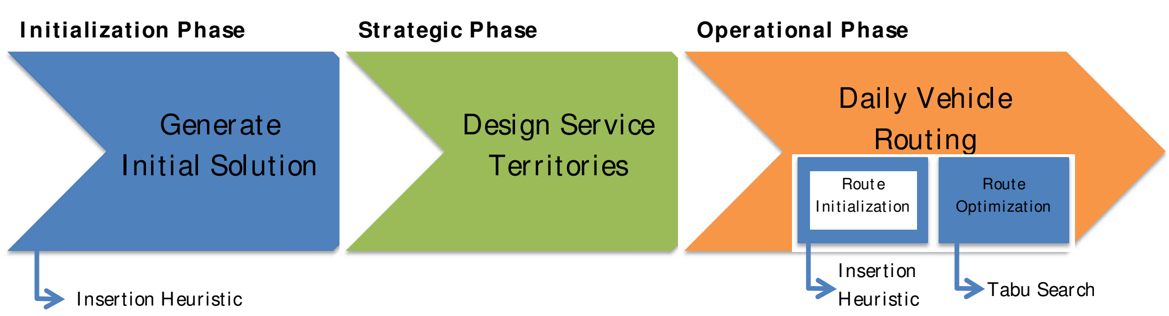

Figure 3. Three-phase approach to solve a VRP with fixed service territories

1. Similar to Wong and Beasley (1984), our initialization phase generates independent solutions for a number of sample days, on which a VRPTW is solved without considering consistency requirements. For the routing in this phase, we implement a simple insertion heuristic to quickly generate solutions for the sample days. We adopt the objective function and the time window handling introduced by Nagata et al. (2010), which allows the temporary violation of time window and capacity constraints.

2. In the strategic phase, we design a number of fixed service territories based on the initial solutions created in the previous phase. The aim of this strategic phase is to generate a subdivision of the delivery area which is robust with respect to both consistency and flexibility requirements. The building of service territories has to rely on historical data from the initialization phase, because the demand in the consecutive operational phase is not known in advance.
3. In the operational phase, daily routing is conducted on the basis of the fixed service territories developed in the strategic phase. The generated service territories contain a predefined percentage of all customers and are exclusively visited by a single driver. The remaining customers are assigned to the service territories on a daily basis. Thus, the problem to be solved in this operational phase is a VRPTW with the additional feature, that part of the customers are preassigned to a specific driver. As solution method, a TS heuristic based on the intra-route optimization method Or-opt and a simple relocation heuristic for the inter-route exchange of customers is used. In order to ensure that feasible routes are generated in the daily routing phase, we permit the exceptional expulsion of individual customers from their service territory.

Subcontracting

If the SPS outsources parts of its daily deliveries to subcontractors, the underlying VRP model significantly changes to a VRPPC, where customers can either be served by owned vehicles or by a subcontractor. In this case, we apply a VNS heuristic based on cyclic-exchange neighborhoods (Stenger et al., 2010b). Compared to the state-of-the-art approaches, the heuristic proves able to significantly reduce the computing times without a significant loss in solution quality. This is highly relevant for practical purposes, where the time available for determining daily route plans is tightly restricted. Furthermore, we extended the VRPPC to multiple depots, in order to decide to which subcontractor a customer should be assigned or from which self-owned depot it should be served. The resulting problem is called Multi-Depot VRP with Private Fleet and Common Carriers (MDVRPPC) (Stenger et al., 2010b).

CONCLUSION

In this paper, we described an integrated logistics planning framework which is designed to meet crucial requirements of the small package shipping industry. The framework incorporates a data analysis and forecast tool as well as tools for location and route planning. The information obtained from the analysis and forecast tools serves as input for the planning tools. Concerning the route planning, we identified the integration of subcontractors as well as the consideration of driver familiarity as crucial factors. We presented two intelligent approaches to deal with driver familiarity – an approach with semi-fixed delivery areas solved with a TS heuristic and an ACO approach with driver specific travel and service times. In order to incorporate subcontractors in the daily routing, we described the multi-depot extension of the VRP with private fleet and common carriers. Additionally, considering subcontractors is also highly relevant making depot location decisions. In order to simultaneously determine optimal depot locations as well as the assignment of delivery areas to subcontractors, we presented an LRP with Subcontracting Option (LRPSO) that extends the classical LRP.

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